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Alcohol-impaired motorcyclists versus car drivers: A comparison of crash involvement and legal consequence from adjudication data

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ABSTRACT

Introduction: Driving under the influence (DUI) increases the probability of motor-vehicle collisions, especially for motorcycles with less protections. This study aimed to identify commonalities and differences between criminally DUI offenses (i.e., with a blood alcohol concentration (BAC) of 80 mg/dL or higher) committed by motorcyclists and car drivers. *Methods:* A total of 10,457 motorcycle DUIs and 8,402 car DUIs were compared using a series of logistic regression models, using data extracted from the documents of adjudication decisions by the courts of Jiangsu, China. *Results:* The results revealed that offenders from the high-BAC group (i.e., 200 mg/dL or higher) accounted for more than 20% of the total DUI offenses, and were more likely to be involved in a crash and punished with a longer detention. Motorcyclists had a higher likelihood of crash involvement, and were also more likely to be responsible for single-vehicle crashes associated with higher odds of injury sustained, compared to alcohol-impaired car drivers. In the verdict, motorcycle offenders were more likely to receive a less severe penalty. *Conclusions:* Interventions are clearly required to focus on reducing in the high-BAC group of offenders. For alcohol-impaired motorcyclists, their risks of crash and injury against BAC climb more steeply than the risks for car drivers. The factors including frequent occurrences, uncertainty of detection, and short-term sentences may weaken the deterrence effect of the criminalization of motorcycle DUI. *Practical Applications:* The traffic-related adjudication data support traffic safety analysis. Strategies such as combating motorcycle violations (e.g., unlicensed operators or driving unsafe vehicles), undertaking education and awareness campaigns, are expected for DUI prevention.

1. Introduction

Alcohol-impaired driving has been recognized as a major contributor to fatal road crashes. A report released by the World Health Organization (WHO) shows that 5% to 35% of all road deaths around the world are reported as alcohol related (WHO, 2018). A host of effective strategies has been used to address this problem, including enhancing law enforcement against impaired driving (Chang et al., 2012), education and awareness campaigns (Beck, 2009; Chao et al., 2009), and the use of technology (e.g., ignition interlocks; Shulman-Laniel et al., 2017). Among them, enacting and enforcing legislation on driving under the influence (DUI) is wildly adopted. Overall, 174 countries have national drink-driving laws in place, and 136 of them have blood alcohol concentration (BAC) threshold limits (WHO, 2018).

In mainland China, there is a rapid increase in both motor transport and alcohol consumption; laws against DUI mirror those found in other nations. Driving or riding any motor vehicle after drunkenness (i.e., BAC $\geq$ 80 mg/dL), regardless of causing a crash or not, is recognized as a dangerous driving crime. According to the Eighth Amendment to the Criminal Law of China, which was put into effect on 1st May 2011, the crime of dangerous driving is a misdemeanor punishable by penalties of up to six months detention with a fine. Additionally, drivers' licenses are disqualified, and offenders are banned from reapplying for five years. The lesser offense of "driving after drinking" (i.e., BAC ranged from 20 to 80 mg/dL) is also illegal but is not deemed as a criminal offense. That is, offenders are imposed on administrative sanctions including license suspension and fining. Non-motor vehicle DUI offenses, including drunk driving of bicycles, tricycles, and electric bicycles with a BAC above 80 mg/dL, are also banned by the Road Traffic

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Safety Law of China. These non-motor vehicle offenders suffer administrative penalties as well.

The criminalization of alcohol-impaired driving is a contentious issue, although it has a deterrent effect that allows for a reduction in deaths and injuries caused by DUI (Asbridge et al., 2004; Chang et al., 2020). Evidence has been found that after the criminalization of drunk driving from 2011, there is a weak downward trend of road-traffic injuries in China (Zhao et al., 2016; Fei et al., 2020). It is different from that in the United States where some states do not classify impaired driving offenses as crimes, while others consider DUI a misdemeanor criminal offense (NCSL, 2019). In China, drivers are arrested and charged with dangerous driving if their BACs surpass 80 mg/dL. Once convicted, offenders' criminal records will not be eliminated for life. As the punishment in criminal procedure is much more severe than in administrative procedure (i.e., a criminal conviction has serious adverse effects upon one's career or education options; Ewald, 2019), criminalizing DUI results in some punishments seen as overly strict. For example, once Chinese government officials are convicted of dangerous driving, they are removed from public office.

The criminal charge of DUI occurs with great frequency resulting in a high cost of adjudication and sanctioning (Miller et al., 2006), which is another issue of criminalizing DUI that is a concern. In addition to DUI, three other types of behaviors (i.e., speeding, overweight overloading, and illegal transportation of dangerous chemicals) are charged with the crime of dangerous driving in China. According to the data released by Supreme People's Procuratorate (SPP) of China, the crime of dangerous driving is the most frequently prosecuted, with a total of 322,041 offenders in 2019, accounting for 17.7% of all prosecutions (SPP, 2020). Among all the offenders convicted of dangerous driving, the data extracted from the document of adjudication decisions (DADs) by Supreme People's Court of China (SPC) indicated that 99% involved DUI (SPC, 2016). A large amount of government funds have been spent on legal and adjudication services, and corrections programs (including incarceration; Wang, 2020). In light of these events, policymakers are seeking appropriate approaches for controlling DUI crime effectively, without further restraining budgets and worsening prison conditions.

Compared to car drivers, motorcyclists are not protected by a vehicle body, which makes them a particularly vulnerable group of road users. The report from the National Highway Traffic Safety Administration (NHTSA) revealed that in the United States, 27% of the motorcyclists involved in fatal crashes had BACs of 80 mg/dL or higher (NHTSA, 2018). Additionally, motorcycle riding requires more skills and coordination. Riding motorcycles under the influence of any amount of alcohol significantly decreases operators' ability of safe driving (Ahmed et al., 2020). The operators may experience a loss of balance and coordination, which makes it hard to maneuver around obstacles without falling. Evidence has been found that alcohol-impaired motorcyclists are almost twice more likely to be involved in single-vehicle crashes than in multiple-vehicle crashes (Shankar, 2003; Sarmiento et al., 2020; Thompson et al., 2020). The motive of criminalizing DUI is to maintain public safety and protect people from harm by other people engaged in illegal activity. However, according to the law of China, alcohol-impaired motorcyclists who are at-fault in non-collision crashes are charged with the crime of dangerous driving as well. This "tough on crime" policy not only leads to considerable DUI convictions but also raises the debate on the rationality of criminalizing motorcycle DUI that is less dangerous to the general public.

Each DUI criminal offense is associated with an adjudication describing judgment or decision by a judge after all of the evidence is reviewed. All Chinese criminal judgments (except those involving state secrets and juvenile crimes) are disclosed on the official website (it's mandatory). The published judgments (i.e. DADs) on DUI offenses contain a lot of information, such as offenders' demographics, measured BAC, vehicle type, collision damage, traffic violations associated with DUI, and sentencing outcomes (i.e., detention time, fines amount, and probation). Therefore, it provides a new perspective for assessing the severity of crash and punishment of alcohol-impaired driving and riding respectively.

Focusing on 18,859 offenses of DUI convicted of dangerous driving, which are recorded in DADs by the courts of Jiangsu, China, the present research aims to investigate factors that affect crash involvement and legal consequence of DUI offenses committed by motorcyclists and car drivers. Additionally, it aims to identify and analyze differences between motorcycle DUI and car DUI with respect to BAC levels, offenders' demographics, environment-related factors (i.e., season, time of day), and the aggravating and mitigating circumstances considered in sentencing. The term "car" used in this study refers to an automobile that has door beams and a roof to provide protection from impact or rollover, including a sedan, truck, van and so forth. The term "motorcycle" refers to a two-wheeled or three-wheeled vehicle that is powered by a motor and has no pedals.

After the introduction, the rest of this paper is organized as follows. Section 2 summarizes related work and Section 3 presents the data sources and the hypotheses. In Section 4, the procedure of analysis is explained. Results on the descriptive statistics and factors influencing crash involvement and legal consequence of DUI offenses are reported in Section 5. Discussions and implications are presented in Section 6. The study is concluded in Section 7 with remarks on future research.

2. Literature review

Traditional economic models of criminal behavior have straightforward predictions that raising the expected cost of crime via increasing apprehension probabilities or punishments deter the crime (Becker, 1968). Thus, government agencies commonly use deterrence-centered penalties to prevent the occurrence of alcohol-related crashes and fatalities (e.g., driving prohibition, incarceration, and fines; Chan et al., 2017). Some research supports the idea that punishment curbs offending. For example, Asbridge et al. (2004) found that Canada's first per se law that criminalized DUI had a specific deterrent effect that resulted in a reduction of drinking-driver fatalities. Based on the daily aggregate road-traffic injury (RTI) data provided by the First-Aid Service Command Center in Guangzhou from 2009 to 2012, Zhao et al. (2016) confirmed that the criminalization of drunk driving in China since 2011 had led to moderate reductions in RTIs. By tracking felony-level DUI probationers in Texas, USA for a period of 8 years, results from a series of event history analyses indicated that the severity of punishment had a significant effect on the success of probation for DUI probationers (Lee & Teske, 2015).

However, not all DUI studies report consistent findings about the deterrence doctrine (Cavanaugh & Franklin, 2012; Bouffard et al., 2017). William et al. (1991) reported the evidence that punitive legislation aimed at general deterrence was less effective at reducing drunk driving fatalities than mandatory seat belt use laws and beer taxes. By comparing rehabilitation and punishment strategies with data from a sample of DUI offenders, Taxman and Piquero (1998) found that rehabilitation sentences appeared to reduce the likelihood of recidivism more than punishment sentences. Similarly, following a sample of 514 incarcerated drunk drivers for 24–45 months in Alberta, Canada, Weinrath and Gartrell (2001) observed that shorter sentences were less effective in discouraging drunk driving recidivism, while sentences longer than 6 months did not produce additional benefits.

BAC level is generally used as the prima facie evidence for objectively defining criminally DUI. The study by Stringer (2018) unveiled that alcohol was not the primary causal agent in low BAC crashes (i.e., BAC between 10 and 70 mg/dL). But as BAC increased, drivers were more likely to be responsible for the crashes they were involved in. Many countries such as China, United States, and Canada have set 80 mg/dL as the legal BAC limit for DUI. This is supported by the evidence that once BAC is above 80 mg/dL, drivers are more likely to be involved in fatal crashes (del Río & Alvarez, 1999; NHTSA, 2018). BAC levels not only have influence on the risk of crash involvement (Fell et al., 2010; Yao et al., 2018; Ahmed et al., 2020) but also affect punishments and sanctions on DUI offenses. The findings of Hansen (2015), consistent with deterrence theory, revealed that increasing the severity of punishment along BAC distribution was helpful to deter drunk drivers involved in fatal crashes.

Alcohol consumption is a very common factor associated with motorcycle crash involvement (Jou et al., 2012) in that it impairs riders' abilities to maintain balance while riding (Seiniger et al., 2012). By measuring basic riding skills considered important to motorcyclist safety, Creaser et al. (2009) found that the alcohol effects leading to more task performance errors were evident at BAC levels ranged from 20 to 80 mg/dL. Motorcycle riders have less protection in crashes. When a crash occurs, the threat of injury or death to motorcyclists is magnified by physical exposure compared to that of car drivers (Robertson et al., 2002; Hsieh et al., 2016; Medeiros & Nadanovsky, 2016; Thompson et al., 2020). Using a case-control study designed with New Zealand data, Keall et al. (2013) found that the rate of increase in fatal injury risk with increasing BAC was similar between motorcyclists and car drivers, but because of the nature of the vehicle, motorcyclists at BAC of 80 mg/dL had 20 times the fatality risk compared to car drivers.

The traffic-related information collected by the adjudication data system support the traffic safety analysis. For example, Costich and Slavova (2015) used the data from judicial system administrative agency in Kentucky, USA to evaluate the effect of the primary safety belt law implementation. By analyzing the difference in court dispositions and sentence outcomes between monitored and non-monitored DUI cases, Shinar (1992) found that the court monitoring was an effective tool in affecting the adjudication process, which had potential benefits for reducing DUI. However, to our knowledge, the adjudication data has not been previously attempted for analyzing the difference between motorcycle and car DUI offenses.

The objective of this study is to: (1) distinguish the criminally DUI outcomes in terms of crash involvement and judicial punishment for alcohol-impaired motorcyclists and car drivers, respectively, using the data extracted from DADs; (2) identify commonalities and differences between motorcycle and car DUI offenses associated with BAC levels; and (3) discuss current challenges and gaps in the criminalization of motorcycle DUI.

3. Data sources and hypotheses

3.1. Data sources

This study uses a rich DAD database of criminally DUI offenses provided by Jiangsu High People's Court of China. The analysis is administered by the judicial administrative authority of Jiangsu. Offenders' personal identification information is removed for privacy protection.

The database contains almost complete groups of documents issued in 2014 and 2015, and a part of the groups issued in 2012, 2013, and 2016. The five-year data are aggregately analyzed considering that no change occurs in the implementation of DUI law from 2012 to 2016, and assuming the temporal effect across the year is minimal. In order to process the unstructured texts in DADs, the method of text mining is applied to derive critical information from those texts. Keywords and key phrases are extracted to identify the terms that describe offenders' demographics, BAC values, vehicle type, collision damage, sentencing outcomes, and so forth. After removing the duplicate files and the files missing the information of vehicle type, BAC values and sentencing outcomes, 18,859 of DUI cases convicted of dangerous driving crime are studied, including 10,457 motorcycle DUI cases and 8,402 car DUI cases. There is no bias in the analysis since both car drivers and motorcyclists are evaluated for the same range of DUI (i.e., BAC $\geq$ 80 mg/dL).

3.2. Hypotheses

This study makes use of DAD dataset to unveil how crash involvement and judicial outcomes are influenced by BAC levels, vehicle type, and other risk factors. First, although Stringer (2018) found that low BAC (i.e., BAC between 10 and 70 mg/dL) was a largely inconsequential contributor to crashes, we expect that, for the criminally DUI offenses with BACs of 80 mg/dL or higher:

H1: the occurrence of crash involvement is positively associated with BAC levels.

Second, a number of case-specific factors will be considered in DUI sentencing, including offenders' DUI record and criminal history, impact of the DUI on any victims, regret or remorse expressed by offenders, and so on, while we believe that:

H2: BAC level plays a dominant role in DUI sentencing.

Third, vehicle type has effect on crashes and sentencing outcomes as well as BAC level. On one hand, as mentioned earlier, alcohol-impaired motorcyclists are more likely to be involved in crashes and responsible for single-vehicle crashes (Shankar, 2003; Sarmiento et al., 2020; Thompson et al., 2020). This yields the following hypothesis:

H3: offenders of motorcycle DUI are more likely to endanger their own safety for the same BAC level.

On the other hand, judges who handle motorcycle DUI cases are accordingly subject to the balance between the enforcement of law and the protection of motorcyclists' interests. They may give the motorcycle offenders more lenient sentences instead of following the principle of impartiality. We thus expect:

H4: judges are lenient with motorcyclists who are convicted of the crime of dangerous driving.

In the following sections, we will test the above four hypotheses using quantitative analyses.

4. Method

The differences between criminally DUI offenses committed by motorcyclists and car drivers are quantified using a series of logistic regression models, by which the effects of explanatory variables on crash involvement and legal consequences are estimated.

4.1. Measures

4.1.1. Outcome variable

Two sets of dependent variables are used to measure the outcomes of DUI offenses, namely, crash and punishment. The first set includes a dummy variable, CRASH INVOLVEMENT, which is denoted by Y_c and assigned a value of 1 if DUI offenders are involved in a crash that causes injury, death, or property losses to themselves or other people, and 0 if impaired drivers or riders are apprehended before a collision occurs. The collision pattern information such as whether offenders are involved in single or multiple vehicle crashes is also extracted.

The other set includes two discrete variables and one dummy variable characterizing the LEGAL CONSEQUENCE. Two kinds of legal penalties (i.e., criminal detention and fine punishment) are imposed on DUI offenders in China. According to the *Handbook on Convictions and Sentencing of DUI Cases in Jiangsu* (short for Handbook, released jointly by Jiangsu Higher People's Court, Jiangsu People's Procuratorate, and Jiangsu Public Security Department in 2013), the fine punishment should correspond to the detention time, that is, a detention of one month corresponds to a fine of ¥1,000. A maximum six-month detention is stipulated for dangerous driving crime, while fine amounts exceeding ¥6,000 are observed in 86 cases. Since only 6.6% of offenders are sentenced to a detention of four months or higher, the detention time denoted by Y_d is set as a discrete variable with 4 levels representing 0–1 months, 2 months, 3 months, and 4 months or higher. Accordingly, the outcomes of the fine penalty Y_f are classified into 4 levels representing the fines of ¥1,000 or less, ¥2,000, ¥3,000, and ¥4,000 or higher. A dummy variable Y_p is used to show whether offenders are put under probation. It is assigned a value of 1 if it is an aggravated DUI and probation is not applicable, and 0 otherwise.

4.1.2. Exposure variable

Both BAC level and vehicle type are regarded as exposure variables that measure the changes in DUI outcomes. According to the Handbook, for each 50 mg/dL increase in BAC, a one-month detention can be added to determine the benchmark sentence. Specifically, for offenders with BACs between 80–130 mg/dL the benchmark detention is one month, for offenders with BACs between 130–180 mg/dL it is two months, and so on. Since only 11.5% cases are observed with a BAC above 230 mg/dL, the measured BACs are grouped into four categories: 80–130, 130–180, 180–230, and >230 mg/dL, which is in line with the number of categories for criminal detention and fine punishment. The BAC level is accordingly characterized by a discrete variable X_{BAC}. A dummy variable X_v is used to define vehicle type, and is assigned a value of 1 for motorcycles, and 0 for cars.

4.1.3. Confounding factors

The following factors are regarded as confounders that influence both the dependent and independent variables.

- **Demographics**. Not all of the DADs reported offenders' socioeconomic status (e.g., gender, age, educational background) because such information is not a mandatory requirement for adjudication documents. However, it is provided by some DADs. Three variables characterizing gender ($x_{m,1}$), educational background ($x_{m,2}$), and age ($x_{m,3}$) are measured.
- **Time-related factors**. Most DADs record the date and the time of offenses, thereby extracting confounders in terms of season ($x_{m,4}$) and time of day ($x_{m,5}$). The variables describing seasons are defined according to the Bureau of Meteorology Category, China.
- **Aggravating circumstances for DUI sentencing**. The aggravating factors resulting in harsher punishments are mandatory to be recorded. Variables lead to a long-term detention including offenders with illegal and criminal records ($x_{n,1}$), DUI repeat offenses ($x_{n,2}$), unlicensed operators (including driving without a license, driving with an inappropriate license, and driving with a suspended license) ($x_{n,3}$), unsafe vehicles which do not comply with the safety standards ($x_{n,4}$), operating for commercial purposes ($x_{n,5}$), driving in safety enhancement zones (e.g., a limited access highway, express way, or downtown area) ($x_{n,6}$), driving with the intent of avoiding checks ($x_{n,7}$), and crash involvement (Y_c).
- **Mitigating circumstances**. These include no crash involvement, good behavior after being pulled over by police, showing remorse and desire to avoid a repeat DUI, and so forth. These circumstances are described by a single composite variable, which is denoted as $x_{n,8}$, indicating whether any of the mitigating circumstances occurs.

4.2. Statistical analysis

The effect of the exposure variable X_{BAC} is first estimated by a univariate regression model. The model is then modified by adding potential confounders separately to control confounding in the analyses. That is, the variation in DUI outcomes is explained by a set of regression models with two variables (i.e., X_{BAC}) and one of the confounders. The confounder, which owns a 95% level of confidence, is then selected as the explanatory variable for regressions with more than two independent variables (i.e., X_{BAC} and other confounders owing 95% level of confidence). For the model with crash involvement Y_c as the dependent variable, the potential confounders include gender, educational background, age, season, time of day, prior illegal and criminal records, DUI repeat offenses, unlicensed operator, unsafe vehicles, and driving in safety enhancement zones. Owing to the principle of equality in law, the offenders' demographics and time-related factors are not considered in the models that predict legal consequences. The confounding effects of the aggravating and mitigating factors on sentencing are examined. Remarkably, crash involvement is regarded as a confounder for the regression of legal consequences.

After justifying the decisive role of X_{BAC} on the outcomes of motorcycle and car DUIs, respectively, the exposure X_v, which indicates vehicle type is then added to the regression models with controls for BAC levels. The variation in damage facts is analyzed in terms of crash involvement (Y_c), single-vehicle crashes (denoted as Y_c^1), and single-vehicle crashes that cause injuries and death (denoted as Y_c^2). As detention Y_d and fines Y_f have multiple ordered categories, the effect of X_v is estimated by ordered logistic regressions. A binary logistic regression is established to compare the probation rate between motorcyclists and car drivers.

The multicollinearity issues are addressed by performing pairwise correlation analyses for the exposure variables and confounders as well as calculating the variance inflation factors for each regression model. A likelihood ratio test is performed to evaluate the regression performance, which compares the likelihood of the data under the full model against the likelihood of the data under a model with no predictors. The results of the logistic regression analyses are presented as odds ratios (OR) with 95% confidence intervals (CI).

5. Results

5.1. Descriptive statistics

5.1.1. Number of motorcycle DUI

55.4% of DADs provided by Jiangsu High People's Court are motorcycle DUI cases. The percentage is higher than the data released by SPC (i.e., the frequency of motorcycle DUI cases accounts for 37.7% across the country from January 2014 to September 2016; SPC, 2016). The province of Jiangsu is located in eastern China, with mild climate and flat terrain, which is suitable for riding motorcycles. Fig. 1 presents the number of private-owned vehicles in Jiangsu from 2000 to 2017, which is recorded by Jiangsu Statistical Yearbook. Motorcycles accounted for 95.80% of private-owned vehicles in 2000, which decreased to 14.92% in 2017. This is partly because of the rapid growth of private cars

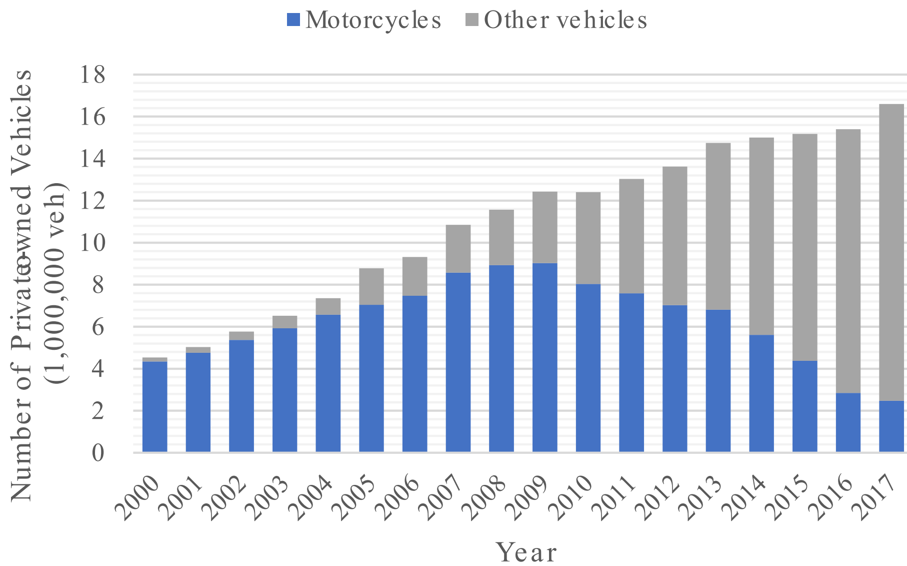

Fig. 1. Number of private-owned vehicles in Jiangsu, China from 2000 to 2017.

and partly because of the motorcycle restriction policies. Aimed at preventing adverse effects caused by motorcycles (i.e., motorcycle-related accidents, pollution, and congestion), motorcycle restriction policies were introduced to the cities of Nanjing, Changzhou, Suzhou, Nantong, Huai'an and other cities in Jiangsu; these restrictions included at least one of the following: stopping issuing motorcycle licenses to drivers who do not possessed a local hukou ("household registration"), banning motorcycles from downtown areas or main streets, compulsory scrapping of motorcycles in 10 years, and more.

Owing to the tough restrictions, cities in Jiangsu are facing a grim situation in that there are a large number of motorcyclists driving with an expired license or riding unlicensed motors that do not comply with safety standards. According to the statistics of traffic violations extracted from the DAD database, 37% of motorcyclists are unlicensed operators compared to a 5.2% proportion of car drivers. 23.7% DADs report unlicensed vehicles or without inspections, of which motorcycles account for 95%. It is accordingly inferred that actual motorcycle ownership is much larger than the official record. Unlicensed rider is one of risk factors resulting in alcohol-related crashes (Jou et al., 2012; Shaker et al., 2014), thereby exposing Jiangsu to a serious problem of motorcycle DUI.

5.1.2. BAC levels

A descriptive analysis of BAC levels is carried out to provide insight on the alcohol consumed by offenders (Table 1). Owing to the legal BAC limit, no cases are observed with a BAC less than 80 mg/dL. The percentages of slightly drunk offenses (i.e., with a BAC between 80 and 130 mg/dL) are 36.6% among motorcycle DUI cases and 31.7 % among car DUI cases. As to the categories of BAC between 130–180, 180–230, and >230 mg/dL, lower proportion of motorcycle DUI cases occur compared to car DUIs. The data grouped by vehicle type are analyzed using the Kolmogorov-Smirnov test (BAC is used as a continuous variable). The test results reject the null hypothesis that BAC distributions of motorcyclists and car drivers are similar ($D = 0.056$, $p < 0.001$). On average, alcohol-impaired motorcyclists have a slightly lower BAC than car drivers.

5.1.3. Crash involvement and legal consequences

Table 2 summarizes the outcomes of crash involvement and legal consequences across vehicle types. 72.4% of DUIs report crash involvement. The occurrence of crash involvement for motorcyclists is higher than that of car drivers (77.0% vs. 66.8%). The offenders without crash involvement are mostly apprehended by the police at various times, for example, at sobriety checkpoints, when they fall asleep on the road, when they pick a quarrel or trouble after drinking, and so forth.

As shown in Table 2, a majority of the offenders are sentenced to a detention of two months or shorter, namely 85.2% among motorcyclists and 79.8% among car drivers. The amount of the fines has a distribution trend similar to that of detention time. The highest percentage of fines is observed at ¥2,000 and ¥1,000 or less (45.1% and 25.4%, respectively). Probation is applicable for 38.3% of motorcyclists and 29.4% of car drivers.

5.1.4. Offenders' demographics and time-related factors

The information on offenders' gender is reported in 4,383 DADs (Table 3). As would be expected, 98.8% of DUI offenders are male, whereas the proportion of female drivers in China accounts for 31.5% as of 2019 (MPS, 2020). This is in line with the findings of

Table 1
Descriptive statistics of BAC levels.

BAC level (mg/dL)	Motorcycle			Car		
	n (%)	Mean	Standard Deviation	*n* (%)	Mean	Standard Deviation
80–130	3,831 (36.6)	106.6	13.7	2,668 (31.7)	108.0	13.4
130–180	3,368 (32.2)	154.3	14.4	2,778 (33.1)	155.0	14.3
180–230	2,136 (20.4)	201.9	14.1	1,937 (23.1)	201.7	13.9
>230	1,122 (10.7)	266.9	33.6	1,019 (12.1)	268.6	37.1
Total	10,457 (100.0)	158.6	54.2	8,402 (100.0)	164.6	54.9

Table 2
Descriptive statistics of crash involvement and legal consequence.

Categories	Variables	Values	Motorcycle n (%)	Car n (%)	All samples n (%)
Crash involvement	Involved in a crash Y_c	Yes	8,048 (77.0)	5,613 (66.8)	13,661 (72.4)
Legal consequence	Detention time Y_d (month)	≤1	4,080 (39.0)	2,911 (34.6)	6,991 (37.1)
		2	4,826 (46.2)	3,798 (45.2)	8,624 (45.7)
		3	961 (9.2)	1,043 (12.4)	2,004 (10.6)
		≥4	590 (5.6)	650 (7.7)	1,240 (6.6)
	Fine amounts Y_f (¥)	≤1,000	2,891 (27.6)	1,893 (22.5)	4,784 (25.4)
		2,000	4,758 (45.5)	3,738 (44.5)	8,496 (45.1)
		3,000	1,654 (15.8)	1,609 (19.2)	3,263 (17.3)
		≥4,000	1,154 (11.0)	1,162 (13.8)	2,316 (12.3)
	Probation Y_p	Not applicable	6,455 (61.7)	5,931 (70.6)	12,435 (65.9)

Table 3
Descriptive statistics of confounders of offenders' demographics and time-related factors.

Variables	Values	Motorcycle n (%)	Car n (%)	All samples n (%)
Gender $x_{m,1}$	Female	13 (0.5)	38 (2.2)	51 (1.2)
	Male	2,618 (99.5)	1714 (97.8)	4,332 (98.8)
	Missing	7,826	6,650	14,476
Educational background $x_{m,2}$	Uneducated	48 (3.0)	8 (0.8)	56 (2.1)
	Primary school	425 (26.4)	98 (9.6)	523 (19.9)
	Middle school	887 (55.1)	500 (49.0)	1,387 (52.7)
	High school	210 (13.0)	241 (23.6)	451 (17.1)
	College degree or above	40 (2.5)	173 (17.0)	213 (8.1)
	Missing	8,847	7,382	16,229
Age $x_{m,3}$	≥56	132 (7.8)	41 (3.7)	173 (6.2)
	18–25	101 (6.0)	59 (5.3)	160 (5.7)
	26–35	335 (19.8)	387 (34.7)	722 (25.7)
	36–45	583 (34.5)	418 (37.5)	1,001 (35.7)
	46–55	540 (31.9)	209 (18.8)	749 (26.7)
	Missing	8,766	7,288	16,054
Time of day $x_{m,4}$	Morning (5:00–9:59)	3,100 (29.9)	1,919 (23.1)	5,019 (26.9)
	Noon (10:00–14:59)	2,415 (23.3)	882 (10.6)	3,297 (17.7)
	Afternoon (15:00–18:59)	264 (2.5)	149 (1.8)	413 (2.2)
	Evening (19:00–22:59)	3,929 (37.9)	3,793 (45.6)	7,722 (41.4)
	Night (23:00–4:59)	646 (6.2)	1,577 (19.0)	2,223 (11.9)
	Missing	103	82	185
Season $x_{m,5}$	Spring (March–May)	2,487 (23.8)	1,950 (23.2)	4,437 (23.6)
	Summer (June–September)	2,402 (23.0)	2,000 (23.8)	4,402 (23.4)
	Autumn (October–November)	2,993 (28.7)	2,232 (26.6)	5,225 (27.7)
	Winter (December–February)	2,560 (24.5)	2,213 (26.4)	4,773 (25.3)
	Missing	15	7	22

Schwartz and Beltz (2018) and Portman et al. (2013) that percentage of female DUI drivers is much lower than that of males. Amongst five educational background groups (reported by 2,630 DADs), 74.8% of offenders are less educated (i.e., uneducated, primary, or junior education level), of which motorcyclists and car drivers account for 69.2% and 30.8%, respectively. The offenders' ages are recorded in 2,806 DADs and grouped into five categories: 18–25, 26–35, 36–45, 46–55, and ≥56. Offenders aged 36–45 are responsible for the largest number of offenses (35.7%), and offenders aged 18–25 contribute to the smallest number (5.7%). This is unlike the United States where teens and young adults are more likely to drive while impaired (NHTSA, 2018). In China, the minimum age for applying for a drivers license is 18 years old. It is a luxury for young adults to own a car, while in the United States it is quite common and is essential for daily life.

As would be expected, the evening period from 19:00 to 22:59 has the highest percentage of DUIs, accounting for 41.4% of DADs reported. The effects of seasonal variations are not obvious; it is observed that the largest number of offenses (27.5% of DADs that reported the date) occurred in autumn.

Table 4
Descriptive statistics of aggravating and mitigating circumstances.

Variables	Motorcycle n (%)	Car n (%)	All samples n (%)
Prior illegal and criminal records $x_{n,1}$	984 (9.4)	980 (11.7)	1,964 (10.4)
DUI repeat offenses $x_{n,2}$	91 (0.9)	73 (0.9)	164 (0.9)
Unlicensed operator $x_{n,3}$	3,866 (37.0)	434 (5.2)	4,300 (22.8)
Unsafe vehicles $x_{n,4}$	4,243 (40.6)	222 (2.6)	4,465 (23.7)
Commercial operating $x_{n,5}$	0 (0.0)	1,989 (23.7)	1,989 (10.5)
Driving in safety enhancement zones $x_{n,6}$	30 (0.3)	169 (2.0)	199 (1.1)
Avoid checks $x_{n,7}$	83 (0.8)	350 (4.2)	433 (2.3)
Mitigating circumstances $x_{n,8}$	10,373 (99.2)	8,305 (98.8)	18,678 (99.0)

5.1.5. Aggravating and mitigating circumstances

Table 4 illustrates the occurrence of the aggravating and mitigating circumstances considered in DUI sentencing. 10.4% of offenders are found with illegal and criminal records other than

DUI offenses. In line with the findings of Hansen (2015), strict punishment on DUI seems helpful to discourage a repeat of the offense; very few DUI repeat offenses are reported (0.9%). The challenges of unlicensed operators and unsafe vehicles have been mentioned above. 10.5% of offenders are found to be driving commercial vehicles transporting passengers and property while intoxicated; all of them are car drivers. 1.10% of offenses occurred in safety enhancement areas, which have a high risk of endangering public safety. 2.3% of offenders have the intent to avoid checking. The number of motorcyclists driving in safety enhancement zones or avoiding checks are lower than those of car drivers. The mitigating factors are considered almost in all DADs (99.0%).

5.2. Associations between BAC, confounding factors and crash involvement

5.2.1. Pairwise associations

A univariate logistic regression is first used to examine the unadjusted association between BAC levels and crash involvement. As shown in Table 5, DUI with high BAC has an increased likelihood of crash involvement. Compared to offenders who are slightly drunk (i.e., with a BAC range from 80 to 130 mg/dL), driving at a BAC higher than 230 mg/dL is 4.47 and 3.95 times more likely to be involved in a crash for motorcyclists and car drivers, respectively.

The estimated effect for each potential confounder is from logistic regression models with controls for BAC levels. Offenders' demographic characteristics (such as gender, age, educational background) are not found to significantly affect the likelihood of crash involvement. Likewise, whether car drivers operate vehicles for commercial purposes is not found as a statistically significant predictor. These variables are thus not presented in Table 5.

The odds ratios reveal that winter has higher odds of crash involvement than summer and spring for both motorcycle and car DUIs. Contrary to our expectation, although the highest proportion of DUIs occurred in the evening, motorcycle DUIs are approximately 43% more likely (i.e., 1/0.70 = 1.43) to be involved in a crash in the morning than in the evening. For car drivers, the highest likelihood of a crash occurring for alcohol-impaired driving is at noon. Because sobriety checkpoints are usually set up in the evening when impaired driving often occurs, it seems helpful to prevent alcohol-related crashes.

Offenders with a prior illegal or criminal offense are associated with less frequency of crash involvement. They are assumed to respond to the past punishment and consequently avoid the reoccurrence of offenses, which criminologists call "specific deterrence." That is, the experience of punishment helps to reduce the likelihood of criminal acts by those who have previously committed them (Stafford & Warr, 1993). Similarly, offenders who have a prior arrest or conviction for DUI are less likely to be involved in a crash. Particularly, motorcyclists who have previously been caught for impaired riding are approximately four times less likely (1/0.25 = 4) to be involved in a crash. A similar phenomenon is observed in Yao et al. (2018), which found that offenders with drinking problems had a lower risk of crash involvement at any time of the day.

As would be expected, offenders who are unlicensed or driving unsafe vehicles are more likely to be involved in a crash. Because driving a car without a license is less common compared to riding an unlicensed motorcycle, the effect of unlicensed car drivers on alcohol-related crashes is not statistically significant. Offenders are assumed to drive more carefully in safety enhancement zones, owing to the consensus that this act is dangerous and will lead to a harsh punishment.

5.2.2. Adjust odds ratios

Binary logistic regression is performed to examine the major determinants of alcohol-related crashes. The key confounding factors statistically significant in the models with controls for BAC are set as independent variables of the regression model. As a preliminary analysis, all independent variables have to be tested for their independence. Spearman's correlation coefficients indicate weak correlations amongst dependent variables (r ranged from −0.09 to 0.29 for motorcycles, and from −0.08 to 0.23 for cars); therefore,

Table 5
Risk factors of crash involvement.

Factors	Values	Motorcycle		Car	
		Unadjusted OR (95% CI)	Adjusted OR (95% CI)	Unadjusted OR (95% CI)	Adjusted OR (95% CI)
BAC X_{BAC} (base: 80–130 mg/dL)	130–180	2.13 (1.91–2.37)***	2.10 (1.89–2.35)***	1.65 (1.48–1.84)***	1.67 (1.49–1.86)***
	180–230	3.57 (3.10–4.13)***	3.54 (3.06–4.10)***	3.19 (2.80–3.65)***	3.26 (2.85–3.74)***
	>230	4.47 (3.67–5.48)***	4.51 (3.69–5.56)***	3.95 (3.32–4.73)***	3.99 (3.34–4.79)***
Season $x_{m,5}$ (base: spring)	summer	0.75 (0.66–0.86)***	0.81 (0.72–0.91)***	0.65 (0.57–0.75)***	0.71 (0.64–0.80)***
	autumn	0.88 (0.78–1.00)	n.s.	0.89 (0.78–1.01)	n.s.
	winter	1.67 (1.45–1.93)***	1.80 (1.58–2.05)***	1.22 (1.06–1.40)**	1.33 (1.18–1.49)***
Time of day $x_{m,4}$ (base: morning)	noon	0.72 (0.63–0.82)***	0.70 (0.61–0.79)***	1.28 (1.07–1.55)**	1.22 (1.03–1.45)*
	afternoon	0.68 (0.51–0.92)*	0.64 (0.48–0.87)**	0.78 (0.55–1.12)	n.s.
	evening	0.70 (0.62–0.79)***	0.72 (0.65–0.81)***	0.63 (0.56–0.71)***	0.61 (0.56–0.68)***
	night	1.16 (0.92–1.47)	n.s.	1.05 (0.91–1.22)	n.s.
Prior illegal and criminal records $x_{n,1}$ (base: no)	yes	0.82 (0.70–0.96)*	0.75 (0.64–0.89)***	0.78 (0.67–0.90)***	0.76 (0.66–0.88)***
DUI repeat offenses $x_{n,2}$ (base: no)	yes	0.25 (0.16–0.39)***	0.25 (0.16–0.40)***	0.49 (0.30–0.79)**	0.46 (0.28–0.75)**
Unlicensed operator $x_{n,3}$ (base: no)	yes	1.45 (1.32–1.61)***	1.34 (1.21–1.49)***	1.12 (0.91–1.39)	n.s.
Unsafe vehicles $x_{n,4}$ (base: no)	yes	1.49 (1.35–1.65)***	1.38 (1.25–1.53)***	1.77 (1.29–2.46)**	1.72 (1.25–2.41)**
Driving in safety enhancement zones $x_{n,6}$ (base: no)	yes	0.43 (0.20–0.96)*	n.s.	0.56 (0.41–0.76)***	0.56 (0.41–0.77)***
Model's fit	number of samples	/	10,349	/	8319
	likelihood ratio test	/	855.37	/	702.27
	degrees of freedom	/	12	/	11

"n.s.": indicates the factor is not significant at the 5% level.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

no multicollinearity issues are expected. 10,349 samples of motorcycle DUI and 8,319 samples of car DUI with the complete information of independent variables are applied to the regressions.

As shown in Table 5, for motorcycle DUIs, the effect of the risk factor of driving in safety enhancement zones is no longer statistically significant. An increase in the BAC is significantly related to the likelihood of a crash, confirming the hypothesis H1 that BAC levels of 80 mg/dL or higher are positively associated with crash involvement.

5.3. Associations between BAC, confounding factors and detention time

5.3.1. Pairwise associations

The associations between BAC level, confounders, and detention time are examined by a series of ordered logit models. The effects of BAC levels are first estimated when no confounders are under control. The odds ratios reveal that as BAC rises, there is a drastic increase in the likelihood that offenders will be sentenced to a long-time detention. Specifically, offenders riding or driving with BAC above 230 mg/dL are approximately more likely to be detained longer than those who are slightly drunk (i.e., 335 times for motorcyclists and 322 times for car drivers, respectively; Table 6).

With controls for BAC levels, the effects of each of the aggravating and mitigating factors are examined. Whereas crash involvement is one of the aggravating factors for sentencing, Y_c is set as an independent variable in the regression.

As shown in Table 6, almost all aggravating factors illustrate an increased likelihood of long-time detention, and consistent with intuition, the mitigating factor decreases the likelihood of long-time detention. The aggravating factor of DUI repeat offenses ($x_{n,2}$) for motorcyclists is not found to significantly affect the length of detention time, while for car drivers who are repeat offenders, they are 2.24 times more likely to be punished with a long-time detention.

5.3.2. Adjust odds ratios

Two ordered logit models are used to establish the relationships between BAC levels, aggravating factors, mitigating circumstances, and detention time for riders and drivers, respectively. In the motorcycle model, the aggravating factor of driving in safety enhancement zones ($x_{n,6}$) and mitigating circumstances ($x_{n,8}$) are not performed as statistically significant predictors. For the car model, except for the variable $x_{n,4}$ which characterizes unsafe vehicles, the coefficients of the other variables are statistically significant. The multicollinearity is proved to be weak. The results presented in Table 6 indicate that the odds of being detained longer increase as BAC rises, which supports hypothesis H2: there is a positive association between BAC levels and the severity of DUI punishment.

5.4. Comparative analysis of damage fact

Aimed at offering an insight into the threat caused by DUI to the safety of motorcyclists themselves, the damage fact of motorcycle and car DUIs is compared in terms of three dependent variables, namely, crash involvement Y_c (Yes = 1, No = 0), single-vehicle crashes Y_c^1 (Yes = 1, No = 0), and single-vehicle crashes that cause injuries or death Y_c^2 (Yes = 1, No = 0). A single-vehicle crash is one where only the offenders are involved in the crash and harm themselves (e.g., slip down, fall into a river, or hit roadside objects). Cases in which passengers of the offenders get injured or die are included in the group of single-vehicle crashes as well. 15.8% of motorcycle DUIs and 12.1% of car DUIs are involved in single-

Table 6
Risk factors of detention time.

Factors	Values	Motorcycle		Car	
		Unadjusted OR (95% CI)	Adjusted OR (95% CI)	Unadjusted OR (95% CI)	Adjusted OR (95% CI)
BAC X_{BAC} (base: 80–130 mg/dL)	130–180	8.34 (7.51–9.26)***	8.35 (7.51–9.30)***	8.42 (7.47–9.49)***	9.10 (8.04–10.31)***
	180–230	53.58 (46.25–62.18)***	52.26 (45.00–60.83)***	53.74 (46.06–63.03)***	56.68 (48.25–66.75)***
	>230	334.97 (280.52–400.76)***	337.05 (281.08–405.01)***	322.15 (266.95–390.68)***	347.44 (285.55–423.75)***
Prior illegal and criminal records $x_{n,1}$ (base: no)	yes	2.43 (2.12–2.79)***	2.36 (2.05–2.71)***	1.85 (1.61–2.12)***	1.83 (1.59–2.11)***
DUI repeat offenses $x_{n,2}$ (base: no)	yes	1.51 (0.97–2.32)	n.s.	2.24 (1.40–3.56)***	2.89 (1.77–4.70)***
Unlicensed operator $x_{n,3}$ (base: no)	yes	1.94 (1.78–2.11)***	1.73 (1.58–1.89)***	2.72 (2.24–3.32)***	2.50 (2.04–3.06)***
Unsafe vehicles $x_{n,4}$ (base: no)	yes	1.49 (1.37–1.62)***	1.19 (1.09–1.30)***	1.43 (1.08–1.88)*	n.s.
Commercial operating $x_{n,5}$ (base: no)	yes	/	/	1.21 (1.09–1.34)***	1.16 (1.04–1.29)**
Driving in safety enhancement zones $x_{n,6}$ (base: no)	yes	0.44 (0.19–0.96)*	n.s.	2.50 (1.82–3.42)***	2.91 (2.11–4.02)***
Avoid checks $x_{n,7}$ (base: no)	yes	2.15 (1.37–3.36)***	1.87 (1.18–2.96)**	3.49 (2.80–4.35)***	2.80 (2.24–3.50)***
Crash involvement Y_c (base: no)	yes	2.21 (1.99–2.47)***	2.15 (1.93–2.40)***	2.61 (2.36–2.89)***	2.64 (2.38–2.93)***
Mitigating circumstances $x_{n,8}$ (base: no)	yes	0.63 (0.41–1.00)*	n.s.	0.67 (0.45–1.00)*	0.60 (0.40–0.91)*
Model's fit	number of samples	/	10,457	/	8402
	likelihood ratio test	/	7180.04	/	6130.91
	degrees of freedom	/	8	/	11

"n.s.": indicates the factor is not significant at the 5% level.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

vehicle crashes. 6.4% of motorcycle DUIs are responsible for single-vehicle crashes and cause injuries or death, while the proportion for car DUI is only 1.1%.

The vehicle type (X_v) and the BAC level (X_{BAC}) are set as explanatory variables in the logistic models. Since this study focuses on the associations between vehicle type and damage, only the effects of X_v are presented in Table 7. As mentioned above, the proportion of motorcycle DUI reporting crashes is significantly higher than that of car DUI. The regression results in Table 7 indicate that, if BAC is controlled, a person riding a motorcycle while intoxicated is 1.83 times more likely to be involved in a crash compared to driving a car. This could be explained from two perspectives. On one hand, as has been found by previous studies (Maistros et al., 2014), a motorcycle requires more skill and coordination for operation than a car. When under the influence of alcohol, it is more difficult for riders to operate the vehicle safely. On the other hand, the police often set up checkpoints, hold up, and inspect cars with drivers suspected of drunk driving. This effectively curbs the occurrence of alcohol-related crashes by cars.

The odds ratios illustrate that motorcyclists are almost 22% more likely to be involved in single-vehicle crashes than car drivers. To give further insight into the severity of crashes, the number of single-vehicle crashes that lead to offenders or their passengers sustaining injuries or dying is then examined. The results show that alcohol-impaired motorcyclists are nearly seven times more likely to harm themselves compared to car drivers. This verifies H3 that motorcycle offenders are more likely to be involved in a crash and sustain injuries.

5.5. Comparative analysis of legal consequence

Two ordered logit models and one binary logistic regression are performed to examine the effect of vehicle types on detention time, fines, and probation decision with controls for BAC levels and other aggravating factors, respectively. Because motorcycles are not allowed to operate for commercial purposes, DUI offenses committed by commercial vehicles are excluded from the samples. A total of 16,870 samples of criminally DUI offenses are applied to the regression models.

As presented in Table 6, the variables of DUI repeat offenses ($x_{n,2}$), unsafe vehicles w ($x_{n,4}$), driving in safety enhancement zones ($x_{n,6}$), and mitigating circumstances ($x_{n,8}$) do not performed as statistically significant predictors for detention time in the adjusted motorcycle or car model (these variables do not significantly affect the likelihood of fines amount either), hence they are not used to test the effect of vehicle type. Moderate correlations are found between vehicle types and unlicensed operators ($r = 0.38, p < 0.001$). Variance inflation factors (VIF), which detect multicollinearity in the regression analyses are calculated; no predictor has a VIF above 10

Table 7
The effect of vehicle type on damage fact.

Damage fact	Factors	Values	OR (95% CI)
Crash involvement Y_c	Vehicle type (base: car)	motorcycle	1.83 (1.71–1.95) ***
Single-vehicle crashes Y_c^1			1.22 (1.12–1.33) ***
Single-vehicle crashes that cause injuries or death Y_c^2			6.92 (5.48–8.82) ***

*$p < 0.05$, **$p < 0.01$.
*** $p < 0.001$.

(O'Brien, 2007). Thus, multicollinearity is not considered. The odds ratios and their statistical significances, as well as the models' fit are summarized in Table 8. The odds ratios reveal that the likelihood of being sentenced to a longer detainment or a higher fine is increased by 50% for car drivers (i.e., 1/0.65 = 1.54, 1/0.68 = 1.47) with controls for BAC and other aggravating factors.

Most people begin to experience blackouts and lose consciousness once the BAC surpasses 200 mg/dL (Awareawakealive), hence alcohol-impaired driving or riding with a BAC above 200 is an aggravating DUI resulting in harsh punishment. According to the Handbook, imposing probation has to take the following circumstances into consideration: (a) causes injuries, death or heavy property losses to other traffic participants (denoted as Y_c^3); (b) with a BAC above 200 mg/dL (denoted as X_{bac}^{200}); (c) operating for commercial purposes ($x_{n,5}$); (d) driving in safety enhancement zones ($x_{n,6}$); and (e) with the intent of avoiding checks ($x_{n,7}$). Once the aforementioned factors are committed by offenders, probation is very likely to be inapplicable. The variable $x_{n,6}$ is not found as a statistically significant predictor for the probation of motorcycle DUIs, thus the factors Y_c^3, X_{bac}^{200}, $x_{n,7}$ as well as X_v are considered in the regression of Y_p.

57.9% of motorcycle DUIs and 50.2% of car DUIs are found to cause injuries, death, or heavy property losses to other people, and in that case, it is 1.51 times more likely that a probation is inapplicable. Offenders with a BAC of 200 mg/dL or higher account for 21.0% of motorcycle DUI offenses and 23.2% of car DUI offenses, which is similar to the findings of Sun et al. (2014). It is 11.63 times more likely not to apply probation compared to offenders with a BAC less than 200 mg/dL. The odds ratio illustrates that for offenders with the intent of avoiding checks, probation is 4.15 times more likely to be inapplicable. Regarding the effect of vehicle type, offenders of motorcycle DUIs are about 1.49 times more likely (i.e., 1/0.67 = 1.49) to have a probation compared to car drivers. The effect of vehicle type on legal consequence confirms H4 that alcohol-impaired motorcyclists receive lesser punishment with controls for other factors.

6. Discussion and implications

6.1. Risk of crash associated with high BAC

By utilizing the data from DADs on alcohol-impaired driving and riding, this study investigates the variations in criminally DUI offenses committed by motorcyclists and car drivers. A series of logistic regression models are developed, and four hypotheses are tested. As hypothesized, the BAC level serves as a major determinant of damage fact and legal consequence of criminally DUI offenses. In line with the previous studies (Keall et al., 2013; Stringer, 2018; Ahmed et al., 2020), the likelihoods of crash involvement for both motorcycles and cars present a notable positive correlation with BAC levels. In particular, the risk of crash involvement increases significantly, especially for scenarios where offenders have high BACs above 230 mg/dL (Table 5).

Little efforts have been made to investigate crash risk associated with high BAC levels over 200 mg/dl because of limited samples. Keall et al. (2004) found a flattening in the rate of increasing risk of fatal injury when BAC was above 200 mg/dl. They also speculated that the high-BAC group of offenders might have a high degree of tolerance to alcohol, thereby enabling them to drive with a relatively lower risk of fatal crash involvement. It is impossible for us to estimate the likelihood of offenders' fatality associated with BAC using DAD data, because all offenders convicted of DUI survived alcohol-related crashes. Even so, our estimates illustrate that the risk curve of crash involvement steepens as higher BAC levels are reached.

Table 8
The effect of vehicle type on legal consequence.

Legal consequence	Factors	Values	OR (95% CI)
Detention time Y_d (month)	Vehicle type X_v (base: car)	motorcycle	0.65 (0.61–0.70)***
	Involved in a crash Y_c (base: no)	yes	2.41 (2.22–2.61)***
	BAC X_{BAC} (base: 80–130 mg/dL)	130–180	8.31 (7.63–9.05)***
		180–230	52.06 (46.38–58.50)***
		>230	323.04 (280.66–372.28)***
	Prior illegal and criminal records $x_{n,1}$ (base: no)	yes	2.20 (1.97–2.44)***
	Unlicensed operator $x_{n,3}$ (base: no)	yes	1.91 (1.76–2.08)***
	Avoid checking $x_{n,7}$ (base: no)	yes	2.67 (2.14–3.33)***
	Model's fit	number of samples	16,870
		likelihood ratio test	11767.7
		degrees of freedom	8
Fine amounts Y_f (¥)	Vehicle type X_v (base: car)	motorcycle	0.68 (0.63–0.72)***
	Involved in a crash Y_c (base: no)	yes	1.44 (1.35–1.55)***
	BAC X_{BAC} (base: 80–130 mg/dL)	130–180	4.47 (4.14–4.83)***
		180–230	15.20 (13.86–16.67)***
		>230	52.52 (46.84–58.93)***
	Prior illegal and criminal records $x_{n,1}$ (base: no)	yes	1.47 (1.33–1.61)***
	Unlicensed operator $x_{n,3}$ (base: no)	yes	1.66 (1.54–1.78)***
	Avoid checking $x_{n,7}$ (base: no)	yes	1.77 (1.45–2.17)***
	Model's fit	number of samples	16,870
		likelihood ratio test	7323.602
		degrees of freedom	8
Probation Y_p	Vehicle type X_v (base: car)	motorcycle	0.67 (0.62–0.72)***
	Causes injuries, death or heavy property losses of other traffic participants Y_c^3 (base: no)	yes	1.51 (1.41–1.62)***
	BAC≥200 X_{bac}^{200} (base: no)	yes	11.63 (10.13–13.42)***
	Avoid checking $x_{n,7}$ (base: no)	yes	4.15 (2.92–6.11)***
	Model's fit	number of samples	16,870
		likelihood ratio test	2509.8
		degrees of freedom	4

*$p < 0.05$, **$p < 0.01$.
*** $p < 0.001$.

The high-BAC group of offenders are more likely to be problem drinkers and to report drinking and driving more often (Fell et al., 2010). Driving or riding with a BAC above 200 mg/dL has already been regarded as an aggravate DUI by the law of Jiangsu, consequently a drastic increase in the likelihood of being sentenced to a severe punishment is observed. As described in Table 8, offenders with BAC above 230 mg/dL are associated with a risk of long detainment that is 323 times the risk for slightly drunk offenders. Meanwhile, probation is 11.63 times more likely to be inapplicable once BAC is above 200 mg/dL. It is known that offenders with a BAC above 200 mg/dL account for more than 20% of DUI offenses in Jiangsu and other cities in China (Sun et al., 2014). The deterrence-centered penalties seem not as effective as expected.

6.2. Risk of crash associated with motorcycle

Theorists and researchers have previously noted that motorcyclists' risk of crash and injury against BAC climbs more steeply than the risk for car drivers (Jou et al., 2012; Keall et al., 2013; Ahmed et al., 2020). This is further demonstrated by our findings that alcohol-impaired riding results in more crashes than alcohol-impaired driving (Table 2). Moreover, motorcyclists are found to have a significantly higher likelihood of being responsible for single-vehicle crashes. Among the single-vehicle crashes caused by motorcyclists, 40.2% result in injuries or death, which confirms that alcohol-impaired riding makes motorcyclists extremely vulnerable in a collision. The perniciousness of DUI offenses to other traffic participants are considered as an adjudicative factor in sentencing. By comparing judicial outcomes, judges are found more lenient with motorcycle offenders in practice. Specifically, with controls for BAC and other risk factors, there is an approximately 50% decrease in the likelihood of motorcyclists being sentenced to a harsh penalty.

Jiangsu and other areas in China are confronted with a serious problem of motorcycle DUI. More than 94% of motorcycle offenders received short sentences of 3 months or less, whereas Weinrath and Gartrell (2001) found that the deterrent effect of sentence length was not linear; short sentences of four months or less did not deter DUI as effectively as a six-month sentence. Considering the deficiencies of punishment sentences, it is worth the effort to try other ways to prevent motorcycle DUIs. The effects of risk factors addressed in this work have important implications.

In particular, the results reveal that traffic violations associated with DUIs (e.g., unlicensed operators or driving unsafe vehicles) increase the risk of crash involvement (Table 5). Compared to car drivers, there is a much higher proportion of unlicensed riders as well as riding unsafe motorcycles (Table 4). Hence, regulating the behaviors of riders and combating their traffic violations is of great urgency. Moreover, motorcycle offenders are relatively less educated (Table 3), which is consistent with the findings of Kuo et al. (2020). Some riders may not be aware that riding after drinking is against the law and has a high possibility of sustaining injuries and even death. Promoting safe behaviors among motorcyclists by public awareness campaigns is helpful to enhance their compliance to traffic laws.

6.3. Challenges of criminalizing motorcycle DUI

To some extent the deterrent effect of criminalizing DUI is uncovered by our analysis with the DAD data. Specifically, for both motorcyclists and car drivers, the DUI recidivism rate is relatively low (Table 4). Offenders with criminal records or those once arrested for DUI seem more cautious because they are less likely to be involved in a crash (Table 5). For alcohol-impaired motorcyclists, because of their lenient sentences, the possible effects of heightened severity of punishment need to be further explored. In addition to the concern on the severity of punishment, there are two challenges confronting the criminalization of alcohol-impaired riding.

One challenge is the frequent occurrence of offenses. Our results illustrate that Jiangsu is faced with a larger number of motorcycle DUI offenses. The data released by the official website of China Judgment Online reveal that the number of adjudications on DUI approximately accounts for more than 25% of the criminal cases sentenced by the courts of Jiangsu, which consumes a large quantity of litigation resources. Aimed at speeding up the processing of DUI cases, many courts in China have adopted the expedited DUI court program, which is greatly improving the efficiency of the trial of criminally DUI. For instance, the People's Court of Haidian District, Beijing requires to complete a DUI investigation, prosecution, and verdict within 48 h (Wang, 2020). However, Bouffard and Bouffard (2011) found that the swift processing of DUI offenders through specialized courts did not appear to have a deterrent effect.

The other challenge is the certainty of punishment, which plays an important role in the reduction of DUI offenses (William et al., 1991; Bouffard et al., 2017). By using roadside sobriety checkpoints, the probability of detection as well as the certainty of punishment are increased. The low rate of crash involvement in the evening (Table 5) stands as proof of the effect of the certainty of punishment because the sobriety checkpoints are often set up at that time. However, checkpoints are usually set in urban areas where riding motorcycles is not allowed, and most of the time motorcyclists are found to be alcohol impaired only after their crashes are reported. The deterrent effect of the certainty of punishment may not be applicable to motorcyclists.

The revision of legislation on DUI is under discussion in China at the moment. The factors such as the uncertainty of detection, swift sanctions, and short-term sentences may weaken the deterrent effect of the criminalization of motorcycle DUI. If not criminalizing alcohol-impaired motorcyclists, instead, imposing administrative sanctions and undertaking education and awareness campaigns, the limited judicial resources would be utilized more effectively.

7. Conclusions

Based on the data extracted from DADs on DUI offenses, crash involvement and legal consequence between motorcycle DUI and car DUI committed by offenders with BAC of 80 mg/dL or higher are compared in this study. Four hypotheses are supported by our findings: (1) the occurrence of crash involvement is positively associated with BAC levels; (2) BAC level plays a dominant role in DUI sentencing; (3) the likelihood for an alcohol-impaired motorcyclists to be involved in a crash and sustain injuries is relatively higher; and (4) the likelihood for alcohol-impaired motorcyclists to be punished severely is relatively lower. It is also found that, with regard to motorcycle DUI, the effectiveness of criminal sanctions in curbing DUI offenses and alcohol-related crashes may not be significant. The findings have significant implications on law enforcement agencies to identify and develop countermeasures and awareness initiatives, which helps to make appropriate modifications in rider and driver behaviors.

Utilizing the DAD data is an innovation of this study; however, some limitations are observed. One is that the DAD data are textual and unstructured. In order to protect privacy, information on offenders' demographic characteristics is not recorded by a considerable proportion of DADs, which may lead to bias in adjudication outcomes (e.g., the financial status of offenders is usually considered when applying for a fine punishment). Besides, detailed information on the driving activities (e.g., horizontal curves, speeds, seatbelt use, helmet use), which contributes to crash occurrence, is not contained in DADs as well. Because the main purpose of this study is to find an association other than provide a prediction, the conclusions are not affected by the missing data. Another limitation is that the deterrent impact on fatality reduction cannot be assessed when all offenders survive alcohol-related crashes. In addition, the deterrent impact of administrative penalties on buzzed driving (i.e., driving with a BAC less than 80 mg/dL) cannot be assessed either. The effect of enforcement and punishment on buzzed driving and fatality reduction of alcohol-related crashes should be further studied using the merged administrative data.

Compared to the crime of DUI manslaughter or DUI murder, DUI offenses convicted on the charge of dangerous driving receive less severe penalties because alcohol-impaired riders or drivers usually do not cause the deaths of passengers, occupants of other cars, or pedestrians. Further studies can also be carried out to investigate the differences in influence factors among these DUI-related crimes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Alcohol-related deaths among young passengers: An analysis of national alcohol-related fatal crashes

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ABSTRACT

Introduction: There is consensus that riding with an impaired driver (RWI) constitutes a major threat to public health. The aim of this study was to characterize the factors contributing to the motor-vehicle deaths of 15–20 year-old (y/o) passengers that RWI with a peer. *Method:* Secondary analyses of the 2010–2018 Fatality Analysis Reporting System. 5,673 passengers aged 15–20 y/o killed while riding in passenger cars with a driver aged 21 or older, 3,542 of these drivers also aged 15–20 y/o. Analyses were conducted between October 2019 and December 2020. *Results:* Sixty-three percent of the young passengers were killed while riding with a driver 15–20 y/o. Of these drivers, 26.8% had a blood alcohol concentration (BAC) >0.00 g/dL and 77.1% had a BAC $\geq$0.08 g/dL. Compared with those occurring during the day on weekdays, fatalities of young passengers who RWI with a peer driver with a BAC $\geq$ 0.08 g/dL often occurred on weekend nights (OR = 8.2) and weekday nights (OR = 5.2), and when the passenger and driver were both male (OR = 1.8). Race/ethnicity was not a significant contributor to RWI fatalities. *Conclusions:* Most 15–20 y/o RWI fatalities occurred on weekends, at night, when the driver was a young peer with a high BAC, and the passenger and driver were male. The high prevalence of fatalities in these high-risk situations suggests that young driver-passenger dynamics may contribute to alcohol-related fatalities. *Practical Applications:* To curb RWI fatalities among underage passengers, countermeasures should focus not only on underage drinking drivers and riders, but also on drinking drivers of all ages. Prevention should increase focus on situations in which both the young passenger and young driver are males.

1. Introduction

In the United States, graduated driver licensing (GDL) restrictions have been effective tools to reduce youth involvement in crash fatalities (Vanlaar, Mayhew, et al., 2009; Fell, Jones, et al., 2011). Nevertheless, motor-vehicle crashes are the leading cause of unintentional injury death for every age 5–23 (Webb 2018), particularly when the driver is a young person driving at night (Chen, Baker, et al., 2000; Fell, Todd, et al., 2011; Shults & Williams, 2016). In 2015, 21% of all 15–20 year old (y/o) fatally-injured drivers had a BAC of 0.08 g/dL or higher (National Center for Statistics and Analysis, 2017) even though according to zero tolerance laws, the illegal limit for the underage group (<21 y/o) is between 0.00 g/dL and 0.02 g/dL, depending on the state. About 21% of the youth aged 20 y/o reported riding with a driver impaired by alcohol (RWI) in the past year (Li, Ochoa, et al., 2018). Examining a survey of high school students in Canada and the United States, Leadbeater and colleagues (Leadbeater, Foran, et al., 2008) reported that 52%-55% of the students reported "ever" riding with an impaired driver (RWI) aged 21 y/o or more, while 21%–33% of the students reported "ever" riding with an impaired peer (Leadbeater, Foran, et al., 2008). There is consensus that RWI constitutes a major public health concern as RWI is not only a major health-risking behavior, but also known as an antecedent of future driving while impaired (DWI) by alcohol (NCSA, 2012; Evans-Whipp, Plenty, et al., 2013; Li, Simons-Morton, et al., 2014).

RWI among teenagers has been found to be associated with rural residence (O'Malley & Johnston, 1999), and increasing with

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age (Sabel, Bensley, et al., 2004). The association of RWI with sex or race/ethnicity is less clear. Some studies have found that young females are more likely to RWI than males (Jelalian, Alday, et al., 2000; Harris, Johnson, et al., 2017). One study reported that those most likely to RWI were males (Everett, Shults, et al., 2001). Still, other studies found no significant association between passenger's sex and RWI (Adlaf, Mann, et al., 2003; Hultgren, Turrisi, et al., 2018). One study by Grube and Voas found no association between the passengers' race/ethnicity and their likelihood of RWI (Grube & Voas, 1996). Yet other studies found RWI more common among Latino youth than non-Latino White youth (O'Malley & Johnston, 1999; Walker, Treno, et al., 2003; Yellman, Bryan, et al., 2020). Vaca and colleagues also found RWI to be common among Latino youth, but only at certain ages (Vaca, Li, et al., 2016).

This study aimed to characterize young passengers who did RWI. More specifically, we aimed to assess the associations of sex and race/ethnicity with crashes in which passengers aged 15–20 y/o were killed while riding with a peer driver also aged 15–20 y/o. We hypothesized that most young passenger fatalities in the context of RWI occur on weekend nights because alcohol use and DWI among young drivers are prevalent on weekend nights (Tin, Ameratunga, et al., 2008; Goncy & Mrug, 2013). We examined whether the percentage of fatally injured passengers aged 15–20 y/o who died while riding with a peer driver was higher for Latinos than for any other racial/ethnic group. Because of sex difference in DWI involvement (Romano, Kelley-Baker, et al., 2008; Vaca, Romano, et al., 2014; Webster, Staton, et al., 2019), we expected to confirm that passengers aged 15–20 y/o are more likely to die in a RWI crash while riding with a male peer than a female peer. We also assessed whether the sexes of both the driver and passenger moderates that effect. We hypothesized that among passengers aged 15–20 y/o who died while riding with a peer also aged 15–20 y/o, the likelihood who were engaged in RWI at the time of the crash was higher when the driver was a young male driving a young male passenger (M_p-M_d) than when a young male was driving a young female passenger (F_p-M_d).

2. Methods

2.1. Data

Crash data were obtained from the 2010–2018 Fatality Analysis Reporting System (FARS). After discarding fatalities that involved vehicles other than passenger cars (e.g., buses, snowmobiles, motorcycles, trucks), crashes with missing information on drivers' age, and crashes outside the scope of this study (e.g., police chases; non-moving vehicles), 5,673 fatally-injured passengers aged 15–20 y/o remained in the file. When assessing drivers' alcohol use and to avoid double counting, drivers of vehicles in cases in which more than one passenger was present at the time of the crash were counted only once. Of the 5,673 fatally injured passengers aged 15–20 y/o in the file, of particular interest were the 3,542 who were riding with a driver also aged 15–20 y/o at the time of the crash.

2.2. Measures

2.2.1. Blood Alcohol Concentration (BAC)

About 65% of all drivers in the file have a measured BAC. Using multiple imputation, the FARS estimates the BAC of those with a missing BAC measure (Subramanian, National Center for, et al., 2002). We grouped drivers in three BAC categories: BAC = 0.00 g/dL; 0.00 /dL < BAC < 0.08 g/dL; and BAC ≥ 0.08 g/dL.

2.2.2. Day of the week and time of the day

Crashes were grouped as occurring on weekends (Friday to Sunday), or weekdays (remaining days), and either at nighttime (from 8p.m. to 6 a.m.) or daytime (remaining hours).

2.2.3. Number of occupants

Vehicles were grouped as carrying two versus more than two occupants (the driver and the 15–20 y/o passenger(s)) at the time of the crash.

2.2.4. Sex of passenger & driver

For cases in which the fatally injured passenger was the sole passenger of the car, we considered whether the fatally injured passenger was a female riding with a male driver (F_p-M_d), a female riding with a female driver (F_p-F_d), a male passenger riding with a male driver (M_p-M_d), or a male passenger riding with a female driver (M_p-F_d). A fifth level was added to indicate when there were three or more occupants.

2.2.5. Rural vs. urban setting

Using FARS coding we assigned each crash to either a rural or urban setting.

2.2.6. Race and ethnicity

Since 1988, the National Highway Traffic Safety Administration (NHTSA), working with the National Center for Health Statistics (NCHS), has been matching the records of road users fatally injured in crashes with their death certificate information in the NCHS Hyde cause-of-death (HCOD) file. This information appears in the FARS, although only on the deceased (i.e., the race and ethnicity of the surviving drivers is missing). The FARS informs separately on the deceased's race (variable "Race," with 19 categories, including White, Black, American Indian, Other, and unknown) and ethnicity (variable "Hispanic Origin," with 9 categories including Mexican, Puerto Rican, Cuban, Other Hispanic Origin, and Unknown). For this study, the following four groups were considered: Latinos, non-Latino Blacks, non-Latino Whites, and non-Latino of Other race.

2.3. Statistical analyses

We conducted cross-tables to examine the bivariate distribution of demographics and crash characteristics related to riding with a drinking driver. For each bivariate condition, prevalence of drivers at each of the three BAC level under examination were estimated. Comparisons were based on the 95% confidence intervals (95%CI) of the prevalence estimates Next, we ran a multinomial logistic regression model to assess the joint contribution of all factors identified by the bivariate analyses as contributors to the likelihood that fatally-injured adolescent passengers age 15–20 y/o were riding with a peer-aged driver with a 0.00 g/dL < BAC < 0.08 g/dL, and BAC ≥ 0.08 g/dL than with respect to BAC = 0.00 g/dL (the reference level of the dependent variable). Main effects as well as dual interactions between all main effects were examined. We used SAS v9.4 for all analyses. We accounted for the additional variance introduced by the multiple imputation of BAC values by: (1) running 10 separate regressions, one for each of the 10 imputed BAC values; and (2) summarizing the results while accounting for standard errors with the Proc MIanalyze SAS procedure. Analyses were conducted between October 2019 and December 2020.

Table 1
Fatally injured passengers aged 15–20 y/o by driver age and BAC.

Drivers' BAC (g/dL)	Driver Age (years)														
	15–20			21–25			26–35			36 and over			All		
	N	% (95% CI)		N	% (95% CI)		N	% (95% CI)		N	% (95% CI)		N	% (95% CI)	
0.00	2592	73.2		596	56.1		231	58.0		547	81.5		3966	69.9	
		71.7	74.6		53.1	59.1		53.2	59.1		78.6	84.5		68.7	71.1
0.01–0.049	111	3.1		44	4.1		15	3.8		14	2.1		184	3.2	
		2.6	3.7		3.0	5.4		3.0	5.4		0.9	3.0		2.8	3.7
0.05–0.079	107	3.0		42	4.0		18	4.5		9	1.3		176	3.1	
		2.3	3.4		2.9	5.3		2.9	5.3		0.5	2.2		2.6	3.5
≥0.08	732	20.7		380	35.8		134	35.8		101	15.1		1347	23.7	
		20.1	22.8		33.5	39.3		33.5	39.3		12.2	17.6		23.2	25.4
BAC > 0.00	950	26.8		466	43.9		167	43.9		124	18.5		1707	30.1	
		26.0	28.9		41.8	47.8		41.8	47.8		15.3	21.1		29.4	31.8
All (ROW)	3542	62.4		1062	18.7		398	7.0		671	11.8		5673	100.0	
		61.9	64.3		17.5	19.4		6.1	7.3		10.7	12.3			

Source: FARS 2010–2018. BAC stands for blood alcohol concentration in grams per deciliter. BAC was either measured or imputed in the file. The values in row labeled All BAC > 0.00 represents the sum of the previous 3 rows. 95% CI indicates 95% confidence interval. Total number of passengers aged 15–20 y/o do not sum up to 5,673 due to missing information on drivers' age. The association between BAC level and driver's age was statistically significant ($p < .0001$). Cells in gray were left empty due to small sample size.

3. Results

Table 1 shows that between 2010 and 2018, a total of 5,673 passengers aged 15–20 y/o were killed while riding in passenger cars with a driver of known age. Of the 5,673 passengers aged 15–20 y/o in the file, a total of 3,542 (62.4%) died while riding with a driver also aged 15–20 y/o; a percentage significantly larger than the 18.7%, 7.0%, and 11.8% who died while riding with a driver aged 21–25 y/o, 26–35 y/o, and 36 y/o and over, respectively. Furthermore, Table 1 shows that the percent of the fatally injured passengers 15–20 y/o that died when riding with a BAC > 0.00 g/dL driver was significantly lower when the driver was also aged 15–20 y/o (26.85%) than when the driver was aged 21–25 y/o (43.9%) or aged 26–35 y/o (42.0%), and significantly higher than when the driver was aged 36 y/o or over (18.5%).

Of the 950 fatalities of passengers aged 15–20 y/o who were riding with a BAC > 0.00 g/dL driver also aged 15–20 y/o, 732 (77.1) was BAC ≥ 0.08 g/dL. Also shown in Table 1 is that for the 15–20 y/o passengers, riding with a BAC > 0.00 g/dL driver was less prevalent when their drivers were 36 y/o and over than when of younger age. This result, at least in part, relates to many of the 36 y/o and over being adult family members, caretakers, or other non-peer adults of the 15–20 y/o passengers.

Factors contributing to individuals aged 15–20 y/o riding with BAC > 0.00 g/dL drivers also aged 15–20 y/o: The results in Table 2 further illustrates that most of the 15–20 y/o passengers that died when riding with a drinking peer, occurred when the underage peer driver was at BAC ≥ 0.08 g/dL. Table 2 also shows that the proportion of passengers aged 15–20 y/o who died while riding with a drinking peer did not vary significantly by the drivers' race/ethnicity.

The results in Table 2 also show that the percentage of passengers aged 15–20 y/o who died while riding with a drinking peer was significantly higher when the driver was a male than a female, both when the driver was 0.00 g/dL < BAC < 0.08 g/dL (6.8% when the driver was male, 4.6% when female) and BAC ≥ 0.08 g/dL (22.9% when the driver was male, 14.9% when female). When there were only two occupants in the vehicle, both the sex of the passenger and the driver were associated with the driver being BAC ≥ 0.08 g/dL at the time of the crash. Although male drivers were more likely to be BAC ≥ 0.08 g/dL than female drivers, this prevalence is less common if the male was driving a female (F_p-M_d, 19.1%) than another male (M_p-M_d, 25.0%), although this difference was not statistically significant. Nevertheless, the degree of overlap between the confidence intervals was minimal and suggests the lack of significance could be attributed in part to sample size limitations. In the 59.6% of the cases in which there were more than two occupants in the crashed vehicle, the distribution of the drivers' BAC did not differ statistically from cases in which there were only two occupants in the vehicle and the driver was a male. The urbanicity of the location of the crash was not significantly associated with the BAC of the driver. The percentage of BAC ≥ 0.08 g/dL drivers increased with age, a result that is expected since alcohol use increases with age (Masten, Faden, et al., 2009).

As expected, the percentage of passengers aged 15–20 y/o who were riding with a BAC ≥ 0.08 g/dL peer was significantly higher on weekend nights (41.5%) or on weekdays at nighttime (35.9%) than on weekdays at daytime (11.6%) or weekends at daytime (13.5%). These results are consistent with current knowledge showing that drinking and driving is more prevalent at night, particularly on weekends (Romano et al., 2008).

3.1. Logistic regression

Table 3 shows the odds ratio (OR) for the main effects included in the logistic regression modeling the BAC level of a 15–20 y/o individual driver of a fatally injured 15–20 y/o passenger. Overall, the results of the logistic regressions support the findings of the bivariate analyses. The fatally injured 15–20 y/o passengers were more likely to be found riding with a BAC ≥ 0.08 g/dL or a 0.00 g/dL < BAC < 0.08 g/dL peer on a weekend night (OR = 8.20, OR = 6.20, respectively) or on a weekday night (OR = 5.18; OR = 3.90, respectively) than on a weekday at daytime. When there were only two occupants in the vehicle, the likelihood the driver was BAC ≥ 0.08 g/dL was significantly higher when both the driver and passenger were male than when both were female (OR = 1.77). Although in Table 3, the overlapping confidence intervals corresponding to each level of the "Sex of the Passenger and Driver" variable seems to indicate that a vehicle with "3+ occupants" is as much likely to have been driven by a 0.00 g/dL < BAC < 0.08 g/dL, or BAC ≥ 0.08 g/dL driver than a 2-occupants vehicle, such a lack of significance is caused by our partitioning of all 2+ occupant vehicles into 4 dyads (M_p-F_d, F_p-M_d, M_p-M_d, and F_p-F_d). After collapsing these four 2+ occupant dyads into a single level indicating there were only "2 occupants" in the vehicle, a comparison between this level and the "3+ occupants" level (not shown in Table 3) showed that the likelihood the peer driver was 0.00 g/dL < BAC < 0.08 g/dL

Table 2
Percent of passengers aged 15–20 y/o who died while RWI drivers also aged 15–20 y/o by crash and driver's characteristics and drivers' BAC.

N (Col %)			Driver's BAC					
			BAC = 0.00		0.00 < BAC < 0.08		BAC ≥ 0.08	
			Row %		Row %		Row %	
			95%CI		95%CI		95%CI	
Driver's Race/Ethnicity	Black	114	73.8		6.0		20.3	
		12.4	65.7	81.8	1.6	10.3	12.9	27.6
	Latino	147	66.6		5.3		28.1	
		16.0	59.0	74.2	1.7	8.9	20.8	35.4
	White	516	71.0		6.7		22.3	
		56.0	67.1	74.9	4.5	8.9	18.7	25.9
	Other	144	67.4		5.9		26.7	
		15.6	59.7	75.0	2.1	9.7	19.5	34.0
Driver's sex	Male	2,539	70.3		6.8		22.9	
		71.7	68.5	72.1	5.8	7.7	21.3	24.6
	Female	1,002	80.5		4.6		14.9	
		28.3	78.0	82.9	3.3	5.9	12.7	17.1
Sex of Passenger & Driver	F_p-F_d	248	83.5		2.6		13.9	
		7.0	78.9	88.1	0.6	4.6	9.6	18.2
	M_p-F_d	147	85.1		2.4		12.5	
		4.2	79.4	90.8	0.1	4.8	7.2	17.9
	F_p-M_d	359	76.0		4.9		19.1	
		10.1	71.6	80.4	2.7	7.2	15.0	23.1
	M_p-M_d	677	69.2		5.8		25.0	
		19.1	65.7	72.7	4.1	7.6	21.7	28.2
	3+ Occupant	2110	71.9		7.1		20.9	
		59.6	70.0	73.9	6.0	8.2	19.2	22.7
Urban/Rural	Rural	1,089	73.3		6.1		20.5	
		30.8	70.7	76.0	4.7	7.6	18.1	22.9
	Urban	2,438	73.2		6.1		20.7	
		68.9	71.4	74.9	5.2	7.1	19.1	22.3
Driver's Age	15	89	82.9		2.8		14.3	
		2.5	75.1	90.7	0.1	6.1	7.0	21.5
	16	425	85.6		3.2		11.1	
		12.0	82.3	89.0	1.6	4.9	8.1	14.1
	17	700	79.9		5.1		15.0	
		19.8	76.9	82.9	3.4	6.7	12.4	17.7
	18	929	72.4		6.5		21.2	
		26.2	69.5	75.2	4.9	8.0	18.6	23.8
	19	774	67.4		8.0		24.6	
		21.9	64.0	70.7	6.1	9.9	21.6	27.7
	20	624	64.3		7.0		28.7	
		17.6	60.5	68.0	5.0	9.0	25.2	32.3
Weekday/Weekendand Time of the Day	WEEKDAY	842	85.1		3.3		11.6	
	DAY	21.3	78.3	91.9	0.2	6.7	5.5	17.7
	WEEKDAY	703	56.4		7.6		35.9	
	NIGHT	17.8	48.6	64.3	3.4	11.8	28.3	43.5
	WEEKEND	796	84.3		2.3		13.5	
	DAY	20.1	78.3	90.3	0.0	4.7	7.9	19.1
	WEEKEND	1200	47.2		11.3		41.5	
	NIGHT	30.4	40.7	53.7	7.2	15.5	35.0	47.9
All		3541	73.2		6.1		20.7	
		100.0	71.7	74.6	5.4	6.9	19.3	22.0

Source: FARS 2010–2018. RWI indicates the percentage (%, and its 95% lower and upper confidence limits) of passengers aged 15–20 y/o who died while driving with a driver aged 15–20 y/o who recorded a positive blood alcohol concentration (BAC > 0.00 g/dL). [b]Race/ethnicity is present in the FARS only on the deceased. Therefore, the race/ethnicity of the surviving drivers is missing. Members to more than one racial/ethnic group are included in the "Other" category. The first letter of the $\mathbf{F_p}$-$\mathbf{F_d}$, $\mathbf{M_p}$-$\mathbf{F_d}$, $\mathbf{F_p}$-$\mathbf{M_d}$, and $\mathbf{M_p}$-$\mathbf{M_d}$ combinations indicates the driver's sex, the second letter indicates the sex of the passenger. For instance, the $\mathbf{F_p}$-$\mathbf{M_d}$ combination indicates a Female driver and a Female passenger. "Weekend, day" denotes a crash that occurred on a Friday, Saturday, or Sunday Day. "Weekend, night" denotes a crash that occurred on a Friday, Saturday, or Sunday Night; "Weekday, day," denotes a crash that occurred on a Monday, Tuesday, Wednesday, or Thursday Day. "Weekday, night" denotes a crash that occurred on a Monday, Tuesday, Wednesday, or Thursday Night. The number of occupants includes the driver.

was significantly higher when there were 3+ occupants in the vehicle than when there were only 2 (OR = 1.5, not shown in Table 3). The ORs the driver was 0.00 g/dL < BAC < 0.08 g/dL or BAC ≥ 0.08 g/dL also increased with the driver's age.

4. Discussion

Although studies focusing on youth involvement in alcohol-related fatal crashes are not new, most have focused on the fatally injured driver (Tefft, Williams, et al., 2013; Simons-Morton, Ehsani, et al., 2017). Studies focusing on the passengers who died while riding with an impaired driver (RWI) are far less frequent, and typically based on self-reported data (Poulin, Boudreau, et al., 2007; Cartwright & Asbridge, 2011). RWI studies based on crash data are less frequent in part due to the challenges posited by the absence of information on driving exposure (i.e., all events in the file are crashes), and the imprecise determination of drivers' impairment. In this study, we attempted to address some of these limitations by looking at the BAC of the young passengers' drivers, as BAC relates with impairment and RWI. Although BAC cannot accurately indicate impairment and subsequently any identification of RWI based on BAC lacks precision, we argue that passengers

Table 3
Multinomial logistic regression for variables modeling the likelihood of RWI by drivers' BAC levels.

		Drivers' BAC (Ref: BAC = 0.00)					
		0.00 < BAC < 0.08			BAC ≥ 0.08		
		OR	95%LCI	95%UCI	OR	95%LCI	95%UCI
Day of the week and Time of the Day	Weekend, day	1.03	0.69	1.55	1.13	0.56	2.25
	Weekend, night	**6.20**	**4.61**	**8.34**	**8.20**	**4.56**	**14.77**
	Weekday, night	**3.90**	**2.77**	**5.49**	**5.18**	**2.69**	**9.96**
	Weekday, day (Ref)						
Sex of Passenger & Driver	M_p-F_d	0.77	0.17	3.57	0.76	0.36	1.57
	F_p-M_d	1.81	0.61	5.33	1.16	0.64	2.10
	M_p-M_d	2.17	0.80	5.89	**1.77**	**1.04**	**3.03**
	3+ occupants	2.60	0.98	6.86	1.34	0.81	2.21
	Fp-Fd (Ref)						
Driver's Age	15 y/o	0.96	0.18	5.22	1.30	0.60	2.82
	17 y/o	1.74	0.86	3.54	1.45	0.88	2.38
	18 y/o	2.13	0.98	4.63	**2.04**	**1.25**	**3.32**
	19 y/o	**2.75**	**1.25**	**6.04**	**2.46**	**1.56**	**3.88**
	20 y/o	**2.44**	**1.07**	**5.57**	**3.24**	**2.01**	**5.22**
	16 y/ o (Ref)						
Urbanicity	*Urban*	0.93	0.67	1.29	0.97	0.78	1.22
	Rural (Ref)						
Race /Ethnicity							
	Black	0.66	0.42	1.03	**0.71**	**0.49**	**1.04**
	Latinx	1.07	0.67	1.69	0.99	0.74	1.32
	Other	1.12	0.77	1.63	0.97	0.75	1.26
	White (ref)						

Source: FARS 2010–2018. OR stands for odds ratio. BAC stands for blood alcohol concentration in g/dL (grams per deciliter). The dependent variable (BAC) has 3 levels: BAC ≥ 0.08 g/dL, 0.00 g/dL < BAC < 0.08 g/dL, and BAC = 0.00 g/dL, the reference group. BAC was either measured or imputed in the file. (Ref) indicates the reference level. The first letter of the F_p-F_d, M_p-F_d, F_p-M_d, and M_p-M_d combinations indicates, for crashes in which there were only 2 occupants in the vehicle, the passenger's sex, the second letter indicates the sex of the driver. For instance, the F_p-F_d combination indicates a Female passenger riding with a Female driver. "Weekend, day" denotes a crash that occurred on a Friday, Saturday, or Sunday Day. "Weekend, night" denotes a crash that occurred on a Friday, Saturday, or Sunday Night; "Weekday, day," denotes a crash that occurred on a Monday, Tuesday, Wednesday, or Thursday Day. "Weekday, night" denotes a crash that occurred on a Monday, Tuesday, Wednesday, or Thursday Night. The number of occupants includes the driver.

who were riding with a BAC ≥ 0.08 g/dL driver aged 15–20 y/o were RWI. Furthermore, because for underage, novice drivers, alcohol impairment may start at relatively low BACs (Peck, Gebers, et al., 2008), we argue that 15–20 y/o passengers were RWI when riding with drivers at any positive BAC. Regardless of the merits of considering 15–20 y/o drivers at any BAC > 0.00 g/dL level as impaired, our finding that most (77.1%) of the BAC > 0.00 g/dL young drivers in the file were BAC ≥ 0.08 these criteria yield similar results. Such heavy drinking among the underage drivers not only occurred despite minimum legal drinking laws, but often occurred at nighttime, particularly on weekends, which suggests the driving of these minors related to some festive environments.

Our findings that most (62.4%) of the fatally-injured 15–20 y/o passengers died while riding with a driver also aged 15–20 y/o confirm previous reports showing that 57% of the teen passengers who died in a crash in 2018 were driven by another teenager (IIHS 2019); and shows that despite the large majority (about 89%) of licensed U.S. drivers being aged 21 y/o or older, most 15–20 y/o passengers who were fatally injured in a crash, died while riding with a peer. However, when alcohol is considered, we found that when a passenger 15–20 y/o died while riding with a drinking driver, it was less likely that the drinking driver was also a peer aged 15–20 y/o, than an older driver. This finding is in line with previous self-reports showing that 52%-55% of high school students self-reported "ever" RWI with a driver aged 21 y/o or more, and 21%–33% self-reported "ever" RWI with a peer (Leadbeater, Foran, et al., 2008). The finding that the drivers of 15–20 y/o passengers are more likely to be impaired when they are age 21 y/o or older suggests that zero-tolerance laws alone are not enough to prevent the death of passengers aged 15–20 y/o who die in an alcohol-related crash. As such, this finding points out that in order to curb RWI fatalities among underage passengers, it is necessary to implement and/or enhance the countermeasures that have been proven to be effective against drinking drivers of all ages (e.g., sobriety checkpoints; Fell, Lacey, et al., 2004).

While an alcohol-related fatality among 15–20 y/o passengers is more likely to occur when the passenger is riding with an older driver, this should not be viewed as an indication that fatalities of 15–20 y/o passengers that occur when they are riding with a 15–20 y/o driver are of no or little importance. As already shown, 62.4% of all 15–20 y/o passengers who died in a crash were riding with a 15–20 y/o driver. Thus, although for an individual 15–20 y/o passenger the likelihood that her/his driver is impaired is lower when the driver is also 15–20 y/o than when older, by sheer numbers, slightly more than half of the 15–20 y/o passengers who died while RWI died while riding with a 15–20 y/o driver (54% of BAC ≥ 0.08 g/dL drivers). This result emphasizes the need to also increase our efforts to implement and/or enhance the countermeasures that have been shown to be effective against underage drinking drivers (e.g., zero tolerance laws).

Our finding that for fatally injured 15–20 y/o passengers, the likelihood the driver was BAC ≥ 0.08 g/dL was lower when the driver was also 15–20 y/o than when the driver was older, and that most of these passengers that died were riding with another 15–20 y/o passenger, suggesting that while alcohol contributed to most fatalities when the driver was older than 21 y/o, reasons other than alcohol are behind a sizable number of fatalities involving 15–20 y/o drivers. Besides alcohol, distractions, inexperience, speeding, and drowsiness are some of the most frequent contributors to crashes among young and novice drivers (Groeger, 2006; Klauer, Guo, et al., 2014; Simons-Morton, Guo, et al., 2014). The finding that the likelihood of an RWI fatality when the driver was 0.00 g/dL < BAC < 0.08 g/dL was higher when more than one passenger was present at the time of the crash than when only one passenger was present may indicate that driving with multiple passengers is a source of additional distraction to the young drinking drivers, further increasing the odds that a passenger would die in a fatal crash with the driver at 0.00 g/dL < BAC < 0.08 g/dL. Regarding the lack of significance of this factor when the driver was BAC $\geq$ 0.08 g/dL, we speculate that when the driver is heavily impaired (BAC $\geq$ 0.08 g/dL), alcohol is the main source of risk and the distractions created by additional passengers do not contribute to crash risk as much as when the distraction occurs at lower BACs.

One of the aims of this study was to assess whether race/ethnicity was a factor contributing to RWI fatalities among 15–20 y/o passengers. In our analysis, we found that race/ethnicity was not a factor influencing the likelihood of RWI fatal crashes. Another study aim was to assess whether the sex of the 15–20 y/o drivers and passengers was associated with the passengers dying in alcohol-related crashes. We found that when there were only two occupants in the vehicle, the sexes of the young driver and young passenger affects the likelihood the passenger was RWI. Among the young passengers who died in an alcohol-related crash, it is less likely to find a young female passenger riding with a young male driver, than a male passenger riding with another young male. There is a need to better understand the context of young driver-passenger dynamics, particularly among young dyads, and how such dynamics affect alcohol use and alcohol-related crashes. It might be possible that variation in how the driver-passenger dynamics plays out could explain some of the discrepancies on the role of race/ethnicity on RWI reported in the literature. Regardless, advancing the understanding of the driver-passenger dynamics is needed for the design of efficient and effective interventions to deter young people from engaging in RWI.

Of course, the most effective form of prevention is reducing impaired driving by providing alternatives to driving and to drinking. With respect to driving, these alternatives include public transportation, riding sharing, parental responsibility legislation, and designated driver programs. Other evidence-based countermeasures include high-visibility enforcement of zero tolerance laws (Johnson, 2016); programs and interventions to reduce accessibility of alcohol to minors (Komro & Toomey, 2002; Flewelling, Grube, et al., 2013; Fell, Fisher, et al., 2009; Wagenaar, Harwood, et al., 2005); communities efforts to limit alcohol outlet density (Chen, Grube, et al., 2010); the enactment and enforcement of ordinances such as alcohol retailer compliance checks (Elder, Lawrence, et al., 2007; Erickson, Smolenski, et al., 2013); keg registration (Ringwalt & Paschall, 2011); or social host ordinances that include strict liability and civil penalties (Paschall, Lipperman-Kreda, et al., 2014).

The findings provide some support for extending extant GDL passenger restrictions to age 20. Older teen-young adult might be neurodevelopmentally mature enough to be able to navigate social situation or context that would allow them to avoid engaging in RWI or DWI. Also, it is possible that better trained novice drivers aged 18–20 y/o would be able to navigate the context that might typically precede an impairing situation associated with alcohol use (despite being illegal) with better chances to avoid a crash and survive than less skilled drivers. Although this study provides some support for extending GDL programs, the evidence is far from conclusive and needs more examination.

This study has several limitations. Impairment by alcohol cannot be precisely established from the FARS. Drugs other than alcohol may have also contributed to the crashes examined. Unfortunately, as indicated by the agency that manages the database, drug-related crashes cannot be reliably studied from the FARS (Berning & Smither, 2014; Romano, Torres-Saavedra, et al., 2017). Information on driver's race and ethnicity was incomplete, as it is only available on the deceased occupants in FARS. Another important limitation of this study is that analyses are not adjusted by crash exposure. Although relevant and novel, our study was based only on fatal crashes, subsequently it does not take nonfatal and non-crashed RWI events into account.

5. Conclusions

Among 15–20 y/o passenger deaths, the majority occurred while riding with peer drivers. In nearly 27% of these cases, the driver had been drinking, and when the driver was drinking, about 77% of them had been drinking heavily. In order to curb RWI fatalities among underage passengers, it is necessary to enhance the implementation of countermeasures focused not only on underage drinking drivers, but also policies restricting drinking drivers of all ages.

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Association between driver and child passenger restraint: Analysis of community-based observational survey data from 2005 to 2019

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ABSTRACT

Introduction: Crash data suggest an association between driver seatbelt use and child passenger restraint. However, community-based restraint use is largely unknown. We examined the association between driver seatbelt use and child restraint using data from a state-wide observational study. *Methods:* Data from Iowa Child Passenger Restraint Survey, a representative state-wide survey of adult seat belt use and child passenger safety, were analyzed. A total of 44,996 child passengers age 0–17 years were observed from 2005 to 2019. Information about driver seatbelt use and child restraint was directly observed by surveyors and driver age was reported. Logistic regression was used to examine the association between driver seatbelt use and child restraint adjusting for vehicle type, community size, child seating position, child passenger age, and year. *Results:* Over the 15-year study period, 4,114 (9.1%) drivers were unbelted, 3,692 (8.2%) children were completely unrestrained, and another 1,601 (3.6%) children were improperly restrained (analyzed as unrestrained). About half of unbelted drivers had their child passengers unrestrained (51.8%), while nearly all belted drivers had their child passengers properly restrained (92.3%). Compared with belted drivers, unbelted drivers had an 11-fold increased odds of driving an unrestrained child passenger (OR = 11.19, 95%CI = 10.36, 12.09). The association between driver seatbelt use and child restraint was much stronger among teenage drivers. Unbelted teenage drivers were 33-fold more likely (OR = 33.34, 95%CI = 21.11, 52.64) to have an unrestrained child passenger. *Conclusion:* These data suggest that efforts to increase driver seatbelt use may also have the added benefit of increasing child restraint use. *Practical applications:* Enforcement of child passenger laws and existing education programs for new drivers could be leveraged to increase awareness of the benefits of seatbelt use for both drivers themselves and their occupants. Interventions aimed at rural parents could emphasize the importance of child safety restraints.

1. Introduction

Unrestrained children riding in motor vehicles are at significant increased risk of crash-related injury and death (Agran et al., 1992; Chan et al., 2006; Lee et al., 2015). Proper installation of age-appropriate child restraint systems, such as child safety seats or booster seats, and correct placement of children in restraints increase safety. Evidence shows that proper child restraint can reduce the risk of crash-related injury by 50–75% (Arbogast et al., 2004; Arbogast et al., 2009; Lee et al., 2008). As a result, guidelines for proper child safety seat use based on variables such as age, height, and weight have been established by the American Academy of Pediatrics (AAP) (2019) and the National Highway Traffic Safety Administration (NHTSA) (2019). Currently, all 50 states and District of Columbia have child passenger safety legislation and enforcement (Governor's Highway Safety Association, 2019). These efforts have led to an increase in child safety seat use reaching 90.9% across the United States in 2018 (Enriquez, 2019) and a decline in child passenger fatalities (National Center for Statistics and Analysis, 2019).

Although the use of child safety restraint has improved over time in the United States (Enriquez, 2019; Winston et al., 2004), there remain a substantial number of children killed while riding in motor vehicles, many of whom are not properly restrained. In 2018, about one third of child passengers 0 to 12 years old fatally

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injured in motor-vehicle crashes in the United States were unrestrained (Insurance Institute for Highway Safety, 2020). A more thorough understanding of factors influencing the use of child safety restraints is needed. Understanding these factors is important for targeted interventions and promoting optimal child passenger safety practices.

Prior research has reported an association between driver seatbelt use and child passenger restraint compliance (Roehler et al., 2019; Privette et al., 2018; Agran et al., 1998; Miller et al., 1998). However, these studies were conducted using crash data and might not depict an accurate picture of the distribution of child occupants in compliance with restraint guidelines. Given the difference in reported prevalence of overall child restraint use and the far lower prevalence of use reported in crash data, information on how to focus child seat use campaigns on high-risk drivers is warranted.

In this study we investigated the association between driver seatbelt use and child safety restraint use and examined if this association varied by factors such as driver age, vehicle type, and rurality.

2. Methods

2.1. Study population

Data analyzed in this study were derived from Iowa Child Passenger Restraint Survey conducted by the University of Iowa Injury Prevention Research Center and led by the Iowa Governor's Highway Traffic Safety Bureau. The survey is a representative statewide survey of adult seat belt use and child passenger restraint use and observes approximately 3,000 drivers and their child occupants each year. The survey uses a stratified sampling scheme where the strata were determined by the population sizes of the communities. Approaches were taken so that the proportion of the overall sample in each stratum was close to both the proportion of the overall state population in the corresponding stratum, and the proportion of the state child population in the corresponding stratum. Within each stratum, survey locations were selected to ensure that all geographic regions of the state were well represented.

The survey was conducted at gas stations or other frequented locations in communities (e. g., swimming pools, aquatic centers, and community center parking lots) where the surveyor could approach motor vehicles carrying passengers who appeared to be up to 17 years of age. When the surveyor approached the vehicle, they asked the driver if they would be willing to participate in a child passenger safety survey. If the driver agreed, the surveyor confirmed the driver age (<18 or $\geq$18) and the child's age(s), and quickly observed if the child was restrained and the child location within the vehicle. If the child was restrained, the surveyor noted the type of child restraint (child safety seat, booster seat, seat belt, none). Drivers of unrestrained children observed were reminded of Iowa child passenger law and offered a brochure outlining both current Iowa law and best practices. From 2005 through 2019, a total of 45,780 children ages 0–17 years were observed. We excluded 784 (1.7%) children with missing information on child restraint use, child's age, and vehicle type. Thus, our final analytical sample was 44,996.

2.2. Variables of interest

2.2.1. Driver seatbelt use and child passenger restraint

Information about driver seatbelt use and child restraint was directly observed. For a child who was restrained, we used the child's age and the type of restraint to determine whether the child was properly restrained in accordance with Iowa law (State of Iowa, 2010). A child passenger whose age was under 1 year and restrained with a child safety seat was classified as properly restrained, otherwise was coded as unrestrained. A child passenger whose age was from 1 year to 5 years and restrained with a child safety seat or a booster was classified as properly restrained, otherwise was coded as unrestrained. A child passenger whose age was from 6 years to 11 years and restrained with a child safety seat, a booster, or a seatbelt was classified as properly restrained, otherwise was coded as unrestrained. A child passenger whose age was from 12 years to 17 years and restrained with a booster or a seatbelt was classified as properly restrained, otherwise was coded as unrestrained. Completely unrestrained children and improperly restrained children were combined and analyzed as unrestrained.

2.2.2. Covariates

Communities were categorized as rural (fewer than 2,500 residents), town (2,500–9,999 residents), small urban (10,000–49,999 residents), and urban (50,000 residents or greater). Data on vehicle type were reported by surveyors and coded as car, pickup truck, pickup truck with a club cab (has an extra row of seats), van, and SUV. Other information collected in the survey included the seating position of child passenger within the vehicle (front seat vs. back seat) and the driver age (<18 or $\geq$18). Of note, prior to 2009, data on driver age was not collected.

2.3. Statistical methods

Characteristics of the study population are presented as frequency tabulations by driver seatbelt status. Multivariable logistic regression was used to calculate adjusted odds ratios (ORs) and corresponding 95% confidence intervals (CIs), which were used to identify factors associated with unrestrained child passengers. To investigate whether risk factors depend on the driver age, models were run separately for teen drivers (16–17 years old) and adult drivers (18+ years old). The stratified analysis by driver age was based on data from 2009 to 2019 because data on driver age were not collected prior to 2009. Covariates examined in the multivariable logistic regression models were community size, vehicle type, child seating position (front versus back), child passenger age, and year. All analyses were performed in SAS 9.4.

3. Results

Over the 15-year study period, 4,114 (9.1%) drivers were unbelted, 3,692 (8.2%) children were completely unrestrained, and another 1,601 (3.6%) children were improperly restrained and analyzed as unrestrained. Table 1 shows the characteristics of the study population by driver seatbelt status. About half of unbelted drivers had their child passengers unrestrained (51.8%), while nearly all belted drivers had their child passengers properly restrained (92.3%). About three in four belted drivers and four in five unbelted drivers transported child passengers ages 1–11 years old. Unbelted drivers were most common in rural communities (34.5%), while belted drivers were most frequent in urban communities (38.5%). Belted drivers were more likely to have child occupants positioned in the back of the vehicle compared to unbelted drivers (78.4% vs 67.3%). Among unbelted drivers, passenger cars (42.7%) and SUVs (19.0%) were the most frequent vehicles used. Among belted drivers, passenger cars were the most frequent vehicles used (38.6%), followed by vans (27.2%). For drivers with available information on age, most child passengers were driven by drivers 18 years or older.

The results from the multivariable models are shown in Table 2. Compared with belted drivers, unbelted drivers had an 11-fold

Table 1
Characteristics of study population by driver seatbelt use status.

Variables	Driver belted	
	Yes (n = 40882) n (%)	No (n = 4114) n (%)
Child passenger restrained		
Yes	37,720 (92.3)	1,983 (48.2)
No	3,162 (7.7)	2,131 (51.8)
Child passenger age		
<1 year	1,172 (2.9)	58 (1.4)
1–5 years	15,806 (38.6)	1,411 (34.3)
6–11 years	15,613 (38.2)	1,843 (44.8)
12–17 years	8,291 (20.3)	802 (19.5)
Type of restraint used		
Belted	20,940 (51.2)	993 (24.1)
Booster	8,455 (20.7)	499 (12.1)
Child Safety Seat	9,806 (24.0)	611 (14.9)
None	1,681 (4.1)	2,011 (48.9)
Seating position within the vehicle		
Back	32,045 (78.4)	2,768 (67.3)
Front	8,837 (21.6)	1,346 (32.7)
Vehicle type		
Car	15,802 (38.6)	1,756 (42.7)
Pickup	1,169 (2.9)	437 (10.6)
Pickup club cab	3,066 (7.5)	542 (13.2)
SUV	9,718 (23.8)	780 (19.0)
Van	11,127 (27.2)	599 (14.5)
Driver age		
16–17	1,463 (3.6)	157 (3.8)
18+	26,351 (64.4)	2,092 (50.9)
Missing	13,068 (32.0)	1,865 (45.3)
Community		
Rural (<2,500 residents)	6,990 (17.1)	1,420 (34.5)
Town (2,500–9,999 residents)	8,542 (20.9)	996 (24.2)
Small urban (10,000–49,999 residents)	9,616 (23.5)	782 (19.0)
Urban (≥50,000 residents)	15,734 (38.5)	916 (22.3)

Prior to 2009 data on driver age was not collected.
Unrestrained child passenger: completely unrestrained or improperly restrained (A child passenger whose age was under 1 year and restrained with a child safety seat was classified as properly restrained, otherwise was improperly restrained. A child passenger whose age was from 1 year to 5 years and restrained with a child safety seat or a booster was classified as properly restrained, otherwise was improperly restrained. A child passenger whose age was from 6 years to 11 years and restrained with a child safety seat, a booster, or a seatbelt was classified as properly restrained, otherwise was improperly restrained. A child passenger whose age was from 12 years to 17 years and restrained with a booster or a seatbelt was classified as properly restrained, otherwise was improperly restrained.

increased odds of having unrestrained child passengers (OR = 11.19, 95%CI = 10.36, 12.09). The association between driver seatbelt use and child passenger restraint was much stronger among teenage drivers. Unbelted teenage drivers were 33-fold more likely (OR = 33.34, 95%CI = 21.11, 52.64) to have unrestrained child passengers. Compared to child passengers under 1 year old, child passengers 1–5 years and 12–17 years old were 11 times more likely (OR = 11.50, 95%CI = 6.28, 21.07) and almost 17 times as likely (OR = 16.71, 95%CI = 9.09, 30.73) to be unrestrained, respectively, while child passengers 6–11 years were 7 times more likely (OR = 7.26, 95%CI = 3.96, 13.31) to be unrestrained. Compared with urban communities, rural communities were associated with 18% increased odds of having unrestrained child passengers (OR = 1.18, 95%CI = 1.08, 1.29).

Compared with car drivers, pickup drivers were 64% more likely to have an unrestrained child passenger (OR = 1.64, 95%CI = 1.42, 1.89). Vehicles such as van and SUV were associated with decreased odds of unrestrained child passengers compared to passenger cars. Child passengers positioned in the back of the vehicle were almost 8-fold more likely to be unrestrained when the driver was a teenager (OR = 7.69, 95%CI = 5.41, 10.92) and 1.4-fold more likely to be unrestrained when the driver was an adult (OR = 1.40, 95%CI = 1.23, 1.59). Increasing year was associated with decreased odds for unrestrained child passengers.

4. Discussion

This study found that 90.9% of observed children riding in motor vehicles were restrained. A similar percentage was reported by the National Occupant Protection Use Survey (NOPUS) in 2018 (Insurance Institute for Highway Safety, 2020). The 2018 NOPUS data showed that 90.4% of child passengers under age 8 were restrained and 91.3% of children 8–15 years old were belted. The NOPUS is conducted annually and occupants of stopped vehicles are observed from the roadside at intersections controlled by stop signs or stop lights. The NOPUS roadside observers subjectively estimate vehicle occupants' age, while data on age is directly gathered from drivers in the Iowa Child Passenger Restraint Survey. In addition, the NOPUS does not collect information on the type of safety restraint, limiting their ability to assess whether a child restraint was age appropriate. Earlier studies have reported much lower percentages of child restraint use than those reported in the current study and the NOPUS survey. In Michigan in 1999, studies showed that 74.5% of children under 4 years of age were in safety seats (Eby & Kostyniuk, 1999) and 57.8% of children 4–15 years were restrained (Eby, Kostyniuk, & Vivoda, 2001). A child restraint study conducted in 2002 across several states (Arizona, Florida, Mississippi, Missouri, Pennsylvania, and Washington) reported that 62.3% of children riding in motor vehicles were restrained (Decina & Lococo, 2005). The higher percentage of child restraint use observed in recent years may be partially explained by the strengthening in child restraint laws as well as enforcement and parental behavioral changes (Governor's Highway Safety Association, 2019; Winston et al., 2004).

This study provides supporting evidence that a driver's seatbelt use is strongly associated with child passenger restraint use. The association of unbelted drivers with unrestrained child passengers was much stronger among teenage drivers. The findings from this study are consistent with previous studies reporting that unbelted drivers are more likely to have unrestrained child occupants in the vehicle. For example, a study examining factors associated with unrestrained child passengers using national crash data collected between 2011 and 2015 found a strong association of a driver seatbelt use with a child passenger being unrestrained and the strength of the association was inversely proportionate to the child age (Roehler, Elliott, Quinlan, & Zonfrillo, 2019). Using nonfatal data, the study found that 0- to 8-years old unrestrained passengers and 9- to 15-years old unrestrained passengers were 15 times and 18 times more likely to have unrestrained drivers, respectively. A similar trend in the associations was observed across the same age groups but weaker when fatal crash data were analyzed. Findings from other studies based on crash data also concur with the results of the current study, showing that unrestrained child passengers are more likely have unbelted drivers (Privette et al., 2018; Agran et al., 1998; Miller et al., 1998). These crash data have limitations. First, they might not provide an accurate distribution of children riding in compliance with restraint guidelines, a fundamental shortcoming. Second, data on occupant restraint use in a crash might not be accurate, especially when information on restraint use was reported by the child passenger or the driver. Inaccurate reporting of safety restraint use may occur when occupants have left their vehicles before the police arrived or occupants may falsely report the use of restraints to avoid tickets. Our study overcomes these limitations by using a sample weighted to the state population and by directly observing the use of driver seatbelt and child passenger restraint.

Studies have consistently shown that rural drivers are less likely to wear a seatbelt (Ash et al., 2014; Baker et al., 2000; Beck et al., 2017). The current study found that rural communities were associated with unrestrained child passengers independent of the driver seatbelt status. This finding is consistent with a previous

Table 2
Factors associated with child passengers being unrestrained.

Variables	Multivariable ORs and 95% CI		
	ALL drivers	Teen drivers (16–17 years)	Adult drivers (18+)
Driver belted			
No	11.19 (10.36, 12.09)	33.34 (21.11, 52.64)	15.36 (13.76, 17.14)
Yes	1.00	1.00	1.00
Child passenger age			
<1 year	1.00	1.00*	1.00
1–5 years	11.50 (6.28, 21.07)		11.39 (5.82, 22.29)
6–11 years	7.26 (3.96, 13.31)		7.85 (4.01, 15.39)
12–17 years	16.71 (9.09, 30.73)	8.07 (4.57, 14.25)	17.58 (8.95, 34.52)
Community size			
Rural (<2,500 residents)	1.18 (1.08, 1.29)	1.78 (1.16, 2.73)	1.25 (1.09, 1.43)
Town (2,500–9,999 residents)	1.10 (1.01, 1.20)	1.28 (0.84, 1.95)	1.13 (0.99, 1.29)
Small urban (10,000–49,999 residents)	1.13 (1.04, 1.24)	1.69 (1.08, 2.66)	1.06 (0.93, 1.21)
Urban (≥50,000 residents)	1.00	1.00	1.00
Vehicle type			
Pickup	1.64 (1.42, 1.89)	1.72 (0.90, 3.30)	2.08 (1.67, 2.58)
Pickup club cab	0.98 (0.88, 1.10)	1.13 (0.61, 2.07)	1.03 (0.88, 1.20)
SUV	0.59 (0.54, 0.65)	1.52 (0.97, 2.39)	0.60 (0.53, 0.69)
Van	0.55 (0.51, 0.60)	0.57 (0.29, 1.12)	0.66 (0.58, 0.76)
Car	1.00	1.00	1.00
Seating position within the vehicle			
Back	1.08 (0.99, 1.19)	7.69 (5.41, 10.92)	1.40 (1.23, 1.59)
Front	1.00	1.00	1.00
Year	0.88 (0.87, 0.88)	0.84 (0.79, 0.89)	0.93 (0.92, 0.95)

Notes:
Overall odds ratio (OR) was calculated using data from 2005 to 2019.
Stratified odds ratios (ORs) were calculated using data from 2009 to 2019 because prior to 2009 data on driver age was not collected.
All models adjusted for community size, vehicle type, child seating position (front versus back), child passenger age, and year.
*For the teen driver model, child passenger age groups < 1 year, 1–5 years, and 6–11 years were combined into one group because the model estimates were otherwise unstable.

study reporting a lower use of child restraint in crashes occurring in rural communities compared to urban settings (Agran, Anderson, & Winn, 1998). The lower use of safety restraints in rural communities may be explained by differences in the perceived importance of using child safety restraint. One previous study showed that urban parents were much more concerned about the risk of child injury in a crash than were rural parents (Ebel et al., 2006).

Other factors associated with unrestrained child passengers included the vehicle in which the child was traveling and the child seating position. We found that vans and SUVs were less likely to have unrestrained children compared to passenger cars. These data are consistent with the 2018 NOPUS data, which showed that restraint use was highest for vans & SUVs and lowest for passenger cars (Enriquez, 2019). We found that the association between child seating position and restraint use depends on the driver age. Among teen drivers, back seat was strongly associated with a child being unrestrained. It would be quite helpful to understand what might have caused this effect modification to inform interventions to increase child occupant protection use.

This study has some limitations. Data on the child's height and weight, which are helpful to determine appropriate restraint requirements, were not available due to challenges and accuracy of collecting this information in the field. As a result, we used only the child's age to determine whether the child was properly restrained. Because the appropriate child safety restraint depends on the child's age, height, and weight, it remains possible that we may have misclassified some child passengers. However, a possible misclassification is unlikely to change the conclusions of our study since only 3.6% of children were classified as improperly restrained while 8.2% of children were completely unrestrained. Moreover, data collectors did not determine whether child safety restraints were properly installed or fastened. These details would be helpful to determine whether the restraint meets AAP best practices.

Notwithstanding these limitations, the current study may have important implications. These data suggest that efforts to increase child restraint use may also have the added benefit of increasing driver seatbelt use, and, similarly, that highly visible enforcement of child passenger laws (Governor's Highway Safety Association, 2019) coupled with focused messages addressing both driver and child occupant protection may be helpful in increasing restraint use for both occupant groups. Given the strong relationship between driver seatbelt use and child safety restraint among teen drivers, enforcement of child passenger laws (Governor's Highway Safety Association, 2019) combined with an emphasis of restraint use in education programs for new drivers could be leveraged to increase seatbelt use for both drivers themselves and their occupants. Interventions aimed at rural parents could emphasize the importance of child safety restraints. This study demonstrates an opportunity to promote driver belt use integrated with child safety seat use, especially in rural areas.

5. Conclusions

Unbelted drivers were strongly associated with unrestrained child passengers in a state-wide observational study and the association was much stronger among teenage drivers. Rural communities were also associated with unrestrained child passengers independent of the driver seatbelt status. These data suggest that efforts to increase child restraint use may also have the added benefit of increasing driver seatbelt use. This study demonstrates an opportunity to promote driver belt use integrated with child safety seat use, especially in rural areas.

Conflicts of interest

None.

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Beach and patio umbrella injuries treated at emergency departments

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ABSTRACT

Introduction: Beach and patio umbrellas may cause injury. There is limited published information on injuries due to beach and patio umbrellas. This study sought to describe beach and patio umbrella injuries reported to United States emergency departments (EDs). *Method:* An analysis was performed of beach and patio umbrella injuries using data from the National Electronic Injury Surveillance System during 2000–2019. *Results:* An estimated 5,512 beach umbrella injuries and 7,379 patio umbrella injuries were identified. The patient was age 40 years or older in 62.1% of the beach umbrella and 65.1% of the patio umbrella injuries. The patient was female in 68.0% of the beach umbrella and 66.9% of the patio umbrella injuries. Wind was reported involved in 50.6% of the beach umbrella and 27.5% of the patio umbrella injuries. The most frequently reported injuries with beach and patio umbrella injuries, respectively, were laceration (44.0% vs 33.0%), contusions or abrasions (19.8% vs 19.0%), and internal organ injury (16.6% vs 17.0%) and most often affected the head/neck (60.2% vs 44.0%) and upper extremity (16.3% vs 30.1%). *Conclusions:* The majority of patients with beach and patio umbrella injuries treated at EDs were age 40 years or older and most patients were female. For both types of umbrella injury, the most frequently reported injury was laceration followed by contusions or abrasions and internal organ injury, and the body part with the highest proportion of injuries was the head/neck followed by the upper extremity. *Practical Applications:* Persons should use sturdier models of beach or patio umbrella, use a rocking motion to dig into the sand and secure the beach umbrella with a metal anchor and screws, add weight to the bottom of the umbrella, and tilt the umbrella into the wind. Policy-makers should educate the public about the potential dangers of beach and patio umbrellas.

1. Introduction

A beach umbrella is a large umbrella with a central pole that has a pointed bottom used to spike the pole into the sand (Metheney, 2018). If not properly secured, wind can uproot a beach umbrella from the sand and propel it, potentially causing injury if it hits someone (BBC News, 2019; MBC12.com, 2019; Wise, 2019). The U.S. Consumer Product Safety Commission (CPSC) reported an estimated 2800 people went to emergency departments (EDs) during 2010–2018 for injuries of varying severity caused by beach umbrellas (BBC News, 2019; MBC12.com, 2019; Wise, 2019). Deaths related to beach umbrella injuries have been reported (Harris et al., 2018; Quatrehomme et al., 2016; Ventura Spagnolo et al., 2016). In July 2019, several U.S. Senators asked the CPSC to provide data on beach umbrella injuries and create recommendations to make beach umbrellas safer (BBC News, 2019; MBC12.com, 2019; Wise, 2019).

A patio or table umbrella tends to be heavier and have a thicker pole than a beach umbrella. The patio umbrella pole usually fits inside a hole in the center of a table. Unlike a beach umbrella, the pole of a patio umbrella has a flat bottom and a base (Metheney, 2018). Patio umbrellas also may cause injuries (Vaughn, 2008).

Published information on beach and patio umbrella-related injuries is limited to case reports (Harris et al., 2018; Quatrehomme et al., 2016; Ventura Spagnolo et al., 2016). The objective of this study was to describe beach and patio umbrella related injuries treated at EDs.

2. Materials and methods

This retrospective epidemiologic study used data downloaded from the U.S. National Electronic Injury Surveillance System (NEISS) website (https://www.cpsc.gov/cgibin/NEISSQuery/home.aspx). The NEISS, operated by the CPSC, collects data on consumer product-related injuries in the United States from the EDs of approximately 100 hospitals representing a stratified probabilistic

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sample of the more than 6000 U.S. hospitals with six or more beds and 24-hour EDs. The NEISS stratified sample is based on ED size and geographic location. Professional NEISS coders view the medical charts at the selected hospitals and collect and code information including patient demographics and basic injury information, such as injury diagnosis, body parts affected, and location where the injury occurred as well as a brief narrative describing the incident (U.S. Consumer Product Safety Commission, not dated; U.S. Consumer Product Safety Commission, 2019). Data are publically available and de-identified; therefore, the study is exempt from institutional review board approval.

Cases were injuries involving beach and patio umbrellas reported to NEISS during 2000–2019. The NEISS database contains three numeric fields (Product_1, Product_2, Product_3) for coding the type of product(s) involved in an injury. According the NEISS coding manual (U.S. U.S. Consumer Product Safety Commission, 2019), both beach and patio umbrellas are to be assigned product code 1660 (Umbrellas). However, other types of umbrellas, such as hooked handle umbrellas and golf umbrellas, also would be assigned product code 1660. Moreover, beach and patio umbrellas might have been assigned product codes other than 1660 by mistake. In order to identify as many injuries involving beach and patio umbrellas as possible, all records where the Product_1, Product_2, or Product_3 fields contained the product code 1660 or the Narrative text field contained the letter grouping "umbrel" (regardless of product codes) were identified. The Narrative fields of the resulting records then was reviewed for any mention of "beach," "sand," "patio," "table," "park," or "picnic," in order to identify the subset of records of injuries due to beach or patio umbrellas. This subset of records comprised the cases for the study. Records involving beach umbrellas and patio umbrellas were divided into two groups so that injuries due to beach umbrellas and injuries due to patio umbrellas could be examined separately. A total of 288 case records were retrieved and included in the study set consisting of 111 beach umbrella and 177 patio umbrella records.

The records were used to determine national injury estimates. A national estimate (the sum of the numbers in the Weight numeric field in the NEISS database) is based on the sample weight assigned to each record based on the inverse probability of the hospital being selected for the NEISS sample. The distribution of the national estimates for beach and patio umbrella-related injuries separately was calculated for patient age group, sex, and race; date of treatment (year, season, day of week); circumstances under which the injury occurred, location where the injury occurred; disposition; diagnosis; and body part affected. The public NEISS database does not contain a coded variable that describes the exact circumstances that led to the injury. Initial review of the Narrative field identified several general circumstance categories under which the injury occurred. Each record was assigned one of these circumstance categories: setting up/opening the umbrella, taking down/closing the umbrella, the umbrella fell, wind affected the umbrella, hit by umbrella (not otherwise specified), other (e.g., dropped umbrella, tripped over umbrella, finger caught in umbrella), unknown.

Ninety-five percent confidence intervals (CIs) were calculated for the estimates according to instructions provided by the CPSC: If the estimate is greater than 239,380, then the coefficient of variation (CV) is a fixed value, i.e., $1/(-8.6453 + 1.7368*\mathrm{LN}(239380)) \sim = 0.08$. If the estimate is less than 239,380, then the CV is calculated using the following formula, $1/(-8.6453 + 1.7368*\mathrm{LN}(\mathrm{Estimate}))$. The 95% CI is then calculated using the formula 95% CI = estimate ± (1.96*estimate*CV). The CPSC considers an estimate unstable and potentially unreliable when the number of records used is <20, the estimate is <1,200, or the coefficient of variation (CV) is >33% (U.S. Consumer Product Safety Commission, not dated). As a result, any calculated national estimates that are <1,200 should be considered statistically unstable and potentially unreliable. For those variable subgroups where the estimate was <1,200, 95% CIs were not calculated.

3. Results

During 2000–2019, 111 beach umbrella-related injuries were identified, resulting in a national estimate of 5,512 beach umbrella-related injuries (95% CI 3,802–7,222). During the same time period, 177 patio umbrella-related injuries were identified, resulting in a national estimate of 7,379 patio umbrella-related injuries (95% CI 5,259–9,498). Table 1 shows the distribution of beach and patio umbrella-related injuries by patient demographics. Patients age 40 years and older accounted for 3,423 (62.1%) of the estimated beach umbrella-related injuries, with a mean age of 43.5 years (range 0–84 years), and 4,807 (65.1%) of the estimated patio umbrella-related injuries, with a mean age of 47.4 years (range 0–88 years). Most of the patients with either type of umbrella-related injury were female and the majority of patients were white.

Fig. 1 shows the annual estimated number of beach and patio umbrella-related injuries and Table 2 presents the distribution of beach and patio umbrella-related injuries by the circumstances of the injury. For both types of umbrella-related injury, the annual estimated number of injuries varied from year to year but tended to be higher during the latter part of the study period, with the majority occurring during 2012–2019. The highest proportion of both beach and patio umbrella-related injuries occurred during June–August followed by March-May, with relatively few reported during December–February. Most of both type of umbrella-related injury were treated during Saturday–Monday. The highest proportion of both types of injuries occurred when wind affected the umbrella, although this proportion was higher for beach umbrella-related injuries than for patio umbrella-related injuries. The majority of beach umbrella-related injuries occurred at a place of recreation or sports, while the majority of patio umbrella-related injuries occurred at home followed by other public property.

When the diagnosis and affected body part were examined (Table 3), for both types of umbrella-related injuries, the highest proportion of injuries were laceration followed by contusions or abrasions, internal organ injury, sprain or strain, and fracture. The body part with the highest proportion of injuries was the head or neck followed by the upper extremity, lower extremity, and trunk. The majority of patients were treated or examined at the ED and released (Table 3).

4. Discussion

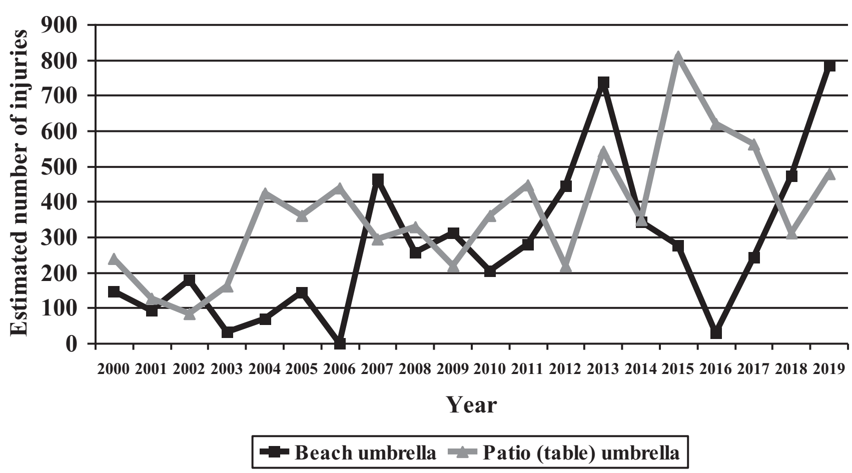
This study characterizes beach and patio umbrella-related injuries treated at EDs. Although both types of umbrella can cause serious injury, published information on such injuries is limited to case reports (Harris et al., 2018; Quatrehomme et al., 2016; Ventura Spagnolo et al., 2016). The majority of patients were found to be age 40 years or older with patients experiencing patio umbrella-related injuries tending to be older than patients experiencing beach umbrella-related injuries. Most of the patients were female. It may be that adults age 40 and older and female are more likely to use beach and patio umbrellas or are more likely to experience injuries treated at EDs when using these umbrellas.

Although the annual estimated number of both beach and patio umbrella-related injuries varied from year to year, the estimated number of injuries was higher during the latter part of the study period, with 60.4% of the beach umbrella-related injuries and

Table 1
Demographic characteristics of beach and patio umbrella-related injuries treated at emergency departments, National Electronic Injury Surveillance System, 2000–2019.

Variable	Beach umbrella			Patio (table) umbrella		
	Est.	%	95% CI	Est.	%	95% CI
Age (years)						
0–19	990	18.0	–	1,254	17.0	598–1,910
20–39	1,099	19.9	–	1,318	17.9	644–1,992
40–59	1,928	35.0	1,087–2,770	2,253	30.5	1,326–3,180
60+	1,494	27.1	771–2,218	2,554	34.6	1,549–3,559
Sex						
Male	1,764	32.0	967–2,561	2,441	33.1	1,465–3,417
Female	3,748	68.0	2,447–5,049	4,938	66.9	3,358–6,518
Race						
White	3,167	57.5	2,008–4,327	4,444	60.2	2,978–5,909
Black/African American	161	2.9	–	420	5.7	–
Asian	30	0.5	–	5	0.1	–
Native Hawaiian/Pacific Islander	0	0.0	–	74	1.0	–
Other	156	2.8	–	188	2.5	–
Not stated	1,998	36.3	1,138–2,858	2,248	30.5	1,322–3,173
Total	5,512		3,802–7,222	7,379		5,259–9,498

Est. = Weighted estimate (sum of the Weight field in the National Electronic Injury Surveillance System database). The numbers in the Weight field are not whole numbers but include decimals. As a result of rounding to whole numbers when performing analyses, the sum of the estimates for a given variable might not equal the total. The Consumer Product Safety Commission considers an estimate unstable and potentially unreliable when the estimate is <1,200.
95% CI = 95% confidence interval. Not calculated if the estimate is <1,200.



The Consumer Product Safety Commission considers an estimate unstable and potentially unreliable when the estimate is <1,200.

Fig. 1. Annual estimated number of beach and patio (patio) umbrella-related injuries treated in United States emergency departments, National Electronic Injury Surveillance System (NEISS).

52.7% of the patio umbrella-related injuries occurring during 2012–2019. This increase may be due to an increase in the use of beach and patio umbrellas, an increase in injuries resulting from use of these umbrellas, and/or an increase in persons injured by these umbrellas visiting EDs. Alternately, it may be that the individuals completing NEISS records may have been more likely in recent years to document that the umbrellas involved in injuries were beach or patio umbrellas. Another potential explanation may involve changes in the hospitals participating in the NEISS. Hospitals gradually rotate in and out of the NEISS; hospitals joining or leaving the surveillance system can have a substantial influence on national estimates, depending on the category of injury.

The highest proportion of beach and patio-umbrella related injuries occurred in the June-August followed by March-May. The majority of injuries to both types of umbrella were treated during the weekend and Monday. This might be expected because people in the United States may be more likely to visit the beach or use an outdoor table during warmer weather in summer and spring and less likely in the winter when it is cold. In addition, people might be more likely to have the free time to visit the beach or be at outdoor tables during the weekend.

Wind accounted for the highest proportion of both beach and patio umbrella-related injuries. Furthermore, 10.2% of beach umbrella-related injuries and 12.6% of patio umbrella-related injuries occurred when the patient was hit by an umbrella (not otherwise specified). In a portion of these cases, the wind may have caused the umbrella to hit the patient but wind was not specifically mentioned in the Narrative field. If beach and patio umbrellas are not adequately secured, wind may pick them up and blow them into people. Even if the umbrellas are not blown away, wind may cause them to sway, causing them to strike people. A higher proportion of beach umbrella-related injuries (50.6%) than patio umbrella-related injuries (27.5%) were due to wind. Beach umbrellas usually are anchored to the ground simply by driving the pointed bottom of the pole into sand while patio umbrellas usually are threaded through a hole in a table and inserted into a weighted base. As a result beach umbrellas may be more likely than patio umbrellas to be unsecured by the wind and blown into people,

Table 2
Circumstances of beach and patio umbrella-related injuries treated at emergency departments, National Electronic Injury Surveillance System, 2000–2019.

Variable	Beach umbrella			Patio (table) umbrella		
	Est.	%	95% CI	Est.	%	95% CI
Treatment year						
2000–2003	451	8.2	–	610	8.3	–
2004–2007	679	12.3	–	1,517	20.6	788–2,247
2008–2011	1,052	19.1	–	1,359	18.4	674–2,045
2012–2015	1,801	32.7	994–2,608	1,918	26.0	1,080–2,757
2016–2019	1,529	27.7	796–2,262	1,974	26.8	1,121–2,828
Treatment month						
December–February	70	1.3	–	477	6.5	–
March–May	1,577	28.6	831–2,324	2,577	34.9	1,566–3,587
June–August	3,303	59.9	2,110–4,496	3,141	42.6	1,988–4,294
September–November	562	10.2	–	1,184	16.0	–
Treatment day of week						
Saturday–Monday	2,941	53.4	1,838–4,044	4,147	56.2	2,751–5,543
Tuesday–Friday	2,571	46.6	1,561–3,580	3,232	43.8	2,057–4,407
Circumstance						
Wind affected umbrella	2,787	50.6	1723–3851	2,029	27.5	1,161–2,898
Setting up/opening umbrella	764	13.9	–	1,566	21.2	823–2,309
Hit by umbrella (not otherwise specified)	560	10.2	–	931	12.6	–
Umbrella fell	610	11.1	–	685	9.3	–
Taking down/closing umbrella	165	3.0	–	565	7.7	–
Other	411	7.5	–	1,336	18.1	657–2,016
Unknown	215	3.9	–	266	3.6	–
Location						
Place of recreation or sports	4,960	90.0	3,375–6,545	167	2.3	–
Home	84	1.5	–	4,680	63.4	3,159–6,200
Other public property	287	5.2	–	1,003	13.6	–
School	0	0.0	–	5	0.1	–
Not recorded	181	3.3	–	1,524	20.7	792–2,255
Total	5,512		3,802–7,222	7,379		5,259–9,498

Est. = Weighted estimate (sum of the Weight field in the National Electronic Injury Surveillance System database). The numbers in the Weight field are not whole numbers but include decimals. As a result of rounding to whole numbers when performing analyses, the sum of the estimates for a given variable might not equal the total. The Consumer Product Safety Commission considers an estimate unstable and potentially unreliable when the estimate is <1,200.
95% CI = 95% confidence interval. Not calculated if the estimate is <1,200.

Table 3
Diagnosis and disposition of beach and patio umbrella-related injuries treated at emergency departments, National Electronic Injury Surveillance System, 2000–2019.

Variable	Beach umbrella			Patio (table) umbrella		
	Est.	%	95% CI	Est.	%	95% CI
Diagnosis						
Laceration	2427	44.0	1455–3400	2432	33.0	1458–3406
Contusions or abrasions	1092	19.8	–	1405	19.0	706–2103
Internal organ injury	912	16.6	–	1253	17.0	597–1909
Strain or sprain	402	7.3	–	644	8.7	–
Fracture	162	2.9	–	578	7.8	–
All other/unknown	517	9.4	–	1067	14.5	–
Body part						
Head/neck	3318	60.2	2121–4514	3247	44.0	2068–4427
Upper extremity	898	16.3	–	2224	30.1	1304–3144
Lower extremity	854	15.5	–	1084	14.7	–
Trunk	286	5.2	–	823	11.2	–
Other/unknown	157	2.8	–	0	0.0	–
Disposition						
Treated or examined and released	5240	95.1	3591–6889	7061	95.7	5010–9113
Treated and transferred to another hospital	0	0.0	–	77	1.0	–
Treated and admitted for hospitalization	205	3.7	–	225	3.0	–
Left without being seen/against medical advice	67	1.2	–	16	0.2	–
Total	5,512		3,802–7,222	7,379		5,259–9,498

Est. = Weighted estimate (sum of the Weight field in the National Electronic Injury Surveillance System database). The numbers in the Weight field are not whole numbers but include decimals. As a result of rounding to whole numbers when performing analyses, the sum of the estimates for a given variable might not equal the total. The Consumer Product Safety Commission considers an estimate unstable and potentially unreliable when the estimate is <1,200.
95% CI = 95% confidence interval. Not calculated if the estimate is <1,200.

possibly causing injury. However, injuries also may occur when people set up or open the umbrellas, taken down or close the umbrellas, or fall over the umbrella.

While the majority of beach umbrella-related injuries occurred at a place of recreation or sports, most of the patio umbrella-related injuries occurred at home or other public property. According to the NEISS coding manual (U.S. Consumer Product Safety Commission, 2019), the beach is assigned the location code for "Place of recreation or sports."

This study has limitations. Cases were identified by searching those records with Product code 1660 or the Narrative field text including the letter grouping "umbrel" for any mention of "beach," "sand," "patio," "table," "park," or "picnic" in the Narrative field. Beach and patio umbrella-related injuries where this Product code was not assigned or any of the key phrases used would not have been included in this investigation. Although the Narrative field might mention a beach or patio umbrella, it does not necessarily mean that the umbrella in question was what is thought of as a beach or patio umbrella. It may be that a patio or other umbrella was documented as a beach umbrella and vice versa. Furthermore, the assignment of a circumstance category to each record was based on limited information in the Narrative field and involved a degree of subjectivity. In addition, the selection of records for the study and assignment of circumstance category of the injury was performed by a single person. Moreover, the patient race was not stated in the ED record for 30–40% of the records, thus limiting the analysis of race. Also, the NEISS database only includes those injuries treated at an ED; the NEISS database does not include injuries not managed at an ED. Furthermore, relatively few beach and patio umbrella-related injuries were identified. As a result, some of the national estimates calculated in the analyses of the variables were <1,200 and thus unstable and potentially unreliable. Similar analyses involving beach and patio umbrella-related injuries using other data sources with larger numbers of cases would be useful to verify the observations made in this study.

5. Conclusions

Beach and patio umbrella-related injuries treated at EDs tended to increase over the 20-year period of the study. The majority of patients were age 40 years or older and most patients were female. The injuries most often occurred during the summer and spring. The highest proportion of beach and patio-umbrella-related injuries were reported to involve the wind. While beach umbrella-related injuries most often occurred at a place of recreation and sports, patio umbrella-related injuries most often occurred at home or other public property. For both types of umbrella-related injury, the most frequently reported injury was laceration followed by contusions or abrasions, internal organ injury, sprain or strain, and fracture, and the body part with the highest proportion of injuries was the head or neck followed by the upper extremity, lower extremity, and trunk. The majority of patients were treated or examined at the ED and released.

Practical applications include precautions that can be taken by those who use beach and patio umbrellas to reduce or prevent injuries. People should use sturdier models of beach or patio umbrella, use a rocking motion to dig into the sand and secure the beach umbrella with a metal anchor and screws, add weight to the bottom of the umbrella, and tilt the umbrella into the wind (BBC News, 2019; Wise, 2019). People should take care when opening and closing the umbrellas. Policy-makers should educate the public about the potential dangers of beach and patio umbrellas. Since injuries most often occurred during the summer and spring, education activities should be targeted during those seasons.

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None.

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Comparative judgements of crash risk and driving ability for speeding behaviours

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ABSTRACT

Introduction: Preliminary research has indicated that numerous drivers perceive their risk of traffic crash to be less than other drivers, while perceiving their driving ability to be better. This phenomenon is referred to as 'comparative optimism' (CO) and may prove to inhibit the safe adoption of driving behaviors and/or dilute perceptions of negative outcomes. The objective of this study was to investigate comparative judgments regarding crash risk and driving ability, and how these judgments relate to self-reported speeding. *Method:* There were 760 Queensland motorists comprised of 51.6% males and 48.2% females, aged 16–85 (M = 39.60). Participants completed either a paper or online version of a survey. Judgments of crash risk and driving ability were compared to two referents: the average same-age, same-sex driver, and the average same-age, same-sex V8 supercar champion. *Results:* Drivers displayed greater optimism when comparing their crash risk and driving ability to the average same-age, same-sex driver (respectively, 72%, 72.4%), than when comparing to a V8 supercar champion (respectively, 60%, 32.9%). When comparing judgements of crash risk and driving ability to a similar driver, it appears that participants in the present study are just about as optimistic about their risk of crash (i.e. 72%) as they are optimistic about their driving ability (i.e. 74.2%).

1. Introduction

For every 1% increase in a driver's average speed, their risk of fatal injury increases by 4% (World Health Organisation, 2020). Despite legal and non-legal efforts to deter drivers from exceeding speed limits, an overwhelming proportion of fatal and nonfatal traffic injuries continue to be related to speeding. In the state of Queensland in Australia, 20.4% of crashes in 2018 involved a speeding driver or rider (Queensland Government Department of Transport and Main Roads, 2018), while in the state of New South Wales at least 39% of fatal traffic injuries in 2019 were found to be related to speeding (New South Wales Government, 2019). Similar trends have emerged internationally, with New Zealand statistics finding that speed contributed to 27% of fatal traffic injuries in the period between 2017 and 2019 (Ministry of Transport, 2019), while in British Colombia, Canada, speed contributed to almost one-third (30%) of fatal crashes in 2019 (Insurance Corporation of British Colombia, 2019). Serious injuries due to speeding are also a major road safety and public health concern (World Health Organisation, 2020). For instance, in addition to the 136 drivers fatally injured due to speeding in New South Wales in 2019, there were 1,071 drivers seriously injured and 1,180 moderately injured (New South Wales Government, 2019). Similarly, in New Zealand, an additional 408 serious injuries were recorded in 2019, where speeding was a factor, on top of 74 fatal injuries (New Zealand Transport Agency, 2019).

Enforcement operations for speeding in Australia have been mostly focused on increasing the perception of apprehension through mobile and fixed speed cameras (Freeman, Kaye, Truelove, & Davey, 2017). Such initiatives stem directly from the principles of classical deterrence theory, which proposes that people are less likely to offend when the punishment for that offense is perceived to be certain, swift and severe (Akers & Sellers, 2013). While legal measures are important for deterring speeding behaviors, research continues to demonstrate that classical deterrence items explain only a small proportion (e.g., 18%) of the variance in self-reported speeding behavior (Truelove et al., 2017). As a result, there remains the need to consider (and identify) other perceptual factors that extend beyond classic deterrence (outlined below), which may promote or inhibit speed limit violations.

While humans' capacity to recognize risk has long attracted researchers' attention (Kuo, Talley, & Huang, 2020), such academic pursuits have rarely extended to consider how individuals esti-

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mate and compare risk for everyday tasks. Nevertheless, seminal research by Weinstein (1980) found that people perceive themselves to be more likely than others to experience positive outcomes in the future, and less likely to experience negative outcomes. This phenomenon is referred to as 'optimism bias' (Weinstein, 1980) and has since been recognized to operate in a range of behaviors, including music piracy (Nandedkar & Midha, 2012), smoking (Prokhorov et al., 2003), injury in the work place (Caponecchia, 2010), and also driving behaviors (Delhomme, 1991; Dalziel & Job, 1997). In regard to the latter, preliminary research on comparative optimism within the field of road safety has found that drivers generally perceive their driving ability to be better than other drivers (Delhomme, 1991; Horswill, Waylen & Tofield, 2004), and their risk of crash (Harré, Foster & O'Neil, 2005; Gosselin, Gagnon, Stinchcombe, & Joanisse, 2010) and risk of sanctions (Delhomme, Verlhiac, & Martha, 2009) to be lower than that of other drivers.

On one hand, optimism has been associated with a lower likelihood of adopting safe behaviors on the road (Delhomme, 1994; Wickens, Watson, Mann, & Brands, 2019). For instance, drug drivers have been found to express comparative optimism in their perceived risk of collision in comparison to other drivers (e.g., less likely; Wickens et al., 2019). Similarly, research by White, Eiser, and Harris (2004) found that mobile phone users perceived their risk of crash to be less than their peers. Comparative optimism may also influence drivers to ignore important safety messages that can also influence their safety (Walton & McKeown, 2001). Conversely, comparative optimism has also been related to safe driving behaviors (Causse, Delhomme, & Kouabénan, 2005; Causse, Kouabénan, & Delhomme, 2004; Harris & Middleton, 1994; Martha & Delhomme, 2009). For instance, Causse et al. (2005) found that drivers justified their superiority in driving ability by the fact that they are more observant of road rules, whereas other drivers were more likely to violate road rules and lack controllability of their vehicle.

However, research is scant that has investigated comparative judgments regarding crash risk and driving ability simultaneously, and how these judgments correspond to speeding behaviors. One speeding study with French motorists found that the majority of participants considered themselves less likely to be caught for speeding or cause a crash due to speeding, compared to other drivers (Delhomme et al., 2009). However, this comparative optimism was related to less reported offending (compared to those who were pessimistic about their risk of crash/detection for speeding), indicating that participants were realistic in their comparative judgments. Martha and Delhomme (2014) conducted a similar study, but with drivers who had lost their license and were completing a driving course to accrue driver license points. This study similarly found that participants were realistic about their risk of getting a ticket for speeding (relative to their reported speeding behavior), however participants were not realistic about their judgment of crash-risk due to speeding (Martha & Delhomme, 2014). While these findings provide some insight into how comparative judgments regarding crash risk correspond to speeding behaviors, these studies were conducted only with French samples. Research has yet to investigate comparative judgments regarding crash risk and driving ability, and how these respond to speeding behaviors and perceptions of future crash and ticket risk, within an Australian sample. Further, questions remain as to how far motorists' comparative judgments extend. For example, if comparative judgments change when comparing ability to a superior driver, such as a professional race car driver. Understanding the degree that motorists are realistic or unrealistic about their crash risk, is crucial for improving road safety (particularly the development of effective tailored countermeasures such as messaging campaigns, training). Specifically, different preventive strategies may be necessary for cohorts of motorists who speed but are realistic about their crash-risk, compared to groups who speed but are unrealistic (or diminish) their crash-risk. Given this, it is first necessary to explore the existence and influence of these unrealistic judgments (currently undertaken via examination of speeding practices with an Australian sample).

As a result, the objective of this current research was to apply and expand upon the work of Delhomme (1991), Delhomme et al. (2009), and Martha and Delhomme (2014) to investigate comparative judgments regarding crash risk and driving ability and how these judgments relate to speeding behaviors within a Queensland sample. Specifically, the aims of this study were to:

(a) Examine the extent of comparative optimism in regards to crash risk and driving ability in a sample of Queensland drivers, with comparisons to a same-age, same-sex driver, and a superior driver (e.g., same-age, same-sex V8 supercar champion);
(b) Explore the differences between those who perceive optimism, pessimism, or similar judgments in their crash risk compared to a same-age, same-sex driver, in regards to: their self-reported speeding behavior, traffic history, and perceptions of causing a crash or receiving a fine due to speeding in the future and;
(c) Investigate if such beliefs significantly predict speeding behaviors.

2. Method

2.1. Participants

The study involved 760 Queensland motorists aged 16–85 (M = 39.60, SD = 16.34). Participant demographic information is displayed in Table 1. In regards to licensure in Australia, a motorist progresses from a learners license, to a provisional license and then an open license. An open license is considered the least restrictive license, whereas a learners license is the most restrictive (e.g., no blood alcohol permitted while driving and must be supervised; Austroads, 2020).

2.2. Materials – survey

The survey questionnaire had five sections.

2.2.1. Demographic data and traffic history

Demographic data were collected, including age and gender. Traffic history information was also assessed, including years since obtaining license, weekly driving hours, license type, crash history (yes or no), history of license suspension (yes or no) and reasons for suspension.

2.2.2. Speeding behavior

The dependent variable in the study was speeding, which included two measures of offending behavior, "How often do you exceed the speed limit by more than 5 km/h on a highway?" and "How often do you exceed the speed limit by more than 5 km/h in a town?" These items were scored on a 7-point Likert scale (1 = never, 7 = always). These items were utilized in analyses separately, and also as a combined measure (α = 0.782).

2.2.3. Comparative judgments of crash risk

Comparative judgments of crash risk were assessed with two referents: a similar driver (crash risk compared to the average same-age, same-sex driver) and a superior driver (crash-risk compared to the average same-age, same-sex V8 supercar champion).

Table 1
Participant demographics.

	N	%
Gender		
Male	392	51.60%
Female	366	48.20%
Other	2	0.30%
Weekly Driving Hours		
5 or less	158	21%
6–10	253	33.60%
11–20	10	22.50%
21–30	75	10%
Over 30	97	12.90%
License type		
Learners	52	6.90%
Provisional 1	41	5.40%
Provisional 2	81	10.70%
Open	575	76.20%
Other	11	1.40%
Ever lost license		
Yes	149	20.20%
No	611	79.80%
Reason for License Loss		
Speeding	29	19.50%
Drink Driving	57	38.20%
Loss of demerit points	22	14.80%
Other	25	16.80%
Reason not reported	16	10.70%
Involved in car crash		
Yes	127	16.70%
No	626	82.40%
Not reported	7	0.90%

V8 supercar races are widely-held in Australia, therefore a ‘v8 supercar champion’ was utilized as the superior driving referent. Items were scored on a 7-point scale ranging from 1 (greater crash risk) to 7 (lower crash risk). Lower ratings (1–3) indicated comparative pessimism (CP), a score of 4 indicated similar judgments (SJ) and higher ratings (5–7) indicated comparative optimism (CO). The item assessing crash risk compared to the ‘same-age, same-sex driver,’ was also transformed into a categorical variable to separate those who demonstrated CO, CP, and SJ. Between-group analyses were conducted with the categorical variable, whereas the numeric, continuous variable was utilized in correlational and multivariate analyses.

2.2.4. Comparative judgments of driving ability

Similar to the items above, judgments of driving ability were assessed with two referents: a similar driver (driving ability compared to the <u>average same-age, same-sex driver</u>) and a superior driver (driving ability compared to the <u>average same-age, same-sex V8 supercar champion</u>). These items were adapted from items by Martha and Delhomme (2009) and were scored on a 7-point scale, ranging from 1 (lowest ability) to 7 (highest ability). Lower ratings (1–3) indicated CP, a rating of 4 indicated SJ and higher ratings (5–7) indicated CO.

2.2.5. Perception of future crash and detection for speeding

Two items were included to assess perceptions of receiving a ticket for speeding in the next 3 years, and causing a traffic crash due to speeding in the next 3 years (e.g. “how probable is it that you will receive a speeding ticket in the next 3 years”). These items were adapted from a paper by Martha and Delhomme (2014), and were scored on a 5-point scale from 1 (very low probability) to 5 (very high probability).

2.3. Procedure

A number of urban (i.e., Toowoomba, Emerald, Gold Coast, Logan and Gympie) and regional (i.e., Rocklea, Gold Coast, Logan, Townsville and Ipswich) areas of Queensland were targeted for participant recruitment. Recruitment was designed to make the sample as representative as possible (i.e., urban and regional areas, in person and online samples). Participants completed a paper-version of the survey in public places such as shopping centers or at the Queensland University of Technology. An online version of the survey was also distributed via an internet platform, with both samples reimbursed with a $20 Coles/Myer gift card for their participation. Snowball sampling was also encouraged. Participation in the study was anonymous. Data analysis was conducted using IBM SPSS Statistics (version 26). A Levene’s test of equality of variance demonstrated no statistically significant difference between scores from the online and in-person surveys in regard to key variables such as self-reported town ($p = .101$), highway speeding ($p = .240$), or for perceptions of crash-risk compared to a similar driver ($p = .730$).

3. Results

3.1. Statistical analysis

Firstly, descriptive statistics were analyzed to examine self-reported speeding and to assess the extent of comparative optimism regarding crash risk and driving ability in the sample. No differences were identified between those who completed the online versus paper copy of the questionnaire. To address the second aim, differences between those who perceived CO, CP, or SJ in their crash risk compared to a same-age, same-sex driver were assessed with analysis of variance tests when the dependent variable was continuous or with chi-square tests when the dependent variable was categorical. Finally, correlations were utilized to examine the linear relationships between variables. A linear regression was then conducted to evaluate significant predictors of speeding behaviors, when considering comparative judgments of crash risk and driving ability, traffic history, demographic variables, and perceptions of receiving a ticket or causing a crash due to speeding in the future.

3.2. Self-reported speeding and comparative judgments of crash risk and driving ability

Analysis with the town and highway speeding items individually demonstrated that highway speeding was more common ($M = 2.77$) than town speeding ($M = 2.17$), $t(579) = 14.60$, $p < .001$. However, as acceptable consistency was found between these items ($\alpha = 0.782$), they were subsequently combined to make an aggregate measure of speeding. When looking at the mean of the combined measure of speeding, participants reported engaging in speeding “rarely” to “sometimes” ($M = 2.47$, $SD = 1.22$). Only 14.9% ($n = 113$) of participants reported “never” engaging in speeding, whereas 85.1% ($n = 647$) of participants reported engaging in speeding at least “rarely.” Younger (16–24 years) and older drivers (25 + years) were not found to report significantly different speeding behaviors, $t(247.56) = 1.31$, $p = .192$. However, males reported significantly greater speeding ($M = 2.65$, $SD = 1.32$) compared to females ($M = 2.28$, $SD = 1.08$), $t(743.98) = 4.27$, $p < .001$.

Table 1 displays the proportion of participants who reported CP, CO, or SJ in their crash risk and driving ability compared to a same-age, same-sex driver (similar driver) and a same-age, same-sex V8 supercar driver (V8 driver), as well as the mean and standard deviation of each item. Participants were more optimistic when comparing their crash-risk to a V8 driver (60%), than their driving ability (32.9%) to a V8 driver. The greatest proportion of participants were optimistic when comparing their crash risk to a similar driver (72%). The greatest proportion of CP was reported when participants compared their crash risk to a V8 driver.

Comparative Judgments of Crash Risk and Driving Ability

3.3. Judgments of crash risk compared to same-age, same-sex driver between-group analyses

As displayed in Table 2, the majority of participants CO in their perceived risk of crash compared to a similar driver ($N = 419$, 72%), while approximately one-quarter of participants ($N = 142$, 24%) reported SJ in their crash risk and a small percentage ($N = 20$, 4%) reported CP in their crash risk. A range of between-group tests were conducted to determine if the comparative judgment groups differed in regards to demographic variables, speeding behaviors, traffic history, and perception of causing a crash or receiving a fine due to speeding in the future.

3.3.1. Demographics and traffic history

There were no significant differences across the comparative judgment groups in regards to age, $F(2, 578) = 0.569$, $p = .566$. Similarly, a crosstab analysis with the comparative judgment groups and gender revealed a non-significant chi-square, X^2 (2, $N = 579$) = 3.197, $p = .202$. A crosstab analysis with the comparative judgment groups and self-reported crash in the last three years (Yes/No) revealed a significant chi-square, X^2 (2, $N = 579$) = 14.951, $p = .001$. Specifically, 59% of those who reported a previous crash expressed CO in their crash-risk, 35% reported SJ and 6% expressed CP. A significant chi-square was also found in a crosstab analysis with the comparative judgment groups and previous loss of license (Yes/No), X^2 (2, $N = 564$) = 6.40, $p = .041$. Of those who reported ever losing their license, 71% expressed CO in their crash-risk, 21% reported SJ, and 7% reported CP.

3.3.2. Self-reported speeding

A one-way ANOVA was conducted to assess the differences between the comparative judgment groups in regards to the combined speeding item, although the groups differed in size (see Table 2). There was a statistically significant between-group difference for speeding, $F(2, 575) = 7.96$, $p < .001$. A Tukey's post-hoc test revealed that only those who reported SJ reported a significantly greater speeding compared to those who reported CO. However, when looking at the means alone, in Table 3, the greatest speeding mean was reported by the CP group and the lowest by the CO group.

3.3.3. Future apprehension and crash prediction

There were significant differences across comparative judgment groups in regards to the reported probability of receiving a speeding ticket in the future [Welch's $F(2, 49.32) = 8.68$, $p = .001$]. Specifically, the SJ group ($M = 2.63$) reported significantly greater probability of receiving a speeding ticket compared to CO group ($M = 2.22$). Similarly, there was a significant between-group difference in regards to causing a traffic crash because of speeding in the next 3 years [Welch's $F(2, 48.64) = 3.36$, $p = .043$]. Means for each comparative judgment group are displayed in Table 3. The highest mean for both risk of detection and risk of crash was reported by the CP group, whereas the lowest mean was reported by the CO group.

3.4. Bivariate correlations

Correlations among measures are displayed in Table 4. The items with the strongest positive relationship to speeding were perceived probability of receiving a speeding ticket in the future and perceived probability of causing a crash due to speeding in the future. The comparative crash risk items for both the average same-age, same-sex driver referent and the average same-age, same-sex driver V8 supercar referent, were negatively related to speeding. However, the relationship between the comparative driving ability items and speeding were weak and mostly insignificant. Some weak but significant relationships were identified with the demographic variables, such that younger age, male gender, being involved in a car crash in the previous 3 years, and reports of license loss were found to be related to more frequent speeding.

3.5. Predictors of speeding

A linear regression analysis was conducted in order to investigate the contribution of comparative judgments and perceptions of future crash/apprehension, on the combined measure of speeding. As the demographic variables and items assessing previous crash history and loss of license were found to be significantly related to speeding, these were also included in the regression. However, as hours of weekly driving was not found to be significantly correlated to speeding, it was excluded. The multivariate linear regression analysis predicting speeding behavior was found to be statistically significant, $F(10, 539) = 24.16$, $p < .001$, and predicted 31% of the variance in speeding behavior. As displayed in Table 5, significant predictors of speeding behavior were: ever losing license, car crash in the previous 3 years, pessimism in crash risk compared to the average same-age/same-sex driver, greater perceived probability of receiving a speeding ticket in the next 3 years, and finally, optimism in driving ability compared to the average same-age/same-sex driver.

4. Discussion

The research project aimed to investigate comparative judgments regarding crash risk and driving ability, and how these judgments relate to self-reported speeding. The methodology extends on previous research conducted with French motorists (Delhomme et al., 2009; Martha & Delhomme, 2014; Martha & Delhomme, 2009) by examining comparative judgments of crash risk and driving abilities in a sample of Queensland drivers. Similar to Freeman et al. (2017) who found that 94% of participants reported breaching speed limits in general, the present study also found a large proportion of drivers acknowledged breaching speed

Table 2
Comparative judgments of crash risk and driving ability.

	N	*M*	*SD*	CP		SJ		CO	
				n	%	*n*	%	*n*	%
Crash Risk Compared to Same-Age, Same-Sex Driver	578	5.53	1.25	20	4%	142	24%	416	72%
Crash Risk Compared to a Same-Age, Same-Sex V8 Driver	575	5.00	1.85	145	25%	88	15%	342	60%
Driving Ability Compared to Same-Age, Same-Sex Driver	575	5.37	1.21	26	4.5%	122	21.2%	427	74.2%
Driving Ability Compared to Same-Age, Same-Sex V8 Driver	572	3.88	1.61	237	41.4%	147	25.7%	188	32.9%

Table 3
Speeding behaviors and perceptions of future negative outcomes across CP, SJ and CO groups.

	N	Speeding		Probability - Receiving a Speeding Ticket in Future		Probability - Causing a Crash Due to Speeding in Future	
		M	*SD*	*M*	*SD*	*M*	*SD*
CP	20	3.30	1.380	2.85	1.31	1.95	1.15
SJ	142	3.20	1.465	2.63	1.11	1.77	0.88
CO	416	2.69	1.368	2.22	1.13	1.57	0.85

limits (85.1%). Also similar to previous research, highway speeding was found to be more common than town speeding (Truelove et al., 2017; Freeman et al., 2017).

The research had three aims. The first was to investigate how the sample evaluated their risk of crash and driving abilities compared to a similar driver, and a V8 supercar driver. Interestingly, the proportion of participants who reported optimism, pessimism, or similar judgments in their crash risk, was identical to findings by Delhomme et al. (2009) (72%, 4%, and 24%, respectively). This indicates some level of cross-cultural stability with the psychological construct. It should be noted that participants in the study by Delhomme et al. (2009) were younger drivers aged between 18 and 25 years. However, no age group differences were identified across the comparative judgment categories in the present study, suggesting that comparative judgments may not be influenced by age.

When evaluating comparative judgments of driving ability, the majority of participants demonstrated CO when comparing their ability to a similar driver (74.2%), which reflects findings of Delhomme (1991). When comparing judgments of crash risk and driving ability to a similar driver, it appears that participants in the present study are just about as optimistic about their risk of crash (i.e., 72%), but not as optimistic regarding their driving ability when comparing to a same-age/same-sex driver (i.e., 56.2%). A similar finding emerged for comparisons to a same-age/same-sex V8 supercar driver. For instance, the findings indicate that about one-third of participants reported CO (32.9%) when comparing their driving ability compared to a superior driver, whereas the majority of participants (60%) reported CO in their risk of crash. However, participants reported more optimism when comparing crash-risk and driving ability to a similar driver, than a superior driver. This finding suggest that the majority of motorists acknowledge their limitations in driving abilities compared to a driver who likely has more driving experience and skills than themselves, however, they also perceive there to be less likelihood of crash in general driving than V8 supercar driving.

The second aim was to investigate differences between those who were optimistic, pessimistic, and had similar judgments regarding their risk of traffic crash compared to a same-age/same-sex driver. Similar to findings of Delhomme et al. (2009), the CP group reported the highest mean speeding score. The CP group also reported the highest mean for perceived likelihood of being caught for speeding and being involved in a traffic crash due to speeding. These findings provide support for the idea that some drivers are realistic about (or are cognizant of) their crash-risk (Delhomme et al., 2009) but also demonstrates that motorists speed despite acknowledging the risks (WHO, 2020) associated with the behavior. However, it should be noted that there was only a small proportion of participants in the CP group, highlighting that only a small cohort are aware of the risks associated with their driving behavior. Nonetheless, Truelove et al. (2017) found that those who reported greater speeding also reported less fear of being injured as a result of speeding. Taken with the present findings, this suggests that speeders acknowledge their risk of being in a crash, but may not necessarily fear being injured. This theme warrants further investigation in regards to understanding the etiology and stability of the perception, as well as determining whether such beliefs relate to additional human propensities such as discounting the saliency of future punishments (Freeman et al., 2017).

However, outcomes from the chi-square highlighted that a considerable proportion of participants who reported ever losing their license or being previously involved in a crash were those who reported comparative optimism in their crash risk. This would suggest that drivers are not realistic about their risk of crash, but instead, despite experience with a crash or losing a license (due to offending), numerous drivers still perceive their risk of crash in the future to be less than other drivers. These findings are discussed in more detail with the regression outcomes below.

While the overall regression model for speeding was found to be significant, the explained variance (e.g., 31%) is similar to regression models focusing on deterrence (Freeman et al., 2017). Similar to findings by Delhomme et al. (2009) and Martha and Delhomme (2014), drivers who reported a higher level of speeding also reported the greatest perceived likelihood of receiving a speeding ticket in the next 3 years. This finding provides support for the assertion that past behavior remains a good predictor of future behavior (Forward, 2009; Conner et al., 2007). Interestingly, whereas previous research has suggested that punishment avoidance is a predictor of speeding (Truelove et al., 2017), the results of the regression demonstrate that those who reported ever losing their license were most likely to speed. To some extent, this suggests that some drivers' offending behaviors may be impervious to the threat (and application) of legal sanctions. In addition, this phenomenon may relate to the "resetting effect" (Pogarsky & Piquero, 2003) whereby apprehension for a crime leads to the perception that they are unlikely to be apprehended again in the near future. The regression model also highlighted that those who engage in a greater extent of speeding acknowledge their risk of crash is greater than other drivers, and are more likely to have been involved in a previous crash. This finding further supports the entrenched nature of some drivers' speeding (even in the face of further exposure to negative outcomes) and is aligned with previous research that has demonstrated those who engage in speeding lack fear of the physical consequences associated with the behavior (Truelove et al., 2017). However, the final significant predictor of speeding was perceiving greater driving ability than same-age/same-sex drivers. Taken together, the results indicate that numerous drivers are aware of elevated crash risks, but still perceive their driving ability to be superior to others. In regard to the latter, the proportion of the sample who believed their driving abilities were better than professional race car drivers (e.g., 32.9%) further reinforces the extent of such fallacious beliefs. Further research may find that such risks are mediated (or diminished) by a lack of involvement in serious crashes. Alternatively, it may yet be demonstrated that crash risk remains a hypothetical concern that is offset by cumulative real-time self-assessments of driving behaviors (that can be either accurate or erroneous in nature). At the very least, there is a need to determine whether continuously breaking road rules produces a cumulative (negative) effect upon

Table 4
Bivariate correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	1													
2. Gender	0.011	1												
3. Involved in car crash (Y/N) in last 3 years	0.162**	0.005	1											
4. Lost license (Y/N)	−0.042	0.191**	0.098**	1										
5. Hours of driving per week	0.037	0.003	0.011	−0.137**	1									
6. Probability receiving a speeding ticket in future	−0.165**	−0.206**	−0.170**	−0.169**	0.065	1								
7. Probability causing a traffic crash because of your speeding in future	−0.124**	−0.106**	−0.124**	−0.196**	0.075*	0.489**	1							
8. Crash risk compared to the average same-age, same-sex driver	0.051	0.006	0.190**	0.028	−0.033	−0.232**	−0.173**	1						
9. Crash risk compared to the average same-age, same-sex V8 Supercar champion	0.074	0.072	0.095*	0.011	0.068	−0.171**	−0.109**	0.476**	1					
10. Driving ability compared to the average same-age, same-sex driver	0.108**	−0.004	0.189**	0.005	0.231**	−0.106*	−0.161**	0.310**	0.213**	1				
11. Driving ability compared to the average same-age, same-sex V8 Supercar champion	0.111**	0.052	0.140**	0	0.186**	−0.084*	−0.004	0.221**	0.385**	0.471**	1			
12. Exceed speed in town	−0.061	−0.161**	−0.123**	−0.127**	0.060	0.448**	0.163**	−0.193**	−0.134**	0.038	−0.038	1		
13. Exceed speed on highway	−0.125**	−0.112**	−0.190**	−0.164**	0.021	0.394**	0.281**	−0.173**	−0.146**	−0.018	−0.085*	0.651**	1	
14. Exceed speed town and highway	−0.099**	−0.152**	−0.168**	−0.158**	0.046	0.468**	0.239**	−0.202**	−0.154**	0.013	−0.066	0.924**	0.892**	1

Note: $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, driving ability items scored on a 8-point scale (1 = much worse, 8 = much better), probability of crash/speeding ticket items scored on 5-point scale (1 = very low probability, 5 = very high probability), and crash risk items scored on 7-point scale (1 = much more likely, 7 = much less likely), hours of driving per week (low score = less than 5 h, high score = 30 h or more).

perceptions of risk or enhances a self-fulling belief that they are "able" to offend.

The limitations should be borne in mind when interpreting the findings, including: (a) self-report data whereby people may answer in a socially-desirable manner; (b) additional common method variance (CMV) issues associated with utilizing a single data source and unintended differential effects stemming from the interpretation of anchor items (see af Wåhlberg, 2009 for a comprehensive review of CMV effects); (c) questions also remain regarding participants' capacity to accurately assess their driving behaviors and that of others (including likely disparities between subjective and objective assessment); and (d) the sample may not be representative of the wider driving population. In regard to the latter, the methodology involved convenience sampling (with snowballing) and as a result, questions remain regarding the generalizability of the findings to the broader motoring population. Future research may also benefit from utilizing more robust recruitment methods, including probability sampling. While the small amount of explained variance by the regression may dilute the significance of the results, it is noteworthy that multiple other factors have been found to be related to speeding, including fear of injury and the threat of material loss (Truelove et al., 2017), having a criminal history (Watson, Siskind, Fleiter, Watson, & Soole, 2015), and having role models who speed (Fleiter & Watson, 2005).

5. Concluding remarks

While a significant body of research has focused on comparative judgments with a wide range of negative events (Sweldens, Puntoni, Paolacci, & Vissers, 2014) and shown that rarely are people accurately calibrated in terms of comparisons to others (Menon, Kyung, & Agrawal, 2009), the lack of application within the road safety domain may be considered a significant oversight. The results of this study demonstrate that numerous drivers engage in speeding, despite previously experiencing negative outcomes and being aware that they are at greater risk of future negative outcomes (e.g., crashes and tickets). This study provides preliminary findings that fear-based tactics and legal enforcement strategies to deter speeding behavior may not influence some cohorts (e.g., those at most risk) of the driving population. This finding may prove important considering deterrence theory remains the cornerstone of speed-related enforcement. Instead, it appears that engagement in speeding is more influenced by the perception that one's driving abilities are superior to others. These findings may have implications for designing effective campaigns and training programs, as well as enhancing our theoretical understanding of comparative judgments and the etiology of speeding behavior. Specifically, it appears that messages that are targeted towards a more realistic view of one's driving abilities and reduce perceptions of superiority could be effective. However, questions remain regarding: (a) what aspects of driving ability have the greatest influence on speeding; (b) at what point one perceives their driving ability as "superior" to others; and (c) what range of experiences reinforce such perceptions. Future research may benefit from implementing a more refined operationalization of "driving ability" and assess the effectiveness of different types of media campaigns (i.e., fear based, humorous, and informative) among individuals with differing comparative judgments of risk. It may also be useful to investigate how comparative judgments in crash risk and driving ability operate with other offending behaviors. A greater understanding of how such judgments promote driving violations can only assist in developing effective messages to reduce the ongoing contribution of traffic offences to the road toll.

Table 5
Linear regression predicting speeding.

	B	SE	*β*	Lower	Upper	sr^2
Age	0.002	0.003	0.023	−0.004	0.007	0.000
Gender	−0.124	0.089	−0.052	−0.299	0.05	0.008
Involved in a car crash (Y/N)	−0.299**	0.111	−0.102	−0.518	−0.08	0.012
Lost license (Y/N)	−0.221*	0.109	−0.077	−0.435	−0.007	0.012
Crash risk compared to the average same-age, same-sex driver	−0.119**	0.042	−0.123	−0.201	−0.037	0.002
Crash risk compared to the average same-age, same-sex V8 Supercar champion	−0.014	0.028	−0.021	−0.069	0.042	0.001
Driving ability compared to the average same-age, same-sex driver	0.145**	0.044	0.143	0.059	0.23	0.002
Driving ability compared to the average same-age, same-sex V8 Supercar champion	−0.031	0.033	−0.042	−0.096	0.033	0.001
Probability receiving a speeding ticket in the next 3 years	0.446***	0.045	0.427	0.358	0.533	0.002
Probability causing a traffic crash because of your speeding in the next 3 years	0.068	0.059	0.05	−0.047	0.183	0.003

Note: *$p < .05$, **$p < .01$, ***$p < .001$.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Crash analysis and development of safety performance functions for Florida roads in the framework of the context classification system

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ABSTRACT

Introduction: Safety performance functions (SPF) are employed to predict crash counts at the different roadway elements. Several SPFs were developed for the various roadway elements based on different classifications such as functional classification and area type. Since a more detailed classification of roadway elements leads to more accurate crash predictions, multiple states have developed new classification systems to classify roads based on a comprehensive classification. In Florida, the new roadway context classification system incorporates geographic, demographic, and road characteristics information. *Method:* In this study, SPFs were developed in the framework of the FDOT roadway context classification system at three levels of modeling, context classification (CC-SPFs), area type (AT-SPFs), and statewide (SW-SPF) levels. Crash and traffic data from 2015-2019 were obtained. Road characteristics and road environment information have also been gathered along Florida roads for the SPF development. *Results:* The developed SPFs showed that there are several variables that influence the frequency of crashes, such as annual average daily traffic (AADT), signalized intersections and access point densities, speed limit, and shoulder width. However, there are other variables that did not have an influence in crash occurrence such as concrete surface and the presence of bicycle slots. CC-SPFs had the best performance among others. Moreover, network screening to determine the most problematic road segments has been accomplished. The results of the network screening indicated that the most problematic roads in Florida are the suburban commercial and the urban general roads. *Practical Applications:* This research provides a solid reference for decision-makers regarding crash prediction and safety improvement along Florida roads.

1. Introduction

The development of safety performance functions (SPFs) to predict crash counts at different roadway network elements is the first step toward reducing the number of crashes. This is necessary to enhance traffic safety on our roads. The safety performance function is a regression model used to predict the expected number of crashes based on several factors. Traffic volume is the most influential factor in crash occurrence. However, road characteristics, land use, and other information often have significant effects also. The Highway Safety Manual (HSM) defines the SPF as "an equation used to estimate or predict the expected average crash frequency per year at a location as a function of traffic volume and in some cases roadway or intersection characteristics (e.g., number of lanes, traffic control, or type of median)" (AASHTO, 2010). The importance of SPFs development lies in three main applications: conduct a network screening to specify the most problematic locations, determine the effect of design changes, and evaluate the effectiveness of implementing safety countermeasures (Srinivasan & Bauer, 2013).

Different SPFs were developed in the HSM for different road classes. HSM-SPFs has been developed for road segments on rural two-lane two-way roads, rural multilane highways, urban and suburban arterials, and freeways that have certain base conditions. Therefore, HSM-SPFs do not include geometric, pavement, and environment condition variables. HSM-SPFs of road segments contain only the exposure (annual average daily traffic (AADT)) and the segment length variables. The reason behind this is that road segments that were considered in the HSM-SPFs development have certain road characteristics and conditions. Therefore, base HSM-SPFs can only be used to predict crash counts at road segments that have conditions like the base conditions. However, HSM-SPFs must be calibrated before employed to predict crash counts at road segments that have characteristics and conditions different from the

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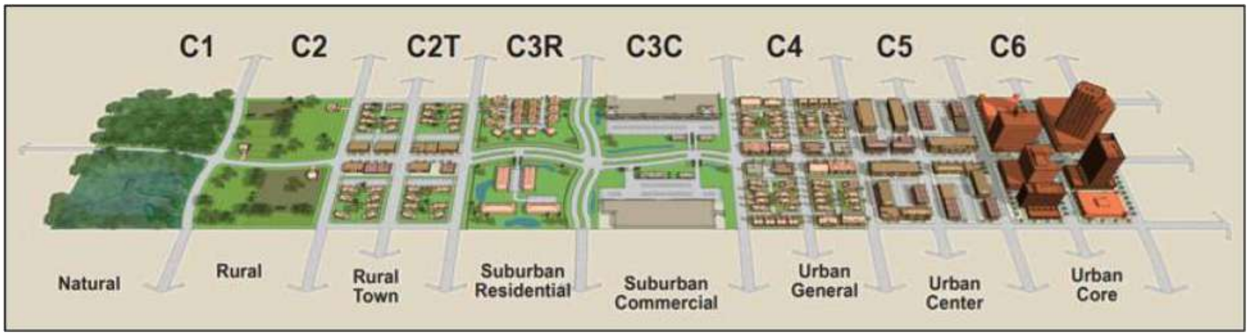

Fig. 1. FDOT context classes (FDOT, 2018).

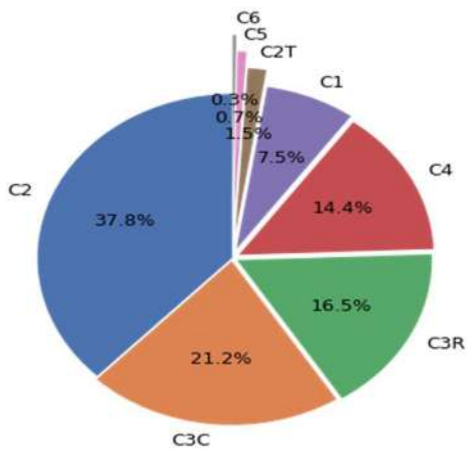

Fig. 2. Percentages of road context classes in Florida.

base conditions by using a set of crash modification factors that adjust the prediction based on the road characteristics (AASHTO, 2010). HSM-SPFs have perfect performance only when they are applied at locations that have demographics and land use conditions similar to conditions of the locations that they were considered for the SPFs development. As a result of this, many studies have been conducted to transfer and localize HSM-SPFs. Meanwhile, several studies developed new SPFs by utilizing local data. It was found in all previous studies that the transferred HSM-SPFs and the local jurisdiction SPFs were having better crash prediction performance than the HSM-SPFs.

Recently, several states tend to develop new systems to classify roads based on different characteristics. The Florida Department of Transportation (FDOT) has developed a new system to classify Florida roads into eight categories based on geographic, demographic, and road characteristics information (FDOT, 2020a). In this study, new SPFs for road segments including all influence variables were developed in the framework of the FDOT context classification system which is not used before for the SPF development for road segments. Moreover, network screening has been accomplished in this study to specify the most problematic road segments in Florida.

2. Literature review

The development of SPFs and the transferability of HSM-SPFs processes have been the focus of attention during the last years and they were amply covered and discussed in many previous studies. Several studies have been performed to transfer the HSM-SPFs into different local jurisdictions, states, and even countries. Mehta and Lou (2013) conducted a study to calibrate and transfer HSM-SPFs for two road types in Alabama: rural two-lane two-way and four-lane divided roads. They found that the calibrated HSM-SPFs have well crash prediction performance. A similar conclusion was drawn by Moraldi et al. (2020) after performing a study to calibrate the HSM-SPF for rural two-lane two-way roads in Germany.

In contrast, many other studies indicated that HSM-SPFs often have low accuracy prediction performance in local jurisdictions. AlKaaf and Abdel-Aty (2015) conducted a study to calibrate and transfer the HSM-SPF for urban four-lane divided roads in Riyadh, Saudi Arabia. In this study, local crash modification factors (CMF) were developed for the calibration process. The results indicated that employing the local CMFs instead of HSM-CMF values gives better prediction performance. A study by Sun et al. (2011) was performed to calibrate the HSM-SPF for rural multilane roads in Louisiana. The results indicated that the HSM-SPF underpredicts the crash frequency. Likewise, Cafiso et al. (2012) found that HSM-SPF underpredicts fatal and severe injury crash frequency on Italy divided multilane roads by 26%. Brimley et al. (2012) performed a study to calibrate and transfer the HSM-SPF of rural two-lane two-way roads in Utah. They found that the HSM-SPF underpredicts the crash frequency by 16%. On the other hand, Srinivasan and Carter (2011) conducted a study to calibrate the HSM-SPF for North Carolina rural divided multilane roads. They found that the HSM-SPF slightly overpredicts (less than 5%) the crash frequency. A similar conclusion has been drawn by Sun et al. (2014) regarding using the HSM-SPF to predict the total crash frequency on Missouri rural divided multilane roads. While Xie et al. (2011) concluded that the HSM-SPF significantly overpredicts the total crash frequency at Oregon rural divided multilane roads by 22%.

Novel techniques have been proposed by some researchers for the HSM-SPFs calibration process instead of using the HSM procedure. Srinivasan et al. (2016) proposed using a calibration function instead of calibration factors for the HSM-SPFs calibration process. Farid et al. (2018) employed the K-Nearest-Neighbors regression for the HSM-SPFs calibration process. Both techniques had better performance than the HSM procedure. However, the K-Nearest-Neighbors technique outperformed the calibration function technique.

Meanwhile, several studies have been conducted to develop specific SPFs by utilizing local crash and road environment data. The negative binomial regression was mainly applied for the development of SPFs process in these studies. A study was conducted by Kim et al. (2015) to develop specific SPFs for Alabama urban and suburban arterials by using three-year crash data. Li et al. (2017) performed a study to develop SPFs for rural two-lane roads in Pennsylvania by using eight-year crash data. The authors adopted

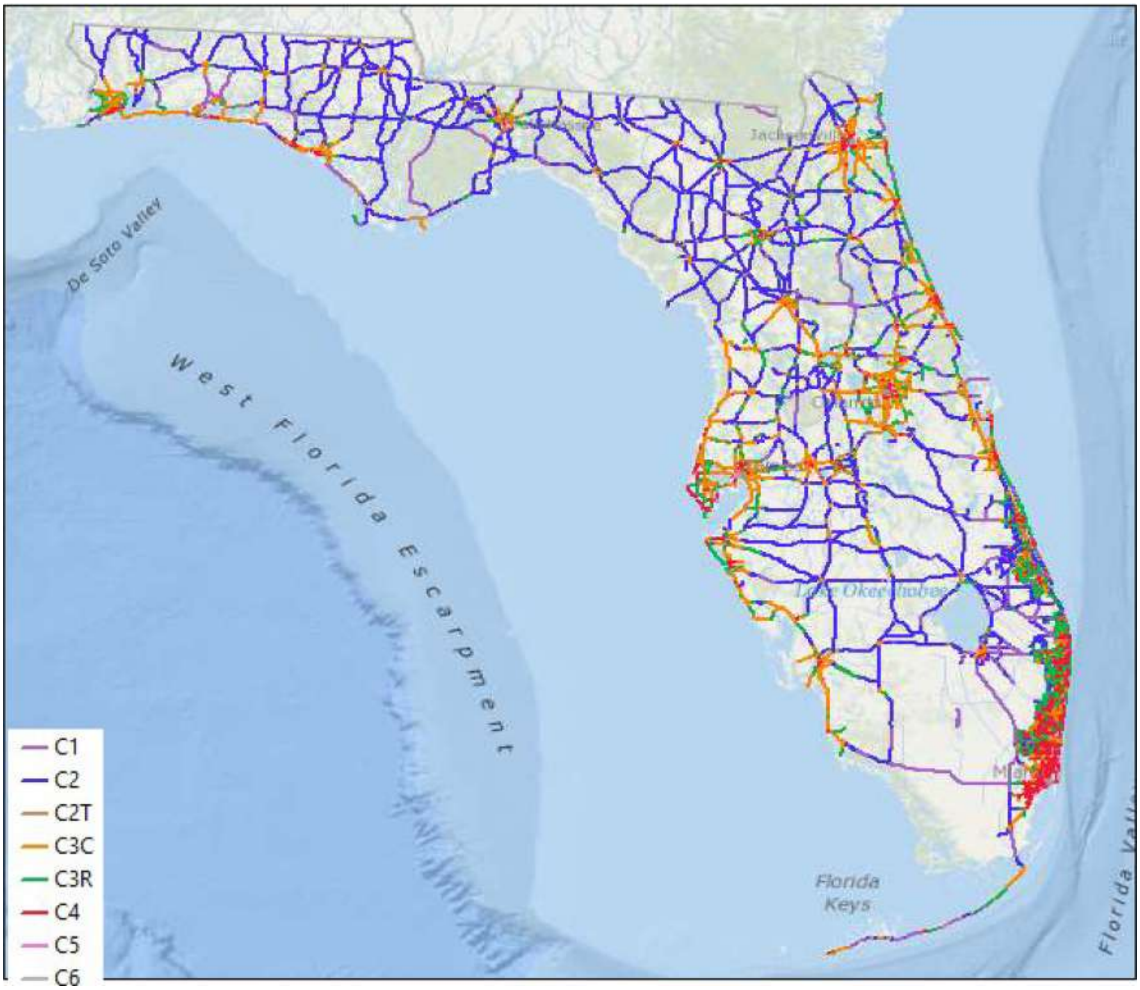

Fig. 3. The FDOT context classifications map.

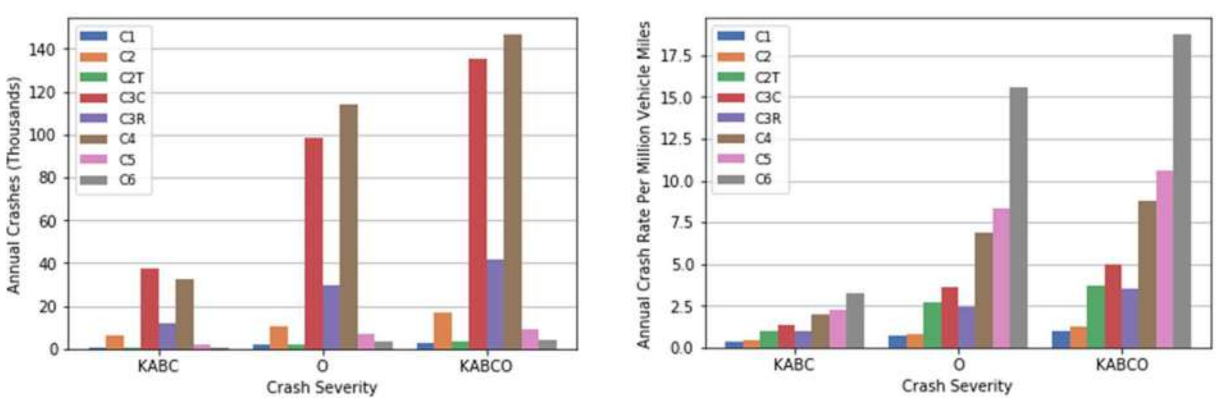

Fig. 4. Histogram of annual crash frequency and annual crash rate by road context class for fatal-and-injury, property damage only (PDO), and total crashes.

three modeling levels for the SFP development and analysis: statewide, engineering district, and county levels. The results indicated that district and county-SPFs have better crash prediction performance than statewide-SPFs. Aziz and Dissanayake (2019) used three-year crash data to develop specific SPFs for rural four-lane divided roads in Kansas. The results indicated that Kansas SPFs outperform HSM-SPFs. Other studies have been conducted outside the United States. Garach et al. (2016) conducted a study to develop SPFs for rural two-lane roads in Spain. Five-year crash data along with several explanatory variables were gathered for this purpose. La Torre et al. (2019) developed jurisdiction SPFs for freeways in Italy. Five-year crash data were obtained in this study. They followed the HSM procedure by production based SPFs along with a set of CMFs for the SPFs calibration. The results indicated that the new developed SPFs have well crash prediction performance at Italian freeways.

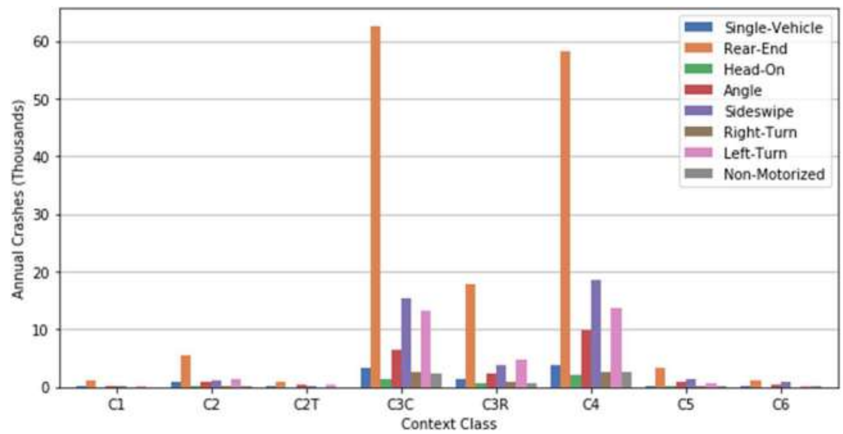

Fig. 5. Histogram of annual crash frequency by crash type and road context class. KABC: fatal-and-injury crashes, O: property damage only (PDO) crashes, KABCO: total crashes.

3. FDOT context classification system

The context classification system was adopted by the FDOT in 2017. Based on this system, roads are classified into eight classes. One of these classes is for natural roads, two classes are for rural roads, and two classes are for suburban roads, while there are three classes for urban streets. Specifically, these classes are C1: natural, C2: rural, C2T: rural town, C3R: suburban residential, C3C: suburban commercial, C4: urban general, C5: urban center, and C6: urban core. Fig. 1 shows these road classes.

Three classification criterions are adopted in this system: distinguishing characteristics, primary measures, and secondary measures. At the first level (distinguishing characteristics), roads are classified based on some diagnostics such as the nature of the area and road connectivity. The second level of classification (primary measures) is used in the absence of distinguishing characteristics. Different road features are used in this level such as land use, building height and placement, location of off-street parking, and roadway connectivity. However, secondary measures (the third level) such as allowed residential and office/retail density and population and employment density could be utilized sometimes for more accurate classification. For example, the C3C roads serve disconnected commercial areas (retail, office, or industrial). The block length is more than 660 ft., and the intersection density is less than 100 intersections per square mile in these areas. Wide parking lots are provided to serve separated buildings with 1 to 4 floors. Fig. 2 shows a pie chart for the proportion of each context class.

Nature roads (C1 class) represent 7.5 % of Florida roads. Most rural roads were classified as C2 (37.8%), while only 1.5 % of roads were classified as C2T roads. More than 37% of roads are suburban roads and they were classified as C3C and C3R with 21.2% and 16.5% percentages, respectively. The majority of urban roads were classified as C4 roads. Only 6.5% of urban roads (1% of Florida roads) were classified as C5 and C6 roads. Fig. 3 shows the FDOT context classification map. The length (in mile) of C1, C2, C2T, C3C, C3R, C4, C5, and C6 roads are 961, 4870, 197, 2736, 2128, 1861, 93, and 36, respectively. It is notable that C2 roads are widespread along the state. C3C roads exist in major cities such as Tallahassee, Jacksonville, Orlando, Tampa, and Miami. C3R and C4 roads are mainly concentrated on the southeast coastal cities such as Fort Pierce, Port St. Lucie, West Palm Beach, and Miami.

4. Data preparation and description

High traffic volume increases the interaction and conflicts between vehicles, which in turn increases the possibility of crash occurrence. Therefore, it is the most significant variable in crash prediction (Saha et al., 2016). So traffic volume must be accurately determined. The base map was first developed based on the map of the context classification (CC) and the average annual daily traffic information. Roadway segments in the context classification map were split according to average AADT value of 2015–2019 years. Consecutive road segments that have the same road identification (RID), CC, and AADT information were merged in pursuit of getting long segments with accurate AADT information.

Florida crashes from 2015 to 2019 were utilized in this study. Since most roads are classified as C2, C3C, C3R, and C4 roads, most crashes occurred on these roads. However, although more than a third of roads were classified as C2 roads, they were subjected to fewer crashes than C3C, C3R, and C4 roads. It was found that most of the crashes happened on C3C and C4 roads. Urban roads (i.e., C4, C5, and C6 roads) had the highest crash rates per million vehicle miles followed by suburban roads (C3C and C3R roads). Nature and rural roads (C1, C2, and C2T roads) had the lowest crash rates. Fig. 4 shows the annual crash frequency and crash rates for different crash severity at the eight road classes, while Fig. 5 shows the annual crash frequency at the eight road classes for every crash type. It was found that rear-end crash type was the most frequent crash type at Florida roads, followed by sideswipe and left-turn crashes.

The road characteristics and environment information was identified based on the FDOT data (FDOT, 2020b). In order to avoid very short road segments, road and environment information was determined for every roadway segment by calculating the weighted average or the weighted majority values within the segment. Different road characteristics were collected such as signalized intersections and access points density (per mile), number of lanes, posted speed limit (in mph), pavement condition (a numeric scale to describe pavement condition, it takes a value from 1 to 5), surface type (asphalt, concrete, or other), surface width (in ft.), median type (paved, raised, vegetation, or other), median width (in ft.), and shoulder type (paved, lawn, curb and gutter, or other), and shoulder width (in ft.). In addition, several pedestrian and bicyclist facility characteristics were collected such as sidewalk width and spacing (in ft.) and the presence of bicycle lane, bicycle slot (a rack for bicycle parking), and shared path.

Table 1 shows descriptive statistics of the prepared data in this study. It is noteworthy that C1 and C2 roads have longer segments than other classes with average segment lengths 2.23 and 2.81 mile, respectively. Average signalized intersection density on C5 and C6 roads are the highest with 4.91 and 5.73 intersections per mile, respectively, because these roads are located in urban areas.

Table 1
Descriptive statistics of crash data and road characteristics and environment information.

Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	C1				C2				C2T				C3C			
T (total annual crash frequency)	6.9	13.5	0	117.6	9.9	13.94	0	199.2	8.34	11.32	0	109.6	44.2	57.21	0	637.2
FI (fatal-and-injury annual crash frequency)	2.16	3.61	0	32.8	3.61	4.72	0	64.6	2.26	3.22	0	31.8	12.16	15.61	0	148.6
PDO (property damage only annual crash frequency)	4.74	10.22	0	100.6	6.28	9.48	0	134.6	6.08	8.34	0	77.8	32.04	42.53	0	499.2
AADT (annual average daily traffic)	11,177	11,472	88	86,800	9,193	8,164	14	57,983	10,315	6,309	620	45,100	25,970	16,317	270	108,500
DVMT (daily vehicle miles traveled)	18,979	33,954	49	382,281	21,006	24,363	16	277,045	6,108	8,767	190	94,221	24,299	29,021	90	330,057
L (segment length in mile)	2.23	3	0.1	25.55	2.81	2.76	0.1	23.44	0.53	0.53	0.1	5	0.87	0.72	0.1	6.62
SID (signalized intersections density)	0.28	1.02	0	8.55	0.17	0.64	0	10.42	1.43	2.49	0	20	1.71	2.07	0	19.42
APD (access points density)	2.9	4.64	0	40.32	3.94	3.83	0	60.87	19.26	10.23	0	61.35	9.26	7.05	0	80.81
NL (total number of lanes)	2.73	1.12	1	7	2.64	1.03	1	6	2.64	0.95	2	6	4.03	1.5	1	9
SL (speed limit in mph)	53.6	7.85	25	65	55.17	6.91	25	70	37.62	6.62	25	65	44.84	6.43	15	65
PC (pavement condition)	3.71	0.58	2	5	3.75	0.56	1	5	3.76	0.5	2.5	5	3.79	0.6	1.95	5
SW (surface width in ft.)	46.06	8.17	22	94.12	45.26	6.79	23.18	92.78	45.04	13.02	20	96	51.51	14.43	20	105.78
MW (median width in ft.)	33.77	30.32	7.77	245.01	26.4	17.6	4	140	20.54	29.35	9	220	25.04	18.11	4.87	417.85
SHW (shoulder width in ft.)	7.13	2.04	2	12.25	6.9	1.77	2	12	4.72	2.17	1.5	17	4.97	2.6	1.53	31.05
SWW (sidewalk width in ft.)	6.81	2.53	4	21.9	5.87	2.89	4	54	5.88	2.67	4	31.95	5.7	1.58	3.41	40.99
SWS (sidewalk spacing in ft.)	14.24	17.37	0	80.8	16.22	17.51	0	100	7.04	6.91	0	56.1	10.3	13.27	0	103.88
PBL (presence of bike lane: 1 = yes, 0 = no)	0.26	0.44	0	1	0.23	0.42	0	1	0.22	0.41	0	1	0.41	0.49	0	1
PBS (presence of bike slot: 1 = yes, 0 = no)	0.18	0.39	0	1	0.22	0.41	0	1	0.1	0.31	0	1	0.37	0.48	0	1
PSP (presence of shared path: 1 = yes, 0 = no)	0.06	0.25	0	1	0.05	0.22	0	1	0.05	0.22	0	1	0.05	0.21	0	1
Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
	C3R				C4				C5				C6			
T (total annual crash frequency)	20	28.47	0	312.2	56.7	73.04	0	854	51.14	50.28	0.8	321.6	52.86	47.97	2.2	263.8
FI (fatal-and-injury annual crash frequency)	5.78	8.14	0	110.4	12.65	14.65	0	133.2	10.77	9.74	0	51	9.02	7.87	0.2	41
PDO (property damage only annual crash frequency)	14.22	20.87	0	214.4	44.04	59.44	0	769.4	40.37	41.67	0.8	270.6	43.85	41.15	1.8	222.8
AADT (annual average daily traffic)	16,811	13,525	128	82,200	24,817	15,641	350	94,000	25,121	15,027	2,020	78,400	18,494	12,662	1,560	64,900
DVMT (daily vehicle miles traveled)	15,742	17,843	34	188,078	17,630	17,851	70	157,642	13,209	14,355	220	110,890	7,707	9,153	168	70,175
L (segment length in mile)	0.99	0.81	0.1	9.59	0.68	0.44	0.1	3.21	0.5	0.35	0.1	2.21	0.41	0.31	0.11	1.74
SID (signalized intersections density)	0.55	1.22	0	12.2	2.08	2.48	0	19.05	4.91	4.86	0	29.41	5.73	6.41	0	26.48
APD (access points density)	9.82	6.75	0	57.14	14.69	8.9	0	66.27	14.4	11	0	59.41	15.42	10.12	0	50.51
NL (total number of lanes)	3.18	1.43	1	8	3.95	1.53	1	8	3.83	1.33	2	8	3.44	1.49	1	8
SL (speed limit in mph)	44.6	7.95	25	65	38.33	6.03	15	55	34.31	5.33	15	45	31.88	3.79	25	45
PC (pavement condition)	3.62	0.53	1	5	3.64	0.57	1	5	3.71	0.58	2.5	5	3.5	0.43	2.5	5
SW (surface width in ft.)	44.99	12.79	20.56	96	51.44	14.41	19.93	96	53.85	14.63	21.26	100.6	57.39	17.03	20	96
MW (median width in ft.)	21.56	14.89	6	272.08	18.8	9.04	2	160	18.46	10.52	3	75	24.47	25.52	6	109
SHW (shoulder width in ft.)	6.07	2.95	1.5	12.81	4.34	2.77	1	20.79	3.75	2.29	1.36	12	4.05	2.35	1.58	12.37
SWW (sidewalk width in ft.)	5.93	1.94	2	42.59	5.81	1.12	0	18	6.39	1.45	3.86	14	8.59	3.24	4	25
SWS (sidewalk spacing in ft.)	12.49	12.99	0	94.97	6.5	8.45	0	92.81	4.32	4.5	0	20.77	2.85	3	0	10.5
PBL (presence of bike lane: 1=yes, 0=no)	0.32	0.47	0	1	0.34	0.47	0	1	0.29	0.46	0	1	0.3	0.46	0	1
PBS (presence of bike slot: 1=yes, 0=no)	0.24	0.43	0	1	0.23	0.42	0	1	0.12	0.32	0	1	0.06	0.24	0	1
PSP (presence of shared path: 1=yes, 0=no)	0.06	0.24	0	1	0.02	0.15	0	1	0.04	0.21	0	1	0	0	0	0

S.D.: standard deviation, Min.: minimum, Max.: maximum.

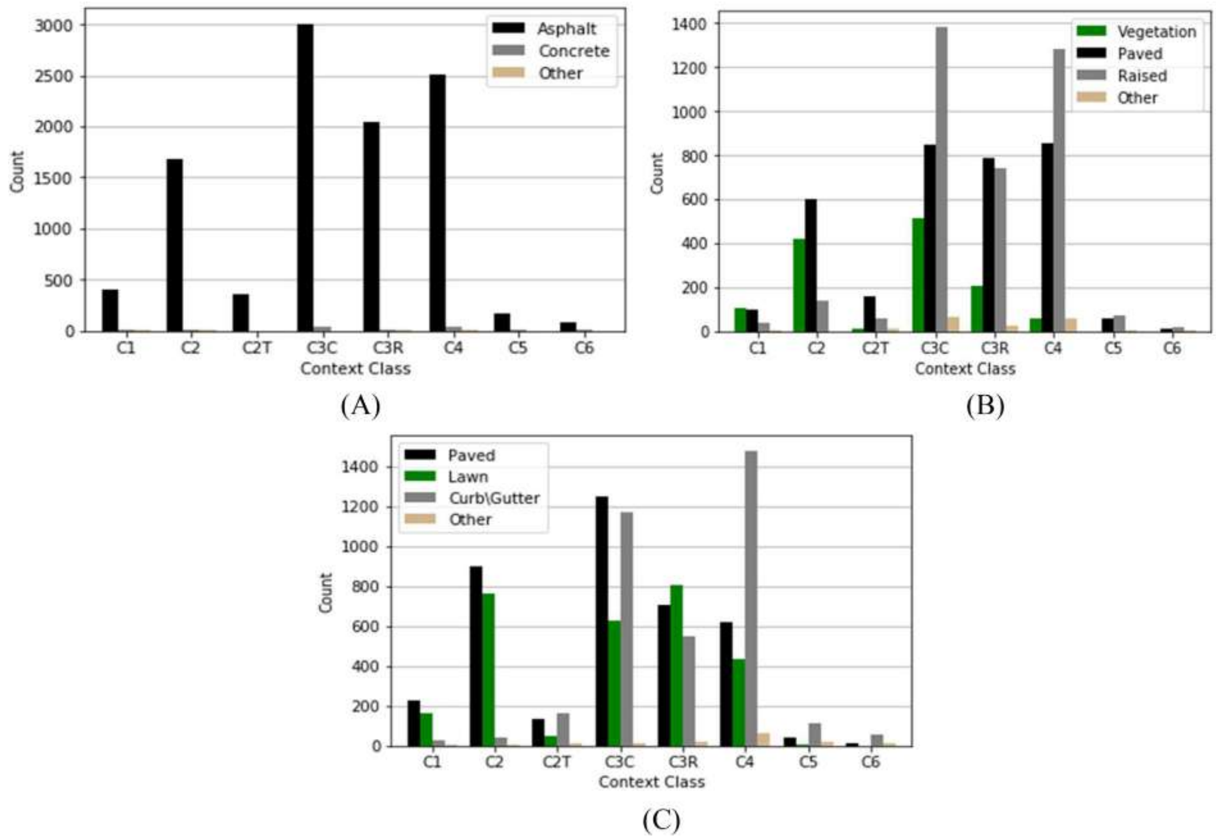

Fig. 6. Histogram of (A) surface, (B) median, and (C) shoulder types by road context class.

C2T and C6 roads have higher average access point densities with 19.26 and 15.42 access points per mile, respectively. The average pavement condition for all road classes is satisfactory (around 3.5). C1 roads have the widest medians and shoulders, while C6 roads have the widest sidewalks.

Fig. 6 shows histograms of surface, median, and shoulder types. The majority of Florida roads have an asphalt surface. Raised median type is more common than paved and vegetation median types on C3C and C4 roads. Raised and paved median types are more common than vegetation median type and they were approximately used equally on C3R, C5, and C6 roads. Rural roads (C2 and C2T roads) mostly have paved median type, while vegetation median type is most popular on natural roads (C1 roads). Shoulders are mostly paved on Florida roads, except on urban roads (C4, C5, and C6 roads) where curb and gutter shoulders are the most common shoulder types. Lawn shoulders are widely used on C3R roads.

5. Research methodology

5.1. Safety performance functions

Different distributions and models were used for the SPFs development. However, the negative binomial regression is commonly employed for SPFs development (Abdel-Aty & Radwan, 2000; Fitzpatrick et al., 2008; Manuel et al., 2014; Mohammadi et al., 2014; Al-Omari et al., 2020) since it is recommended by the HSM (AASHTO, 2010) due to its ability to handle the dispersion in the crash data. Therefore, the generalized linear model with negative binomial distribution was used in this study. To ensure that the negative binomial distribution represents crash counts distribution, the mean and variance of crash counts of every road class were calculated. It was found that the variance is much larger than the mean for all road classes. This means that the crash data are over dispersed, and the negative binomial distribution is appropriate for the SPFs development. Simple (only the exposure and the offset variables were considered) and multi-variable (all variables were used) SPFs of annual crash frequency were developed at three modeling levels: context classification (CC-SPFs), area type (AT-SPFs), and statewide (SW-SPF) levels. Two exposure variables were used in this study; the annual average daily traffic (AADT) as the traditional approach and the daily vehicle miles traveled (DVMT) since it accounts for the segment length and it was used in many studies (Li et al., 2013; Dong et al., 2015; Al-Omari et al., 2020; Abdelrahman et al., 2020). Therefore, two simple SPFs and two multi-variable SPFs (referred to here as full SPFs) were developed for the three modeling levels. Equations (1) and (2) are the employed equations to develop SPFs by using AADT and DVMT exposure variables, respectively. The high correlation between variables was handled before the full SPFs development. Next, full SPFs were developed by using all not highly correlated variables. However, only significant variables with at least a 95% confidence level were kept in the developed models. In pursuit of comparing the prediction performance of CC-SPFs, AT-SPFs, and SW-SPF; simple and full SPFs; and AADT-SPFs and DVMT-SPFs, two types of performance measures were calculated (mean absolute and root mean square errors). Equations (3) and (4) show how to calculate these error measurements.

$$Np = e^{(\alpha+\beta ln(AADT)+\gamma_i X_i+ln(L))} \quad (1)$$

$$Np = e^{(\alpha+\beta ln(DVMT)+\gamma_i X_i)} \quad (2)$$

where,

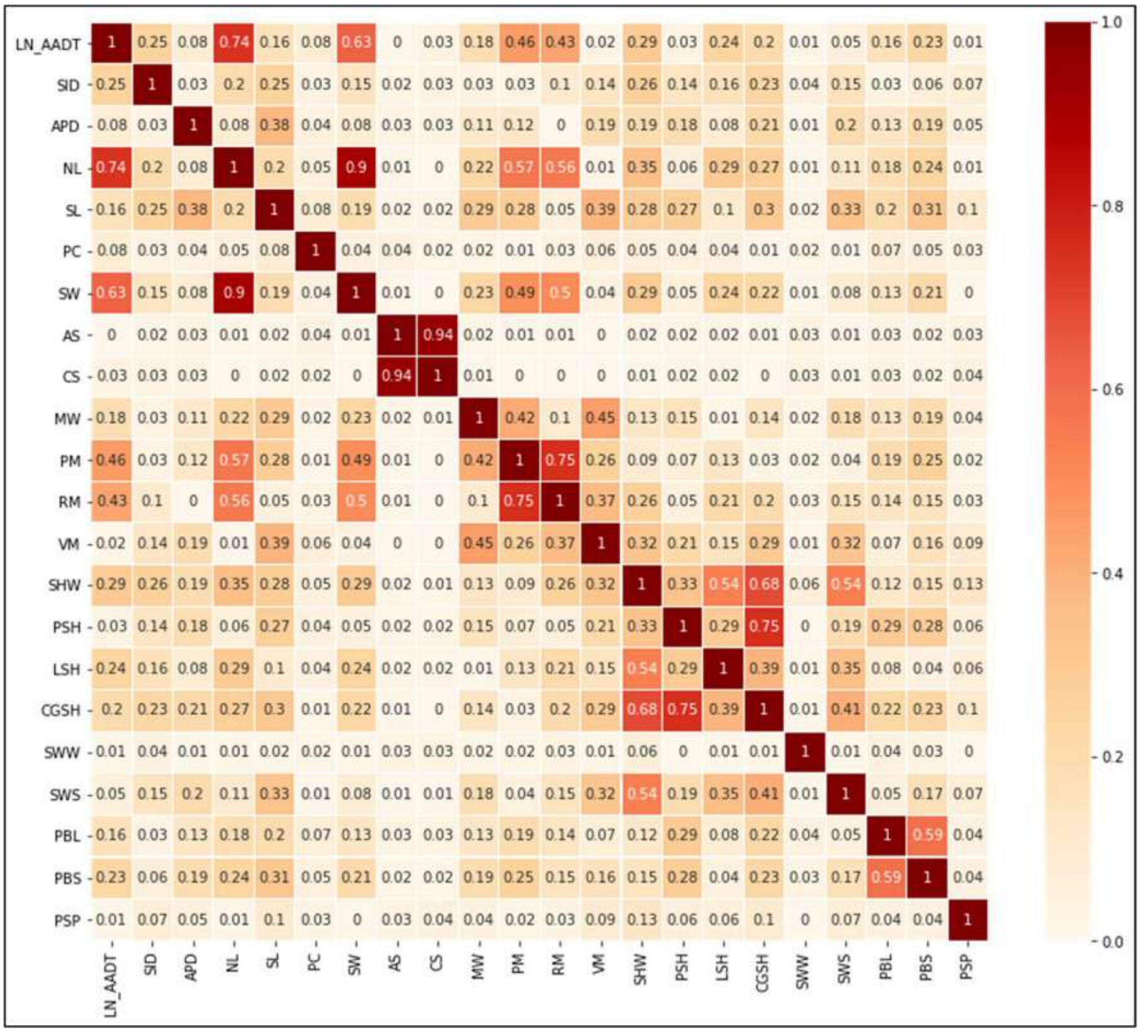

Fig. 7. Correlation matrix of the considered variables.

N_p: predicted annual crash frequency.
α: the intercept's coefficient.
β, γ_i: estimated coefficients.
AADT: average annual daily traffic.
DVMT: daily vehicle miles traveled.
X_i: a set of independent variables.
L: segment length (mile).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|N_p - N_o| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(N_p - N_o)^2} \tag{4}$$

where,

MAE: mean absolute error.
RMSE: root mean square error
N_P: predicted value.
N_O: observed value.
n: number of data points.

5.2. Network screening

One of the most important applications of SPFs is the network screening process. The network screening is a part of the roadway safety management process. In this process, the most problematic roadway segments are identified by descending ranking them based on the potential for safety improvement (PSI) value, which it is referred to as "Excess Expected Average Crash Frequency" in the HSM. The PSI is a measure for the long-term crash frequency reduction. The purpose of the network screening process is to determine the priority of implementing countermeasures to reduce the number and severity of crashes along the roadway network. Several procedures are explained in the HSM to perform network screening. However, the "Excess Expected Average Crash Frequency with EB Adjustments" method is the most powerful procedure since it accounts for regression to the mean and it does not have any limitations. Therefore, it was employed in this study to determine roads that have the highest PSI values. Simple DVMT CC-SPFs for fatal-and-injury (FI) and property damage only (PDO) crashes were developed for the network screening process. SPFs for FI and PDO crashes were used to determine the equivalent property damage only PSI (EPDO-PSI) in order to account for the

Table 2
Simple and full AADT-SPFs for context classification modeling level.

Variable	Estimated Parameter (Standard Error)							
	C1	C2	C2T	C3C	C3R	C4	C5	C6
Simple SPFs								
Intercept	−8.06 (0.5563)	−7.21 (0.2064)	−5.28 (0.7144)	−4.93 (0.2073)	−5.23 (0.2246)	−3.73 (0.1890)	0.89 (0.8370)	−1.15 (1.0005)
Ln (AADT)	1.07 (0.0602)	0.97 (0.0230)	0.88 (0.0777)	0.89 (0.0207)	0.87 (0.0236)	0.81 (0.0190)	0.39 (0.0838)	0.63 (0.1038)
Dispersion	1.37 (0.1078)	0.48 (0.0218)	0.55 (0.0522)	0.68 (0.0179)	0.79 (0.0264)	0.54 (0.0153)	0.63 (0.0649)	0.41 (0.0659)
Observations	418	1,703	366	3,065	2,080	2,590	180	82
LLV	4,893	29,683	4859	451,163	107,609	522,609	30,220	14,271
MAE	8.9	6.5	6.1	28.8	14.2	30.6	33.1	26.9
RMSE	17.6	11.9	11.7	50.4	23.3	53.4	48.5	50.8
Full SPFs								
Intercept	−4.95 (1.3312)	−4.68 (0.2444)	−6.23 (0.7098)	−4.63 (0.2165)	−4.63 (0.3769)	−3.31 (0.2262)	0.32 (0.9692)	−0.68 (0.9856)
Ln (AADT)	1.03 (0.1073)	0.80 (0.0222)	1.05 (0.0815)	0.94 (0.0207)	0.90 (0.0379)	0.72 (0.0223)	0.51 (0.0911)	0.45 (0.0968)
SID	0.30 (0.0618)	0.48 (0.0303)	0.14 (0.0175)	0.17 (0.0070)	0.23 (0.0179)	0.14 (0.0060)	0.10 (0.0137)	0.04 (0.0111)
APD	0.08 (0.0180)	0.06 (0.0056)	0.02 (0.0048)	0.03 (0.0021)	0.03 (0.0046)	0.01 (0.0016)	0.03 (0.0058)	-
NL	-	-	−0.13 (0.0483)	-	-	-	-	-
SL	−0.05 (0.0173)	−0.03 (0.0029)	−0.02 (0.0073)	−0.03 (0.0026)	−0.03 (0.0041)	-	−0.04 (0.0117)	-
PC	-	-	-	-	-	-	-	0.38 (0.1625)
AS	−1.16 (0.5324)	-	-	-	-	-	-	-
MW	-	-	-	-	0.005 (0.0018)	-	-	-
PM	-	-	−0.25 (0.0820)	-	-	-	-	-
RM	-	0.19 (0.0616)	-	-	0.22 (0.0550)	0.13 (0.0317)	-	-
VM	-	-	-	−0.09 (0.0383)	-	-	-	-
SHW	-	-	-	−0.02 (0.0058)	-	0.01 (0.0064)	−0.08 (0.0304)	−0.09 (0.0280)
PSH	-	-	-	-	−0.12 (0.0557)	−0.16 (0.0343)	-	-
SWW	-	-	-	-	−0.04 (0.0136)	-	-	-
SWS	0.01 (0.0060)	-	-	-	-	−0.01 (0.0017)	-	-
PBL	-	-	-	-	−0.20 (0.0535)	−0.08 (0.0306)	-	-
PSP	-	-	-	-	-	−0.29 (0.0954)	-	-
Dispersion	0.67 (0.1290)	0.30 (0.0154)	0.35 (0.0392)	0.43 (0.0126)	0.49 (0.0253)	0.41 (0.0123)	0.42 (0.0482)	0.31 (0.0522)
Observations	94	1,595	366	2,866	971	2,463	159	82
LLV	1,557	29,398	4,916	438,891	75,322	509,927	28,018	14,282
MAE	6.5	5.0	4.4	20.4	14.6	26.5	28.0	23.7
RMSE	13.4	11.0	7.7	35.0	24.0	46.0	40.9	46.6

AADT: annual average daily traffic, SID: signalized intersections density per mile, APD: access points density per mile, NL: total number of lanes, SL: speed limit, PC: pavement condition, AS: asphalt surface, MW: median width, PM: paved median, RM: raised median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, SWW: sidewalk width, SWS: sidewalk spacing, PBL: presence of bike lane, PSP: presence of shared path, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

crash severity during the comparison among roadway segments. Equations 5–10 were used to calculate the EPDO-PSI (AASHTO, 2010).

$$Cn = \frac{N_{p,n}}{N_{p,1}} \tag{5}$$

$$w = \frac{1}{1 + k * \sum_{n=1}^{N} N_{p,n}} \tag{6}$$

$$Ne,1 = w * Np,1 + (1 - w) * \left(\frac{\sum_{n=1}^{N} N_{o,n}}{\sum_{n=1}^{N} C_n} \right) \tag{7}$$

$N_{e,n} = N_{e,1} * C_n$ (8)

$$PSI = \frac{1}{n} \sum_{i=1}^{n} N_{e,n} - N_{p,n} \tag{9}$$

$$EPDO - PSI = PSIPDO + PSIFI * \frac{CC_{FI}}{CC_{PDO}} \tag{10}$$

where,

C_n: annual correction factor for year n.
$N_{p,n}$: predicted crash frequency for year n (from the SPF).
$N_{p,1}$: predicted crash frequency for year 1 in the analysis period (from the SPF).
w: Empirical Bayes weight.
k: overdispersion parameter of the SPF.
$N_{e,1}$: EB-adjusted estimated crash frequency for year 1 in the analysis period.
$N_{o,n}$: observed crash frequency for year n.
$N_{e,n}$: EB-adjusted estimated crash frequency for year n.
PSI: excess expected crashes.
EPDO-PSI: excess expected equivalent property damage only crashes.
PSI_{FI}: excess expected fatal-and-injury crashes.
PSI_{PDO}: excess expected property damage only crashes.
CC_{FI}: crash cost for fatal-and-injury crash.
CC_{PDO}: crash cost for property damage only crash.

6. Results

6.1. Safety performance functions

In pursuit of developing accurate SPFs, variables that have a high correlation with other variables were identified and excluded (if their correlation factor is greater than 0.5) from the SPFs development process. This procedure was conducted before modeling every SPF in this study. For example, Fig. 7 shows the correlation matrix for all variables that were used in modeling the statewide AADT-SPF. It was found that the total number of lanes, surface width, concrete surface, raised median, lawn shoulder, curb/gutter shoulder, sidewalk spacing, and presence of bicycle slot variables have high correlation factors with other variables (such as ln (AADT), asphalt surface, paved median, shoulder width, and pres-

Table 3
Simple and full AADT-SPFs for area type and statewide modeling levels.

Variable	Estimated Parameter (Standard Error)				
	Natural	Rural	Suburban	Urban	Statewide
Simple SPFs					
Intercept	−8.06 (0.5563)	−7.51 (0.2254)	−5.79 (0.1499)	−3.15 (0.1868)	−7.01 (0.1110)
Ln (AADT)	1.07 (0.0602)	1.03 (0.0250)	0.96 (0.0152)	0.76 (0.0188)	1.10 (0.0115)
Dispersion	1.37 (0.1078)	0.65 (0.0249)	0.76 (0.0157)	0.58 (0.0154)	0.99 (0.0136)
Observations	418	2,069	5,145	2,852	10,484
LLV	4,893	34,294	558,612	567,005	1,162,882
MAE	C1: 8.9	C2: 8.8, C2T: 5.4	C3C: 26.1, C3R: 18.9	C4: 31.6, C5: 28.4, C6: 31.3	C1: 37.5, C2: 37.0, C2T: 8.2, C3C: 31.6, C3R: 22.8, C4: 28.5, C5: 29.3, C6: 39.1
RMSE	C1: 17.6	C2: 15.3, C2T: 9.8	C3C: 46.7, C3R: 30.3	C4: 54.2, C5: 43.9, C6: 46.7	C1: 82.3, C2: 61.1, C2T: 17.6, C3C: 58.1, C3R: 38.2, C4: 54.3, C5: 45.1 , C6: 54.1
Full SPFs					
Intercept	−4.95 (1.3312)	−6.19 (0.3666)	−4.76 (0.2104)	−3.47 (0.2190)	−5.40 (0.1222)
Ln (AADT)	1.03 (0.1073)	0.91 (0.0295)	0.95 (0.0194)	0.85 (0.0251)	1.07 (0.0104)
SID	0.30 (0.0618)	0.31 (0.0196)	0.19 (0.0067)	0.11 (0.0052)	0.17 (0.0041)
APD	0.08 (0.0180)	0.05 (0.0031)	0.03 (0.0020)	0.01 (0.0016)	0.02 (0.0012)
SL	−0.05 (0.0173)	-	−0.03 (0.0022)	−0.03 (0.0032)	−0.04 (0.0012)
AS	−1.16 (0.5324)	−0.69 (0.2821)	-	-	-
MW	-	−0.004 (0.0010)	0.002 (0.0009)	-	-
PM	-	-	−0.09 (0.0309)	−0.21 (0.0323)	−0.12 (0.0188)
VM	-	-	−0.11 (0.0383)	-	−0.15 (0.0270)
SHW	-	-	−0.02 (0.0051)	-	−0.02 (0.0038)
PSH	-	-	−0.07 (0.0257)	−0.16 (0.0345)	−0.07 (0.0176)
SWS	0.01 (0.0060)	-	-	−0.01 (0.0017)	-
PBL	-	-	−0.06 (0.0245)	-	-
PSP	-	-	-	−0.20 (0.0987)	-
Dispersion	0.67 (0.1290)	0.40 (0.0195)	0.45 (0.0114)	0.40 (0.0129)	0.48 (0.0083)
Observations	94	1,408	3,888	2,139	8,906
LLV	1,557	32,565	513,668	498,531	1,065,241
MAE	C1: 6.5	C2: 6.7, C2T: 6.2	C3C: 20.7, C3R: 14.6	C4: 29.1, C5: 35.5, C6: 54.6	C1: 8.6, C2: 6.1, C2T: 8.4, C3C: 19.6, C3R: 13.0, C4: 30.6, C5: 51.0, C6: >100
RMSE	C1: 13.4	C2: 11.8, C2T: 11.4	C3C: 36.1, C3R: 22.8	C4: 51.4, C5: 57.8, C6: >100	C1: 15.2, C2: 10.2, C2T: 13.5, C3C: 34.8, C3R: 21.6, C4: 54.4, C5: 91.5, C6: >100

AADT: annual average daily traffic, SID: signalized intersections density per mile, APD: access points density per mile, SL: speed limit, AS: asphalt surface, MW: median width, PM: paved median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, SWS: sidewalk spacing, PBL: presence of bike lane, PSP: presence of shared path, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

ence of bicycle lane). Therefore, they were excluded from the modeling process of the statewide AADT-SPFs.

Tables 2–5 show the developed SPFs for the different levels of modeling. It was found that AADT, signalized intersections density, access points density, pavement condition, median width, and raised median variables have negative effects on traffic safety. These factors have positive coefficients in AADT CC-SPFs. On the other hand, number of lanes, posted speed limit, asphalt surface, paved median, vegetation median, paved shoulder, sidewalk width, presence of bicycle lane, and presence of shared path variables have negative coefficients in AADT CC-SPFs. This means that these factors have a positive effect on traffic safety.

Shoulder width and sidewalk spacing factors have a double safety effect on traffic safety (a positive effect at some road classes, while a negative effect on others). Wide shoulders have positive effect on traffic safety at C3C, C5 and C6 roads. However, it has a negative effect on C4 roads. Large sidewalk spacing has a negative effect on traffic safety at C1 roads. However, it has a positive effect on C4 roads. Similar effects for the aforementioned factors were noticed in DVMT-SPFs. However, there are some differences.

The results indicated that there is no significant difference between the performance of simple and full SPFs. It was noticed that simple and full DVMT-SPFs have better performance than AADT-SPFs for most road classes. Fig. 8 shows MAE values of simple SPFs at the different modeling levels. It was found that the CC-SPFs outperform AT-SPFs and SW-SPF for most road classes and if it is not the case, their error values are not significantly higher than AT-SPFs and SW-SPF error values.

6.2. Network screening

Road segments were ranked in descending order based on the EPDO-PSI value. Table 6 lists and Fig. 9 shows the top twenty road segments that have the highest EPDO-PSI values. These locations have the highest potential for safety improvement by implementing safety countermeasures to reduce the number and severity of crashes along them. It was found that the most problematic road segments are C3C and C4 roads and they are located in the Miami area.

7. Discussion of results

The importance of the development of SPFs lies in the identification of factors that are associated with crash occurrence at every road class and how these factors affect traffic safety. It was found that there are some factors have negative effects, while others have positive effects on traffic safety represented by increasing/reducing the crash frequency. The number of crashes is expected to increase by increasing traffic volumes, signalized intersections, and access point densities because of the large number of traffic conflicts under heavy traffic volumes (especially at signalized intersections and access points where conflicts are concentrated). Prefect pavement condition encourage drivers to drive with a high speed which increases the probability of crash occurrence. The existence of a raised median could cause a rollover of vehicles when a crash happens, while an unraised median is not considered as an obstacle for

Table 4
Simple and full DVMT-SPFs for context classification modeling level.

Variable	Estimated Parameter (Standard Error)							
	C1	C2	C2T	C3C	C3R	C4	C5	C6
Simple SPFs								
Intercept	−3.57 (0.4337)	−4.94 (0.1675)	−4.40 (0.3598)	−3.67 (0.1198)	−4.32 (0.1639)	−3.70 (0.1257)	−0.74 (0.4822)	−2.20 (0.6474)
Ln (DVMT)	0.57 (0.0464)	0.74 (0.0173)	0.76 (0.0428)	0.75 (0.0124)	0.76 (0.0176)	0.80 (0.0134)	0.50 (0.0530)	0.70 (0.0755)
Dispersion	1.24 (0.0979)	0.43 (0.0198)	0.50 (0.0492)	0.62 (0.0164)	0.74 (0.0251)	0.52 (0.0147)	0.56 (0.0582)	0.40 (0.0646)
Observations	418	1,703	366	3,065	2,080	2,590	180	82
LLV	4,928	29,788	4,871	451,342	107,678	522,672	30,232	14,272
MAE	6.0	5.4	5.2	24.2	13.0	29.0	27.8	25.2
RMSE	11.5	10.8	8.9	41.9	21.9	53.1	41.1	40.3
Full SPFs								
Intercept	−5.53 (0.5558)	−5.71 (0.2608)	−5.21 (0.4551)	−4.07 (0.1495)	−4.64 (0.3096)	−4.62 (0.1752)	−1.89 (0.6549)	−2.08 (0.8056)
Ln (DVMT)	0.78 (0.0482)	0.87 (0.0191)	0.89 (0.0433)	0.86 (0.0144)	0.88 (0.0286)	0.93 (0.0185)	0.69 (0.0662)	0.73 (0.0786)
SID	0.34 (0.0568)	0.42 (0.0285)	0.14 (0.0177)	0.16 (0.0071)	0.21 (0.0180)	0.12 (0.0068)	0.08 (0.0166)	0.03 (0.0120)
APD	0.06 (0.0131)	0.05 (0.0056)	0.01 (0.0048)	0.02 (0.0022)	0.03 (0.0047)	0.01 (0.0018)	0.03 (0.0069)	-
NL	0.21 (0.0453)	-	-	0.03 (0.0108)	0.07 (0.0185)	-	-	-
SL	−0.02 (0.0076)	−0.02 (0.0031)	−0.02 (0.0071)	−0.03 (0.0025)	−0.03 (0.0041)	−0.03 (0.0036)	−0.03 (0.0132)	−0.04 (0.0183)
PC	-	0.07 (0.0312)	-	-	-	-	-	-
SW	-	-	-	-	-	0.005 (0.0014)	-	-
AS	-	-	-	-	-	-	-	0.92 (0.3410)
MW	-	-	-	-	0.01 (0.0021)	0.01 (0.0022)	−0.01 (0.0066)	-
PM	-	-	−0.20 (0.0796)	-	-	-	-	-
VM	-	−0.16 (0.0415)	-	-	−0.21 (0.0925)	-	-	-
SHW	-	-	-	−0.03 (0.0056)	-	-	-	−0.07 (0.0323)
PSH	-	-	-	-	−0.11 (0.0556)	−0.14 (0.0368)	-	-
SWW	-	-	-	-	−0.04 (0.0133)	-	-	-
SWS	-	-	-	-	-	−0.01 (0.0017)	-	-
PBL	-	-	-	-	−0.19 (0.0529)	-	-	-
PSP	-	-	-	-	0.25 (0.1104)	-	-	-
Dispersion	0.59 (0.0610)	0.29 (0.0154)	0.36 (0.0394)	0.42 (0.0123)	0.48 (0.0250)	0.36 (0.0132)	0.39 (0.0527)	0.31 (0.0556)
Observations	365	1,589	366	2,866	971	1,701	116	72
LLV	4,167	29,268	4,915	438,933	75,329	434,141	23,520	12,600
MAE	4.8	4.9	4.4	19.9	14.5	30.0	28.5	24.7
RMSE	10.0	10.2	7.6	34.9	23.8	52.0	40.0	41.6

DVMT: daily vehicle miles traveled, SID: signalized intersections density per mile, APD: access points density per mile, NL: total number of lanes, SL: speed limit, PC: pavement condition, SW: surface width, AS: asphalt surface, MW: median width, PM: paved median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, SWW: sidewalk width, SWS: sidewalk spacing, PBL: presence of bike lane, PSP: presence of shared path, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

vehicles. On the other hand, the number of crashes is expected to decrease by providing some conditions. Roads with a high number of lanes provide smooth movement without congestion, therefore reducing conflicts between vehicles. High posted speed limits are only placed on roads with a low intersection and access point densities, therefore maintaining continuous traffic without many interruptions. Unpaved roads are very rare in Florida; therefore, they may cause confusion for drivers. Paved and vegetation median types are not considered as obstacles for vehicles since these median types have a small slope. Paved median and paved shoulders are usually wide. Wide shoulders and sidewalks provide a good separation between the road and the opposite traffic and the roadside environment. Presence of bicycle lane or shared path reduces the number of conflict points between bicyclists and motorized road users. Meanwhile, some factors have a double safety effect. This fluctuation in the effect of these factors on crash occurrence is due to the different road environment between road classes.

The possession of the simple and full SPFs with a similar prediction performance confirms that the FDOT context classification system classifies roads effectively. The importance of this manifests by the development of highly accurate simple SPFs, since obtaining road environment characteristics is a time consuming and hard process. It was observed that simple and full DVMT-SPFs have better performance than AADT-SPFs for most road classes. CC-SPFs have the best performance among other modeling levels due to the low variability in the road environment within the certain road class. This is in line with previous findings that more specific SPFs have better performance.

8. Conclusion

The new FDOT context classification system was highlighted in this study. Roads are classified into eight classes from rural to urban roads according to this system based on geographic, demographic, and road characteristics information. Crash and traffic data from 2015-2019 and road characteristics and environment information were obtained to conduct crash analysis and develop safety performance functions (SPFs) at three modeling levels: context classification (CC-SPFs), area type (AT-SPFs), and statewide (SW-SPF) levels. Simple and full SPFs were developed by adopting annual average daily traffic (AADT) and daily vehicle miles traveled (DVMT) as exposure variables. Network screening was also accomplished in this study to identify the most problematic road segments. It was found that more than a third of road segments are rural roads (C2 roads). According to this system, suburban commercial and urban general roads (C3C and C4 roads) were subjected to most crashes. However, urban roads (C4, C5, and C6) have the highest crash rate per million miles traveled. DVMT-SPFs have better prediction performance than AADT-SPFs. CC-SPFs outperformed AT-SPFs and SW-SPF. It is worth mentioning that there was no significant difference between the developed simple and full SPFs for all road classes. This confirms considering all road environment while classifying the roads based on the FDOT context classification system. The results of the network screening indicated that the most problematic roads in Florida are C3C and C4 roads.

Table 5
Simple and full DVMT-SPFs for area type and statewide modeling levels.

Variable	Estimated Parameter (Standard Error)				
	Natural	Rural	Suburban	Urban	Statewide
Simple SPFs					
Intercept	−3.57 (0.4337)	−3.87 (0.1423)	−4.15 (0.0983)	−3.21 (0.1197)	−3.84 (0.0781)
Ln (DVMT)	0.57 (0.0464)	0.64 (0.0150)	0.78 (0.0103)	0.75 (0.0128)	0.76 (0.0083)
Dispersion	1.24 (0.0979)	0.52 (0.0206)	0.71 (0.0147)	0.54 (0.0146)	0.95 (0.0130)
Observations	418	2,069	5,145	2,852	10,484
LLV	4,928	34,538	558,822	567,106	1,163,256
MAE	C1: 6.0	C2: 5.7, C2T: 5.2	C3C: 23.5, C3R: 15.9	C4: 29.4, C5: 27.1, C6: 30.5	C1: 26.9, C2: 27.2, C2T: 8.0, C3C: 23.8, C3R: 17.1, C4: 31.9, C5: 30.9, C6: 38.3
RMSE	C1: 11.5	C2: 10.9, C2T: 10.1	C3C: 42.6, C3R: 23.5	C4: 53.4, C5: 41.3, C6: 45.1	C1: 40.9, C2: 36.4, C2T: 12.5, C3C: 42.1, C3R: 24.6, C4: 63.5, C5: 48.5, C6: 54.4
Full SPFs					
Intercept	−5.53 (0.5558)	−4.72 (0.1504)	−4.28 (0.1564)	−4.11 (0.1720)	−4.18 (0.0911)
Ln (DVMT)	0.78 (0.0482)	0.74 (0.0161)	0.87 (0.0143)	0.88 (0.0158)	0.88 (0.0087)
SID	0.34 (0.0568)	0.25 (0.0154)	0.18 (0.0071)	0.10 (0.0053)	0.16 (0.0041)
APD	0.06 (0.0131)	-	0.02 (0.0022)	0.01 (0.0017)	0.02 (0.0012)
NL	0.21 (0.0453)	-	0.05 (0.0107)	-	0.11 (0.0066)
SL	−0.02 (0.0076)	-	−0.03 (0.0025)	−0.03 (0.0030)	−0.04 (0.0012)
SW	-	-	-	0.004 (0.0012)	-
MW	-	-	0.003 (0.0009)	-	-
PM	-	-	-	−0.14 (0.0352)	-
RM	-	0.26 (0.0551)	-	-	-
VM	-	−0.15 (0.0431)	-	-	−0.11 (0.0256)
SHW	-	-	−0.02 (0.0056)	-	−0.02 (0.0039)
PSH	-	−0.28 (0.0602)	−0.13 (0.0267)	−0.16 (0.0343)	−0.06 (0.0173)
LSH	-	−0.31 (0.0622)	-	-	-
SWW	-	-	−0.01 (0.0073)	0.03 (0.0112)	-
SWS	-	-	-	−0.01 (0.0017)	-
Dispersion	0.59 (0.0610)	0.38 (0.0165)	0.42 (0.0117)	0.40 (0.0127)	0.48 (0.0082)
Observations	365	2,069	3,162	2,139	8,906
LLV	4167	34,775	471,644	498,545	1,065,348
MAE	C1: 4.8	C2: 5.1, C2T: 5.6	C3C: 21.8, C3R: 16.0	C4: 28.7, C5: 34.8, C6: 57.2	C1: 7.4, C2: 5.7, C2T: 8.3, C3C: 19.9, C3R: 12.4, C4: 29.7, C5: 45.8, C6: >100
RMSE	C1: 10.0	C2: 10.0, C2T: 13.7	C3C: 37.8, C3R: 24.1	C4: 51.8, C5: 53.8, C6: >100	C1: 11.8, C2: 9.6, C2T: 13.2, C3C: 35.7, C3R: 20.6, C4: 53.2, C5: 79.0, C6: >100

DVMT: daily vehicle miles traveled, SID: signalized intersections density per mile, APD: access points density per mile, NL: total number of lanes, SL: speed limit, SW: surface width, MW: median width, PM: paved median, RM: raised median, VM: vegetation median, SHW: shoulder width, PSH: paved shoulder, LSH: lawn shoulder, SWW: sidewalk width, SWS: sidewalk spacing, LLV: log-likelihood value, MAE: mean absolute error, RMSE: root mean square error.

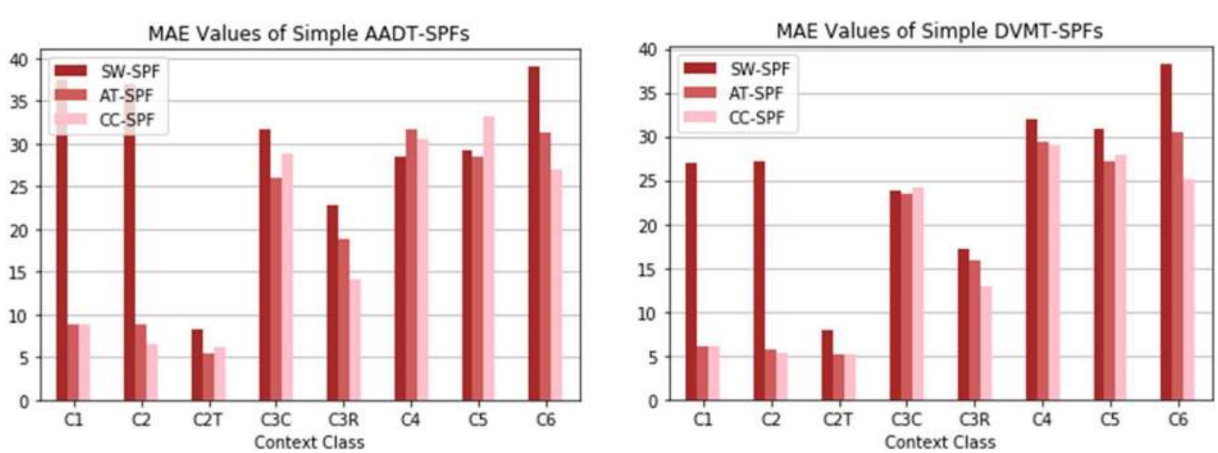

Fig. 8. MAE values of simple CC-SPFs, AT-SPFs, and SW-SPF.

Table 6
The most problematic road segments in Florida.

Road ID	Road Name	Began Post	End Post	CC	Rank
87026000	NE Miami Gardens Dr	5.529	6.584	C3C	1
72160000	San Jose Blvd	1.865	3.322	C3C	2
87080900	NW 79th St	38.493	40.027	C4	3
87008000	NW 135th St	5.102	7.614	C4	4
86210000	Davie Blvd	2.034	3.019	C4	5
86110000	NW 10th St	5.018	6.086	C4	6
75010000	US-92 E	8.638	11.219	C3C	7
87170000	N Miami Beach Blvd	1.477	3.065	C4	8
13010000	14th St W	3.007	4.277	C3R	9
93004000	Glades Rd	4.896	5.512	C3C	10
86040000	Hollywood Blvd	15.649	16.598	C4	11
86040000	Hollywood Blvd	12.486	13.986	C4	12
87038000	NW 103rd St	8.199	8.955	C4	13
87020000	S Dixle Hwy	0.862	3.093	C3C	14
14030000	US Highway 19	0.636	2.511	C3C	15
87240000	NW 27th Ave	10.843	11.113	C4	16
86529500	W Gopans Rd	0.698	1.176	C3C	17
87044000	SW 40th St	3.144	4.223	C4	18
14030000	US Highway 19	8.007	11.474	C3C	19
72220000	103rd St	6.479	7.757	C3C	20

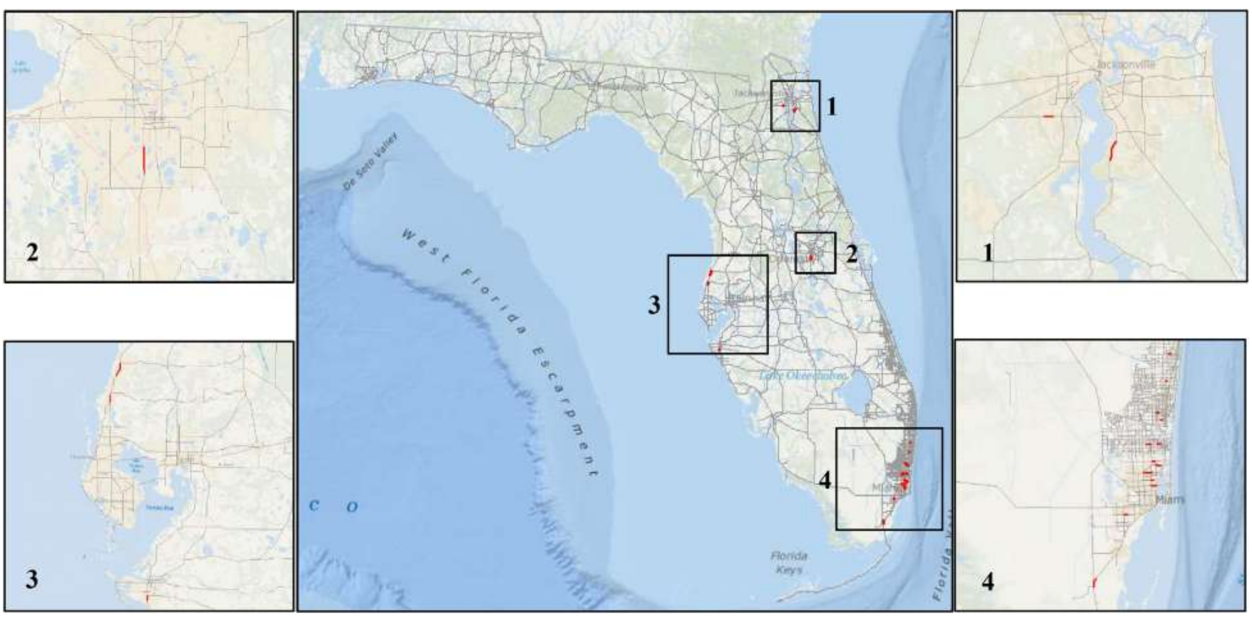

Fig. 9. The most problematic road segments in Florida.

9. Declarations of interest

None.

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Crash proneness? Predictors of repeat crashes in older drivers

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ABSTRACT

Introduction: Older drivers are believed to be prone to crashes due to age-related deterioration of their driving abilities. Currently, little is known about the characteristics of repeat crashers and the factors that predict subsequent crashes among these older drivers. *Method:* A dataset containing the records of crash events that occurred between January 2014 and November 2019 was provided by the Department of Transport and Main Roads (DTMR) in Queensland, Australia. This dataset included 16,973 records of older drivers involved in a single crash and 222 cases in multiple crashes, comprising a total of 17,195 cases. Descriptive and inferential analyses were performed to understand the characteristics of repeat crashers. Survival analysis techniques were used to determine risk factors predictive of subsequent crashes. *Results:* Nearly half (46%) of the repeat crashers were culpable for both of their crashes. Their average age was significantly older than those who were culpable for none or one of their crashes. For older male drivers, riding a motorcycle or driving a heavy vehicle were significant risk factors for having a subsequent crash. The risk for female at-fault drivers being involved in a subsequent crash was 4.53 times greater than those not at-fault. Older female drivers involved in crashes caused by slowing or stopping also presented a higher risk of being involved in subsequent crashes. *Conclusions:* This study identified risk factors for older drivers being involved in repeat crashes; distinctive gender differences in the risk for involvement in repeat crashes were found. *Practical Applications:* To reduce the likelihood of older drivers being involved in subsequent crashes, attention should be directed towards elders living in major cities, male motorcycle riders and heavy vehicle drivers, and at-fault female drivers.

1. Introduction

The term "crash proneness" was first introduced in road safety research about a century ago by Greenwood and Yule (1920) who defined crash-prone drivers as "drivers with a number of crashes higher than expected." In recent years, a number of researchers have asserted that human error rather than coincidence is the main contributor to a traffic crash (Blasco, Prieto, & Cornejo, 2003; Chandraratna, Stamatiadis, & Stromberg, 2006; Petridou & Moustaki, 2000). After analyzing a dataset of bus driver crashes, Blasco et al. (2003) concluded that the cause of crashes among crash-prone bus drivers was human error and not coincidences. These researchers revealed that behind the high number of traffic crashes in bus drivers lay the problems of cognitive and psychomotor skills (Blasco et al., 2003). Petridou and Moustaki (2000) have asserted that a driver's crash proneness is due to either inferior driving capability or habitual risky behaviors. For example, young inexperienced drivers are at a higher crash risk than mature drivers due to their limited on-road experience and possible risk-taking intentions (Chandraratna et al., 2006; Petridou & Moustaki, 2000).

Many researchers have attempted to determine the factors related to crash proneness (af Wåhlberg & Dorn, 2009; Blasco et al., 2003; Chandraratna et al., 2006; Dorn & af Wåhlberg, 2020), but few have had a specific focus on crash proneness and aging. Research investigating the factors associated with crash proneness among drivers of all age groups has revealed that demographic (e.g., age, gender), psychological (e.g., personality traits, aggression), situational (e.g., city size, driving exposure), traffic history (e.g., previous citations, at-fault crashes), and behavioral factors (e.g., drink driving, risky driving practices, road rule violations) are associated with crash proneness (Chandraratna et al., 2006; Das, Sun, Wang, & Leboeuf, 2015; Dorn & af Wåhlberg, 2020; Elliott, Waller, Raghunathan, & Shope, 2001; Ferrante, Rosman, & Marom, 2001; Herzberg, 2009). For the aging population, the main concerns related to crash proneness focus on age-related decline such as reduced physical and cognitive functions, including attention, working memory, visual processing,

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and reaction time (Aksan, Anderson, Dawson, Uc, & Rizzo, 2015; Anstey, Wood, Lord, & Walker, 2005; Daigneault, Joly, & Frigon, 2002; Langford & Koppel, 2006). Such physiological and cognitive decline may result in older drivers being prone to crashes. For example, research has indicated that older drivers are frequently involved in specific types of traffic collisions such as intersection crashes and multi-vehicle collisions (Daigneault et al., 2002; Hing, Stamatiadis, & Aultman-Hall, 2003; Langford & Koppel, 2006; Meyers, 2004), and are highly likely to be responsible for the crashes in which they are involved (Clarke, Ward, Bartle, & Truman, 2010; Mayhew, Simpson, & Ferguson, 2006). Given that older drivers are more likely to be seriously injured or to die as a result of a traffic crash due to their fragility (Boufous, Finch, Hayen, & Williamson, 2008; Langford & Koppel, 2006; Lombardi, Horrey, & Courtney, 2017), it is essential to better understand the issue of crash proneness in this population.

To address the gap in the literature, this study aimed to understand the characteristics of older drivers who had multiple crashes by analyzing state-wide datasets between 2014 and 2019 in Queensland, Australia. These datasets contained almost six years of crash records including demographic, vehicle, and crash details of drivers aged 60 years and older. The focus of the research was to estimate the probability that an older driver will be involved in a subsequent crash after the initial crash within the observation period. In this study, crash-prone drivers are defined as those who have had two or more traffic crashes during the period 2014 to 2019. The terms crash-prone, crash proneness, and repeat crasher are used interchangeably. The aims of this study were:

a) To understand the driver and crash characteristics of repeat crashers amongst older drivers;
b) To use the initial crash characteristics to estimate the risk of older drivers being involved in a subsequent crash.

2. Method

2.1. Datasets and variables

A crash dataset for the period of January 2014 to November 2019 were provided by the Department of Transport and Main Roads (DTMR) in Queensland Australia. These data are electronic records based on motor-vehicle crashes reported by the Queensland Police Service (QPS) that resulted from the movement of at least one road vehicle on a road or road-related area involving death or injury to any person (Department of Transport and Main Roads, 2016). The complete dataset contained 34,889 crash records including motor-vehicle drivers, pedestrians, cyclists, and animal riders (e.g., horse riders). For this study, pedestrians and non-motor vehicle riders were excluded from the dataset, resulting in a main dataset containing 17,417 crash records of motor-vehicle drivers and motorcycle riders aged 60 years and over who survived their initial crash. For clarity, if a driver turned 60 years of age during the study period, only the initial and any subsequent crash event, from age 60, were included in the analysis.

In these records, 222 drivers who were involved in two or more crashes during the observation period were labelled as "repeat crashers." Their initial and subsequent crash records were identified from the main dataset and merged into individual records by matching de-identified drivers license ID. Another 16,973 records were older drivers involved in crashes on a single occasion during the observation period and were labelled as "single crashers." The final dataset contained a total of 17,195 cases.

For each crash record, a list of crash attributes (independent variables) was selected for analysis. These variables were categorized as:

1. Human factors: driver age, gender, vehicle type, drink or drug driving, speeding, fatigue, distraction and at-fault status.
2. Environmental factors: time of crash (e.g., peak hour: weekdays 6–9 am and 2–6 pm, off-peak hour: 10 am–1 pm and weekend, and night-time: 7 pm–5 am), area of crash (e.g., major cities, inner regional and outer regional areas), lighting condition and road condition.
3. Crash results: crash type (e.g., hit pedestrian, single or multi-vehicle crash), severe injury and minor injury.
4. Crash characteristics: driver's intended action (e.g., go straight ahead, right turn, left turn, etc.), roadway feature (e.g., T junction, crossroad, roundabout, etc.), traffic control (e.g., operating traffic lights, give way sign, etc.) and crash nature (e.g., angle crash, rear-end crash, etc.).
5. Other variables: additional variables were formulated using the existing data to better understand the crash events. These variables included: (a) the occurrence of subsequent crash ("yes" for repeat crashers and "no" for single crashers); (b) the duration between two crashes (months); (c) the sum of at-fault status in two crashes, with 0 occasions representing not-at-fault in both crashes and two occasions representing at-fault in both crashes.

It is noteworthy that the data included rare events in crashes, such as crashes that occurred at railway crossings or involved overturned vehicles. Rare events can often cause biased results in statistical procedures due to the effect being underestimated or overestimated (Guns & Vanacker, 2012; King & Zeng, 2001). In this study, variables that were rare (e.g., crossing railway, vehicle overturned, etc.) were grouped into the category "other." Making a U-turn, which is not a particularly common event, was grouped with variables of similar concept (namely making a right turn or a left turn) and incorporated into a new category called "change direction."

2.2. Statistical analysis

It is assumed in this study that single crashers represent the broad population of older drivers who were randomly involved in crashes. Conversely, repeat crashers were seen as crash-prone drivers who have a higher chance of being involved in traffic collisions.

The first part of the analysis aimed to understand the characteristics of repeat crashers and their initial and subsequent crashes. Descriptive and inferential tests (ANOVA and Chi-Square tests) were performed to provide an overview of the crash-prone drivers and their crash events. The second part of the analysis aimed to identify risk factors and the probability of older drivers being involved in subsequent crashes. Survival analysis techniques (Cox proportional hazard regression) were used to estimate the independent association of each factor with the likelihood of older drivers experiencing a subsequent crash. The outcome variable for this survival analysis model is the occurrence of the subsequent crash (yes or no for crash recurrence). The survival period known as "time to fail" was measured using the duration (months) between the initial and the subsequent crash. For single crashers, that is for those who did not experience a subsequent crash, their survival time was considered unknown. The survival period was the time between the initial event and the end of the observation period, which was deemed to be "censored" in the statistical analysis procedure (Bradburn, Clark, Love, & Altman, 2003a, 2003b; Clark, Bradburn, Love, & Altman, 2003a, 2003b; Ferrante et al., 2001).

Four groups of factors (human factors, environmental factors, crash results, and crash characteristics) were entered into the regression model. For each factor with more than two variables, one variable was chosen as the "reference variable" and the risk ratios of other variables were calculated relative to the reference value. The hazard ratio (HR) in the Cox proportional hazard regression is the risk ratio (RR) of each variable, which represents the relative risk of the drivers in this particular variable. For example, if the risk ratio is 1.50 in male drivers, the relative risk of male drivers experiencing a subsequent crash is 1.5 times higher than for female drivers.

3. Results

3.1. Repeat crashers

The characteristics of 222 older drivers with repeat crashes, including 158 (71.17%) males and 64 (28.83%) females, are analyzed in this section. At the time of their initial crash, the average age was 68.57 years (SD = 7.26; min, max = 60, 93), with the majority (n = 184, 82.9%) being under 75 years of age. On average, the time between initial and subsequent crashes was 18.23 months (median = 15 months; min, max = 0, 65), with seven older drivers experiencing two crashes within the same month. No significant differences were found in the duration of crash reoccurrence (that is the time between initial and subsequent crash) between gender, age groups (age between 60 and 74 years and 75 years and over), and at-fault status. Although not included in the main analysis, it is noteworthy that seven older drivers experienced more than two crashes in the observation period, among them were one female and six males. One male driver in his sixties had four crashes and the remaining six drivers had three crashes each.

Table 1 presents details of the at-fault status, vehicle type, crash type, and casualties of the initial and subsequent crashes. Among the repeat crashers, more than 60% were responsible for their initial or subsequent crashes. Female drivers showed a higher proportion of culpability in their initial crash than male drivers, however, the culpability rate was lower in their subsequent crashes. Most repeat crashers drove light vehicles. Among the repeat crash group, more males drove heavy vehicles and rode motorcycles than females. More than 70% of the initial and subsequent crashes involved multiple vehicles. The initial crashes resulted in a total of 276 casualties, including 3 fatalities and 107 hospitalizations. The subsequent crashes resulted in a further 291 causalities, with 7 fatalities and 117 hospitalizations.

When examining the at-fault status of the repeat crashers, nearly half (n = 102, 45.95%) were responsible for both crashes, while less than one-fifth (n = 37, 16.67%) were not at-fault in both crashes. Age was found to be significantly associated with at-fault status. ANOVA tests showed a significant trend of increasing age and at-fault status. On average, drivers who were responsible for both collisions were significantly older (mean age = 70.22 years) than those who were not at-fault in both collisions (mean age = 66.41 years). Chi-square tests revealed no difference between gender and at-fault status (Table 2).

Table 3 lists the crash characteristics of the initial and subsequent crashes. In the initial crash events, older female drivers were more likely to be involved in collisions when changing direction (right turn, left turn or U-turn) than male drivers. The result showed a higher proportion of rear-end collisions in the subsequent crash (initial crashes: 30.18%; subsequent crashes: 40.99%) and this increment mostly occurred in female older drivers (8.86% increase in males, 15.38% in females). In reference to both initial and subsequent crash events, a higher proportion of female repeat crashers were involved in crashes when decelerating (slowing down or stopping). Male repeat crashers were more likely to be involved in crashes where there was no traffic control, while females appeared to have more crashes where the traffic was controlled by traffic lights, a give way sign, or a stop sign.

3.2. Single and repeat crashers

The sample of single and repeat crashers comprised 17,195 older drivers. The average age of those who had a single crash was 69.11 years (SD = 7.55; min, max = 60, 102), which was not significantly different from the repeat crashers (Mean age = 68.57 - years). Table 4 illustrates that, of the 16,973 single crashers, 61.75% were male. While the proportion of male single crashes was lower than that of the male repeat crashers (71.17%), there was no statistical difference. Chi-square tests revealed that a significantly higher proportion of repeat crashers were drivers of heavy vehicles and motorcycle riders ($\chi^2 = 46.46$, $p < .001$). No significant differences in age, environmental factors, crash results, and crash characteristics between single and repeat crashers were found in the analyses.

Tables 5 and 6 present the results of the survival analyses. For the whole sample, Table 5 shows that at-fault status and age group did not posit any significant risk for older drivers being involved in subsequent crashes. However, motorcycle riders (RR = 3.50; 95% CI = 2.20–5.58) and heavy vehicle drivers (RR = 2.23; 95% CI = 1.47–3.37) were found to be at significantly higher risk of having recurrent crashes than light passenger vehicle drivers. Drink and drug driving, speeding, fatigue, and inattentive driving were not risk factors for involvement in subsequent crashes among the older drivers in this study.

The risk of having a subsequent crash was 1.6 times (RR = 1.66; 95% CI = 1.01–2.71) greater for those who had a night-time crash compared to those whose initial crash was during peak hour. Older drivers involved in crashes that occurred in inner regional areas

Table 1
At-fault status, vehicles and crash results of initial and subsequent crashes.

		Initial crashes			Subsequent crashes		
		n = 222	Male (n = 158)	Female (n = 64)	n = 222	Male (n = 158)	Female (n = 64)
At-fault status	At-fault	145 (65.32%)	91 (61.39%)	48 (75.00%)	142 (63.96%)	106 (67.09%)	36 (56.25%)
Vehicle type	Light vehicle	166 (74.77%)	104 (65.82%)	62 (96.87%)	164 (73.87%)	101 (63.92%)	63 (98.44%)
	Heavy vehicle	30 (13.51%)	29 (18.35%)	1 (1.56%)	32 (14.41%)	32 (20.25%)	0 (0.00%)
	Motorcycle	26 (11.71%)	25 (15.82%)	1 (1.56%)	26 (11.71%)	25 (15.82%)	1 (1.56%)
Crash type	Multi-vehicle	164 (73.87%)	115 (72.78%)	49 (76.56%)	169 (76.13%)	113 (71.52%)	56 (87.50%)
	single vehicle	47 (21.17%)	36 (22.78%)	11 (17.19%)	45 (20.27%)	38 (24.05%)	7 (10.94%)
	hit pedestrian	11 (4.05%)	7 (4.43%)	4 (6.25%)	8 (3.60%)	7 (4.43%)	1 (1.56%)
Casualties	Total	276			291		
	Fatalities	3			7		
	Hospitalisation	107			117		
	Medical treatment	125			123		
	Minor injury	41			44		

Table 2
Gender and age differences by at-fault status.

At-fault status	0 occasions	1 occasion	2 occasions	Statistical tests
Average age (years)	66.41	67.51	70.22	$F_{(2, 219)} = 5.365$, $p = .005^{***}$
Total	37 (16.67%)	83 (37.39%)	102 (45.95%)	
Male	28 (17.72%)	57 (36.08%)	73 (46.20%)	$\chi^2 = 0.63$, $p = .73$ *NS*
Female	9 (14.06%)	26 (40.63%)	29 (45.31%)	

Table 3
Characteristics of the first and second crashes.

		Initial crashes			Subsequent crashes		
		n = 222	Male (*n* = 158)	Female (*n* = 64)	*n* = 222	Male (*n* = 158)	Female (*n* = 64)
Crash Nature	Angle	75 (33.78%)	53 (33.54%)	22 (34.38%)	49 (22.07%)	31 (19.62%)	18 (28.13%)
	Rear-end	67 (30.18%)	47 (29.75%)	20 (31.5%)	91 (40.99%)	61 (38.61%)	30 (46.88%)
	Hit object	29 (13.06%)	18 (11.39%)	11 (17.19%)	27 (12.16%)	22 (13.92%)	5 (7.81%)
	Sideswipe	19 (8.56%)	12 (7.59%)	7 (10.94%)	23 (10.36%)	19 (12.03%)	4 (6.25%)
	Fall from vehicle	13 (5.86%)	13 (8.23%)	0 (0.00%)	8 (3.60%)	7 (4.43%)	1 (1.56%)
Intended Action	Go straight ahead	126 (56.76%)	99 (62.66%)	27 (42.18%)	144 (64.86%)	108 (68.35%)	36 (56.25%)
	Change direction	42 (18.92%)	25 (15.82%)	19 (26.57%)	39 (16.66%)	24 (15.19%)	11 (17.19%)
	Slowing or stopped	40 (18.02%)	25 (15.82%)	15 (23.44%)	31 (13.97%)	17 (10.76%)	14 (21.88%)
Roadway Feature	No roadway feature	89 (40.09%)	70 (44.30%)	19 (29.69%)	104 (46.58%)	79 (50.00%)	25 (39.06%)
	T junction	56 (25.23%)	40 (25.32%)	16 (25.00%)	50 (22.52%)	31 (19.62%)	19 (26.69%)
	Crossroad	38 (17.12%)	22 (13.92%)	16 (25.00%)	31 (13.96%)	22 (13.92%)	9 (14.06%)
	Roundabout	14 (6.31%)	8 (5.06%)	6 (9.38%)	14 (6.31%)	9 (5.70%)	5 (7.81%)
Traffic Control	No traffic control	126 (56.76%)	95 (60.13%)	31 (48.44%)	143 (64.41%)	105 (66.46%)	38 (59.38%)
	Operating traffic lights	42 (18.92%)	26 (16.46%)	16 (25.00%)	40 (18.02%)	30 (18.99%)	10 (15.63%)
	Give way or stop sign	48 (20.72%)	32 (20.26%)	14 (21.88%)	33 (14.86%)	17 (10.76%)	16 (25.01%)

Table 4
Characteristics of single and repeat crashers.

		Single crashers (*n* = 16.973)	Repeat crashers (*n* = 222)
At-fault status	At-fault	10,325 (60.83%)	147 (66.22%)
Gender	Male	10,481 (61.75%)	158 (71.17%)
Vehicle type	Light vehicle	15,128 (89.13%)	166 (74.77%)
	Heavy vehicle	1,049 (6.18%)	30 (13.51%)
	Motorcycle	796 (4.69%)	26 (11.71%)
Crash type	Multi-vehicle	13,354 (78.68%)	162 (72.97%)
	Single vehicle	2,931 (17.27%)	49 (22.07%)
	Hit pedestrian	593 (3.49%)	9 (4.05%)

(RR = 0.56; 95% CI = 0.38–0.83) were less likely to experience a subsequent crash compared to those whose crash was in a major city. Lighting condition and road condition were not risk factors for older drivers being involved in subsequent crashes. Similarly, crash results (e.g., single- or multiple-vehicle crash and injury severity) and crash characteristics (e.g., traffic control, roadway feature) were not predictors of subsequent crashes.

Previous findings on repeat crashers indicate that gender difference may be at play. Therefore, the same groups of factors were entered into the regression process to estimate their risk effect on male and female older drivers. Table 6 shows that driving heavy vehicles (RR = 1.96; 95% CI = 1.26–3.04) or riding motorcycles (RR = 3.24; 95% CI = 1.96–5.36) placed older males at nearly twice to more than three times the risk of experiencing another crash compared to light passenger vehicle drivers.

For female older drivers, their at-fault status demonstrated a 4.53 times (RR = 4.53; 95% CI = 2.00–10.25) higher probability of being involved in subsequent crashes compared to those who were deemed not responsible for their initial crash. In addition, the risk of a subsequent crash for female older drivers whose initial crash was due to slowing down or stopping was over four times (RR = 4.15; 95% CI = 1.79–9.60) greater than those who were going straight ahead.

4. Discussion

It is widely accepted that crash prediction is a difficult endeavor as the range of contributing factors varies for each event. Using almost six years of data from Queensland DTMR, Australia, this study examined the characteristics of older drivers involved in repeat crashes. The characteristics of the initial crash event were used to estimate the extent to which each risk factor contributed to subsequent crashes among older drivers. Findings suggested that, in general, older drivers had a higher risk of subsequent crashes when driving in major cities. It is understandable that older drivers driving in built-up areas may have an inflated risk of crash involvement due to traffic volume and complexity of the road network (Bayam, Liebowitz, & Agresti, 2005; Obeidat, 2018). Risk driving behaviors (such as drink and drug driving, speeding, fatigue, and inattentive driving) were not predicting factors for involvement in subsequent crashes among the older drivers in this study. This result may be due largely to the small proportion of older drivers engaging in such risky behaviors (Langford & Koppel, 2006; Rakotonirainy, Steinhardt, Delhomme, Darvell, & Schramm, 2012). The current sample showed that, on average, only 3.5% of crashes were related to these risky driving behaviors. Given such a small percentage, this result may need to be interpreted with caution. However, it is noted that the finding is in keeping with previous research, which found drink driving was a factor in only 2.2–5.9% of older drivers who crashed (Langford & Koppel, 2006; Rakotonirainy et al., 2012).

The current study found that nearly half (45.95%) of the older drivers involved in repeat crashes were deemed responsible for both their initial and subsequent crashes. The average age of these

Table 5
Risk factors associated with subsequent crashes among older drivers.

		B	Sig.	RR	95.0% CI	
					Lower	Upper
Category 1: Human factors						
At-fault status	Yes	0.30	0.10	1.35	0.94	1.93
Age group	75 and over	−0.14	0.43	0.87	0.60	1.24
Type of vehicle	Light vehicle	Ref.				
	Motorcycle	1.25	***<0.001***	3.50	2.20	5.58
	Heavy vehicle	0.80	***<0.001***	2.23	1.47	3.37
Drink or drug driving	Yes	−0.29	0.41	0.75	0.38	1.48
Speeding	Yes	−0.31	0.76	0.73	0.10	5.31
Fatigue	Yes	−0.25	0.61	0.78	0.30	2.01
Distraction	Yes	0.14	0.59	1.16	0.68	1.95
Category 2: Environmental factors						
Time of crash	Peak hour	Ref.				
	Off-peak hour	−0.14	0.33	0.87	0.66	1.15
	Night-time	0.50	***0.04***	1.66	1.01	2.71
Area of crash	Major cities	Ref.				
	Inner regional	−0.57	***<0.001***	0.56	0.38	0.83
	Outer regional and remote areas	−0.38	0.06	0.68	0.46	1.02
Lighting condition	Yes	0.20	0.52	1.22	0.67	2.22
Road condition	Yes	−0.40	0.15	0.67	0.38	1.16
Category 3: Crash results						
Crash type	Hit pedestrian	Ref.				
	Single vehicle	0.24	0.53	1.27	0.60	2.69
	Multiple vehicle	−0.15	0.67	0.86	0.45	1.67
Severe injury	Yes	−0.28	0.16	0.76	0.52	1.11
Minor injury	Yes	0.02	0.91	1.02	0.74	1.41
Category 4: Crash characteristics						
Intended actions	Go straight ahead	Ref.				
	Change direction	−0.19	0.35	0.83	0.56	1.22
	Slowing or stopped	0.22	0.31	1.24	0.82	1.88
Roadway feature	No roadway feature	Ref.				
	T junction	0.16	0.47	1.17	0.76	1.81
	Crossroad	0.00	0.99	1.00	0.58	1.72
	Roundabout	0.01	0.97	1.01	0.50	2.05
Traffic control	No traffic control	Ref.				
	Operating traffic light	0.29	0.24	1.33	0.83	2.14
	Give way or stop sign	0.75	0.06	2.12	1.00	4.49

drivers was significantly older than those who were deemed at-fault for none or one of their crashes. Previous research has found that drivers over 75 years are more likely to cause a crash than their younger counterparts (Clarke et al., 2010; Hing et al., 2003; Rakotonirainy et al., 2012), and the culpability rate increased significantly with age (Clarke et al., 2010). Findings of this study confirm the robust relationship between age and crash culpability and the risk of causing subsequent crash as the drivers become older. More specifically, this study found that, with increasing age, when older drivers were at-fault for their initial crash, they were likely to also be responsible for their subsequent crash.

It is evident from this study that older drivers who crashed are not a homogenous group as distinctive gender differences in the risk for involvement in repeat crashes were found. For older male drivers, riding a motorcycle significantly increased their risk of involving in a subsequent crash. A range of issues may contribute to the high risk of motorcycle crashes, including control errors (e.g., trouble handling the bike), riding speed, traffic errors, traveling in unexpected places (e.g., gaps between vehicles), as well as climate and road conditions (Tunnicliff et al., 2012; Wells et al., 2004). The low conspicuity (e.g., small and irregular outline) of the motorcyclists together with being in the blind spot of other motor-vehicle drivers is thought to be an additional factor associated with the risk of motorcycle crashes (Wells et al., 2004). The major disincentive to motorcycle riding is the high risk of fatal and severe injury, estimated to be more than 20 times the risk compared to passenger vehicle drivers (NHTSA, 2019; Van Elslande et al., 2014). For older motorcycle riders, the injury severity increases due to their declined physical strength (e.g., bone density), flexibility and possible pre-existing comorbidities (Fitzpatrick, Rakasi, & Knodler, 2017), resulting in higher incidence of thoracic injury, especially multiple rib fractures (Dischinger, Ryb, Ho, & Braver, 2006). Although researchers have found that the proportion of motorcycle riders aged 60 years and over is relatively low compared to riders in other age groups (Allen et al., 2017; de Rome & Senserrick, 2011; Hidalgo-Fuentes & Sospedra-Baeza, 2019), concern has been raised that older riders were more likely to be responsible for their crashes (de Rome & Senserrick, 2011). Findings from the current study demonstrate the high risk of older motorcycle riders being involved in recurrent crashes and highlight the need for comprehensive investigation of crash risk and injury prevention for older motorcycle riders.

Additionally, for older males, driving heavy vehicles increased the risk of being involved in subsequent crashes by more than two-fold compared to driving light passenger vehicles. Heavy vehicle drivers in this study were mostly professional drivers such as bus, articulated truck, or road train drivers. Previous studies have argued that the high crash involvement of heavy vehicle drivers may result from their increased exposure and the high level of driving demand featuring long distances and hours (Brodie, Lyndal, & Elias, 2009; Mooren, Grzebieta, Williamson, Olivier, & Friswell, 2014). Therefore, it is reasonable to assume that the decline of sensory, physical, and cognitive functions in older heavy vehicle drivers may affect their work ability and lead to more

Table 6
Risk factors associated with subsequent crashes among male and female older drivers.

		Male					Female				
		B	Sig.	RR	95.0% CI		B	Sig.	RR	95.0% CI	
					Lower	Upper				Lower	Upper
Step 1: Human factors											
At-fault status	Yes	−0.03	0.89	0.97	0.65	1.46	1.51	***<0.001***	4.53	2.00	10.25
Age group	75 and over	−0.28	0.24	0.75	0.47	1.20	0.04	0.90	1.04	0.58	1.86
Type of vehicle	Light vehicle	Ref.					Ref.				
	Motorcycle	1.17	***<0.001***	3.24	1.96	5.36	1.46	0.17	4.29	0.54	34.40
	Heavy vehicle	0.67	***<0.001***	1.96	1.26	3.04	1.58	0.12	4.87	0.65	36.41
Step 2: Environmental factors											
Time of crash	Peak hour	Ref.					Ref.				
	Off-peak hour	−0.18	0.28	0.83	0.60	1.16	−0.11	0.68	0.90	0.53	1.51
	Night-time	0.40	0.17	1.49	0.84	2.64	0.71	0.15	2.03	0.77	5.40
Area of crash	Major cities	Ref.					Ref.				
	Inner regional	−0.69	***<0.001***	0.50	0.31	0.81	−0.42	0.22	0.65	0.33	1.29
	Outer regional	−0.34	0.14	0.71	0.45	1.12	−0.66	0.13	0.52	0.22	1.23
Step 3: Crash results											
Crash type	Hit pedestrian	Ref.					Ref.				
	Single vehicle	0.46	0.32	1.59	0.64	3.96	−0.28	0.69	0.76	0.19	2.97
	Multiple vehicle	0.08	0.84	1.09	0.48	2.45	−0.82	0.18	0.44	0.13	1.45
Severe injury	Yes	−0.41	0.09	0.66	0.42	1.06	0.12	0.73	1.13	0.57	2.22
Minor injury	Yes	−0.02	0.93	0.98	0.67	1.45	0.28	0.37	1.32	0.72	2.43
Step 4: Crash characteristics											
Intended actions	Go straight ahead	Ref.					Ref.				
	Change direction	−0.33	0.19	0.72	0.44	1.18	0.11	0.75	1.11	0.58	2.14
	Slowing or stopped	−0.09	0.71	0.91	0.56	1.49	1.42	***<0.001***	4.15	1.79	9.60
Roadway feature	No roadway feature	Ref.					Ref.				
	T junction	0.09	0.72	1.10	0.66	1.84	0.39	0.35	1.47	0.65	3.35
	Crossroad	−0.37	0.28	0.69	0.35	1.36	0.88	0.07	2.41	0.92	6.27
	Roundabout	−0.42	0.35	0.65	0.27	1.60	1.09	0.07	2.96	0.91	9.65
Traffic control	No traffic control	Ref.					Ref.				
	Operating traffic light	0.37	0.22	1.44	0.81	2.58	0.14	0.73	1.15	0.51	2.63
	Give way or stop sign	0.72	0.13	2.05	0.81	5.19	0.86	0.20	2.37	0.63	8.86

involvement in crashes (Duke, Guest, & Boggess, 2010; Kloimüller, Karazman, Geissler, Karazman-Morawetz, & Haupt, 2000). An early study revealed that the risk of heavy vehicle drivers being involved in crashes increased when they reached the aged of 63 years and over (Campbell & Sullivan, 1991); however, a more recent study suggested otherwise (Guest, Boggess, & Duke, 2014). Guest et al. (2014) found that heavy vehicle (rigid and articulated trucks in particular) drivers aged 65 years and older were not more likely to cause a crash than drivers of other age groups. The conflicting findings indicate that more research is needed to focus on the crash risk of older heavy vehicle drivers.

An important study finding was the crash proneness of older female drivers. The current study found that, among older female drivers who crashed, those deemed at-fault for their initial crash were highly likely to be involved in a subsequent crash than those were not at-fault. Additionally, older female drivers in this sample were more likely to experience a subsequent crash if their initial crash was caused by slowing down or stopping. These results may reflect previous research findings regarding various driving maneuvers that prove to be problematic for older drivers, such as difficulties in gap acceptance and estimation, turning against oncoming traffic, and lane changing (Bayam et al., 2005; Chandraratna & Stamatiadis, 2003; Clarke et al., 2010; Lombardi et al., 2017). These common driving maneuvers require complex yet agile cognitive abilities, such as perceptual awareness, and the calculation of speed and distance in a fast paced, moving environment (Chandraratna & Stamatiadis, 2003; Lombardi et al., 2017). Thus, older drivers may resolve the complex traffic tasks by slowing down or stopping to allow more processing time, which in itself can become a danger for crash involvement (Bayam et al., 2005). These findings are important in a time of population aging. Older females have a longer life expectancy, are more likely to live alone as they become older, and are of a cohort where holding a driver's license is commonplace (Australian Bureau of Statistics, 2019; Oxley, Langford, & Charlton, 2010). Thus, it is important for older people, particularly older females, to understand that their involvement in an at-fault crash likely pre-disposes them to a future crash. This information may provide a signal for older females to evaluate their driving risk and highlights the need for safety interventions for older female drivers involved in at-fault collisions.

While this study provides an important addition to the scant literature on crash proneness among older drivers, a number of limitations need to be considered. First, all crash data were compiled from crashes reported by Queensland police officers/units. The determination of at-fault status relies heavily on the police officer's experience(s) at the scene of the crash. Thus, inconsistency and bias in reporting may exist between crash events and/or between crash investigators. Therefore, the culpability rates should be interpreted with caution (af Wåhlberg & Dorn, 2007). Second, the datasets only contain "in scope" crash events, which means crashes with no injury to any person and crash events occurring in car parks or private driveways are considered "out of scope" in Queensland (DTMR, 2016). The exclusion of "out of scope" events likely reduces the number of crashes involving older drivers. Thus, the current analysis may under-represent the crash events of older drivers. Third, this analysis contains crash records from 2014 to 2019. The number of older drivers involved in repeat crashes is relatively small (about 1.3% of the sample); however, those who were involved in subsequent crashes presented distinctive risk factors compared to those who were not. Further research using a larger sample size and over a more extended time period may help to further understand the characteristics of older crash-prone drivers. Last, results of this analysis are further limited as the crash datasets lack information about older drivers' individual differences (e.g., health status, medication) and driving exposure. Despite these limitations, the current findings highlight some important trends for furthering the general understanding of recurrent crash involvement in older drivers.

5. Conclusion

The current population-based study is unique in the literature as it contributes to recognizing the high-risk groups of older drivers who were likely to be involved in subsequent crashes after their initial crash event. The study confirmed that culpability history, environmental, and situational factors contribute to crash proneness. However, other predictors were discussed regarding broader crash proneness and were sufficiently nuanced to justify focusing specifically on an older population. Several of the findings may be useful for public health and safety messaging at the individual and community level, as well as for health professionals and policy makers. Two crash-prone groups, namely older male motorcyclists and heavy vehicle drivers, were evident from the study. In addition, older female drivers who crashed were highly prone to a subsequent crash if they were deemed at-fault in their initial crash. This information translates into the need for a close assessment and better resources to address the specific problems of this group, and provides information on how to potentially maintain safe mobility. In summary, as life expectancy increases, more people at older ages are having to make decisions in regard to their professional driving career (e.g., older truck drivers), motorcycle riding activities, and to plan for when and how to limit or cease driving. The study's findings may assist older drivers in their decision making around continuation, modification to, or cessation of driving. Finally, the study highlights the need for further research to separate older drivers in the analysis to better understand their specific crash patterns and injury prevention strategies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Determining the risk of driver-at-fault events associated with common distraction types using naturalistic driving data

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ABSTRACT

Introduction: Studies thus far have focused on automobile accidents that involve driver distraction. However, it is hard to discern whether distraction played a role if fault designation is missing because an accident could be caused by an unexpected external event over which the driver has no control. This study seeks to determine the effect of distraction in driver-at-fault events. *Method:* Two generalized linear mixed models, one with at-fault safety critical events (SCE) and the other with all-cause SCEs as the outcomes, were developed to compare the odds associated with common distraction types using data from the SHRP2 naturalistic driving study. *Results:* Adjusting for environment and driver variation, 6 of 10 common distraction types significantly increased the risk of at-fault SCEs by 20-1330%. The three most hazardous sources of distraction were handling in-cabin objects (OR = 14.3), mobile device use (OR = 2.4), and external distraction (OR = 1.8). Mobile device use and external distraction were also among the most commonly occurring distraction types (10.1% and 11.0%, respectively). *Conclusions:* Focusing on at-fault events improves our understanding of the role of distraction in potentially avoidable automobile accidents. The in-cabin distraction that requires eye-hand coordination presents the most danger to drivers' ability in maintaining fault-free, safe driving. *Practical Applications:* The high risk of at-fault SCEs associated with in-cabin distraction should motivate the smart design of the interior and in-vehicle information system that requires less visual attention and manual effort.

1. Introduction

Road safety involves an intricate web of interplaying roles by the driver, the traffic, and the road, and not every element is under the control of the driver. Distractions have long been established as a leading cause of automobile accidents. Studies thus far have focused on automobile accidents that involve driver distraction. However, it is hard to discern whether distraction played a role if fault designation is missing, because an accident could be caused by an unexpected external event through no fault of the driver. Understanding the human factors involved in at-fault crashes may be most relevant to pinpointing risky driver behaviors that are potentially avoidable. Therefore, this study seeks to determine the effect of distraction in at-fault safety critical events (SCEs) by: (a) teasing out the effect of distraction from common traffic scenarios and road conditions, and (b) comparing the strength of association between distraction and at-fault SCEs against all-cause SCEs regardless of fault designation.

1.1. Distraction

Studies have examined the prevalence, the effects, and the mechanism of driver distraction on automobile accidents. Eight percent of fatal crashes and 15% of injury crashes in 2018 (most recent year available) were reported as affected by distraction, and that was 2,841 people killed and 400,000 people injured (National Highway Traffic Safety Administration, 2020). By consumption of attention resources, researchers put distraction into two classes: (a) visual distraction (eyes-off-the-road) and (b) cognitive distraction (mind-off-the-road), with cognitive distraction disrupting the allocation of visual resources to driving scenes and slowing the process of oncoming information (Liang & Lee, 2014; Savage et al., 2020). Common distractions include cell-phone use, interaction with passengers, eating, and adjusting the radio or climate controls. Cell phone use and texting, especially among teen drivers, has been extensively studied (Yannis et al., 2014; Carney et al., 2018; Ebadi et al., 2019; Qin et al., 2019; Seaman et al., 2017); driver interaction with passengers has also been studied (Theofilatos et al., 2018; Zhang et al., 2019). Driver distraction can be detected by video recognition and even solely relying on

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vehicular data with high accuracy in a nonintrusive fashion (Eraqi et al., 2019; Ye et al., 2017).

1.2. At-fault accidents

There is limited literature that specifically studies at-fault accidents as opposed to all-cause automobile accidents. Fault determination requires manual analysis, lacks a universal definition (Dorn & af Wåhlberg, 2019), and is not always available in datasets. The U.S. Department of Transportation identified 17 Unsafe Driving Acts (UDA) to be the criteria for fault assignment (i.e., fault was assigned if any factor was coded for a given driver), including judgment, speed-related, right-of-way or headway-related, and lane change or lane position problems (Council et al., 2003). Existing studies on at-fault accidents focused on driver characteristics (Sagar et al., 2020; Penmetsa et al., 2017; Tseng, 2012) and improper driving maneuvers (Mohammadzadeh Moghaddam et al., 2017; Wu & Hsu, 2021). The lack of studies on predicting at-fault crashes was also noted (Wu & Hsu, 2021). No studies have examined the association between distraction and at-fault events by our search.

1.3. Risk estimation

To estimate road injury risks, studies traditionally rely on police and emergency department records (Regev et al., 2018; Sagar et al., 2020), which are representative of the population, although crash-specific details are not always fully recalled or captured (Regev et al., 2017). To analyze driver or environment impacts on accidents, simulated studies can capture a wide array of variables during a trip, but the studies usually focus on a small subset of the population of interest (e.g., teenage drivers). Large-scale naturalistic driving studies may enjoy the best of both worlds. On one hand, its study size and naturalistic setting can be used to construct study designs reflective of real-world exposure. On the other hand, it captures a variety of variables via pre-fitted motion and vision sensors that can be helpful for retrospective analysis of what transpired on the road, possibly with high fidelity.

In summary, the past literature indicates that driver distraction plays an important role in automobile accidents, but there is a need to further verify these findings with fault data. None of the previous studies have associated at-fault accidents with specific distraction types. Such an analysis could help define the effect of distraction on drivers' ability to maintain safe, fault-free driving and inform efforts to improve road safety by reducing hazardous driver distraction.

2. Materials and methods

2.1. Data source

Data from the 2nd Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS) (Dingus et al., 2014) were used for this study. The dataset included human expert annotated variables based on video recordings of trips that captured the activities and environments both inside and outside of the cabin of the subject vehicles in real-world road settings. Annotated variables from the video reduction process make it possible to retrospectively analyze the characteristics of the trips involving at-fault incidents, including the dependent variables derived from "event severity" and "fault," the independent variables derived from "secondary tasks," and seven control variables including weather, lighting, roadway surface, profile (e.g., uphill, downhill) and curvature, presence of roadway junctions, as well as traffic density.

2.2. Study design

The SHRP2 dataset allows a case-cohort study design that is appropriate for time-variant risk exposure approximated by the odds ratio (Dingus et al., 2016; Guo, 2009). In this study, cases were identified as SCEs that include all levels of crashes but low-risk tire strikes as well as near crashes. Non-cases were sampled from the baseline in a balanced fashion that the number of trips selected for each driver is proportional to the total traveling time when they were in the study (i.e., balanced-sample baseline; Hankey et al., 2016). Said in another way, the cases and non-cases were in terms of the outcome of a trip (i.e., whether an SCE took place), and all of the trips may be exposed to the independent variable (i.e., distraction). The cases were further differentiated by fault assignment, namely, at-fault SCEs, in which the subject vehicle driver was at fault, and all-cause SCEs regardless of fault. As a result, a total of 7,962 all-cause SCEs, among which 4,908 were at-fault, and 19,998 balanced-sample baseline trips were selected for the analysis (Table 1). They were generated by 3,542 participating drivers.

2.3. Data analysis

We designed a generalized linear mixed model (GLMM) with random intercepts as one driver can generate multiple trips in the dataset. The rationale behind choosing this model is two-fold: first, a multivariate regression can produce adjusted risk estimates that account for scenarios when multiple distraction types or environmental risk factors were present concurrently. Second, compared to regular linear regression, the mixed-effect model can reflect the latent heterogeneity in driver characteristics that might impact the individuals' risk levels when distracted. The model is as follows:

$$g(E(y)) = X\beta + Zu + \varepsilon$$

$$E(y) = P(Y = y|X, Z)$$

$$g(\cdot) = log\left(\frac{p}{1-p}\right)$$

where y is the outcome variable; $g(\cdot)$ is the logistic link function for a binomial outcome; p is the estimated probability of a positive outcome; X is a matrix of N trips and q variables; β is a $q \times 1$ vector of the fixed-effect regression coefficients; Z is a matrix of N trips and d drivers designating the driver-specific random effects; u is a $d \times 1$ vector of the random intercepts; and ϵ is the general error term not explained by the model.

Two separate models were run, one with at-fault SCEs as the outcome and the other with all-cause SCEs, because we wanted to understand whether a particular kind of distraction particularly increases the driver's at-fault risk compared to all-cause SCEs.

The input variables, types of distraction, were engineered from the annotated secondary tasks. First, the secondary tasks were mapped into 10 distraction types (Table 2) in addition to a "no secondary task" category based on their semantic meanings and the ordering found in the SHRP2 Researcher Dictionary for Video

Table 1
Event distribution.

Result in safety critical events?		Subject vehicle driver at fault?	
		Yes	No or NA
Yes	Crash	766	282
	Near crash	4,142	2,772
No	Baseline	0	19,998

Table 2
Distraction type mapping.

Distraction Type	Secondary Tasks
Entertainment	• Talking/singing, audience unknown • Dancing • Reading • Writing
External distraction	• Looking at previous crash or incident • Looking at pedestrian • Looking at animal • Looking at an object external to the vehicle • Distracted by construction • Other external distraction
Food and beverage	• Reaching for food-related or drink-related item • Eating with utensils • Eating without utensils • Drinking with lid and straw • Drinking with lid, no straw • Drinking with straw, no lid • Drinking from open container
In-cabin objects	• Moving object in vehicle • Insect in vehicle • Pet in vehicle • Object dropped by driver • Reaching for object, other • Object in vehicle, other
Interaction	• Passenger in adjacent seat - interaction • Passenger in rear seat - interaction • Child in adjacent seat - interaction • Child in rear seat - interaction
IVIS (in-vehicle information system)	• Adjusting/monitoring climate control • Adjusting/monitoring radio • Inserting/retrieving CD (or similar) • Adjusting/monitoring other devices integral to vehicle
Mobile device	• Cell phone, holding • Cell phone, talking/listening, hand-held • Cell phone, talking/listening, hands-free • Cell phone, texting • Cell phone, browsing • Cell phone, dialing, hand-held • Cell phone, dialing, hand-held using quick keys • Cell phone, dialing, hand-held using voice-activated software • Cell phone, locating/reaching/answering • Cell phone, other • Table device, locating/reaching • Tablet device, operating • Tablet device, viewing • Tablet device, other
Personal hygiene	• Reaching for personal body-related item • Combing/brushing/fixing hair • Applying make-up • Shaving • Brushing/flossing teeth • Biting nails/cuticles • Removing/adjusting clothing • Removing/adjusting jewelry • Removing/inserting/adjusting contact lenses or glasses • Other personal hygiene
Smoking	• Reaching for cigar/cigarette • Lighting cigar/cigarette • Extinguishing cigar/cigarette
Other secondary tasks	• Other nonspecific internal eye glance • Other secondary task • Unknown type (secondary task present)

Reduction Data (Virginia Tech Transportation Institute, 2015). For example, all secondary tasks involving a cell phone or a tablet were grouped into "mobile device." Next, the distraction types were converted into dummy variables. Finally, because up to three secondary tasks were annotated, the three corresponding distraction types were combined for each trip. If a trip involved two secondary tasks belonging to the same distraction category, the category was labeled as 1 denoting the presence of one or more secondary tasks in the same distraction category. For example, a driver can be annotated as both dialing and subsequently talking on the phone during the video epoch. This treatment is due to the consideration that secondary tasks within the same category tend to involve a series of related tasks, whereas having two secondary tasks in different categories suggests a higher level of distraction that is non-trivial.

The control variables were treated as categorical with the least demanding driving scenario as the reference group for regression. For example, 'no adverse weather condition' was coded 0 and all other adverse weather conditions were coded 1. The analysis was performed in R using library lme4 (Bates et al., 2015; R Core Team, 2020).

3. Results

3.1. Distribution of distraction types

Distraction occurs frequently, in fact, the majority (55.8%) of the selected trips involved one or more distraction types (Table 3). Interaction with a passenger (14.5%), external distraction (11.0%), and mobile device use (10.1%) were among the most common distraction, while smoking (1.1%), food & beverage consumption (3.1%), and adjusting the in-vehicle information system (IVIS) (3.9%) were the least common. Next, we will examine the risk level associated with individual distraction types.

3.2. Risk estimate

Overall speaking, the presence of distraction, regardless of type, doubled the odds of SCEs (OR = 2.1), and the difference between at-fault and all-cause SCEs was minimal (Table 4). Delving into the specific categories, 6 of 10 distraction types significantly increased the risk of at-fault and all-cause SCEs to varying degrees after adjusting for environmental factors (Fig. 1). While *entertainment, personal hygiene, IVIS, external distraction* and *mobile device use*, in ascending order of ORs, increased the odds of at-fault SCEs by 20–140%, the odds of at-fault SCEs was raised by 1330% related to *in-cabin objects*. Among the individual secondary tasks grouped under in-cabin objects, "moving object in vehicle" (e.g., an object fell off the seat when the driver stopped hard at a traffic light) and "reaching for object, other" not only had the most occurrences but also disproportionately associated with at-fault events ($p < 0.001$) (Table 5).

Comparing the estimated ORs of at-fault to all-cause SCEs, the lower bounds of the at-fault ORs associated with *external distrac-*

Table 3
Proportion of distraction types ($N = 27{,}960$).

Distraction Type	*n* (%)
Entertainment	2,453 (8.8)
External	3,072 (11.0)
Food & Beverage	853 (3.1)
IVIS	1,082 (3.9)
In-Cabin Objects	2,101 (7.5)
Interaction	4,062 (14.5)
Mobile Device	2,812 (10.1)
Personal Hygiene	1,149 (4.1)
Smoking	305 (1.1)
Other	1,015 (3.6)
None	12,651 (45.2)

Table 4
Odds ratios of safety critical events associated with distraction types.

	At-fault SCEs		All-cause SCEs	
	Odds Ratio (95% CI)	*p*-value	Odds Ratio (95% CI)	*p*-value
Distraction, regardless of type	2.1 (2.0–2.3)	<0.001 ***	2.1 (1.9–2.2)	<0.001 ***
Entertainment	1.2 (1.0–1.3)	0.024 *	1.1 (1.0–1.2)	0.067
External	1.8 (1.6–2.0)	<0.001 ***	1.3 (1.2–1.4)	<0.001 ***
Food & Beverage	0.8 (0.6–1.0)	0.031 *	0.7 (0.6–0.9)	0.001 **
In-cabin Objects	14.3 (12.4–16.5)	<0.001 ***	12.3 (10.8–13.9)	<0.001 ***
Interaction	0.9 (0.8–1.1)	0.260	0.9 (0.8–0.9)	0.001 **
IVIS	1.7 (1.4–2.1)	<0.001 ***	1.4 (1.2–1.7)	<0.001 ***
Mobile Device	2.4 (2.2–2.7)	<0.001 ***	1.8 (1.6–2.0)	<0.001 ***
Personal Hygiene	1.6 (1.4–2.0)	<0.001 ***	1.4 (1.2–1.6)	<0.001 ***
Smoking	1.2 (0.8–1.8)	0.355	1.1 (0.8–1.5)	0.653
Other	0.9 (0.7–1.1)	0.155	0.8 (0.6–0.9)	0.004 **

Significance codes: <0.001 '***' 0.001–0.01 '**' 0.01–0.05 '*'.

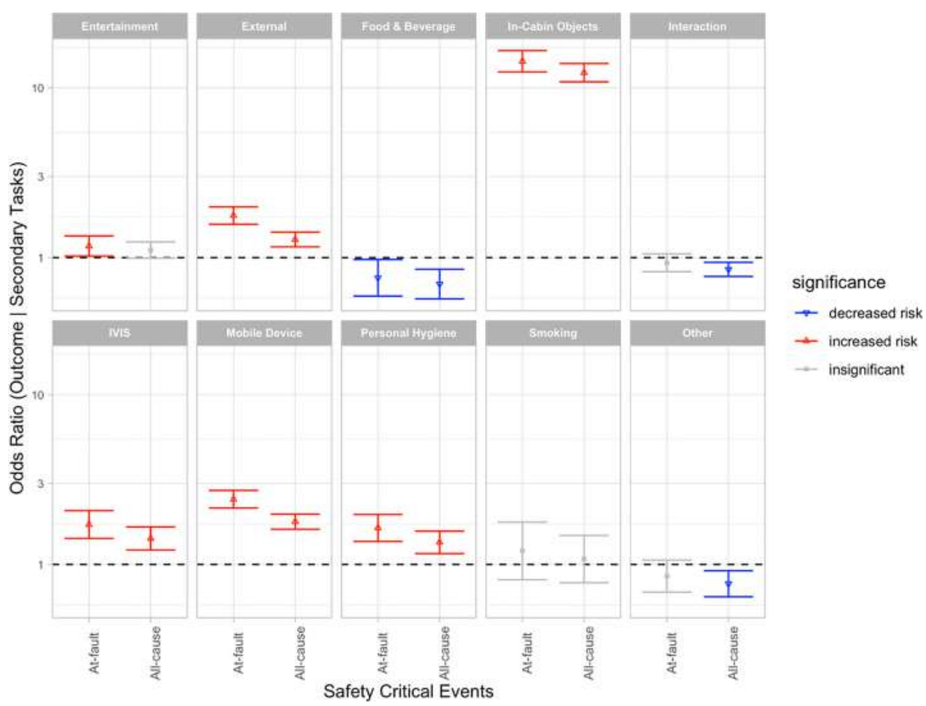

Fig. 1. Odds ratio comparison of at-fault and all-cause SCEs by distraction type.

tion and *mobile device use* were higher than the upper bounds of the ORs of all-cause SCEs without overlap (Fig. 1), suggesting that these distraction types significantly increased the risks of faulty driving that led to an SCE.

On the other hand, *food and beverage consumption* in driving significantly decreased the odds of at-fault and all-cause SCEs by 20–30%. *Interacting with a passenger* and *other secondary tasks* in the vehicle did not modify the risk of at-fault SCEs but slightly reduce the chance of all-cause SCEs. In other words, although not significantly, having these two distractions still raised the chance of at-fault SCEs compared to all-cause SCEs. *Smoking* was not significantly associated with either at-fault or all-cause SCEs.

Table 5
Distribution of secondary tasks related to "in-cabin objects" distraction.

Secondary Task	Subject vehicle driver at fault?	
	Yes	No or NA
Moving object in vehicle	772	447
Reaching for object, other	321	208
Object in vehicle, other	248	434
Pet in vehicle	21	47
Object dropped by driver	2	2
Insect in vehicle	1	0

4. Discussion

4.1. Principal findings

In this study, we quantified the at-fault SCE risks associated with common distraction types using a mixed-effect model that allows for driver variation. The most hazardous source of distraction is in-cabin objects (OR = 14.3) followed by mobile device use (OR = 2.4) and external distraction (OR = 1.8), with the latter two also showing an elevated risk of at-fault SCEs beyond that of all-cause SCEs. Not only were mobile device use and external distraction the most dangerous among distraction types, but they were also among the most commonly occurring (10.1% and 11.0%, respectively).

The study findings are consistent with previous research about the detrimental effect of mobile device use on driver performance, and also highlighted another type of activities, namely, in-cabin objects, that has an even greater impact. The distraction of in-cabin objects results in manual activities that require the coordinated control of the eye movement with hand movement and the processing of visual input to guide reaching or grasping. Considering the commonality between the manipulation of in-cabin objects and mobile device use, it seems the most dangerous distraction types involve transient inattention from both eyes-off-the-road and hand-off-the-wheel. Compared to in-cabin objects, external distraction implies eyes-off-the road but does not require hands-off-wheel, or more importantly, eye-hand coordination.

On the flip side, we also examined what variables are not significantly associated with at-fault SCEs. When drivers have food and beverages or interaction with passengers, their overall risk of SCEs was slightly reduced, suggesting a small protective effect. This may be explained by lower traveling speed or less challenging traveling conditions when the driver carries out such tasks and it is worth investigating as a next step. Interaction with passengers is more of a cognitive distraction than visual, therefore, our finding is consistent with previous research that visual distraction has much stronger effects on driving performance and accident hazard (Peissner et al., 2011). Still, the odds ratios of at-fault SCEs were slightly raised by these two distractions. In addition, smoking is the only annotated distraction that is not significantly associated with at-fault or all-cause SCEs. Considering these three distraction types altogether, none of them direct the driver's visual attention off the roadway ahead in a substantial way, which might be the reason why they are relatively harmless compared to others.

4.2. Limitations and future research

The study findings should be interpreted with limitations. First, the grouping of distraction types is manual and based on the semantic meanings of the descriptions of the secondary task, not characterized by quantifiable measures of the extent of visual/cognitive distraction it causes. The result is distraction types understood by common sense and meaningful sample sizes of subgroups that reduce biases related to small samples in regression. A future research direction is to study how the secondary tasks can be clustered based on how they affect the kinematic measures of the vehicle. Second, the reasons that certain distraction types are more (or less) hazardous were not examined in this study. For example, we speculated that food and beverage consumption may be associated with lower vehicle speed, thus, reducing the risk of all-cause SCEs. However, the theory requires further investigation. Research on how drivers adapt their driving behaviors while engaging in secondary tasks is needed (Oviedo-Trespalacios et al., 2016). Third, driver characteristics were not included as control variables in the study. This was a deliberate decision to be compatible with the mixed-effect model that already factors in a random effect on individual drivers. Including driver characteristics (e.g., gender and age) would make interpretation of the coefficients counterintuitive - we would be suggesting "for the same driver, their at-fault risk may be modified if they change gender/age." Although not explicitly controlling for tangible driver characteristics, the mixed-effect model does account for driver heterogeneity.

4.3. Practical applications

The high risk of at-fault SCEs associated with in-cabin objects serves as empirical evidence that in-cabin activities that require eye-hand coordination present grave danger to drivers' ability to maintain fault-free maneuver of the vehicle. Most straightforwardly, this should motivate the design of the vehicle interior that securely stores owner items while allowing for easy access. Although in this study IVIS (OR = 1.7) has a much lower risk than in-cabin objects, the study finding is cautionary for the design of future IVIS, given the rising popularity of touchscreen control panels that require much more visual attention and manual effort compared to physical knobs. In our wild but realistic imagination, we envision that future connected wearable technology can detect driver states such as drowsiness and perspiration to automatically inform in-cabin climate control and adjust to driver comfort without manual input. In addition, our findings provide hazardous distraction types that computer vision based in-cabin sensing technologies (Kaliouby et al., 2020) can learn to recognize.

5. Conclusions

Focusing on at-fault events improves our understanding of the effect of distraction in potentially avoidable automobile accidents. Adjusting for environment and driver variation, 6 out of 10 common distraction types significantly increase the risk of at-fault SCEs by 20-1330%. The three most hazardous sources of distraction were handling in-cabin objects (OR = 14.3), mobile device use (OR = 2.4), and external distraction (OR = 1.8), with the latter two also among the most commonly occurring (10.1% and 11.0%, respectively). The study findings provide evidence that in-cabin distraction that require eye-hand coordination presents grave danger to drivers' ability to maintain fault-free, safe driving.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Evaluation of driver performance with a prototype cyber physical mid-block crossing advanced warning system

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ABSTRACT

Introduction: Using connected vehicle technologies, pedestrian to vehicle (P2V) communication applications can be installed on smart devices allowing pedestrians to communicate with drivers by broadcasting discrete safety messages, received by drivers in-vehicle, as an alternative to expensive fixed-location physical safety infrastructure. *Method:* This study consists of designing, developing, and deploying an entirely cyber-physical P2V communication system within the cellular vehicle to everything (C-V2X) environment at a mid-block crosswalk to analyze drivers' reactions to in-vehicle advanced warning messages, the impacts of the advanced warning messages on driver awareness, and drivers' acceptance of this technology. *Results:* In testing human subjects with, and without, advanced warning messages upon approaching a mid-block crosswalk, driver reaction, acceptance, speed, eye tracking data, and demographic data were collected. Through an odds ratio comparison, it was found that drivers were at least 2.44 times more likely to stop for the pedestrian with the warning than without during the day, and at least 1.79 times more likely during the night. Furthermore, through binary logistic regression analysis, it was found that driver age, time of the day, and the presence of the advanced warning message all had strong, significant impacts with a confidence value of at least 98% ($p < 0.02$) on the rate at which drivers stopped for the pedestrian. *Conclusions:* The results from this study indicate that the advanced warning message sent within the C-V2X had a strong, positive impact on driver behavior and understanding of pedestrian intent. *Practical Applications:* Pedestrian crashes and fatality rates at mid-block crossings continue to increase over the years. Connected vehicle technology utilizing smart devices can be used as a means for communications between pedestrians and drivers to deliver safety messages. State and local city planners should consider geofencing designated mid-block crossings at which this technology operates to increase pedestrian safety and driver awareness.

1. Introduction

While current designs have aided pedestrians in crossing roadways at mid-block crossings, conflicts still arise due to the confusion these designs can cause between pedestrians and motor vehicles (Ibrahim, Karin, & Kidwai, 2005). Mid-block crosswalks are dangerous for both pedestrians and drivers because communication between the pedestrian and driver is non-verbal and each individual pedestrian decides when it is safe to cross (Katz, Zaidel, & Elgrishi, 1975). These instances are increased when a designated mid-block crossing is installed at the crossing of a greenway with a roadway due to the higher volume of pedestrians and cyclists crossing. Sometimes these mid-block crossings are across roadways where mid-block crossings are uncommon or unexpected, thus exposing users to an uncomfortable environment.

Multistage mid-block crossings can increase delay because vehicles at all approaches must wait to interpret the pedestrian to non-verbally communicate their desire to cross (Katz et al., 1975). Communication between the pedestrian and driver becomes more complicated when a mid-block crossing crosses a road with a 3-lane or more cross section because one vehicle at a multi-lane approach can block an adjacent vehicle's view of a pedestrian in the mid-block crossing. Connecting pedestrians and vehicles to provide advanced warnings that anticipate potential collisions should help to eliminate crossing confusion and ambiguities.

Visual communication confusion aside, the balance of existing laws and safety can create further confusion at mid-block crossings. Virginia law requires drivers to yield to pedestrians in the crosswalk; however, along routes such as the Washington & Old

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Dominion (W&OD) and Mt Vernon Trails in Northern Virginia, mid-block crossings are signed such that the pedestrians must stop for traffic. Legally, the drivers are required to stop at the crosswalk should someone be within it; however, it is unclear what to anticipate from drivers as they may yield to pedestrians either expecting them to cross even though pedestrians are supposed to stop and wait until no oncoming traffic is approaching or may not yield knowing that pedestrians are supposed to give the right away to all oncoming traffic.

Due to the unique nature of mid-block crossings, the unclear and inconsistent rules of right of way, and the difficulty of establishing visual communication between pedestrian and driver, mid-block crosswalks prove to be confusing and dangerous. This study consists of designing, developing, and deploying a P2V communication based cyber-physical system (CPS) at a mid-block crosswalk designed to create an entirely virtual advanced warning system for a mid-block crosswalk within the cellular vehicle to everything (C-V2X) environment without the need for installing physical safety infrastructure and technology.

1.1. The dangers of mid-block crosswalks

Unsignalized mid-block crosswalks pose a unique and confusing scenario for all roadway users as driver and pedestrian communication, or the lack thereof, is paramount in understanding the safety of these designs. In the National Highway Traffic Safety Administration (NHTSA) 2017 annual report released in 2019, pedestrian fatalities increased by 35% over the 10 year span from 2008 through 2017 (U.S. Department of Transportation National Highway Traffic Safety Administration, 2019). Furthermore, this NHTSA report states that the percentage of pedestrian fatalities of total fatalities in traffic crashes each year increased over this same 10 year span from 12% in 2008 to 16% in 2017, and that 73% of these fatalities did not occur at intersections (U.S. Department of Transportation National Highway Traffic Safety Administration, 2019).

With respect to the state that this experiment was conducted, 13.2% of total traffic fatalities were pedestrians in Virginia (U.S. Department of Transportation National Highway Traffic Safety Administration, 2019). The Virginia Department of Transportation's (VDOT) Pedestrian Safety Action Plan released in May of 2018 states that 51% of pedestrian injury crashes and 66% of pedestrian fatal crashes occurred at mid-block crossings (Virginia Department of Transportation, 2018). This report also showed that Northern Virginia, where the W&OD and Mt Vernon Trails are located, had the second highest percent of pedestrian fatal crashes in Virginia over the years of 2012–2016 and the highest percent of pedestrian injury crashes in all of the state (Virginia Department of Transportation, 2018). Furthermore, the report states that 71% of pedestrian fatal crashes occurred in dark or unlit conditions (Virginia Department of Transportation, 2018). In the Virginia Pedestrian Crash Assessment published by VDOT representing an analysis between the years of 2012 and 2016, it was discovered that pedestrian crashes accounted for 1.4% of all reported traffic crashes, but accounted for 12.5% of all traffic fatalities (Virginia Department of Transportation, 2017). Loudon County, the City of Alexandria, Fairfax County, and Arlington County all ranked within the top 10 cities and counties for pedestrian injury and fatal crashes (Virginia Department of Transportation, 2017).

It would feel appropriate, then, to implement a form of control of pedestrians at these mid-block crossings. A 2017 study conducted by Coeugnet et al. studied the effectiveness of a vibrotactile wristband on older pedestrian crossing behavior in a simulated environment, alerting pedestrians as to whether they were making a safe crossing decision. Results indicated that older pedestrians responded in accordance with the wristband 51.6% of the time, however, simulated collisions did not fall to zero (Cœugnet et al., 2017). A study conducted by Zhuang and Wu also found that pedestrians have poor crossing behavior at controlled pedestrian crossings, often overestimating their ability to cross controlled intersections with countdown timers (Zhuang & Wu, 2018). New timers with required crossing speeds reduced risky crossing behaviors in pedestrians, but did not altogether prevent them (Zhuang & Wu, 2018). While these studies reduced risky crossing behaviors, they did not mitigate the unpredictability of pedestrian behavior at crosswalks. Furthermore, Zhai et al. (Zhai, Huang, Sze, Song, & Hon, 2019) found that the effects of jaywalking and risky driving behavior on pedestrian crash severity were most prevalent under rainy conditions (Zhai et al., 2019).

In order to attempt to combat the unpredictability of pedestrians, the city of St. Louis rewrote their laws requiring all trail users to stop and yield to vehicles at trail-roadway intersections. St. Louis deemed that trail-roadway intersections were not in fact intersections, but simply trail crossings. Thus, in order to control pedestrians at such crossings, St. Louis removed all striping at these crossings and installed stop signs and warning messages along their trails, indicating that it is state law that all trail users stop and yield to vehicles (Lindeke, 2015; Oleary, 2015). Ultimately, pedestrians operated as usual, with some obeying the signage posted and others ignoring these warning and stop signs and crossing with the assumption that motorists will yield to them as the new state law stated.

A similar case can be seen in Virginia at identical intersection types along the vast network of greenways in Northern Virginia. There are stop signs and warning messages along the trails at intersections with roadways, yet there is still some confusion at such crossings. Whether it be pedestrians ignoring the signs and walking into the roadways with the assumption that they have the right of way or pedestrians stopping as the signage demands, yielding to vehicles, only to encounter vehicles yielding at the crosswalk to pedestrians, leaving pedestrians to cross with the assumption that vehicles in adjacent lanes will do the same. Such uncontrolled mid-block crossings foster unpredictable and unsafe situations, leaving all of the decision-making at these intersections in the hands of each individual, thus increasing the potential of possible incidents.

1.2. Advanced warning messages

For this study, the presence of the on-board GPS system is deemed as negligible, as most vehicles and drivers already have a display present while they are driving, whether it be part of the vehicle or a smart device mounted on their dashboard. Since this application has both a visual and auditory warning message, the way in which drivers interpret and react to an advanced warning message must be accounted for in order to best test the application for effectiveness. Providing drivers with pertinent information from which they can make a decision sounds like a positive approach to addressing road safety, but information provided at the wrong time can drastically change driver behavior. Should a message be sent to a driver well before a scenario arises or before the driver has a visual on the scenario, the alert may be considered a false alarm, therefore leading to mistrust in the messaging system; too late and the driver may behave drastically and inappropriately (Lee and Moray, 1992; Wan et al., 2016). A study conducted in 2016 found that, providing drivers with an advanced warning message of an oncoming collision had the strongest impact in reduced kinetic energy (braking of vehicle) at a lead time of 4 to 8 seconds (Wan, Wu, & Zhang, 2016).

Furthermore, the acceptability of onboard advanced warning messages is paramount to their impact on driver behavior. Cristea et al. conducted a study to examine drivers' acceptance and understanding of onboard advanced warning messages, finding that drivers positively reacted to the onboard warning messages and expressed confidence in the onboard messages (Cristea & Delhomme, 2014). A similar study conducted by Hajiseyedjavadi et al. also found that advanced onboard alerts significantly increased the likelihood that younger drivers would glance towards latent pedestrian hazards and that advanced alerts led to safer driving behavior around a possible pedestrian threat (Hajiseyedjavadi et al., 2018). A 2018 study conducted by Wu et al. also evaluated whether auditory warning characteristics of an onboard collision alert system effected drivers' avoidance behaviors in a driving simulator and found that all tested warning alerts reduced collision rates and shortened reaction times (Wu, Boyle, Marshall, & O'Brien, 2018).

Concerns regarding driver distraction with respect to technology within vehicles, especially among younger age groups, and reliance on advanced warning messages have also been analyzed in previous studies. Earlier studies from the 2000s highlighted the potential negative effects of technology within vehicles (especially among younger drivers), however, with the inclusion of assistive driving technologies in more recent studies, distraction has become less of a concern (Lee, 2007; Mccartt et al., 2006). More recently, in 2017, both Jermakian et al. and Kidd et al. have found that integrated collision warning systems were not associated with distracted behaviors across all age groups (Jermakian et al., 2017; Kidd and Buonarosa, 2017).

A key distinction between these studies and the mid-block crossing application addressed in this paper is that an overwhelming majority of advanced warning systems rely on a reactive approach to an already occurring event (i.e., a collision warning recognizing a pedestrian within the path of a vehicle), whereas the application in this paper relies on a proactive approach, where the pedestrian is alerting the driver of their intent to cross the crosswalk before they even do so. Furthermore, previous studies had focused primarily on driver distraction due to the introduction of new technologies, whereas the research conducted in this paper investigated the CPS warning application's potential for increasing driver awareness of pedestrian intent to cross.

2. Purpose and scope

With new technologies being released to the public, the number of incidents involving vehicles and vulnerable road users can be minimized. The research discussed in this paper describes and analyzes the development and deployment of a pedestrian to vehicle (P2V) connectivity system via cellular vehicle to everything (C-V2X) technology designed to increase driver awareness of pedestrians at mid-block crosswalks.

Designated mid-block crossings have been modified over time to increase the safety and functionality for pedestrians and motorists. Mid-block crosswalks can incorporate refuge gaps, staggered halves, and curb extensions; however, mid-block crosswalks are not always safe because they can create unpredictable scenarios for both drivers and pedestrians. With the surge of connected vehicle (CV) technology and push for increased alternative modal usage penetration into overall travel mode choice, there are more opportunities to connect pedestrians and vehicles and provide road users with increased situational awareness, potentially reducing the number of vehicle–pedestrian incidences.

The scope of this project was to develop an entirely cellular, cyber-physical C-V2X application to replace physical safety technology that both pedestrians and motorists can install on their smartphones or tablets to give users the ability to communicate with each other at mid-block crossings via discrete safety messages and analyze the safety impacts and performance metrics of said application. Advanced warning messages differ from currently deployed technologies in vehicles, for example automatic braking, as this technology takes a pro-active approach in preventing incidents rather than a reactive approach. Personalized advanced warning messages sent to drivers inform them of the pedestrian's intent to cross, potentially increasing the driver's awareness of the pedestrian's presence and intent at the upcoming crosswalk, limiting the number of incidents observed, and limiting the ineffectiveness of visual communication. Furthermore, C-V2X technology that only relies on a cellular network for operation such as this application eliminates the need for deploying costly CV technology, such as short-range communications and WIFI devices on-site, increasing the extent of the CV network coverage and operability without physical infrastructure like in previous studies (Suzuki, Raksincharoensak, Shimizu, Nagai, & Adomat, 2010). The development of this application was also designed to be integrated into typical GPS navigation applications (like WAZE or Google Maps), differentiating itself from on board devices designed for advanced warnings currently deployed in many modern vehicles (lane departure warning, collision warning, etc.), while providing warning messages on a familiar platform that typically does provide warning messages.

3. Materials & methods

This project aimed to expand connected vehicle technology to include vulnerable road users in the connected environment. Mid-block crosswalk treatments vary by region and operational needs; often, a mid-block crosswalk is striped but receives no active infrastructure support, such as flashing warning lights, to warn pedestrians and drivers of a potential conflict. The application was designed to create an advanced warning CPS for a mid-block crosswalk through geofencing – a process of using GPS technology to virtually draw geographic boundaries, or geospaces, which allow mobile technologies to trigger a response when within the defined space – designated areas in which users will be able to interact with each other via smartphone or tablet, as seen in Fig. 1.

The geofenced cellular network delineates three geofenced areas:

1. A geofence encompassing the mid-block crosswalk and adjacent sidewalk for the Pedestrian Geofence.
2. Two geofences adjacent to either side of the mid-block crosswalk for the Vehicle Geofence.

3.1. Concept of operations

The advanced warning mobile application was designed such that it used wireless communications to create an environment consisting of stagnant virtual mid-block crossings, overlapping the existing mid-block crossings, which users could interact with. When a pedestrian is in range of the designated crossing, the virtual environment recognizes that a user is present and enables the user to broadcast their presence and intent to cross at the crossing. Drivers need to be equipped with the application so that they may interact with the virtual network, as well. When the driver is within a designated range of the virtual crosswalk and a pedestrian broadcasts a notification of their presence at the mid-block crossing using the mobile application, a visual and audible advanced warning message is transmitted to the driver, warning them that a pedestrian is present.

The proposed application was designed to run as the primary screen on the phone and will serve as a proof of concept. Further development can have the application operate in the background of the smart device or integrated into other GPS technologies,

Fig. 1. Mid-block crossing user during the experiment with driver and pedestrian geospaces highlighted in red and green, respectively.

seamlessly allowing users to view their GPS and be alerted from the crossing via visual and audible messaging.

This application needs only standard signage, pavement markings, and cellular signal from two smart devices (one in vehicle and one on the pedestrian's person) in order for proper operation at a mid-block crossing. The application was designed so that it would limit the cost and materials needed to operate and maintain active warning technology at mid-block crossings.

3.2. System overview

The CPS was created using localized, designated geospaces, using GPS navigational systems (in this instance, Google Maps) at mid-block crossings. Users in the geospaces have the ability to interact with the virtual crosswalk; the interaction between users and the environment is limited to user request and solely personal-message oriented. Users have the option to define themselves as a Pedestrian or Motorist upon opening the application and are allowed to alter roles between trips. The system architecture and data flow for messaging of the CPS is displayed in Fig. 2 and the user interface of the application is shown in Fig. 3.

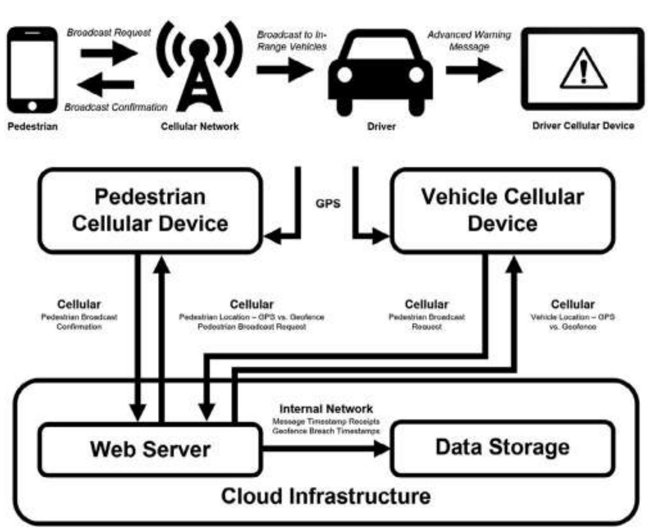

Fig. 2. System architecture.

The test course for this experiment was determined to be a lap around the Federal Highway Administration's Turner Fairbank Highway Research Center located in McLean, Virginia. The test course is a two-lane cross section, bi-directional road that encircles the research center. There is one mid-block crosswalk present along the course, as indicated by the red square in Fig. 4.

There are sidewalks leading up to the mid-block crosswalk that the pedestrian utilized for his approach during testing and signalized intersections border both approaches of the mid-block crosswalk. Considering the Wan study, a lead time of 4 to 8 seconds provides the best response from drivers receiving advanced collision warning messages (Wan et al., 2016). Since the speed limit on the test roadway is 25 mph and the median lead time for sending a message is 6 seconds, it was determined that the appropriate distance from the crosswalk that a message was to be sent was 220 feet. A utility marker was placed alongside the roadway at this point to indicate for the researcher acting as the pedestrian when he should press the button as the vehicle approached the crosswalk. In testing, it was found that the advanced warning message was delivered at an average distance of 215.85 feet from the crosswalk with a standard deviation of 26.05 feet, yielding a range of 189.81 feet to 241.91 feet. Driver approach speeds at the instant the message was received averaged at 20.34 mph with a standard deviation of 2.63 mph and a range of 11.95 to 27.28 mph. Based on these statistics, the shortest theoretical reaction advanced warning lead time would be 4.74 seconds at a speed of 27.28 mph and distance of 189.81 feet, still falling within the recommended 4–8 seconds as suggested in the Wan study. Performance testing with the application analyzed latency, defined as the time it takes for a device to encode and send a hyper-text transfer protocol request to the server and then receive and decode the response, which was found to be an average of 130.947 milliseconds for the driver side of the application and 83.208 milliseconds on the pedestrian side of the application.

Test subjects each drove a total of four laps around the facility in which the first and third laps no pedestrian was present and for the second and fourth laps a pedestrian was present attempting to cross the crosswalk with and without the warning application. The names Lap 1 and Lap 2 are given for the second and fourth laps of the testing cycle to indicate the first and second laps in which the test was conducted. Subjects were also tested in both day and night conditions for this experiment. During the daytime period, drivers were split into two groups: Group A saw the pedestrian attempt to cross the crosswalk without the warning application on

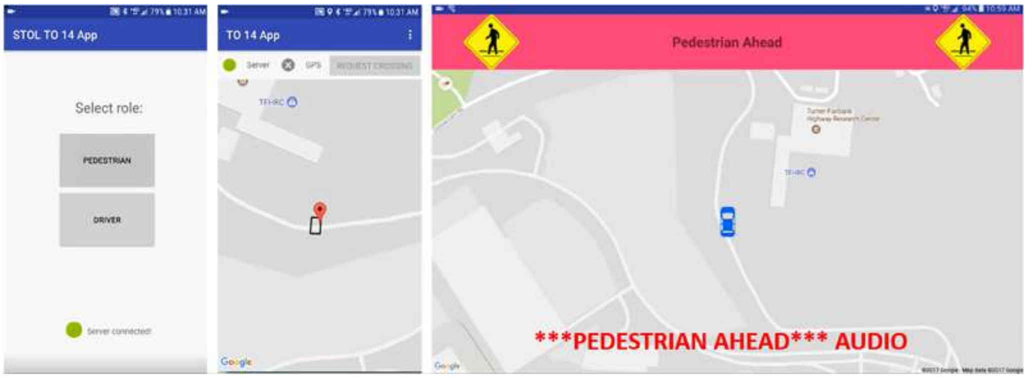

Fig. 3. (Left to right) Application initiation screen, pedestrian user interface showing location of user and crosswalk, driver user interface with alert (audio of a tri tone, woman's voice saying "pedestrian ahead", and a second tri tone plays when message is received).

Lap 1 and with the application on Lap 2. Group B experienced the warning application on their Lap 1 and no warning on their Lap 2 to analyze the effects that repeated measure learning might have on the subjects' willingness to yield to the pedestrian. The nighttime testing subjects experienced the same scenario order as Group A from the daytime testing.

Subjects were briefed before experimentation and were informed that the study was designed to study their reactions to advanced warning messages in general. Multiple advanced warning message examples were provided including, in order: Construction Ahead, Pedestrian Ahead (the actual warning message they would receive), Curve Speed Warning, and Pothole Ahead. Subjects were also told that they would be driving around the facility for a few minutes to familiarize themselves with the vehicle before leaving the facility for the actual study, which was not the case as the study was conducted after the first lap was completed around the facility.

3.3. Dataset demographics

A total of 124 subjects were recruited from the northern Virginia area, representative of the community that lives in the northern Virginia area. The subjects were split into two age groups – the "Young" group consisted of subjects 45 years of age or younger and the "Old" group consisted of ages 46 and older. 92 of these subjects were tested during the daytime and 32 of these subjects were tested during the nighttime, and no subjects tested in both day and night conditions. Table 1 details the count totals of subjects based on Age, Gender, and Time of Day.

3.4. Data collection for analysis

In this report, four major data types were considered to understand the behaviors of drivers with the advanced warning message.

The first data source considered was drivers' reaction to the warning message. This was defined as the percentage of drivers stopping for the pedestrian with and without the advanced warning message.

The second data source considered was drivers' stated preference data. This was collected through a posttest questionnaire regarding the drivers' perceptions of the application. Responses were recorded on a five point Likert scale ranging from 1 to 5 – with responses of 1 indicating strongly disagreeing with the state-

Table 1
Dataset demographics. Bold values indicate the two time periods this study was conducted, daytime and nighttime.

	Count
Day	**92**
Female	46
Old	28
Young	18
Male	46
Old	23
Young	23
Night	**32**
Female	16
Old	9
Young	7
Male	16
Old	6
Young	10
Grand Total	**124**

Fig. 4. (Left to right) Test track with direction and crosswalk location, distance from crosswalk where message is to be sent to the driver.

ment and responses of 5 indicating a strong agreement with the statement – and analyzed perceptions of how much drivers believed it improved their awareness of the pedestrian, whether drivers found the technology distracting, and whether or not drivers would like to see this technology integrated into commonly used GPS routing applications.

The third data source considered was drivers' collected eye tracking data. The eye tracking software, SmartEye, collected the location the driver is looking as a vector in 3-dimensional space. This information was overlaid on the recorded video from the forward-facing camera installed in the vehicle to analyze where the driver was looking during the experiment. The eye tracking data were recorded at a rate of 120 Hz, which resulted in very accurate detailing when and for how long drivers were looking somewhere. Eye tracking accuracy analysis was conducted by a researcher visually watching a video playback of the scenario with a gaze tracker overlaid on the screen indicating where the driver was looking during the test. Using MAPPS v2017.1, researchers were able to select these time frames to analyze and pull the exact amount of data they needed from the study. To best understand how often the driver was looking at the pedestrian, researchers were able to use a tool in the eyesDx MAPPS software to draw a region of interest on top of the video footage captured by the forward-facing camera around the pedestrian in multiple frames of the test track.

The last data source considered was the drivers' kinetic data, which was collected via the on-board vehicle control area network (CAN) bus. The vehicle's standard data collection protocol was deemed appropriate as it collected speed (MPH), location (GPS), acceleration rate, deceleration rate, steering wheel angle, and break application (a binary measurement is the brake is pressed or not pressed).

4. Results & discussion

During the daytime, a total of 92 subjects were tested and during the nighttime a total of 32 subjects were tested for a grand total of 124 test subjects.

4.1. Yielding rates & odds ratios

The first measure of effectiveness that was considered was the effect of the warning application on the driver's yielding rate. During the daytime, 45% of drivers in Group A stopped for the pedestrian without the warning during Lap 1, whereas on Lap 2 with the warning they stopped 80% of the time. Group B during the day stopped 73.1% of the time with the warning during Lap 1 and 63.5% of the time without the message during Lap 2. During the nighttime, drivers stopped for the pedestrian 75% of the time without the warning during Lap 1 and 90.6% of the time with the message during Lap 2. The odds ratios for indicating the likelihood that drivers will stop with the warning message for each of the different test laps is shown in Fig. 5.

Looking at the odds ratios in Fig. 5, it is found that, in all of the scenarios, drivers were more willing to stop for the pedestrian with a warning message than without one. The confidence intervals displayed found for each odds ratio with a confidence of 95%; with respect to the confidence intervals, none of the scenarios show any odds ratio values under 1, indicating that at the lower confidence of 95%, all of the scenarios are still likely to show that drivers are more willing to yield for the pedestrian with the advanced warning message. In particular, drivers on their first exposure to the pedestrian were 2.44 times more likely to stop for the pedestrian during the day and 1.79 times more likely to stop for the pedestrian at night with the advanced warning (Warn vs No Warn Day – Lap 1 and Warn vs No Warn Night in Fig. 5, respectively). These results are consistent with previous studies and regarding the effects of RFB activation and driver yielding rates along similar roadways (Al-Kaisy et al., 2016; Hunter et al., 2012; Shurbutt and Van Houton, 2010).

Furthermore, the odds ratios for the questionnaire responses are shown in Fig. 5. These odds ratios indicate the likelihood for the driver to be in agreement with the statements provided in the questionnaire regarding whether the warning increased the drivers' awareness of the pedestrian (Increased Awareness), whether the application is a technology that drivers would like to see incorporated into other GPS applications (Technological Acceptance), and whether drivers didn't find the application distracting (Found Not Distracting). For each survey question, it was found that the driver was more likely to give positive feedback for the application if the driver stopped for the pedestrian. With a confidence value of 95%, only the Increased Awareness category saw a lower confidence value lower than 1, indicating that it is possible that the application increased all drivers' awareness of the pedestrian, regardless of whether the driver stopped or didn't stop. An interesting case was seen in the Found Not Distracting responses, where drivers were 7.9 times more likely to say the application didn't distract them if they stopped for the pedestrian. Such a large odds ratio demands consideration of the instances that were false positives, in this case those who didn't find the message distracting but still didn't stop for the pedestrian. Only 21 of the subjects didn't stop for the pedestrian with the warning application and 14 of those subjects noted that they did not find the application distracting. Of those 14 drivers, 11 were older drivers

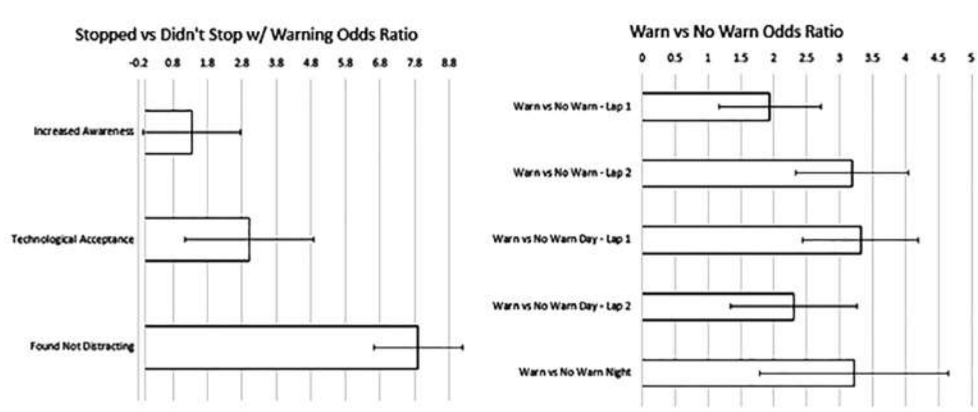

Fig. 5. (Left to right) Odds ratios for the driver reaction (Stopped vs Didn't Stop) for the Warning vs No Warning analysis, Odds ratios for the driver stated preference data for the Stopped vs Didn't Stop Scenario.

(45 years of age or older), 9 were female, and 8 received the warning message on Lap 1. From these demographics it may be considered that older drivers may not be as willing to stop for the pedestrian, even if they did not find the application distracting.

4.2. Binary logit model

To best understand the impacts of the many variables in the experiment on the yielding decisions of the drivers, binary logistic regression analyses were conducted on select cases for the study. The binary logit model follows the following form:

$$Y = log_b \frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$$

Where:

Y = Expected Outcome (i.e. Stop or Didn't Stop)
p = probability of stopping for pedestrian
β = "degree of change" coefficient
X = independent variable (i.e. Age, Warning Message, Gender, etc.)
n = subject number

Due to the nature of real-world experimentation, there were some limitations to the study that impacted data yields. For each of the logit models displayed in this report, different subject totals were found due to data loss and/or poor eye tracking. Table 2 displays the variable coding for each binary logit model considered and the frequencies for each data field.

The variable values, standard errors, and significance values with a confidence value of 95% for three select binary logit models are presented and considered in this analysis, the results of which are shown in Table 3.

The first binary logit model – All Subjects – included all 124 subjects. This model was split by 72 of the subjects not receiving the message on their first lap and 52 of them receiving the message on their first lap. This model considered age (Age), gender (Gender), time of the day (TimeOfDay), the order in which the warnings were received (Lap), and the presence or lack thereof of the advanced warning message (Message). Due to data losses in the speed and eye tracking data for subjects throughout the experiment, these variables weren't considered for the All Subjects model. The significant variables in this model form were found to be Age, TimeOfDay, and Message. Considering all subjects, it was found that younger drivers were more willing to stop for the pedestrian, that drivers were more likely to stop for the pedestrian during the nighttime than the daytime, and that drivers were more willing to stop for the pedestrian with the warning message. Both the Message and TimeOfDay variables had larger coefficient values, indicating that these had a strong influence over whether or not the driver stopped for the pedestrian. With respect to the higher rate of yielding for the pedestrian at night – a possible explanation to consider is the character of the test environment at this time: during the nighttime hours, the facility was closed and only the researcher and security of the federal facility were present during the experiment, whereas during the day workers were present and walking around the facility, so drivers may have been more "on guard" than normal during the night hours. It should be noted that the Lap variable does show as significant with a confidence value of 90%, indicating that drivers were more likely to stop for the pedestrian during their second exposure to the pedestrian, possibly indicating that there was some in-test learning during the repeated measures study. This Lap variable may also be influenced by the order in which subjects received the message, with an uneven balance in the order in which messages were received a bias may have been introduced into this model.

The second binary logit model – Eye Tracking Subjects – included 87 total subjects, 59 from the daytime and 28 from the nighttime experiments. This model was split by 59 of the subjects not receiving the message on their first lap and 28 of them receiving the message on their first lap. This model considered age (Age), gender (Gender), time of the day (TimeOfDay), the order in which the warnings were received (Lap), the presence or lack thereof of the advanced warning message (Message), and the percentage of time the driver looked at the pedestrian while the pedestrian was visible up to the moment the driver stopped for the pedestrian, or drove through the crosswalk (PercPedLook). The significant variables in this model form were found to be Age, TimeOfDay, and Message. Considering this subject group, it was found that younger drivers were more willing to stop for the pedestrian, that drivers were more likely to stop for the pedestrian during the nighttime than the daytime, and that drivers were more willing to stop for the pedestrian with the warning message. All of these variables had larger coefficient values, indicating that they had a strong influence over whether or not the driver stopped for the pedestrian. Interestingly, this model shows that the Lap variable becomes insignificant, whereas in the All Subjects model, it

Table 3
Binary logit model results for the three selected models.

Variable	β	Std Error	df	*P*-value
All subjects				
Age (1)	−0.795	0.307	1	0.010
Gender (1)	−0.257	0.298	1	0.389
Time of Day (1)	−1.006	0.393	1	0.010
Lap (1)	−0.521	0.301	1	0.084
Message (1)	−0.984	0.304	1	0.001
Constant	3.063	0.527	1	0.000
Eye tracking subjects				
Age (1)	−1.212	0.381	1	0.001
Gender (1)	−0.241	0.355	1	0.497
Time of Day (1)	−0.978	0.420	1	0.020
Lap (1)	−0.575	0.372	1	0.123
Message (1)	−0.907	0.374	1	0.015
% Time Looking at Pedestrian	1.031	0.774	1	0.183
Constant	2.629	0.580	1	0.000
No missing data				
Age (1)	−1.065	0.456	1	0.02
Gender (1)	0.059	0.419	1	0.888
Lap (1)	−0.768	0.434	1	0.077
Message (1)	−1.197	0.441	1	0.007
Speed	−0.084	0.082	1	0.303
% Time Looking at Pedestrian	2.049	0.961	1	0.033
Constant	2.982	1.754	1	0.089

Table 2
Variable encodings for generated in SPSS for the binary logit models.

Dependent variable coding			
Action			Value
Didn't Stop			0
Stopped			1
Categorical variable coding			
		Frequency	Value
Message	No Warn	124	1
	Warn	124	0
Gender	Female	62	1
	Male	62	0
Time of Day	Day	92	1
	Night	32	0
Lap	1st Lap	53	1
	2nd Lap	72	0
Age	Old	66	1
	Young	58	0

could be considered significant. The PercPedLook variable is found to not be significant in this model, however, this model is worth considering as the last model – No Missing Data Subjects – shows this variable to become significant.

The third binary logit model – No Missing Data Subjects – included 58 subjects, all of which were part of the daytime experiment. This model was split by 30 of the subjects not receiving the message on their first lap and 28 of them receiving the message on their first lap. This model considered age (Age), gender (Gender), time of the day (TimeOfDay), the order in which the warnings were received (Lap), the presence or lack thereof of the advanced warning message (Message), the percentage of time the driver looked at the pedestrian while the pedestrian was visible up to the moment the driver stopped for the pedestrian, or drove through the crosswalk (PercPedLook), and the approach speed at which the driver was travelling at the average distance from the crosswalk that the message was received by drivers (Speed). The significant variables in this model form were found to be Age, Lap, Message, and PercPedLook. Considering this subject group, it was found that younger drivers were more willing to stop for the pedestrian, that drivers were more willing to stop for the pedestrian on their second lap, that drivers were more willing to stop for the pedestrian the longer they looked at them, and that drivers were more willing to stop for the pedestrian with the warning message. The Message, Age, and PercPedLook variables had larger coefficient values, indicating that these had a strong influence over whether or not the driver stopped for the pedestrian.

A binary logit model for speed was considered as well without the eye tracking data, however, speed was not found to be significantly impactful on the model and nor was it found to become significant in the No Missing Data Subjects model, therefore, the model is not reported.

5. Conclusions & Future work

This research aimed to develop a cyber physical, C-V2X application that could be easily integrated into typical GPS navigation applications that provided proactive, advanced warning messages to drivers of pedestrians' presence and intent to cross at mid-block crosswalks.

From the analysis conducted, a few conclusions can be made that indicate the positive performance of the advanced warning message.

First, the odds ratio tests for the warning versus no warning case on lap order shows that, across the board, those who received the advanced warning message were more willing to stop for the pedestrian than without it.

Second, it was found that in the odds ratio comparison between driver reaction (stopped vs. didn't stop) and stated responses in the questionnaire that those who did stop for the pedestrian were more likely to rate the application positively. An argument can be made, however, that the ideal scenario for this odds ratio test be 1 for each questionnaire statement, indicating that there isn't a difference in perception of the application between those that did and didn't stop for the pedestrian, with all subjects reporting positive feedback. This in mind, the most important questionnaire response, whether the application increased the drivers' awareness of the pedestrian, has an odds ratio of 1.35 and a confidence interval below 1. In this analysis, 88.9% of the subjects indicated that the application increased their awareness of the pedestrian, validating this ideal scenario.

Third, regarding the binary logit models, it can be concluded that driver age, the time of the day that subjects were tested, and the presence of the advanced warning message all had strong, significant impacts on the rate at which drivers stopped for the pedestrian. Most importantly, the presence of the advanced warning message was found to be very significant across all models, showing an increase in the likelihood for the driver to stop for the pedestrian, further indicating that the message had a positive impact on driver behavior.

As mentioned in Section 4.1, 21 subjects did not stop for the pedestrian when they received the advanced warning message. After the study was completed and subjects were debriefed and told the actual goal of the study, they were asked to provide any comments or suggestions for the application – of the 21 subjects who didn't stop, 13 subjects left responses. Comments left by the subjects showed no clear trends, though, three cited that the message came too late as the primary reason they didn't stop. The full responses of these 13 subjects are shown in Table 4.

Future work on this application and its methods can be conducted to better the application's performance as well as better

Table 4
Comments from subjects who didn't stop when they received the advanced warning message.

Post-Test Comments – Didn't Stop with Advanced Warning Message			
Age	Gender	Lap Message Received	Comments
23	F	1st Lap	The software jolted me and scared me for a second. Suggest that come with an explanation that the sound comes up at any time. Perhaps instruct the driver to remain calm while it is talking
45	F	1st Lap	Have notification sent earlier
35	F	1st Lap	Perhaps a control or two where the pedestrian comes/approaches the road and begins to walk across to see reaction to moving pedestrian
70	F	1st Lap	Found the study to be very insightful
75	M	1st Lap	Using a GPS would be more challenging. Pedestrian was far away from crosswalk so verbal warning was not useful. Maybe the pedestrian could be closer to the road. Pedestrian was too nonchalant. Could have more pedestrians even crossing the road without a traffic light
34	F	1st Lap	Please add this feature to Waze or google maps
77	F	2nd Lap	Pedestrian warning application helpful if more clearly stated and more succinct and louder. Was unaware of the visual display of the pedestrian warning application
75	M	2nd Lap	More driver education on laws pertaining to mid-block crossings when a pedestrian is waiting to cross, but the driver has the green light. If the driver stops, she could be rear-ended
28	M	2nd Lap	The application increased my awareness, but I felt that it came too late for me to do anything other than slam on my brakes since the pedestrian wasn't actually in the crosswalk I just kept going
54	M	2nd Lap	Reduce volume of pedestrian warning
57	F	2nd Lap	I was confused by the lack of warning the first time
58	F	2nd Lap	It caught me by surprise because I did not know it was there, would be helpful if people knew beforehand it is there
56	F	2nd Lap	Have the messages for crosswalk sooner

understand the impacts the application has on drivers. Firstly, a more robust nighttime testing scenario could be conducted with a more random approach to what lap the driver receives the message – this study only say nighttime drivers receiving the message on Lap 2 of the experiment, which may show some bias towards drivers' learning through repeated measures what the test is actually about. Furthermore, different results may be found in testing this application on a different roadway, preferably not on a government facility such as this experiment was done – there may be some bias in driver behavior due to the pressure of being on a federal facility located right next to the Central Intelligence Agency. Another approach to this experiment would be to test pedestrian interactions and acceptance of the technology and analyze their behavior at mid-block crossings with the application and determine whether this should be a tool for all users or if the application is better suited for use by those with disabilities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Exploring safety knowledge sharing among experienced and novice workers

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ABSTRACT

Introduction: This paper investigates how members of a culinary and hospitality arts program generate, share, and learn safety knowledge via social and identity mechanisms. *Method:* We conducted semi-structured interviews with 20 participants of varying roles and experience (i.e., students, culinary instructors, and restaurant chefs) in the culinary and hospitality arts program at a large polytechnic in western Canada. *Results:* The emergent themes from these interviews indicated that the circulation of safety knowledge relied on the interaction among individuals with various levels of experience, such that those who were more experienced in the culinary arts were able to share safety knowledge with novices, who had less experience. Comparing safety knowledge gleaned from within the school against that gleaned from within the industry highlighted differences between the construction of safety in the two contexts. Notably, many aspects of safety knowledge are not learned in school and those that are may not apply in the industry context. We found that safety knowledge was shared through informal means such as storytelling, a process that allowed members to come to a deep, collective understanding of what safety meant, which they often labeled "common sense." *Conclusion:* We found that safety knowledge was a currency through which participants achieved legitimacy, generated through continual practical accomplishment of the work in interaction with others. *Practical Applications:* Our findings provide novel insights into how safety knowledge is shared, and we discuss the implications of these findings for classroom, work-based learning, and other forms of curricula.

1. Introduction

The definition of "safety" and how it is understood seems to vary widely depending on who you ask: an experienced chef is likely to give a very different account of how to ensure safety in an industrial kitchen compared to that of a novice apprentice. Differences in safety knowledge as a function of experience and role have been documented in a range of work contexts (e.g., Carroll, 1998; Clarke, 1999; Gherardi, 2006; Gherardi, Nicolini, & Odella, 1998; Gherardi & Nicolini, 2000a; Pollnac, Poggie, & Cabral, 1998; Simpson, 1996), and point to several features of how knowledge about safety is learned and shared. First, safety is more than the absence of accidents (Rochlin, 1999). Likewise, "unsafe behavior" is undoubtedly more complicated than individuals acting "unsafely" even after learning the "proper way" of doing things. Green (1997) investigates people's perceptions of accidents and finds that individuals generally understand them as preventable through individual responsibility and basic competence, and this understanding varies by experience. Second, learning about safety is not a "linear practice" (Pink, Tutt, Dainty, & Gibb, 2010, p. 656). The construction of safety knowledge is a continuous and active process achieved through social engagement with other people who are also part of the learning (Gherardi & Nicolini, 2002a). In this way, learning about safety from on-the-job experience or having an intuition (i.e., "gut feeling") about safety comes from social interaction (Kamoche & Maguire, 2010; Nicolini, 2012). Indeed, social interaction is key to understanding safety in the workplace.

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It is therefore unsurprising that, in general, work safety research has moved away from an individualistic conceptualization of safety and safe work behavior toward one that focuses on collective accomplishment and responsibility (Gherardi, 2006; Green, 1997; Llory, 1997; Somerville & Abrahamsson, 2003; Turner & Gray, 2009; Turner & Tennant, 2010). To this end, Holmes and Gifford (1997) argue that occupational health and safety strategies that focus solely on individual behavior change or technical measures will fail because they do not consider the "social context, the hierarchical structure of the industry, or the shared assumptions about risk control through individual skills and responsibilities" (p. 11). The social context is especially important for understanding occupational safety because the meanings of risk and physical danger are socially constructed and develop through individuals interacting with one another to share and learn about these meanings (Simpson, 1996). As such, safety is often difficult to quantify, requiring us to employ other modes of inquiry (e.g., qualitative research) to understand how it is created and maintained.

Circulation of such safety knowledge in a social context—which we describe hereafter as "*safety knowledge sharing*"—is achieved by both experienced and novice workers in interaction. Knowledge about safety is shared through storytelling, formal and informal mentorships, and day-to-day interactions in the course of carrying out tasks and observing how others complete the same tasks. Safety knowledge sharing is an important social process to understand as it underscores how workplace safety is learned, and captures some of the dynamics of safety climate—the shared sense of how safety is "done around here" (Zohar & Luria, 2003).

The goal of this study is to qualitatively investigate how safety knowledge is shared among novices and more experienced workers. In doing so, the study makes three contributions. First, it provides a richer understanding of the features and processes that enable a novice to learn safe work practices through interaction with others (Gherardi, 2006). Second, the study highlights a key aspect of safety knowledge sharing: the conception of safety as "common sense," or knowledge that is not taught in a didactic way in the classroom but rather through informal means and everyday interaction. Third, the findings from this study provide valuable guidance for practice, suggesting ways to identify and facilitate formal and informal opportunities to facilitate safety knowledge sharing.

2. Conceptual background

2.1. Safety knowledge sharing

Knowledge in organizations is an important and ethereal "resource," and the social processes by which it circulates among employees of varying experience involve knowledge transfer—that is, the acquisition of knowledge—and knowledge exchange—that is, mutual knowledge seeking (Wang & Noe, 2010). A common element in both of these processes is knowledge sharing, which refers to the "provision of task information and know-how to help others and to collaborate with others to solve problems, develop new ideas, or implement policies or procedures" (Wang & Noe, 2010, p. 117). Research from multiple disciplines has examined characteristics correlated with knowledge sharing at the individual (e.g., Connelly, Ford, Turel, Gallupe, & Zweig, 2014; Li, Yuan, Ning, & Li-Ying, 2015), team (e.g., Bakker, Leenders, Gabbay, Kratzer, & Van Engelen, 2006; Sawng, Kim, & Han, 2006), and organizational level of analyses (e.g., Connelly & Kelloway, 2003; Nesheim & Gressgård, 2014; Wang, Noe, & Wang, 2014), indicating the importance of interaction among organizational members in facilitating knowledge sharing. Of particular relevance to the current study are the relationships and ties that facilitate knowledge sharing (e.g., Kankanhalli, Tan, & Wei, 2005; Nahapiet & Ghoshal, 1998; Witherspoon, Bergner, Cockrell, & Stone, 2013), such as social networks among employees and their supervisors (e.g., Dysvik, Buch, & Kuvaas, 2015), among colleagues (e.g., Holste & Fields, 2010; Lin, 2007), and among organizational units (e.g., Hansen, 2002; Schulz, 2003). Because social networks describe the patterns of interaction among organizational members to obtain and circulate (safety) knowledge, social interaction is the means through which safety is practically accomplished.

The knowledge sharing literature has primarily focused on the circulation of knowledge among knowledge workers. This narrow focus underserves and misrepresents the importance of knowledge in all jobs, not just those labeled as "knowledge work" (Kelloway & Barling, 2000). As a result, our understanding of how domain- or content-specific knowledge is shared and learned remains limited. For example, knowledge sharing between organizational members is particularly important for jobs that involve "challenging, critical, and extremely time pressured contexts" (Maslen, 2014, p. 83), which accurately describes most jobs that are sensitive to, or prioritize, safety issues in some form. Such jobs may involve, for instance, responsibility for patient safety within health care, ensuring staff and customer safety in the restaurant and hospitality industries, or enacting emergency response procedures to major disasters such as pandemics (e.g., COVID-19) that may endanger organizational, customer, and general public safety. Furthermore, manual labor-intensive jobs concerned with employee safety, such as coal mining, may rely on sharing knowledge as a way to minimize or prevent injuries and accidents (Cullen & Fein, 2005; Kamoche & Maguire, 2010). Thus, understanding how safety knowledge circulates is an essential exercise within many safety–critical organizations.

Research on sharing safety knowledge (e.g., Hayes, 2015; Hayes & Maslen, 2015; Maslen, 2014) has explored a range of physically hazardous contexts in which employees risk injury in the conduct of their work, illustrating how decision-making under physically challenging contexts often requires employees to share safety-related knowledge. For example, Hayes and Maslen (2015) conducted ethnographies in organizations in three separate hazardous industries—a chemical plant, a nuclear power station, and an air navigation service provider—showing that sharing safety knowledge via informal stories enables operations staff to "build 'safety imagination' and assess the safety of their decisions on a daily basis" (p. 724). Indeed, this concept of the "safety imagination"—' 'an ability to think beyond rigid compliance with rules and procedures as a strategy for ensuring ongoing safety" (Hayes & Maslen, 2015, pp. 718-719)—reflects an orientation to transferring and exchanging safety knowledge that is crucial to our exploration of how safety knowledge is shared.

Knowledge sharing is also particularly important for circulating safety-related tacit (unspoken) knowledge. This type of knowledge is rooted in values and expressed in lived experience (Nonaka & Konno, 1998), as well as the interaction among individuals in specific contexts (Alavi & Leidner, 2001). It reflects understanding knowledge that is difficult to articulate (Hayes & Maslen, 2015), and can be described as intuition or a "gut-feeling" (Holste & Fields, 2010). For instance, Leger and Mothibeli (1988) study how the rock formations in a coal mine may "talk" (make sounds) to gold miners, providing "pit sense"—a form of embodied cognition about the imminence of danger, such as cave-ins. Tacit knowledge about safety is difficult to obtain through written instruction (Sauer, 1998), with the circulation and acquisition of this knowledge relying on the interaction among individuals (Nonaka & Konno, 1998); this further illustrates the importance of social interaction in the sharing and learning of safety knowledge.

More generally, safety knowledge sharing is consistent with a social constructionist view of learning: organizational members come to construct a shared understanding of the task or issue at hand (Brown & Duguid, 1991; Lave & Wenger, 1991), and part of this learning involves how to co-create safe work. At the same time, safety knowledge sharing is also consistent with the knowledge-in-practice view (Gherardi & Miele, 2018), in that it may be done informally via stories told by experts as well as through the actual practice of interacting with others while doing the work (Gherardi, 2006; Maslen, 2014). Participation in a community of practice is how novices are socialized into knowledge about working safely. It is also how they construct their identities as they transition from peripheral to legitimate members of the community of practice (see Fig. 1).

2.2. Learning safety through participation in a community of practice

Novices entering an occupational field such as culinary arts are socialized into their roles within the organization—whether that organization is the classroom, a commercial kitchen placement, and their overlap. As part of doing their work, novices observe how more experienced workers complete their work and learn from them. While observing, novices can see tricks of the trade from more experienced workers (Gherardi, 2006) and gain additional knowledge of how everyday work is conducted. Gherardi and Nicolini (2002a) refer to this process as "occupational socialization." Novices learn while actively working on tasks alongside other novices and more experienced colleagues, as Maslen describes: "an important requirement for gaining experience [is] taking responsibility and participating in the work" (2014, p. 85). This participation is what generates knowledge and constitutes knowledge sharing among individuals. It also encourages discussion among experienced workers and novices, furthering a shared understanding of what safety means and looks like in practice. Gherardi (2006) and Nicolini (2012) have investigated extensively the social construction of safety among novice learners (see also Gherardi & Nicolini, 2000a, 2000b, 2002a, 2002b; Gherardi et al., 1998). Gherardi et al. (1998) argue that people "do not learn 'safety'... rather they learn safe working practices" (p. 202) as a participating member of a community of practice (Gherardi & Nicolini, 2000a).

Learning about safety is very much about being socialized into a new identity through interaction with a community of practice (Lave & Wenger, 1991) via *legitimate peripheral participation*—"the process by which newcomers become part of a community of practice" (p. 29) and learn through an "evolving form of membership" (p. 53) that sees individuals transition from novices on the periphery to more legitimate, experienced participants.

While a community of practice is constructed in interaction, it is not necessarily bound by a physical location. The phrase is often used to refer to "co-presence, a well-defined, identifiable group, or socially visible boundaries" (Lave & Wenger, 1991, p. 98). A community of practice is hard to identify because it need not be a visible, co-located group (Nicolini, 2012), but rather a "set of relations among persons, activity, and world over time and in relation with other tangential and overlapping communities of practice," and these communities are always in flux (Lave & Wenger, 1991, p. 98).

Similarly, the fact that novices' participation in the community of practice is "peripheral" does not mean that it is less important or disconnected; rather, it is about being at different stages in the process of learning (Lave & Wenger, 1991). Being an experienced or legitimate member also does not mean that a person has reached a terminal point of expertise or learning (Nicolini, 2012). Learning is about getting to a place where a novice is able to pass as a member of the community by learning a new identity, and seeing, speaking, and acting as a legitimate practitioner (Gherardi, 2006; Nicolini, 2012).

Going through the process of becoming a legitimate practitioner can take place whether formal education provides the context for learning or not (Lave & Wenger, 1991). Studies have found that intentional instruction through schooling is not a prerequisite for learning, but that participation is (Gherardi, 2006; Lave & Wenger, 1991); this is because learning is social and about "belonging, engagement, inclusiveness, and developing identities" (Nicolini, 2012, p. 80). Participants—both novices and experienced practitioners—create the community in which learning takes place, not the other way around.

As a part of working alongside others, novices are socialized by hearing stories. For instance, having conducted interviews with

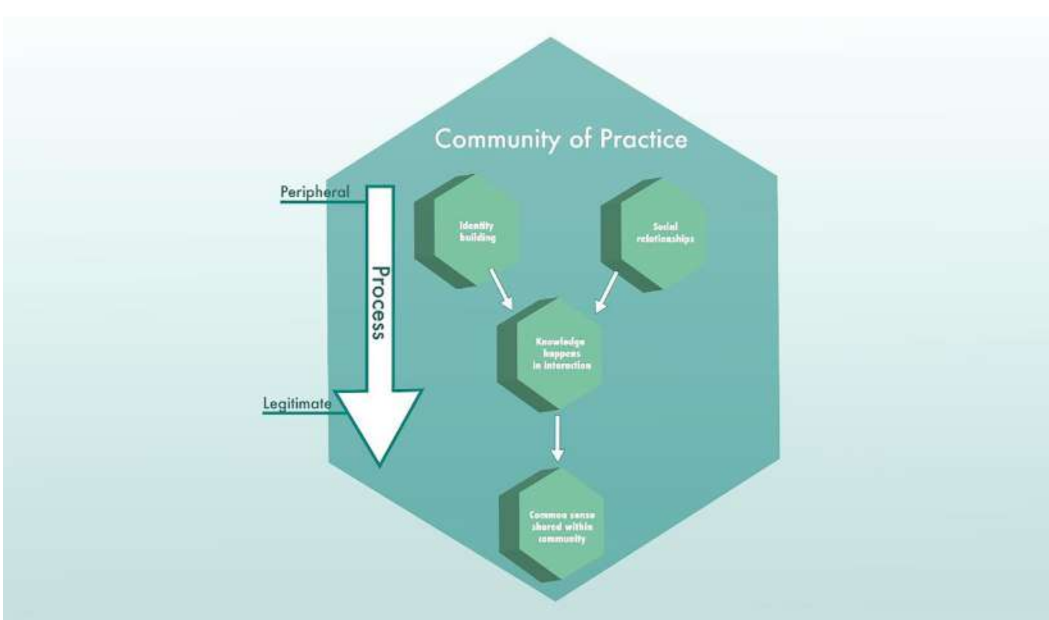

Fig. 1. Becoming a practitioner.

novice and experienced engineers, Maslen (2014) concluded that socialization was an important aspect in sharing safety knowledge. Young engineers drew from experienced engineers' stories (Maslen, 2014), enabling these novice learners to benefit from more experienced engineers' intuition about a particular course of action. Hearing the stories allowed for the development of safety imagination as novices simulated the situation in their own minds and decided what they would have done in those same circumstances (Hayes & Maslen, 2015). These stories are embedded with *knowledge pointers*, important features by which safe working practices are learned (Gherardi, 2006). Knowledge pointers allow less experienced workers to organize ways of seeing, conceiving, and understanding a particular practice, what it means to be a legitimate part of an aspirant occupational group, and the shared knowledge constituting a community of practice.

Using ethnographic data from a building site, Gherardi (2006, pp. 97-98) describes five knowledge points and other discursive practices involved in the learning of safety. These are comprehensive, as Gherardi acknowledges, but not necessarily exhaustive:

> *Highlighting*: being able to watch, look, see, and listen to others as they "carry out meaningful activities" in the generation of safety;
> *Shaping aesthetic feelings*: repeated "exposure to clues and sensory experiences," as well as the language employed, making safety embodied (also in Strati, 2003);
> *Talking in practice and talking about practice:* talking about safety while doing, or talking about doing safety, including stories;
> *Weaving the texture between the social and the material*: mediating the social world with physical artifacts (e.g., training manuals, posters) that support learning about safety; and
> *Supporting the enactment of the new identity*: knowledge and behavior considered appropriate, reinforced by other practitioners.

Safety knowledge sharing through interaction is part of socializing novices into the community of practice to become legitimate participants. From knowledge sharing, "common sense" (i.e., "good sense and sound judgement in practical matters"—Lexico, n.d.) becomes the currency for this identity process. While the word "sense" appeals to something innate, common sense is far from innate (Geertz, 1975). Common sense should be thought of as a "relatively organized body of considered thought" (Geertz, 1975, p. 7) and "largely a result of deliverances of experiences, rather than deliberate reflections upon it" (Geertz, 1975, p. 7).

3. Methods

3.1. Research context—Safety in the kitchen

We elected to focus on culinary settings as the physical dangers of a commercial kitchen are omnipresent and occupational hazards may not always be evident until an accident occurs (Fine, 2008; Lippert, Rosing, & Tendick-Matesanz, 2020). Those working in the kitchen are often in the presence of highly hazardous elements (Cook Articulation, 2019; Agency, 2008), which ethnographic accounts describe as major sources of occupational injury (Fine, 2008; Tsai & Salazar, 2007). Given that working in a kitchen can be physically dangerous, one way to improve safety in this environment may be through sharing safety-related knowledge (e.g., tricks of the trade, workarounds) that others may not know about and role modeling ways of conducting everyday tasks in a safe manner.

3.2. Sample

This study reports on qualitative data from a larger data collection conducted for a project on safety knowledge sharing (Goodbrand, McClelland, Turner, & Uggerslev, 2018). The data in the current study consist of transcripts from 20 in-depth, semi-structured interviews with individuals who had various levels of experience in the culinary industry in a variety of roles: chefs and instructors in the field of apprentice training (e.g., culinary arts, baking, and meat cutting), as well as students at different stages of their education enrolled in apprentice, culinary, and meat cutting programs. We recruited all participants from a culinary arts and professional food studies department of a large polytechnic in western Canada. We made a deliberate effort to recruit participants with different levels of experience and from different culinary fields to represent as broad a population as possible.

3.3. Data collection

In-depth interviews as a method of data collection are ideal for "issue-oriented" studies (Hesse-Biber & Leavy, 2011), and a semi-structured approach allows for an "exchange" between the researcher and the informant. The interviewer's questions are meant to guide the conversation; however, this approach leaves room for the re-ordering and re-wording of questions, and for the interviewer to probe and make clarifications to fit the participant and the situation (Berg & Lune, 2012). A copy of the semi-structured interview guide is included in the Appendix. All interviews were digitally recorded and conducted by the fifth author, and ranged in length from approximately 30 to 90 minutes. A professional transcriber then created a written transcription of each interview. The research team listened to the interviews, read the transcripts, and had focused discussions about the interviews, before commencing formal data analysis using NVivo 11 software (QSR International, 2017) to organize the data.

3.4. Data analysis and coding strategy stages

We organized the interview data using a re-working of Gherardi (2006) five discursive practices described above. As the coding progressed, it became clear that the categories were certainly neither exhaustive nor mutually exclusive, and that subtle differences often allowed data to fit in multiple categories. This development was not interpreted as a limitation of using pre-established categories, but rather as a testament to the complexity of attempting to neatly compartmentalize human experience.

Coding of the data progressed through the following stages. First, interview data were assigned to pre-established categories through structural coding. Second, we used axial coding to review and examine initial codes from each overarching- and sub- category. In these first two stages, ideas and themes were organized through analytic memo- and note- writing. In the third stage, we created "memo/concept" groupings based on themes, systematically discussed each memo, and determined how they related to the overall research questions of how individuals learn about safety and how they share safety knowledge. From this, we constructed a coding map that was a visualization of memos, memo notes, and conversations.

4. Findings

We present our findings in three parts. First, we describe the variation in experience among novices and more experienced practitioners, mitigating the assumption that students come into the culinary arts program as "blank slates" about culinary safety. Second, we describe accounts of the differences in how safety is enacted in classroom versus industrial kitchen settings. Third, we elaborate on the notion of safety as "common sense" that comes from the intersection of experience, reflexivity, and increasing self-identification of novices (i.e., peripheral practitioners) as more experienced members (i.e., legitimate practitioners) of a particular community of practice.

4.1. Students are not blank slates

The interview data show that although the formalized safety instruction that each student receives in school is ostensibly the same, students' experiences in industry contexts when entering culinary programs are not. Students are not proverbial blank slates, and all students enter the culinary, apprenticeship, baking, and meat cutting stages of their programs having had various experiences in kitchen settings. The safety knowledge that students acquired while working in the culinary industry, including examples of behaviors considered "safe" or "unsafe," is shared among classmates, and interviewees often used cross-context examples as reference points when asked about culinary safety. When experiences are shared in this way, students with less experience get the benefit of learning from their peers' "real world" experiences. Below is an example of a culinary student describing lessons learned from the field to the interviewer:

> Interviewer: Can you tell me a little bit about people you have worked with or studied with who have been very safe and what made them safe?
> AS: When I started at [name of local restaurant] I worked with a cook. He went across Europe and he went across kind of everywhere, he's just been everywhere. He just got back from two years in Australia. That guy was just textbook, textbook everything: cleanliness textbook, cooking techniques textbook. Just the way the guy operated. You just watched him. It was like watching a ballet or something. It was graceful watching the guy work because he was just so efficient at what he did and just so technical but he made it look so easy. But even right down to the small things like cleaning as he goes. ... The guy was a great example of just safety in the workplace.
> Interviewer: Nice to hear there are people like that out there.
> AS: Yeah, it is nice. It makes you want to go to work not only just for that but just to learn from the guy.

4.2. Classroom kitchens differ from industry kitchens

The interview data revealed three key differences between the classroom environment and an industry kitchen that affected how safety was handled. First, interviewees expressed that school is a protected environment compared to industry. The school had a nurse who could treat students' injuries, whereas industry relies on practitioners to "own their safety," and in some cases "suck it up" when they get injured, as seen in the following interview excerpt with an apprentice instructor:

> I see a difference where, especially in the first year apprentices that come in, right away if they cut themselves or let's say they get a little burn they think they're dying. So right away they need to get medical attention immediately. Being in school I would say, "Yes, go ahead. Go see the nurse and get it set up" and then they would come back with a bandage all the way around their arm because they burned themselves on the tip of their finger. But in industry, it doesn't work that way. In industry, if it's really severe then yes, we're taking you to the hospital because we don't have a nurse on staff there, we're taking you to medical attention immediately. But if it's just a little nick or a little burn or whatever, "Suck it up princess, go to work." That's the way we encourage it because of the fact that it's small. But there are some small things that can turn very bad.

The second difference pertained to the emphasis on safety in the two environments. In the school environment, safety is explicitly taught, whereas the emphasis on safety in industry settings could range from non-existent to comprehensive (e.g., safety training programs). However, even when novice practitioners are attuned to safety concerns, the nature of actually practicing cooking in an industrial kitchen sometimes trumps those concerns, at least in the short term. As described by an experienced chef:

> If it's just a little nick or if it's something that's a little more uncontrollable, in that business, in that line where you've got all these deadlines and you've got all this production that you're doing that day, wrap it up and get to work, depending on the severity. If it's severe then no, I would definitely, if it was myself cutting it I would basically because we had proper first aid training I would try and wrap it up as good as I can. Get out there and do what I need to do and then I would seek medical assistance after the fact. Because I knew I would always report it. But [that] doesn't happen all the time. If it's a little nick or whatever, it's like put a bandage on it, put a finger cot and get to work. Because that business is that business. You're not going to constantly stop. That was another thing. I had some cooks that were with me at the [name of local restaurant] where they would get a little nick and they wanted to go home. It is like, "No, you're not going home. Wrap it up, tighten it up, we'll make a note of it and get back to work."

Third, the speed with which work has to be performed in industry is considerably higher than in a school environment, which has implications for safe work practices—especially for those with less experience. The school environment emphasizes that things be done correctly rather than quickly, as seen in the interview excerpt below:

> Interviewer: So now here you are, you're thrown into that environment. It's super busy and there's a hazard of some sort. ... How are you able to recognize [or] see that hazard and then how do you deal with it when it's so busy?
> CS: If it's really busy that's what happens because you're not—that's hard to make a habit of recognizing things like that and then you're just trying to crank out food. I think it's easier at school than it is in the workplace because at school you're not being paid to be fast. You have the opportunity to slow down if you need to. I think lots of the time it takes something to happen there's the dish cart by the sink and someone's doing dishes and someone's at the steamer and that's a tight spot. You only have to run back and forth three times and run into people and the dish cart before you need to move the dish cart or you need to scream you're coming around or something. But I think it takes repetition of doing it badly when you're in a tight crunch to realize, "Okay hold on. Wake up." You need to.
> Interviewer: Yeah because you don't have that time to step back and look around and...
> CS: Yeah and I think [of] a simple thing like [the] floor. When are you going to get a mop to come on the line and wipe it up? It's "Okay no, I can [use] paper towel or whatever to..."
> Interviewer: Like kind of a quick fix for now until you can get to it later.

4.3. Safety knowledge as "common sense"

As one interviewee noted, "There's only really so much you can teach people. At the end of the day they need common sense." Many others used this same term to describe safety knowledge. Yet despite its prevalence, interviewees did not share an understanding of how people come to possess common sense. Several participants spoke of common sense as something innate (e.g., "you know not to touch something hot"), while others believed that it was learned (e.g., "you touch something hot and know not to do it again"). At the same time, interviewees in both camps acknowledged that common sense is also based on "deliberate reflections" (i.e., sharing with others how to be safe). We argue in a community of practice, common sense is socially constructed and shared in interactions. More specifically, safety knowledge as common sense has three characteristics: (1) common sense is shared and social; (2) it is a practical accomplishment—something learned and re-enacted; and (3) common sense is a legitimizing device that enables professional identification.

4.3.1. Common sense as shared and social knowledge

Interviewees talked about how they learn safety from their peers and mentors—how watching and interacting with others within the community of practice teaches them "common knowledge." Below is an excerpt from an interview with an apprentice student speaking about how safety knowledge is shared and has been shared with them:

> Listening to guys, they've been around a lot longer than I have. Chef's been in the industry 20–30 odd years. . .. Just past experiences, just common sense kind of things. Just proper sanitation, proper this. Don't cross contaminate, things like that. Just a lot of past experiences really, most of the stuff that I've been told. I've been fortunate to work with a lot of guys with a lot of experience and they have a lot of knowledge to share, not only cooking but with safety as well.

Novices (i.e., "peripheral legitimate practitioners" in community of practice language) often learn about safety in interaction with "legitimate practitioners" (Lave & Wenger, 1991), who simultaneously create and re-create what appears to the novice (and sometimes even to experienced practitioners themselves) to be simply "common sense." Getting to a point where knowledge is considered common sense is a process that takes time, and although some interviewees considered common sense innate, many also viewed it as occurring in interaction with others, as shown in the following excerpt:

> Interviewer: Do you find safety reminders in the kitchen to be helpful?
>
> AS: Sometimes. I could see the benefit for new trainees but for me a lot of the stuff I realize is common sense so I just don't do it. Like don't touch hot things, don't clean the slicer while it's on or plugged in.
>
> Interviewer: So common sense, do you think it's always common sense?
>
> AS: Once you learn it, it becomes common sense. I'm not saying that I innately knew that. I probably left the slicer plugged in the first time I cleaned it but somebody was like, "Oh, you need to unplug that, otherwise you're going to die." And I was like, "Oh, okay. That makes sense."

In this way, common sense is shared and social. It is the interactions surrounding how to do things—things that may appear obvious—that create the conviction that doing things that way is simply common sense.

4.3.2. Common sense as a practical accomplishment

Common sense seems to be accomplished once it becomes an unquestioned habit, which arguably comes with practice. An apprentice student described this process of learning common sense as follows:

> And you work with guys, you'd think that they'd understand proper don't cross contaminate. It's preached a lot and people should know that but you'd be surprised how often I'd have to tell someone to "Get rid of that cutting board" or "Clean that cutting board" or "Clean up that counter" or "Are you going to leave that sitting on the counter all day? Are you going to leave that? What are you doing with that? Get that in an ice bath. You can't leave that in the sink." Things like that. Some things that people I guess don't practice themselves and it shows.

The above excerpt also highlights the notion that common sense is not a given, but that it is accomplished through interaction—through someone telling you what the proper action is, for example. Accomplishing common sense, in turn, gives other practitioners an understanding of the accomplisher's level of legitimacy as a practitioner.

4.3.3. Common sense as a legitimizing device

Another feature of treating safety knowledge as "common sense" is that common sense becomes a kind of currency for professional legitimacy. If a practitioner lacks what is regarded as common sense, they are considered less legitimate in the community of practice. The transition from peripheral to legitimate practitioner therefore involves progressing to a point where acting in a safe manner and taking safety precautions appears as common sense. One chef explained that when he was starting out, his "common sense didn't kick in for a long time."

Thus, common sense surrounding safety is a tell-tale sign of legitimacy, and common sense identifies who is legitimate and who is not. The overarching idea of "supporting the enactment of the new identity" (Gherardi, 2006, p. 98) is about getting to a point where everything about the work becomes common sense. However, curiously, once a practitioner gets to this point, they may not be able to articulate how they got there (Gherardi, 2006; Strati, 2003), as an apprentice student explained: "Like, if you don't know something, come and ask somebody. Or I don't know. I've just been doing it so long it just . . . grows on you, I guess." A baking instructor highlighted the same point in talking to the interviewer:

> Interviewer: Can you tell me about how safety in the kitchen happens?
>
> BI: I think it's through personal experience as well as through experience of others. . . .
>
> Interviewer: So you're saying you're kind of relying on your own experience, your own safety knowledge but you're also relying on everyone in the kitchen to be aware?
>
> BI: Everyone else as well. Kind of like a collective knowledge.

In summary, when there is a shared understanding of the importance of safety—a collective or common knowledge—those who experience safe work practices as common sense draw on it as a source of professional legitimacy.

5. Discussion

The current study sought to understand how safety knowledge was learned and shared among novices and experienced workers in a culinary arts program. Community of practice theory was a useful conceptual apparatus to describe the process by which practitioners learn together, in that "people mutually guide each other through their understandings of the same problems in their area of mutual interest" (Pyrko, Dörfler, & Eden, 2017, p. 389). Three themes emerged from the interviews with these practitioners: (1) the variation in experience of novices in industrial kitchens and what that means for learning about safety in classroom kitchens, (2) the difference between and relevance of safety knowledge in classroom kitchens and industry kitchens, and (3) the processes by which safety knowledge becomes "common sense" connecting novices and experienced practitioners with a common professional identification. The themes highlighted the features that enabled the circulation and sharing of safety knowledge. Interviewees with prior exposure to the culinary industry noted the differences between the classroom and the industry kitchen environment, suggesting differences in how safety is handled and prioritized between these two contexts. These differences also emphasized that some forms of safety knowledge were not learned in school. Interviewees gained varying degrees of exposure to safe and unsafe practices in the culinary industry and brought this awareness into the classroom kitchens, where safety knowledge was shared among other novices (students) and more experienced practitioners (instructors).

The theme of regarding safety knowledge as "common sense" points to the social construction of safety. Understanding common sense as a purely individual characteristic means ignoring the importance of interaction in safety knowledge exchange. According to our interview data, common sense has three overarching characteristics: it is shared and social, it is a practical accomplishment, and it represents a collective understanding that separates peripheral practitioners from legitimate ones. Interactions among novices and experienced interviewees were crucial in developing common sense, as this interaction allowed for sensemaking of the practices required for work tasks. This sharing of safety knowledge in interaction with other practitioners created a "common sense" that was continually re-constituted. In this way, common sense necessitates that a community be held in common (see Fig. 1). In sum, our research highlights the importance of learning and sharing safety knowledge through socialization, interaction, and participation, with strong implications for both theory and practice.

Our findings have several theoretical implications for the knowledge sharing and safety literatures. First, they provide greater understanding of how novices develop knowledge about safe work practices. Specifically, in our research, the process of socialization enabled novices to interact with their more experienced peers; this allowed experienced practitioners to share their safety knowledge with novices in the classroom and professional kitchens. Novices learned from those more experienced, and we saw numerous examples of how novices came to understand how a particular practice was risky or unsafe, developing a shared repertoire of safety knowledge (Iverson & McPhee, 2008).

Second, as evidenced by the fact that safety knowledge among practitioners with varying levels of experience was described as "common sense," we note that safety knowledge is more than learning the steps to complete a task or operate machinery safely. Rather, it is knowledge that becomes integrated with the professional identities of novices as they progress toward becoming a legitimate member of a community of practice. Similarly, other qualitative research has described how safety knowledge was deemed "common sense" by experts in which such safe behavior became second nature (e.g., fishermen; Thorvaldsen, 2013). As such, the findings from the current study add to the existing literature on safety to demonstrate that safe practice comes from a socially constructed understanding of safety knowledge that eventually becomes ingrained or almost like a reflex among experienced individuals. This conceptualization of common sense reflects a form of tacit knowledge that is, by definition, difficult to articulate (Hayes & Maslen, 2015)—certainly more difficult to teach in school or a training session—and is developed through informal interactions with experienced peers who share stories of their experience. These dynamics serve as a basis for *safety climate* (Zohar, 2010), a shared sense of how safety is enacted often from the point-of-view of less experienced members (e.g., employees) reflecting on their observations of the practice of more experienced members (e.g., supervisors).

5.1. Directions for future research

Our work offers at least three directions for future research. First, we suggest that future studies use a variety of organizational contexts to see if the processes by which safety knowledge sharing occurs have some generalizable features. This diversity can be further strengthened by conducting longitudinal interviews to better understand the process of learning and sharing safety knowledge over time. For example, it might be important to follow novices as they progress from peripheral members to legitimate members, with safety knowledge sharing taking on different forms and functions as novices become more experienced. In doing so, research may be able to explore whether there are pivotal events that novices encounter (e.g., sustaining injuries, seeing others injured), and whether particular learning devices (e.g., storytelling, legends) are more useful than others for safety knowledge sharing at different stages.

Second, future research may also seek to understand possible barriers to sharing safety knowledge. One such barrier could be time, with previous research finding a sense of time pressure can reduce knowledge sharing among colleagues (Connelly et al., 2014). Within the culinary industry, time pressure may be amplified within a busy restaurant setting; thus, it may be fruitful to explore whether other potential barriers for sharing safety knowledge exist, with the possibility of work conditions encouraging safety knowledge hiding (Connelly, Černe, Dysvik, & Škerlavaj, 2019). Indeed, a poignant example of safety knowledge hiding came up in the current interviews. An experienced chef described watching a novice pare cauliflowers with an oversized knife, instead of an appropriately sized paring knife. The experienced chef could tell that the novice would eventually plunge the oversized knife through a cauliflower and cut his hand, but described not warning him to teach him a lesson.

Third, an additional opportunity for future research is the intersection of one community of practice comprised of "common sense" about safety and another community of practice in the dining network, such as those involved in the front-of-house operations (e.g., food runners or serving assistants). Kitchen staff have created a safety climate through safe practices learned during training and tacitly through shared experiences; however, other members of staff who form a part of the overall dining experience enter the physical kitchen space without having the same "common sense." Future research could explore how safety knowledge is shared among members in the wider dining network of restaurants.

5.2. Study limitations

The current study has several limitations worth noting. First, what safety knowledge sharing looks like may differ across different communities of practice. As described above, perhaps when practitioners are under time pressure (e.g., working on a grill line in a fast-paced kitchen), the social processes by which safety knowledge is shared may vary. For example, ethnographic research with fishermen from Thorvaldsen (2018) described that sharing safety knowledge may be as simple as shouting "Watch out!" to other crew members. This finding suggests that, under high pressure, it becomes more challenging for novices to grasp the nature of the situation than it would be within a school setting when tasks can be paused for experienced instructors to share safety knowledge in a more considered way. The retrospective approach taken in this study meant that participants were describing salient and memorable examples of how safety knowledge was shared, which has limited purview on the more mundane, taken-for-granted ways that safety may be constructed.

Second and relatedly, safety is a socially desirable topic on which to interview novice and experienced practitioners. Hence, there is a low likelihood that informants would speak about safety in a realistic way at first, instead emphasizing an overly positive approach (e.g., "Of course safety is important!"). As such, our interviews with practitioners about safety knowledge sharing might have been less revealing than they would have been if the knowledge sharing concerned a less sensitive topic, such as sharing culinary expertise (e.g., Sammells & Dubois, 2020).

Third, the current study drew on one-on-one interviews with only 20 practitioners of varying experience, which might be (a) insufficient for thematic saturation and (b) an inadequate approach to describe social processes of a community of practice. Combining interviews with ethnographic observation and approaches that enable description of examples of safety knowledge sharing in social interaction (e.g., group interviews/focus groups; Tucker & Turner, 2013) might be a more appropriate means by which to collect data on social processes.

5.3. Practical implications

The current findings have implications for classroom and other formal approaches to training, especially for those who are considered novices (or peripheral members) in the field. Safety "common sense" comes from continuous practice by practitioners of all experience levels; as such practitioners need to ensure that novices are provided with ample opportunities "to do" and learn by participating. This can be accomplished by incorporating experiential learning (e.g., hands-on activities) during classroom and formal training sessions, implicating a practice-based view on safety knowledge sharing. More specifically, the themes arising herein suggest that safety knowledge sharing includes the transfer and exchange of difficult-to-articulate phenomena (Hayes & Maslen, 2015), which are better taught through the practical accomplishment of work tasks than through formal methods.

Practitioners can use methods of informal learning alongside formal educational training to enable safety knowledge sharing—for instance, creating space and allotting time for practitioners of varying experience levels to interact. Formal approaches could involve the emphasis of safety in shift handovers (e.g., "safety moments" and opportunities for employees to rotate reflection on near misses that happened during the shift); staff meetings to enable structured opportunities for safety knowledge sharing, which is common in medical contexts (e.g., Randell, Wilson, Woodward, & Galliers, 2010); and networking events with practitioners of varying experience to build and diversify professional networks.

Other research in the broader area of knowledge sharing has found that it often occurs within informal spaces (e.g., Waring & Bishop, 2010) or in virtual forums, such as online communities (e.g., Ardichvili, 2008), with sites for discussing workarounds and injuries (e.g., Fubini et al., 2019). These informal spaces give members an opportunity to reflect, learn, and come to a shared understanding of what safe practice means for their particular line and context of work. By deliberately creating opportunities for socialization to occur, practitioners facilitate and encourage organizational members with varying levels of experience to engage with each other, thus facilitating knowledge sharing.

More generally, the need to understand safety knowledge and how it is shared has increased due to the COVID-19 pandemic, which, at the time of this writing, has had immediate implications for workplaces of all types for almost 18 months and will continue to do so for the foreseeable future. Many employees for whom safety at work was never salient are now directly exposed to safety hazards in the workplace and bombarded with safety messaging governing their everyday interactions. Additionally, the safety practices of the culinary industry, along with those in contexts like health care and long-term care, are now heightened, explicit in our interaction in these contexts (e.g., regular handwashing, masks), and no longer understood to be knowledge reserved for organizational insiders (Gulseren, Lyubykh, & Turner, in press). This rapid expansion of safety knowledge and what it means to work safely is a clear example of how becoming a legitimate practitioner within a particular community of practice does not mean the end of learning about safety as "common sense."

6. Conclusion

The current study has explored how safety knowledge sharing occurred among novices and more experienced members of a culinary arts department. In line with a community of practice perspective (Lave & Wenger, 1991), our findings highlight the social mechanisms through which safety knowledge is shared and learned. They emphasize the differences in how safety knowledge is shared in formal educational and industrial kitchen contexts, and how identification with safety knowledge as "common sense"—that is, the collective understanding of what constitutes safe working practices—happens through continued practice and everyday collaboration among novices and experienced practitioners. Moreover, our work illustrates how common sense is also a currency through which novices transition from peripheral practitioners to more legitimate practitioners.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Example questions from interview protocol

Category	Example main questions	Examples follow-up questions
Background	1. Tell me about your role as a culinary instructor/industry chef/student	1a. How many years have you worked in the culinary industry? 1b. In which culinary program are you enrolled? 1c. What is your work and educational experience in the culinary industry?
Safety knowledge sharing	2. How do/did you learn about safety in culinary? 3. How do you teach new trainees to be safe?	2a. Formal education, mentors on the job, through experience 2b. Describe any workarounds employed that increase safety 2c. How do others share their safety knowledge with you (and in what forms—tacit, explicit, implicit)? 3a. Formal safety programs, storytelling, identifying safe and unsafe behaviors as they happen 3b. How do students, co-workers, and kitchen proprietors react to the safety knowledge you share?
Community of practice	4. Tell me about people you have worked with who have been very safe – what made them safe? Tell me about people you have worked with who are not safe – what made them unsafe? 5. Tell me a little about the "badge of honor" worn by some chefs who have experienced accidents but kept working. 6. Tell me about the safety education and incidents that have happened in your classroom this week.	4a. Do gaps exist between safety knowledge learned in-class versus how safety exercised in practice? 4b. In what instances do you think safe work practices are compromised (e.g., during busy periods)? 5a. How do these incidents and stories affect safety? 6a. Thinking about this past week only, what role has safety played in the education that you are providing to your students? 6b. How do these incidents and stories affect safety?

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Factors related to youth self-efficacy for injury prevention bicycle skills

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ABSTRACT

Introduction: Bicycle riding is a common activity for children, but they are prone to bicycle-related injuries. It is well-established that injury prevention measures such as wearing a helmet and correctly riding a bicycle can reduce the severity of an injury and the likelihood of having an accident. However, how to increase bicycle injury prevention behaviors among children, who collectively fail to engage in injury prevention behaviors, is less well understood. Self-efficacy is consistently predictive of injury prevention behavior, making it an important approach to understanding injury prevention skills among this key population. The objective of this study was to explore and identify factors internal to the child as well as factors about his or her environment that predict a child's self-efficacy for injury prevention skills. *Method:* Two generalized linear mixed effects models were created from survey data collected from elementary school students ($n = 2{,}255$) as part of a school-based bicycle education program. Models focused on self-efficacy for riding a bicycle and self-efficacy for wearing a helmet correctly. *Results:* In both models, road safety knowledge, opportunity for skill building through owning appropriate equipment (a bicycle or helmet), and situation through perception of neighborhood safety were predictive. The analyses reveal these variables as key factors for greater confidence, with feeling safe riding in the neighborhood, in particular, emerging as highly predictive of self-efficacy for injury prevention skills. *Conclusions:* These findings highlight the interplay of individual and environmental factors within confidence for injury prevention behavior. Given self-efficacy's strong relationship to prevention behavior, these findings indicate actionable strategies. *Practical Applications:* The key factors highlighted in this study can be used by policymakers to target specific areas (e.g., neighborhood safety) to promote self-efficacy and thus improve injury prevention. These factors can also inform strategies for establishing safety skills in bicycle-safety education programs.

1. Introduction

Bicycle riding is a common source of exercise, entertainment, and transportation for all ages, especially children. Unfortunately, children ages 5–14 experience a high rate of bicycle-related injuries. In the United States, over 200,000 children in this age group are treated in emergency rooms for bicycle-related injuries per year — almost 600 *per day*, on average (National Electronic Injury Surveillance System (NEISS), 2019). These injury rates are indicative of the highest prevalence of bicycle-related injuries of any age group. Elementary school children are at a key age for instilling bicycle-related injury prevention behaviors, as a population in its formative years for developing lifelong bicycle safety habits and with susceptibility to bicycle-related injuries (Hooshmand et al., 2014; Lachapelle et al., 2013). As a result, is important to understand factors related to injury prevention behavior among this population.

As demonstrated by the injury rates, children are clearly prone to bicycle-related accidents and injury. This could be due to environmental factors related to where children ride a bicycle and because riding a bicycle is a skill that requires practice and attention to injury prevention behaviors (Embree et al., 2016; Li et al., 1995; Macpherson et al., 2004). Despite high incidence of injury, children, collectively, fail to engage in bicycle-related injury prevention behaviors. For example, while helmet use is consistently shown to reduce serious head injury and death, less than 50% of children report that they always wear a helmet (Dellinger & Kresnow, 2010; Høye, 2018). Furthermore, given that adults also tend to not wear helmets, investigating injury prevention behaviors in children is important for triggering healthy habits earlier

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in life. What factors may be related to the lack of uptake of injury prevention behavior among this particularly susceptible population? Social cognitive theory models behavior as an interplay of individual and environmental characteristics, with its construct of self-efficacy viewed as a particularly relevant factor in injury prevention behavior (Bandura, 1986; Karl et al., 2018; Strecher et al., 1986).

Confidence in one's ability to perform a behavior, self-efficacy, is consistently predictive of preventative behavior, including injury prevention (Bandura, 1986). Self-efficacy for a particular health behavior is repeatedly used in theoretical models of health behavior and approaches for health behavior change (Conner & Norman, 2007; McAuley et al., 2011; National Cancer Institute et al., 2012). While it was historically viewed as an independent construct within these models, it has emerged as a key determinant of behavior (Bandura, 1986; McNeill et al., 2006; McAuley et al., 2011; O'Leary, 1985; Strecher et al., 1986). That is, in social cognitive theory, self-efficacy is an independent construct among other individual constructs in the individual and environmental factors within the model. However, given the predictive nature of self-efficacy for actual injury prevention behavior, it may be more important to identify individual and environment factors that contribute to self-efficacy (McNeill et al., 2006; McAuley et al., 2011). For example, in terms of bicycle-related injury prevention behavior, Karl and colleagues (2018) evaluated the predictive nature of self-efficacy within the health action process approach model of health behavior change. They found self-efficacy to be strongly predictive of helmet wearing intention. Therefore, self-efficacy as an outcome for which researchers attempt to identify individual and environmental predictive factors may be an additionally valuable way to examine injury prevention behavior.

Despite self-efficacy's strong predictive nature for one's ability to perform preventative behaviors, research to date has neglected to use self-efficacy as a measure for bicycle-related injury prevention among children. Researchers frequently use knowledge of bicycle safety and road rules, demonstration of safety skills (e.g., coming to a complete stop in a test), and attitude towards road rules as measures of a child's injury prevention behaviors (Lachapelle et al., 2013; Macarthur et al., 1998; Richmond et al., 2014). However, these measures turn up futile results for actual injury prevention behaviors (Macarthur et al., 1998; Richmond et al., 2014). That is, even when these measures indicate sufficient injury prevention skills, there is a lack of evidence to show that this corresponds to everyday injury prevention behavior. As such, self-efficacy may serve as a better means through which to gauge actual injury prevention behavior in this population.

The literature on injury prevention behavior with bicycles among children is further limited by its dependence on frequency of helmet use as the only substantially investigated outcome. Asking children whether or not they wear a helmet gathers prevalence information, but it may be too simplistic, failing to be indicative of whether or not the child can wear the helmet correctly. Education programs attempt to increase helmet use, despite inconsistent results among such interventions: there is evidence both for the positive effect of education programs, as well as evidence for a lack of effect of these programs (see Richmond et al., 2014 for review). By contrast, interventions geared towards improving self-efficacy may demonstrate more effective results (Karl et al., 2018). In line with this, an extension of the research beyond factors influencing helmet use prevalence is necessary.

The literature on helmet use does, however, provide preliminary information for the interplay of individual and environmental factors that may correspond to injury prevention skills (Thompson et al., 2002). Social cognitive theory describes the necessity of looking at both these individual and environmental factors in health behavior. Helmet use differs based on individual characteristics, such as race and ethnicity, and age (Dellinger & Kresnow, 2010). Further, characteristics of the child's surroundings may be related to injury prevention skills. For example, helmet use has been linked to education level within the home, household income, and socioeconomic status (Dellinger & Kresnow, 2010; Embree et al., 2016). Therefore, there is a basis in the literature for individual and environmental factors being linked to injury prevention skills among children.

This study extends this reasoning to examine self-efficacy for injury prevention skills based on a variety of individual and environmental factors. With self-efficacy's predictive nature for injury prevention behavior in mind, this study uses social cognitive theory and strategies for increasing self-efficacy to identify factors that contribute to self-efficacy for injury prevention skills. In an extension beyond helmet use frequency, we created two models with self-efficacy for injury prevention skills as outcomes: self-efficacy for riding a bicycle and self-efficacy for wearing a helmet *correctly*. Our models utilized the broad framework of social cognitive theory by including variables falling into both individual and environmental categories. Within this framework, we also included additional factors from the theory and known processes for increasing self-efficacy: behavioral capability, operationalized as opportunity to learn the skill and knowledge; situation, operationalized as perception of the neighborhood; and vicarious learning, operationalized as seeing others riding in the neighborhood (Conner & Norman, 2007; National Cancer Institute et al., 2012). We hypothesized that the variables included in the models would be predictive of self-efficacy based on social cognitive theory, strategies for building self-efficacy, and documented differences in injury prevention behavior based on demographics (Bandura, 1986; Conner & Norman, 2007; Dellinger & Kresnow, 2010; Heslin & Klehe, 2006; National Cancer Institute et al., 2012; Schunk & Zimmerman, 2007).

2. Materials and methods

2.1. Participants

Participants in this study were elementary school children who agreed to be surveyed following their participation in a school-delivered bicycle safety program in one state within the southeastern region of the United States. De-identified survey data were shared with research partners for this study. Forty-nine individual participants were eliminated from the study because they answered less than 10% of the questions on the survey. The remaining 2,255 individuals were included in the study. Participants ranged in age from 8 to 12 years ($M = 9.82$, $SD = 0.80$). Non-Hispanic White was the most frequently reported race or ethnicity at 47.32%, followed by Non-Hispanic Other (19.29%), Non-Hispanic Black (15.61%), and Hispanic (11.84%; 134 participants chose not to provide this information). The sample was evenly split between males (47.32%) and females (48.12%; 103 participants chose not to provide this information). Descriptive characteristics of the sample are given in Table 1.

2.2. Materials

A 40-item questionnaire used in the program contained student self-reported knowledge about bicycle safety and self-efficacy for bicycle safety skills prior to and after the bicycle safety program (Lachapelle et al., 2013). Students were instructed that completing the questionnaire was voluntary. The questionnaire was completed as a component of standard education programing, thus no parent consent was required. The questionnaire contained two self-efficacy questions that could be used by the present analysis as

Table 1
Sample characteristics.

Variable		n (%)
Age*		
	8–10 years of age	1781 (78.98)
	11–12 years of age	409 (18.14)
Gender*		
	Male	1067 (47.32)
	Female	1085 (48.12)
Race and Ethnicity*		
	Hispanic	267 (11.84)
	Non-Hispanic Black	352 (15.61)
	Non-Hispanic White	1067 (47.32)
	Non-Hispanic Other	435 (19.29)
Knowledge, n(%) correct		
	What to do at a stop sign	1396 (61.91)
	How to signal a turn	1050 (46.56)
	When to wear a helmet	1474 (65.37)
	How to wear a helmet correctly	1374 (60.93)
Own a bike, n(%) yes		1736 (76.98)
Own a helmet, n(%) yes		1365 (60.53)

*Values may not add to total sample size due to incomplete surveys among a portion of the sample.

outcomes for our models: self-efficacy for riding a bicycle (Model 1) and self-efficacy for wearing a helmet correctly (Model 2). The questions relevant to the present study were only those that asked about knowledge and self-efficacy *prior* to the bicycle safety program, as an evaluation of effectiveness of the program was not the purpose of this study.

Four types of information were collected from the questionnaire: self-efficacy, bicycle skill knowledge, characteristics of one's neighborhood, and individual demographics. Students reported self-efficacy from 0-10 in riding a bicycle and wearing a helmet correctly: "Before bicycle skills clinic, I could ride a bicycle without training wheels" and "Before bicycle skills clinic, I could wear a helmet correctly." Knowledge questions tested stop sign etiquette, how to signal a turn, when to wear a helmet, and how to wear a helmet correctly. Each question was multiple choice with four options as well as a "Not sure" option. How to wear a helmet correctly ("how do you think you should wear a helmet?") and how to signal a left turn ("what do you think is the correct way to signal turning left?") required students to select the correct picture depiction of these skills among the options. Answer options for how to wear a helmet showed a person wearing a helmet: (a) too far back, (b) without the strap clipped securely, (c) correctly, and (d) too far forward; answer options for how to signal a turn showed a human bicyclist figure from behind with (a) left arm outstretched straight signaling a left turn (correct), (b) left arm at an upward-facing right angle signaling a right turn, (c) right arm outstretched straight, and (d) left arm at a downward-facing right angle. Correct knowledge for when to wear a helmet ("how often do you think you should wear a helmet when riding a bike?") required students to respond "All of the time," rather than "Most of the time," "Sometimes," or "Never;" correct knowledge for what to do at a stop sign ("what did you think bicyclists should do at a stop sign?") required students to respond "Stop and look left right and left again before going," rather than "Slow down and signal to let others know you are going through," "Pull forward until drivers can see you and signal for cars to go first," or "Slow down and look for cars, but keep going if no cars are coming." Characteristics of one's neighborhood were comprised of the following two questions: "Would you feel safe riding a bike in your neighborhood during the day?" and "Do you see many people ride bikes in your neighborhood?" Students could respond "Never," "Sometimes," "Most of the time," or "All of the time" to each of these questions. Demographic questions asked about gender, ethnicity, and age.

The questionnaire was administered only after the program. It thereby required students to reflect on their self-efficacy and knowledge prior to the program with the insight gained from the program (Sibthorp et al., 2007). The retrospective pretest is a tool in behavioral research with self-report data (Nimon et al., 2011; Sibthorp et al., 2007). Research shows that this methodology reduces overestimation of pre-program knowledge and competencies (Moore & Tananis, 2009). For example, students may not be aware of their own incorrect knowledge (or lack of knowledge) prior to the program, with this metacognition reliant on the intervention itself (Moore & Tananis, 2009; Sibthorp et al., 2007).

2.3. Data analysis

We assessed the influence of individual factors and environmental factors on self-efficacy for riding a bicycle (Model 1) and self-efficacy for wearing a helmet correctly (Model 2) through two generalized linear mixed effects models. A full list of variables included in these models is given in Table 2. Age was dichotomized into younger (8–10 years of age) and older (11–12 years of age) students due to different drivers of behavior among younger and older children (Morrongiello & Lasenby-Lessard, 2007). Given the ordinal nature of the self-efficacy outcomes, the models utilized a cumulative logit link and descending option to model likelihood of higher self-efficacy. The models also accounted for the multilevel nature of students at the same schools. Data analysis was performed with SAS version 9.4. Values of $p < .05$ were considered statistically significant.

3. Results

The analysis revealed numerous individual characteristics and environmental factors related to self-efficacy for injury prevention

Table 2
Variables in models.

			Model 1	Model 2
Outcome Variable			Self-efficacy for riding a bicycle	Self-efficacy for wearing a helmet correctly
Individual predictor variables				
	Demographics		Age	Age
			Gender	Gender
			Ethnicity	Ethnicity
	Behavioral capability			
		Opportunity for skill building	Owning a bicycle	Owning a helmet
		Knowledge	Knowledge of what to do at a stop sign	Knowledge of when to wear a helmet
			Knowledge of how to signal a turn	Knowledge of how to wear a helmet correctly
Environmental predictor variables				
	Situation		Feel safe riding in the neighborhood	Feel safe riding in the neighborhood
	Vicarious learning/Modeling		See others riding in the neighborhood	See others riding in the neighborhood

skills. Within the individual characteristics, male students tended to show increased odds for expressing confidence relative to female students. A child's correct knowledge and having the opportunity to learn a skill also showed increased odds. Further, within the environmental factors, feeling safe riding a bicycle in the neighborhood emerged as highly indicative of increased odds for confidence. In the following detailed results, we reported significant increased or decreased odds of self-efficacy for the injury prevention skills. Complete results are given in Tables 3 (Model 1) and 4 (Model 2) (Table 4).

3.1. Self-efficacy for riding a bicycle

In the case of self-efficacy for riding a bicycle, perceived situational factors emerged most predictive, followed by opportunity to learn the skill, knowledge, and gender. Those who feel safe riding a bicycle in their neighborhood all of the time or most of the time had 4.05 and 2.09 times the odds, respectively, of expressing higher confidence in riding a bicycle relative to those who never feel safe. Opportunity to learn the skill through owning a bicycle and knowledge for bicycle safety rules were also highly predictive. Those who own a bicycle showed 2.77 times the odds of expressing higher confidence relative to non-owners and those who are correct in their answer of what to do at a stop sign (1.32) and how to signal a turn (1.34) showed greater odds of expressing higher confidence relative to those who incorrectly answered these questions. Finally, odds of higher confidence were also greater for males (1.26) than females.

Table 3
Results for factors related to self-efficacy for riding a bicycle.

Variable	Odds Ratio (95% CI)	*p*-value
Age (younger*)	1.34 (1.00, 1.82)	0.054
Gender (female*)	1.26 (1.01, 1.56)	0.040
Race and ethnicity (Non-Hispanic White*)		
Hispanic	0.81 (0.57, 1.14)	0.224
Non-Hispanic Black	1.17 (0.84, 1.63)	0.351
Non-Hispanic Other	1.01 (0.75, 1.35)	0.960
Own a bicycle (no*)	2.77 (2.10, 3.63)	<0.001
Stop sign correct (incorrect*)	1.32 (1.05, 1.65)	0.016
Signal turn correct (incorrect*)	1.34 (1.08, 1.67)	0.008
Feel safe riding in neighborhood (never*)		
Sometimes	1.40 (0.92, 2.12)	0.117
Most of the time	2.09 (1.38, 3.15)	<0.001
All of the time	4.05 (2.73, 6.00)	<0.001
See others riding in neighborhood (never*)		
Sometimes	1.08 (0.82, 1.42)	0.600
Most of the time	1.07 (0.74, 1.54)	0.722
All of the time	1.26 (0.84, 1.89)	0.265

*Reference category; CI: confidence interval.

Table 4
Results for factors related to self-efficacy for wearing a helmet correctly.

Variable	Odds Ratio (95% CI)	*p*-value
Age (younger age group*)	1.00 (0.80, 1.26)	0.974
Gender (female*)	1.24 (1.04, 1.48)	0.016
Race and ethnicity (Non-Hispanic White*)		
Hispanic	0.79 (0.58, 1.07)	0.124
Non-Hispanic Black	1.19 (0.90, 1.57)	0.234
Non-Hispanic Other	0.92 (0.73, 1.16)	0.443
Own a helmet (no*)	1.74 (1.42, 2.13)	<0.001
When to wear a helmet correct (incorrect*)	1.85 (1.53, 2.24)	<0.001
How to wear a helmet correct (incorrect*)	1.64 (1.37, 1.96)	<0.001
Feel safe riding in neighborhood (never*)		
Sometimes	1.05 (0.71, 1.55)	0.822
Most of the time	1.17 (0.80, 1.71)	0.415
All of the time	2.44 (1.70, 3.50)	<0.001
See others riding in neighborhood (never*)		
Sometimes	0.87 (0.69, 1.10)	0.250
Most of the time	0.94 (0.70, 1.27)	0.691
All of the time	1.44 (1.03, 2,01)	0.035

*Reference category; CI: confidence interval.

3.2. Self-efficacy for wearing a helmet correctly

A similar pattern was seen for self-efficacy for wearing a helmet correctly, as situation, opportunity to learn the skill, knowledge, and gender again emerged as predictive. Again, feeling safe riding in the neighborhood was most influential, as those who stated they feel safe all the time had 2.44 times the odds of expressing higher confidence compared to those who stated they never feel safe. Additionally, opportunity to learn the skill through owning a helmet showed that those with a helmet had 1.74 times the odds of expressing higher confidence compared to non-owners. Further, knowledge was again predictive and for both knowledge questions included in this model, how to wear a helmet correctly and when to wear a helmet. Those who correctly identified how to wear a helmet correctly and correctly answered that one should always wear a helmet had 1.64 and 1.85 times the odds, respectively, of expressing higher confidence relative to those who incorrectly answered the respective question. Similarly, gender was again influential, with odds of higher confidence increasing by a factor of 1.24 from female to male. In contrast to Model 1, these results also revealed vicarious learning as predictive of self-efficacy. Specifically, those who reported they see others riding in the neighborhood all the time showed 1.44 times the odds of expressing higher confidence relative to those who reported never seeing others riding in the neighborhood.

4. Discussion

This exploratory analysis aimed to identify factors internal to the child, as well as factors about his or her environment, that predict a child's self-efficacy for injury prevention skills. The results revealed that both factors characterized as individual and environmental contributed to the models. Within these categories, the variables that emerged as predictive overlapped substantially with self-efficacy for riding a bicycle and self-efficacy for wearing a helmet correctly. In both models, behavioral capability through opportunity for skill building (owning a bicycle or helmet) and knowledge, as well as perceived situation, were predictive, lending support to our hypotheses. However, our hypothesis regarding the influence of modeling or vicarious learning, through seeing others riding in the neighborhood, was generally countered, as was expected differences based on ethnicity. The results of this study suggest a focus shift from prevalence information and knowledge promotion to fostering self-efficacy in attempts to promote injury prevention behavior among children. As such, identification of these factors, and their dissemination so that they may be acted upon, may help to increase self-efficacy for road safety skills and, in turn, injury prevention behavior.

These results reaffirm the necessity to investigate both individual and environmental factors when examining health behavior, as both categories emerged as predictive. In a divergence from typical factors, however, perhaps the most novel and interesting finding is the highly predictive nature of feeling safe riding a bicycle in the neighborhood. In both the model for riding a bicycle and wearing a helmet correctly, feeling safe riding in one's neighborhood all the time was indicative of increased odds of self-efficacy. These findings extend the research beyond environmental factors such as socioeconomic status and reveal the influence of a perception of safety in the immediate vicinity. That is, self-efficacy and, by extension, injury prevention behavior, may be contingent on safety policies and on psychosocial characteristics. In fact, perception of neighborhood safety has been shown to be a more effective predictor of physical activity than objective measures (e.g., crime rate; Janssen, 2014). Within recreational bicycling literature, perception was an important predictive factor, while objective measures of the environment were not (Ma & Dill, 2016). In these ways, environmental characteristics show a subjective component, reinforcing social cognitive theory's emphasis on the interplay of these features. Future research should examine the features of the neighborhood that influence a child's perception of feeling safe or not feeling safe riding in that environment, thereby complying with the interaction of individual and environmental factors in driving a person's behaviors.

Prior research on the interplay of individual and environmental factors in injury prevention skills led to our hypotheses regarding the influence of demographic factors. However, previous research revealed differences based on race and ethnicity — the demographic factor that did not emerge as predictive in either of our models (Dellinger & Kresnow, 2010). Our analyses in this domain are limited, as, while our sample has students from a variety of racial and ethnic backgrounds, it is comprised mostly of students identifying as White, which may have contributed to lack of evidence for differences based on these factors. That said, prior research that found racial and ethnic differences in helmet use prevalence also had a disproportionate amount of White children in the sample. These discrepancies may demonstrate the difference between investigating factors related to reported behavior and factors related to reported self-efficacy for a skill and indicates a need for additional research on reporting differences between these two question types.

The findings have practical implications. Given that the use of reported self-efficacy for wearing a helmet correctly and riding a bicycle may be more indicative of everyday behavior, the fact that factors were found to be linked to self-efficacy reveals actionable strategies for advancing self-efficacy and injury prevention behaviors (Bandura, 1986; O'Leary, 1985; Strecher et al., 1986). First, the results have implications for policymakers. Those intent on promoting cycling and related injury prevention behavior among children should look at neighborhood safety and perception of such safety. Second, the results reinforce practices by bicycle safety education programs and suggest alterations. There was a demonstrated association between opportunity for skill building, through ownership of a helmet or bicycle, and higher odds of confidence. Such findings support practices by bicycle safety education programs of giving students free helmets (Watts et al., 1997). The adoption of this practice by more programs may not only result in higher helmet prevalence, as documented in the literature, but also relate to self-efficacy for wearing a helmet *correctly*. Alternatively, the findings also suggest that injury prevention behavior is determined by more than knowledge, again asserting that knowledge tests may not be the most appropriate gauge of everyday behavior. Finally, the results demonstrate differences among students for their starting points prior to education safety programs. For example, the finding that boys show higher self-efficacy for wearing a helmet correctly pre-program may indicate that, while girls need more attention regarding helmet fit and buckles, boys are further along in the behavior change process and more so require practicing this skill. Importantly, the identification of these differences pre-program can help program leaders implement more effective programs by creating more targeted interventions. As such, the results provide avenues for policymakers, educators, and future research.

The present study is preliminary and not without limitations. First, while the sample comes from 13 unique elementary schools and is relatively diverse, the fact that all data were collected in one geographic region limits its representativeness. It is a convenience sample collected in varying locations and with different survey administrators. Teachers within the schools acted as survey administrators and, while they were provided with a detailed survey administration guide, the data collection environment was less controlled than is ideal. Second, the analysis was limited to those items addressed in the survey utilized by the bicycle safety program. Therefore, there are additional potentially important factors that further research should add to our investigation. For example, parents have been shown to influence a child's bicycle riding prevalence and behaviors (e.g., Ross et al., 2014; Tal & Handy, 2008); however, we were not able to include parent behaviors in our analysis. Similarly, while an aim of the study was to extend the research in this area beyond reports of behavior prevalence, it would be useful to have this item (i.e., self-reported use of a helmet). Instead, we were limited to the two outcomes reported in this study and prevalence would be an interesting addition to the study in order to directly examine the relationship between self-efficacy for behaviors and reported behavior. Finally, this study is limited by the observational data to an inability to suggest causality. For example, feeling safe riding in the neighborhood may not cause an increase in self-efficacy for wearing a helmet correctly. By contrast, the relationship we found may be mediated by known additional factors related to promoting self-efficacy, such as a practice and experiencing with the skill in one's everyday context (Yeo et al., 2006; Zulkosky, 2009). Such limitations guide approaches for future research.

5. Conclusions

The present study draws attention to the need to employ individual and environmental factors in health behavior and to the role of self-efficacy (i.e., as an outcome) among injury prevention health behavior research. The identification of factors as contributable to reported self-efficacy can aid policymakers in targeting specific areas (e.g., neighborhood safety) and inform strategies used in bicycle-safety education programs. Importantly, these suggestions exist within the refocused aim of concentrating policies and programs on promoting self-efficacy, as perhaps the best approach to understanding and reducing bicycle-related injury. Doing so can keep a population particularly prone to these injuries safer and healthier.

CRediT authorship contribution statement

Kerry A. Howard: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Sarah F. Griffin:** Conceptualization, Methodology, Supervision, Writing - review & editing. **Laura J. Rolke:** Methodology, Data curation, Writing - review & editing. **Kerry K. Sease:** Resources, Supervision, Writing - review & editing.

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Fatal hit-and-run crashes: Factors associated with leaving the scene

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ABSTRACT

Introduction: Hit-and-run crashes are a criminal offense that leave the victim without prompt medical care or the ability to receive financial compensation. *Method:* The purpose of the current study was to quantify the factors associated with the probability that a driver leaves the scene of a fatal crash, using multiple imputation to incorporate information from drivers who were never apprehended and thus whose characteristics were unknown. *Results:* The results of this study show that in addition to driver, vehicle, and environmental factors having significant impacts on the likelihood of a driver fleeing the scene, economic and demographic factors are important as well. *Practical Applications:* This analysis allows for a more holistic understanding of hit-and-run crashes and informs potential countermeasures and future research.

1. Introduction

Hit-and-run crashes are an issue for both traffic safety and law enforcement. This crash type has been pervasive in the United States and in recent years accounted for around 5% of total fatal crashes and claimed approximately 1,800 lives per year, with pedestrians accounting for 66% of those fatalities (Benson et al., 2018). Deaths from hit-and-run crashes have been increasing at a rate of 7.2% per year since 2009 and reached the highest number on record in 2016 (Benson et al., 2018).

Developing a comprehensive understanding of the factors associated with leaving the scene of a crash can be a challenge, as approximately 50% of hit-and-run drivers are never identified. Of those who are identified, drivers who flee fatal pedestrian crashes tend to be younger and male (Solnick & Hemenway, 1994; Solnick & Hemenway, 1995; MacLeod et al., 2012). In these same crashes, drivers of older vehicles are about 45% more likely to flee the scene of a crash than those with newer vehicles (Solnick & Hemenway, 1995; MacLeod et al., 2012). Another common characteristic of identified hit-and-run drivers is a history of traffic violations, including driving under the influence and driving without a valid license. A past DWI conviction increases the odds of committing a hit-and-run when considering pedestrian-involved fatal crashes (Solnick & Hemenway, 1995; MacLeod et al., 2012; Kim et al., 2008). An invalid license also significantly increases the odds of fleeing, by as much as 400% in some studies (Solnick & Hemenway, 1994; Solnick & Hemenway, 1995).

A consistent finding across a range of crash severities and victim types is that hit-and-runs are more likely to occur at night (Solnick & Hemenway, 1994; MacLeod et al., 2012; Tay et al., 2009; Aidoo et al., 2013; Bahrololoom et al., 2016). The roadway functional class and speed limit of the collision site are predictive of the likelihood of a hit-and-run crash, with less congested county and municipal roads being more likely to host hit-and-run crashes (Tay et al., 2009), as are roads with lower speed limits (Solnick & Hemenway, 1995; MacLeod et al., 2012).

A study by Liu et al. (2018) appended Census tract-level data to crash data to examine how the probability of a hit-and-run varied in relation to sociodemographic characteristics of crashes in Michigan. Results indicated that the extent to which driving under the influence adds to the risk of a driver committing a hit-and-run varied regionally. They also found that higher unemployment rates and lower rates of college graduation per population were associated with greater probability that a driver would leave the scene of a crash.

Given the recent increasing trend in hit-and-run fatal crashes in the United States, a better understanding of underlying factors is needed to inform future research and countermeasures. The purpose of the current study was to quantify the factors associated with the probability that a driver leaves the scene of a fatal crash, using multiple imputation to incorporate information from drivers who were never apprehended and thus whose characteristics were unknown. In addition to updating previous research findings with more recent data, the current study seeks to improve understanding of factors associated with drivers leaving the scene of fatal

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crashes by: (a) examining all fatal hit-and-run crashes in the United States rather than only those that involved pedestrians; (b) using the method of multiple imputation to take into account drivers who left the scene and were never identified rather than only those who were caught; and (c) incorporating Census tract-level sociodemographic data from the places where crashes occurred.

2. Methods

The current study investigated driver, vehicle, and environmental factors associated with the probability that a driver who was involved in a fatal crash would leave the scene. Multiple imputation was used to estimate the distributions of driver- and vehicle-related variables among drivers who left the scene and were never identified.

2.1. Data

Data on drivers involved in crashes that occurred on public roads in the United States in the years 2010–2017 and resulted in a death within 30 days of the crash were obtained from the National Highway Traffic Safety Administration (NHTSA) Fatality Analysis Reporting System (FARS). The original data files included a total of 377,749 drivers. Drivers who died (n = 175,011) were excluded from the study because such drivers could not plausibly leave the scene.

Driver-related variables examined were the driver's age, sex, license status, driving under the influence convictions in the past three years, moving violations in the past three years, distance from the driver's home to the location of the crash (linear distance from the centroid of the driver's ZIP code to the latitude/longitude of the crash), and severity of the driver's injuries. Vehicle-related variables examined were the vehicle type, age, owner, and the extent of damage. Crash-related variables examined were the number of vehicles involved in the crash (1 vs. 2+) and whether the crash involved any non-motorists (e.g., pedestrians or cyclists). Environmental variables examined were Census region, season, time of day, day of week, interaction of day and time, speed limit, and lighting conditions. These variables were chosen because they reflect the physical environment in which the crashes occurred. To model sociodemographic characteristics of the places in which the crashes occurred, census tract-level poverty rate, unemployment rate, percent of residents ages 25 and older with at least a high school diploma or equivalent, percent of residents who walk to work, percent of residents who do not identify as non-Hispanic white, and population density were obtained from the U.S. Census Bureau's American Community Survey 2012–2016 five-year data set.

Among drivers who left the scene, a driver was assumed to have not been identified if the driver's age, state of residence, driver license status, and previous driving record were all reported as unknown and the driver was not reported as having been charged with any violation.

2.2. Statistical analysis

Poisson regression was used to estimate the ratio of the adjusted rate of leaving the scene associated with each of the explanatory variables. Adjusted rate ratios (aRRs) were obtained by exponentiating the regression coefficients. Rate ratios rather than odds ratios were preferred because leaving the scene was relatively common for some categories of some explanatory variables (e.g., drivers who struck pedestrians; drivers who lacked a valid license), thus odds ratios would overestimate rate ratios (Cummings, 2009). Poisson regression has been shown to produce unbiased point estimates but overestimate variances when used to model binary outcomes, thus variances were corrected using the robust variance estimator (Zou, 2004; Chen et al., 2018).

Continuous variables were plotted against the probability of hit-and-run using linear, quadratic, and fractional polynomial plots to select the functional form of each variable to include in the model. The percent of residents who walk to work was modeled using the percent and its square; Census tract population density was modeled using the density and its square root; distance from home was modeled using the natural log of the distance. All other continuous variables were modeled as linear.

Drivers who left the scene of crashes and were not identified (3.2% of all drivers) had missing values for most driver- and vehicle-related variables; a small number of cases had missing values for other variables as well. Missing values were imputed using multiple imputation by chained equations (van Buuren et al., 1999). Continuous, ordinal, and categorical variables were imputed using predictive mean matching with three nearest neighbors, ordered logistic regression, and multinomial logistic regression, respectively. Ten independent copies of the data set were created, each with missing values replaced with imputed values.

The performance of the imputation model was assessed by simulating missing data from among complete cases, imputing them, estimating aRRs from the data with the simulated missing values imputed, and comparing them to aRRs obtained using the original values. The procedure is described further and results are provided in the Appendix.

Point estimates of statistics were estimated by computing the statistic in each of the 10 imputed data sets separately and then averaging them. Standard errors were estimated using the method of Rubin (1987) to account for both the variability in the observed data and the uncertainty in the imputed data.

Analyses were performed using statistical software Stata version 15.0 (StataCorp LLC, College Station, TX).

3. Results

Hit-and-run drivers comprised 6.5% of all drivers who survived fatal crashes over the study period. Of drivers who left the scene, 51% were subsequently identified. A majority (59.9%) of the hit-and-run drivers struck non-motorists (Table 1).

Table 1
Surviving Drivers Involved in Fatal Crashes, by hit-and-run status and crash type, United States, 2010–2017.

	Remained at scene (n = 189,394)	Left scene, identified (n = 6,676)	Left scene, not identified (n = 6,405)	Total left scene (n = 13,081)
Crash type	Column %			
Single-vehicle vs. nonmotorist (s)	17.8	55.2	64.7	59.9
Single-vehicle only	8.7	7.9	1.7	4.9
Multiple-vehicle	73.5	36.8	33.6	35.3

3.1. Description of sample

Hit-and-run drivers who were identified tended to be younger than drivers that did not flee: 60% of those who fled were younger than 35 years old, compared with 41% of drivers who remained at the scene (Table 2). Males made up 79% of drivers who left versus 70% who stayed. More than one-third of identified hit-and-run drivers lacked a valid license, compared with fewer than 10% of those who remained at the scene. Hit-and-run drivers were also more likely to have a history of previous DWI convictions and/or moving violations.

Drivers who left the scene tended to drive older vehicles than drivers who did not flee (e.g., 56% of vehicles that left the scene were 10+ years old, compared with 44% of those that remained

Table 2
Percent of surviving drivers who left the scene of a fatal crash in relation to crash characteristics, United States, 2010–2017.

	Remained at scene (n = 189,394)	Left scene, identified (n = 6,676)	Left scene, not identified (n = 6,405)	Total left scene (n = 13,081)
	Column %			
Region				
Northeast	11.6	12.8	10.8	11.8
Midwest	19.6	17.3	15.2	16.3
South	47.7	41.7	45.9	43.7
West	21.1	28.3	28.2	28.2
Season				
Spring	23.8	24.3	22.0	23.2
Summer	26.5	26.8	24.8	25.8
Fall	27.0	26.4	28.2	27.3
Winter	22.7	22.6	25.0	23.7
Day				
Mon-Thurs	53.5	43.5	44.4	44.0
Friday	16.3	15.0	15.8	15.4
Saturday	16.5	21.5	20.7	21.1
Sunday	13.7	20.0	19.1	19.6
Time				
6–8:59 am	10.5	6.9	6.0	6.5
9–11:59 am	11.0	3.8	2.4	3.1
12–2:59 pm	15.3	5.6	3.0	4.3
3–5:59 pm	18.9	8.7	5.7	7.2
6–8:59 pm	17.4	19.7	19.3	19.5
9–11:59 pm	12.8	23.8	26.2	25.0
12–5:59 am	14.1	31.7	37.3	34.4
Speed limit				
≤25 mph	5.4	12.0	9.5	10.8
30–35 mph	15.7	29.7	29.3	29.5
40–45 mph	24.5	28.3	27.2	27.8
≥50 mph	54.5	30.0	34.0	31.9
Lighting				
Daylight	54.9	23.7	12.6	18.3
Dawn/dusk	4.2	4.1	3.2	3.6
Dark	41.0	72.2	84.2	78.0
Towed due to damage				
Yes	65.0	30.4	6.7	19.0
No	35.0	69.6	93.3	81.0
Driver age				
<20	7.5	8.7	0.0	4.4
20–34	33.5	51.3	0.0	26.2
35–49	26.4	23.2	0.0	11.8
50–64	22.0	11.9	0.0	6.1
65–79	8.4	2.6	0.0	1.3
80+	2.0	0.6	0.0	0.3
Unknown	0.2	1.9	100.0	49.9
Driver injury severity				
Not injured	49.2	73.8	43.2	58.8
Possible/minor injury	33.8	17.1	0.9	9.1
Incapacitating injury	15.8	2.1	0.0	1.1
Unknown	1.2	7.1	55.9	31.0

	Remained at scene (n = 189,394)	Left scene, identified (n = 6,676)	Left scene, not identified (n = 6,405)	Total left scene (n = 13,081)
	Column %			
Driver sex				
Female	29.1	19.0	0.5	10.0
Male	70.8	79.1	4.6	42.6
Unknown	0.1	1.9	94.8	47.4
Driver license status				
Valid	90.3	54.6	0.0	31.5
Expired/cancelled/denied	0.8	2.4	0.0	1.4
Suspended/revoked	4.4	16.8	0.0	9.7
Unlicensed	3.5	13.1	0.0	7.5
Unknown	1.0	13.1	100.0	49.9
DWI convictions past 3 years				
0	96.6	79.7	0.0	45.9
≥1	1.8	6.2	0.0	3.6
Unknown	1.6	14.2	100.0	50.5
Moving violations past 3 years				
0	69.2	52.4	0.0	30.2
1	17.3	16.3	0.0	9.4
2	6.5	7.8	0.0	4.5
≥3	5.5	9.4	0.0	5.4
Unknown	1.6	14.2	100.0	50.5
Miles from driver's home				
<5	32.4	42.7	0.1	24.6
5–50	48.6	37.4	0.1	21.6
>50	16.7	6.2	0.0	3.6
Unknown	2.2	13.7	99.9	50.2
Vehicle type				
Car/pickup/van/minivan/SUV	82.7	85.5	24.4	59.6
Large truck/bus	14.8	4.1	1.6	3.0
Motorcycle	1.7	0.8	0.2	0.6
Other	0.3	0.3	0.1	0.2
Unknown	0.6	9.3	73.7	36.6
Vehicle age (years)				
0–4	26.6	15.7	2.6	10.2
5–9	28.7	22.4	3.0	14.2
10–14	26.3	27.5	3.9	17.5
15–19	12.7	16.0	2.5	10.3
20+	5.4	7.1	0.6	4.3
Unknown	0.4	11.3	87.3	43.5
Owner of vehicle				
Driver is owner	52.2	38.3	0.5	22.3
Other private owner	30.4	41.7	2.6	25.1
Business/government fleet	16.7	5.7	0.5	3.5
Stolen vehicle	0.1	1.1	1.1	1.1
Unknown	0.6	13.2	95.2	48.0

at the scene). Drivers who remained at the scene were more likely to be driving their own vehicle or a vehicle registered to a business or government fleet; drivers who left were relatively more likely to be driving a vehicle registered to another party.

Drivers involved in crashes during evening/night hours and on the weekends were much more likely to leave the scene than drivers involved in crashes during daytime hours and on weekdays. Drivers involved in crashes on lower-speed roads were more likely to leave the scene than drivers involved in crashes on higher-speed roads.

Crashes in which surviving drivers fled the scene tended to occur in Census tracts with slightly greater poverty and unemployment rates, slightly lower rates of residents' having completed high school, higher proportions of residents of races other than non-Hispanic white, higher proportions of residents who walk to work, and higher population densities (Table 3). Directionally-similar differences were observed between drivers who left the scene and were identified versus those not identified.

3.2. Factors associated with leaving the scene in multivariable analysis

After imputation of missing values and adjustment for all factors examined in the study, several factors were significantly associated with the proportion of surviving drivers who left the scene (Table 4). Drivers who struck non-motorists were 66% more likely to leave the scene than drivers involved in multiple-vehicle crashes. The rate of leaving the scene decreased with increasing driver age by an average of 12% per decade of driver age. Males were 70% more likely to leave the scene than females. Drivers with an invalid license or no license were more than twice as likely to leave the scene as were validly licensed drivers. Drivers with at least one previous DWI conviction were 54% more likely to leave the scene than drivers with none. The proportion of drivers who left the scene also increased with increasing number of previous moving violations.

Drivers of rental vehicles or vehicles registered to other private individuals were approximately twice as likely to leave the scene as were drivers in their own vehicles; drivers in stolen vehicles were more than three times as likely to leave the scene. Drivers in vehicles registered to a business or government entity were significantly less likely to flee. While drivers of older vehicles were more likely to leave the scene in bivariate analysis, this was not statistically significant after adjustment for other factors including driver injury severity and vehicle damage (not shown).

Drivers who crashed on Saturdays and Sundays were 12% and 18% more likely to leave the scene, respectively, than were drivers who crashed on Monday-Thursday. Drivers who crashed in the evening or overnight hours were much more likely to leave the scene than were drivers who crashed in the morning or early afternoon. Drivers who crashed on roads with speed limits of 40–45 and 50+ miles per hour were 15% and 20% less likely to leave the scene, respectively, than were drivers who crashed on roads with speed limits of 25 miles per hour or lower. Drivers were 0.7% more likely to leave the scene for each 1 percentage point increase in the unemployment rate of the Census tract, and 0.2% more likely to leave the scene for each 1 percentage point increase in the propor-

Table 4
Adjusted rate ratios for leaving the scenes of fatal crashes among drivers who survived, United States, 2010–2017.

	Incidence Rate Ratio (95% CI)	
Driver age (+10 years)	0.88	(0.86–0.90)
Driver sex (male vs. female)	1.70	(1.53–1.89)
Natural log of driver's distance from home	1.02	(0.98–1.06)
Previous DWI convictions (≥1 vs. 0)	1.54	(1.44–1.64)
Previous moving violations (reference = 0)		
1	1.13	(1.08–1.19)
2	1.20	(1.13–1.28)
≥3	1.24	(1.16–1.32)
Driver license status (reference = valid)		
Invalid	2.32	(2.19–2.44)
Unlicensed	2.52	(2.39–2.66)
Driver injury severity (reference = not injured)		
Minor injury	0.61	(0.57–0.65)
Incapacitating injury	0.18	(0.15–0.21)
Owner of vehicle (Reference = driver is owner)		
Other private owner or rental vehicle	1.98	(1.81–2.17)
Business/government fleet	0.59	(0.49–0.71)
Stolen vehicle	3.13	(2.74–3.58)
Vehicle type (reference = car/pickup/van/SUV)		
Large truck/bus	0.80	(0.67–0.97)
Motorcycle	1.03	(0.88–1.21)
Vehicle age (+10 years)	1.03	(0.99–1.06)
Vehicle towed due to damage (yes vs. no)	0.33	(0.31–0.35)
Day of week (reference = Monday–Thursday)		
Friday	1.03	(0.98–1.07)
Saturday	1.12	(1.07–1.17)
Sunday	1.18	(1.13–1.23)
Time of day (reference = 9:00–11:59 am)		
12–2:59 pm	1.02	(0.90–1.14)
3–5:59 pm	1.04	(0.93–1.16)
6–8:59 pm	1.27	(1.13–1.43)
9–11:59 pm	1.62	(1.43–1.83)
12–5:59am	2.06	(1.83–2.33)
6–8:59am	1.42	(1.27–1.60)
Speed limit (reference < 30 miles per hour)		
30–35 miles per hour	0.95	(0.90–1.01)
40–45 miles per hour	0.85	(0.80–0.91)
≥50 miles per hour	0.80	(0.74–0.86)
Lighting conditions (reference = daylight)		
Dawn/dusk	1.43	(1.30–1.58)
Dark	1.61	(1.49–1.73)
Crash type (reference = multiple-vehicle)		
Single-vehicle vs. nonmotorist	1.66	(1.60–1.72)
Single-vehicle only	1.02	(0.94–1.11)
Census tract of crash location		
% below poverty level (+1 pp)	1.000	(0.999–1.002)
% unemployed (+1 pp)	1.007	(1.004–1.010)
% High-school graduate (+1 pp)	1.000	(0.998–1.001)
% not non-Hispanic white (+1 pp)	1.002	(1.01–1.003)

Rate ratios adjusted for region of country; season; Census tract population density, % of workers who walk to work in Census tract, and all other variables in table.
pp = percentage point.

Table 3
Sociodemographic characteristics of fatal crash locations and whether a surviving driver leaves the scene of the crash, United States, 2010–2017.

	Remained at scene (*n* = 189,394)	Left scene, identified (*n* = 6,676)	Left scene, not identified (*n* = 6,405)	Total left scene (*n* = 13,081)
Census tract of crash location	Median (Interquartile range)			
% below poverty level	13.4 (7.8–21.4)	17.1 (10.1–27.1)	20.2 (11.8–31.6)	18.6 (10.7–29.3)
% unemployed (ages 16 +)	6.9 (4.6–10.2)	8.1 (5.3–12.0)	9.0 (5.9–13.3)	8.4 (5.6–12.6)
% High-school graduate (ages 25 +)	87.5 (80.0–92.7)	84.9 (74.9–91.4)	81.5 (71.2–89.3)	83.3 (73.1–90.6)
% race other than non-Hispanic white	27.5 (10.5–56.8)	45.6 (20.2–78.0)	66.6 (34.8–90.5)	55.6 (26.4–86.0)
% of workers who walk to work	0.4 (0–2.3)	1.4 (0–5.3)	2.4 (0.4–8.5)	1.8 (0.1–6.7)
population per square mile	450 (69–2,630)	2,099 (321–5,355)	3,169 (772–6,602)	2,617 (492–6,035)

tion of Census tract residents who identified as a race other than non-Hispanic white.

The proportion of drivers who left the scene also increased with increasing population density across all but the densest Census tracts, before decreasing steeply with further increases in population density at densities greater than approximately 24,000 people per square mile—roughly the densest 4% of all Census tracts nationwide (Fig. 1). Similarly, the probability that a driver left the scene increased with the proportion of workers in the Census tract who walk to work across virtually the entire distribution of walking share observed (Fig. 2). The walking share at which the probability of a driver leaving the scene began decreasing was within the top 0.5% of all Census tracts nationwide with respect to the share of workers who walk. While both of these measures are clearly correlated with pedestrian exposure and drivers who strike pedestrians are more likely to leave the scene than drivers involved in a crash with another vehicle, qualitatively similar relationships between population density, walking share, and the probability of leaving the scene remained even in analysis restricted to multiple-vehicle crashes (not shown).

4. Discussion

The current study sought to quantify the relationships between driver, vehicle, and environmental factors and the probability that a driver who was involved in a fatal crash (and survived) would leave the scene. In addition to confirming the results of several past studies, the use of multiple imputation to enable the inclusion of drivers who were never identified, and the incorporation of external sociodemographic data characterizing the places in which the crashes occurred produced several new insights. It was found that drivers of vehicles registered to others were approximately twice as likely to leave the scene as were drivers operating their own vehicles. Unsurprisingly, drivers of stolen vehicles were yet more likely to leave the scene, and drivers of vehicles registered to a business or government entity—likely the driver's employer—were least likely to flee.

Previous studies have examined the associations of driver- and vehicle-related factors with the odds of leaving the scene among drivers who were eventually identified (MacLeod et al., 2012). However, nearly half of the drivers who left the scenes of fatal crashes were never identified. While it is possible that drivers who are eventually identified after having left the scene of a fatal crash are representative of all drivers who leave the scenes of fatal crashes, it is important to allow for the possibility that they might not be. Thus, the current study used multiple imputation to estimate the distributions of driver- and vehicle-related variables among drivers who left the scene and were never identified, enabling the inclusion of this group of drivers in the analysis as well. The imputation approach used in the current study accounted for relationships of driver- and vehicle-related data with numerous other variables characterizing the circumstances of the crashes and the places where they occurred, among drivers who left the scene and as well as those who remained, thus avoiding the strong distributional assumptions that implicitly underlie complete-case analysis. Nonetheless, results were broadly consistent, at least directionally, with previous studies that only examined drivers who were identified (e.g., (MacLeod et al., 2012), finding that indicate that drivers who are younger, male, have recent moving violations or DWI convictions, or lack a valid license have elevated probability of leaving the scene of a fatal crash. We also find that drivers were most likely to leave the scene in crashes that occurred at night, on weekends, on lower-speed local streets or roads, in higher-density areas (with the exception of the very densest ones), in areas where more people walk to work, and in areas with higher rates of unemployment.

Using Census tract data, the current study found that economic and demographic attributes are predictive of fatal hit-and-run crashes. Similar to findings in Liu et al. (Liu et al., 2018), drivers involved in crashes in areas with higher rates of unemployment are more likely to leave the scene. These findings are in line with studies that more broadly show negative traffic safety outcomes being associated with indicators of lower socioeconomic status. For example, racial disparities in pedestrian injuries and deaths are well- documented (Hamann et al., 2020; Kaufman & Wiebe, 2017); the current study finds that drivers are more likely to leave the scene of a fatal crash in Census tracts in which a greater proportion of the population is non-white. In addition, previous research has found lower levels of education associated with higher rates of motor-vehicle crash fatalities at the individual level (Yu, 2014). Another study found that area-level poverty was strongly associated with rates of traffic injuries for vehicle occu-

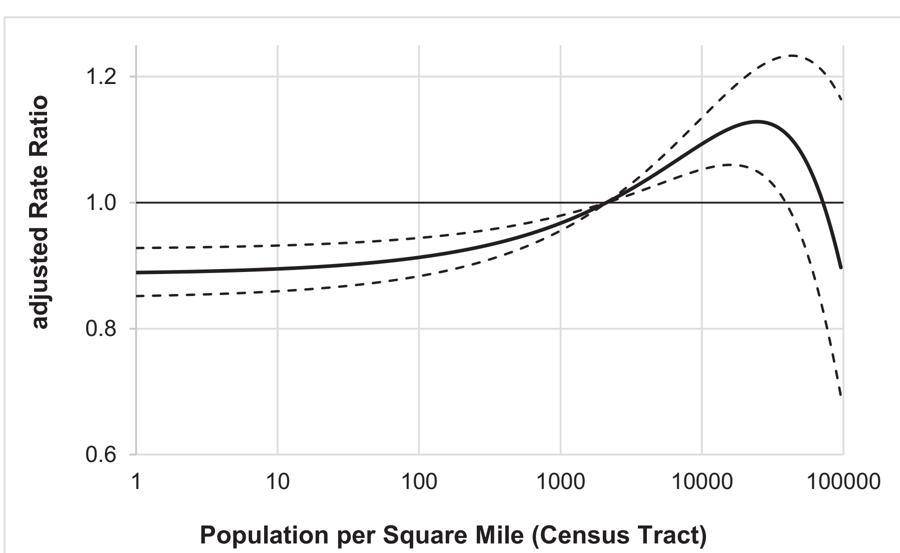

Fig. 1. Adjusted rate ratio for leaving the scene of a fatal crash in relation to population density of Census tract in which crash occurred, relative to Census tract with population-weighted median density for all Census tracts (2109 persons per square mile), adjusted for driver, vehicle, and crash factors. Dashed lines represent 95% Confidence Intervals.

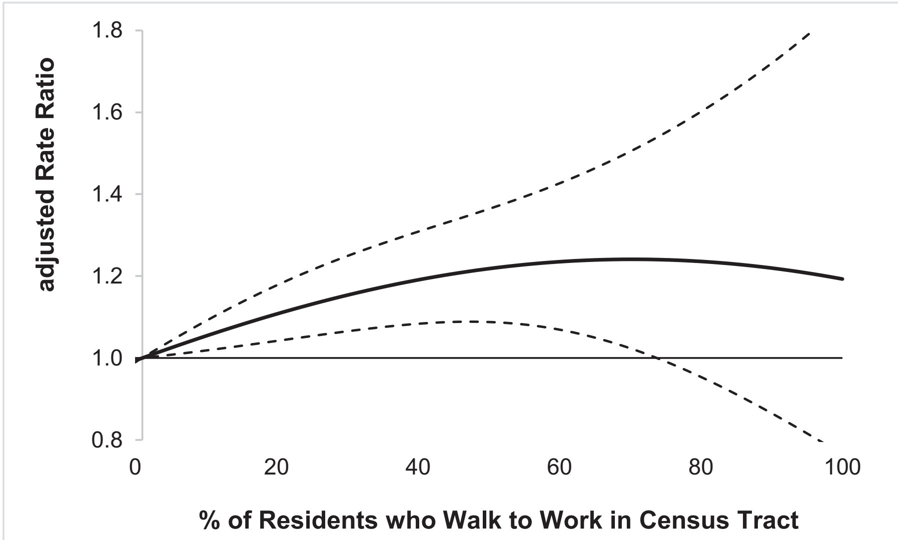

Fig. 2. Adjusted rate ratio for leaving the scene of a fatal crash in relation to percentage of employed residents who walk to work, relative to median walking percentage of all Census tracts in United States, adjusted for driver, vehicle, and crash factors. Dashed lines represent 95% Confidence Intervals.

pants as well as for cyclists and pedestrians, and concluded that much of the increased risk was associated with differences in the roadway environment in poorer versus wealthier areas (Harper et al., 2015). In the current study, tract-level education and poverty rates were associated with hit and run in univariate but not multivariate analysis. Interestingly, the current study also found that among drivers who left the scene of a fatal crash, those who crashed in areas with poorer economic indicators were also more likely to remain at large.

Previous research found that drivers were more likely to leave the scenes of fatal crashes in urban areas than in rural areas (MacLeod et al., 2012). The current study expands upon this by examining the probability of leaving the scene in relation to Census tract density rather than dichotomous classification as urban versus rural. Interestingly, the association of hit-and-run with density appeared to be non-monotonic, increasing with density for all but the densest Census tracts, but then decreasing in the few very densest tracts. The reasons for the reversal of trend among the very densest tracts is unclear; one possibility is that the densest tracts experience greater levels of traffic congestion, making fleeing more difficult. A similar pattern was identified with respect to the proportion of workers who walk to work; the reasons for this are unclear. Notably, this was not fully explained by an increasing proportion of fatal crashes in which the victims were pedestrians—a scenario in which the driver is independently more likely to flee—as the model adjusted for victim type, and a similar pattern was observed in analysis restricted to multiple-vehicle crashes.

Another common finding that our study shares with previous research is that having an invalid license is one of the strongest predictors that a driver will flee (MacLeod et al., 2012). That invalid licenses are a major contributor to hit-and-run has also been demonstrated by research showing that easing the barriers to obtaining a driver's license reduces the proportion of crash-involved drivers who leave the scene (Lueders et al., 2017). Like license status, past DWI convictions are a reliable predictor of leaving a fatal crash, both here and in all previous research.

4.1. Limitations

The current study used the method of multiple imputation to model the distributions of missing variables among drivers who left the scene, which made up nearly 50% of hit and run drivers. Although the imputation model was developed using data from a large number of drivers and included many variables correlated with the probability that a driver left the scene, the results could be biased if the imputation model failed to account for correlations between the values of imputed variables and the probability that their values were missing. This could occur if drivers who fled but were caught differed from drivers who fled and remained at large even after controlling for the other variables in the model. While there is no reason to believe that the age or sex distribution of these groups would differ, it is quite possible these groups might differ in other ways that are difficult to model. For example, factors like the presence of passengers in the fleeing vehicle may influence the decision to stay, but that information is unknown. Another limitation is that this study only examined fatal hit-and-run crashes, and therefore its findings cannot be generalized to non-fatal hit-and-run crashes.

5. Conclusions

This research gives an updated accounting of the factors associated with hit-and-run and an early attempt to understand the civil environment in which these crashes happen by incorporating economic and demographic information into the analysis. Hit-and-run crashes are a criminal issue that current legislation does not seem to be effectively addressing. Future research could focus on understanding the effects that license suspension/revocation and state-level penalties for hit-and-run have on rates of hit-and-run, with the goal of identifying effective countermeasures. Another area that needs more research is understanding why people choose to flee, which could eventually inform more effective countermeasures.

Conflicts of interest

The authors of Fatal Hit-and-Run Crashes: Factors Associated with Leaving the Scene have no conflicts of interest to report.

Appendix

Validation of multiple imputation model

The performance of the imputation model was assessed by simulating missing data from among drivers with no missing values for any of the analysis variables, imputing them, estimating aRRs

Table A1
Adjusted rate ratios for leaving the scene of a fatal crash in 50 simulations in which all variables in table were deleted and imputed for a random 50% of drivers who left the scene, compared with values obtained from complete case analysis of the original data.

		50% of Hit and Run Drivers Deleted & Imputed
	Complete Data	Median (25th, 75th Percentile)[a]
Age (+10 years)	0.86	0.87 (0.86, 0.87)
Sex (male)	1.54	1.51 (1.48, 1.55)
Minor injury vs. none	0.68	0.77 (0.75, 0.79)
Incapacitating injury vs. none	0.16	0.24 (0.22, 0.25)
Invalid license vs. valid license	3.37	2.93 (2.88, 2.97)
No license vs. valid license	3.68	3.55 (3.47, 3.63)
Previous DWI (≥1)	1.77	1.89 (1.83, 1.95)
Previous moving violations – 1	1.12	1.19 (1.17, 1.21)
2	1.22	1.26 (1.23, 1.30)
≥3	1.37	1.28 (1.25, 1.31)
Other's vehicle vs. own vehicle	1.29	1.36 (1.33, 1.37)
Business/govt vehicle vs. own vehicle	0.81	0.90 (0.86, 0.94)
Stolen vehicle vs. own vehicle	5.69	4.14 (3.92, 4.37)
Large truck vs. car	0.61	0.59 (0.56, 0.62)
Motorcycle vs. car	1.00	0.91 (0.85, 0.98)
Vehicle age (+10 years)	1.13	1.13 (1.12, 1.14)
Miles from home (natural log)	0.94	0.96 (0.95, 0.96)

a. Median, 25th percentile, and 75th percentile values of adjusted rate ratio from 50 simulations in which all variables in table were deleted and replaced with imputed values for 50% of drivers who left the scene.

from the data with the simulated missing values imputed, and comparing them to aRRs obtained using the original values.

The original dataset included 163,738 drivers with no missing values for any of the variables included in the imputation model, including 4,935 who left the scene of the crash but were eventually identified. To simulate the pattern of missing data typically present among drivers who left the scene and were never identified, approximately 50% of those who were caught were selected at random, and all of their driver- and vehicle-level variables (age, sex, injury severity, license status, previous DWI convictions, previous moving violations, vehicle age, vehicle type, distance from home, and ownership of vehicle) were deleted. After deletion of these variables, they were then imputed using the same imputation model as in the main analysis.

Poisson regression with robust variance was used to estimate the aRRs for hit and run associated with each variable in the dataset that contained the imputed values of the simulated missing variables. The performance of the imputation model was assessed by comparing these aRRs to those obtained from the original set of all complete cases. The aRRs rather than the values of variables for individual drivers were compared because the purpose of the imputation was to enable the inclusion of drivers with missing values in the estimation of the aRRs, not to recover the values of the variables for any individual driver.

The above-described simulation procedure was performed 50 times independently. Table A1 shows the median and the interquartile range of the aRRs obtained for all analysis variables in each of the 50 simulations, as well as the corresponding actual values from the complete data. aRRs estimated using the imputed values of the deleted observations for half of the hit-and-run drivers generally agreed well with the "true" values estimated from the original data for most variables. Among variables in which there was any nontrivial discrepancy, aRRs estimated from the deleted-and-imputed data were usually closer to 1 than the true values.

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Highway-rail grade crossings accident prediction using Zero Inflated Negative Binomial and Empirical Bayes method

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ABSTRACT

Introduction: Recently the Federal Railroad Administration (FRA) released a new model for accident prediction at railroad grade crossings using a Zero Inflated Negative Binomial (ZINB) model with Empirical Bayes (EB) adjustments for accident history (2). This new model is adopted from the work that was conducted by the authors (3–6). The unique feature of the new FRA model is that it has a single equation for all three warning devices (crossbuck, flashing light, and gates) and uses the same variables regardless of the warning devices at the crossing. Since the New FRA model incorporates the warning device category as one of the variables in its model equation, the predicted accident frequency is higher when a crossing has crossbucks than flashing lights, and higher when it has flashing lights than gates. While this model is significantly better than the old USDOT model (7), its shortcoming is that the single equation does not accurately represent the field condition. *Method:* This paper presents the ZINEBS model (Zero Inflated Negative binomial with Empirical Bayes adjustment System). The ZINEBS model gives three different equations depending on the type of warning device used at the crossings (gates, flashing lights, and crossbucks). The three equations use variables, some of which are common across all warning devices, while other variables are specific to a warning device. The predicted values for the ZINEBS model show a closer agreement with the field data than the new FRA model. This observation was true for all three warning device types analyzed. *Practical Applications:* Based on the results of this study, the ZINEBS compliments the new FRA model and should be used when the single equation is not adequately representing the role of traffic control device types and relevant variables associated with that device type.

1. Introduction

A measure of the safety, perhaps the most important one, of a railroad grade crossing is the expected number of accidents at that grade crossing. The expected crash frequency has been used to rank the sites for engineering improvements. The expected number of crashes is estimated based on initial crash prediction values that are adjusted using accident history (the observed number of accidents at that location). To improve the initial estimate, accident history is used. For over four decades, the practice was to use the USDOT accident prediction formula (Ogden & Cooper, 2020). This formula was developed in the 1980s and only the normalization coefficients of the formula were adjusted periodically. Recently the Federal Railroad Administration released a new model for accident prediction at railroad grade crossings using a ZINB model with EB adjustments for accident history (Broad & Gillen, 2020). This new model is adopted from the work that was conducted by the authors (Mathew et al., 2019; Medina & Benekohal, 2015; Medina et al., 2016; Mathew & Benekohal, 2020) but used only one model for all three traffic control devices (gates, flashing lights, crossbucks). The new FRA model improved upon the USDOT model by multiple measures. Since the New FRA model incorporates the warning device category as one of the variables in its model equation, the predicted accident frequency is higher when a crossing has crossbucks than flashing lights, and higher when it has flashing lights than gates.

This paper presents the ZINEBS model (Zero Inflated Negative binomial with Empirical Bayes adjustment System). This model uses the Zero Inflated Negative Binomial (ZINB) model for the initial prediction followed by the Empirical Bayes method to account for the accident history of the location. The main differences between the ZINEBS model and the new FRA model include: (a) separate models for crossings with different warning device types, (b) the data used in the model development, (c) filters used on the data to create a meaningful dataset, and (d) the variable selection criteria used.

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The ZINEBS model is developed using data from Illinois and the model is validated using an independent dataset from Texas. A comprehensive set of filters (including more filters than what was used in the new FRA model development) is used to filter the data, which results in a meaningful database for use in this analysis. Variable selection in the ZINEBS model is based on forward selection of the variables, ensuring that the selected variables and their coefficients and meaningful and significant. The ZINEBS model gives three different equations depending on the type of warning device used at the crossings (gates, flashing lights, and crossbucks). The predicted values for the ZINEBS model show a closer agreement with the field data than the new FRA model.

After developing and validating the ZINEBS model, it is compared to the commonly used USDOT accident prediction formula (1) (which will be called the USDOT model (old) henceforth) as well as the new FRA accident prediction model (2). The predicted values from the three models are compared to the observed accident counts to see how close the predicted value matches the field data. A better model should give predicted values that are closer to the observed number of accidents.

The rest of the manuscript gives a review of the literature on accident prediction models, a description of the data and methodology used in this research, validation of the methodology, and the comparison made of the ZINEBS model to the USDOT model (old) and the new FRA model.

2. Literature review

2.1. Models developed by the Federal Railroad Administration

The most commonly used accident prediction models in the United States is the USDOT accident prediction formulas. These formulas are given in the Highway Rail Grade Crossing Handbook (FHWA, 2007). These formulas were developed in the 1980s and are credited to Mengert (1979). Further details about the model are given in the Summary of DOT Rail-Highway Crossing Resource Allocation Procedure-Revised (Farr, 1987).

The accident prediction using the USDOT formula involves three steps. In the first step, the initial accident prediction value "a" for crossings is computed by

$$a = K * EI * DT * MS * MT * HP * HL \tag{1}$$

The equations for EI, DT, MS, MT, HP and HL for crossings with different warning device types are given in Table 1.

Please note, the coefficients in the initial accident prediction formula for calculating "a," in the USDOT formulas as mentioned in the Highway Rail Grade Crossing Handbook (FHWA, 2007) are different from the coefficients given in the Summary of DOT Rail-Highway Resource Allocation Procedures-Revised (Farr, 1987). The FRA uses the coefficients mentioned in the Summary of DOT Rail-Highway Resource Allocation Procedures in their Web Accident Prediction System (Federal Railroad Administration, 2020).

In the second step, a "B" value is computed, which is a weighted average of "a" value and the accident history at the crossing.

$$B = \frac{T_0}{T_0+T} * a + \frac{T}{T_0+T} * \left(\frac{N}{T}\right) \tag{2}$$

$$T_0 = \frac{1}{0.05+a} \tag{3}$$

where B is called the adjusted accident prediction value and N is the number of observed accidents in T years and "a" is the initial accident prediction value. In the third step, the adjusted accident prediction value is normalized as shown in the equation below.

$$A = k' * B \tag{4}$$

The current normalization coefficients used by FRA are given in Table 2.

In October 2020, the Federal Railroad Administration (FRA) released a new model to predict accident counts at highway rail grade crossings (Broad & Gillen, 2020). This method is an adaptation of the methodology proposed by the authors in an earlier report (Mathew et al., 2019) discussing the preliminary version of our current work; where the authors used the Zero Inflated Negative Binomial model with Empirical Bayes adjustment to calculate the predicted accident count at a crossing. However, one of the main differences is that the FRA model uses only one equation for all three warning device types, while the authors proposed a different model for each traffic control type. The FRA equation is given below.

$$E[a] = \frac{e^{-8.35992+0.19023*lExpo-0.28478*D_2-0.85770*D_3+0.39346*RurUrb+0.13182*XSurfaceID2+0.68760*lMaxTtSpd+0.10626*lAadt}}{1+e^{1.17084-1.01088*lTotalTr}} \tag{5}$$

where:

lExpo = Exposure, equal to average annual daily traffic times daily trains
D2 = If warning device type is lights = 1, 0 otherwise
D3 = If warning device type is gates = 1, 0 otherwise
RurUrb = If Rural = 0, if Urban = 1
XSurfaceID2 = Timber = 1, Asphalt = 2, Asphalt and Timber OR Concrete OR Rubber = 3, Concrete and Rubber = 4
lMaxTtSpd = Maximum timetable speed
lAadt = Average annual daily traffic
lTotalTr = Total number of daily trains

The variables that start with l (Expo, MaxTtSpd, Aadt, TotalTr) have been transformed as follows: lx = ln(1 + αx), where x is the original variable and α is a factor. The factor α was selected so that for the median value of x, ln(1 + αx) = ln(x)

A few points to be noted about the new FRA model are

1. The filters that they used to clean the dataset includes only seven conditions. The filters include: (1) Public, (2) At grade, (3) Remove closed, (4) Remove missing AADT, (5) Remove missing highway lanes, (6) Remove missing daily trains, (7) Remove missing total tracks. These filters are not comprehensive and may not clean the data adequately (we will present a comprehensive list of filters in Table 3 of this manuscript).
2. They used fewer number of variables than the old USDOT model in their model. They used a graphical (visual) approach to select the variables in the model by plotting the normalized accident count (normalized over exposure and type of warning device) and checking if there is a difference in accident counts. Statistical criteria like AIC were not used in model variable selection.
3. They use one equation for all three warning device types (device type was handled using dummy variables). This approach is not as flexible in variable selection at building a model for each device separately, as it was used in the Old UDOT model.

2.2. Other models for accident analysis

Several studies have been conducted by researchers to develop models for crash data. The Poisson model and the Negative Binomial model are typically used to model accident count data in traffic safety analysis. Various researchers have proposed other methods, including variations on the Poisson model and Negative Binomial model to model crash counts. Lord et al. (2005) in their

Table 1
Initial accident prediction value in USDOT accident prediction formulae.

Warning Device Type	K	EI	DT	MS	MT	HP	HL
Crossbucks	0.0006938	$\left(\frac{Aadt*TotalTrn+0.2}{0.2}\right)^{0.2942}$	$\left(\frac{DayThru+0.2}{0.2}\right)^{0.1781}$	$e^{0.0077*ms}$	1	$e^{-0.5966*(hp-1)}$	1
Flashing Lights	0.0003351	$\left(\frac{Aadt*TotalTrn+0.2}{0.2}\right)^{0.2942}$	$\left(\frac{DayThru+0.2}{0.2}\right)^{0.1781}$	1	$e^{0.1917*MainTrk}$	1	$e^{0.1826*(TraficLn-1)}$
Gates	0.0005745	$\left(\frac{Aadt*TotalTrn+0.2}{0.2}\right)^{0.2942}$	$\left(\frac{DayThru+0.2}{0.2}\right)^{0.1781}$	1	$e^{0.1512*MainTrk}$	1	$e^{0.1420*(TraficLn-1)}$

where:
Aadt is the annual average daily traffic at the crossing.
TotalTrn is total number of trains using the crossing.
DayThru is number of daytime thru trains at the crossing.
MainTrk is the number of main tracks at the crossing.
TrafficLn is the number of highway lanes at the crossing.
ms is the maximum timetable train speed at the crossing.
hp indicates if the highway is paved or not.

Table 2
Normalization coefficients for the USDOT accident prediction formula.

Class	April 2013 Constants (k')
Passive	0.5086
Flashing Lights	0.3106
Gates	0.4846

study (Lord et al., 2005) compared the Poisson, Negative Binomial (Poisson-Gamma model), and Zero Inflated models of motor-vehicle crashes. Park and Lord (2009) proposed the finite mixture regression model for both Poisson mixtures and Negative Binomial mixtures. Geedipally et al. (2012)) used the negative binomial generalized linear model with Lindley mixed effects (NB-L GLM) for analyzing traffic crash data. Zou et al, (2013) developed a two component finite mixture negative binomial model with varying weight parameters using crash data from two datasets; (1) crash data collected at signalized intersections in Toronto, Canada and (2) vehicle crash data that occurred on 4-lane undivided rural segments in Texas. Hallmark et al. (2013) used the Negative Binomial-Lindley generalized linear models to do a before-and-after study to evaluate the impact of paved shoulders on crashes in Iowa. Shirazi et al. (2016) proposed a multi-parameter Negative Binomial generalized linear model with randomly distributed mixed effects characterized by the Dirichlet process (NB-DP) to model crash data. Shaon and Qin (2016) used the Negative Binomial-Lindley (NB-L) and Negative Binomial-Generalized Exponential (NB-GE) on data from South Dakota Department of Transportation. Shaon et al. (2018) proposed a combination of the random parameter negative binomial and negative binomial-Lindley model to account for underlying heterogeneity and address excess over-dispersion (called RPNB-L model).

Studies have been conducted to develop accident prediction models at railroad grade crossings also. Austin and Carson (2002) developed an highway-rail crossing accident prediction model, using negative binomial regression. Oh et al. (2006) developed statistical models to analyze highway rail grade crossing accidents in Korea. This study selected the gamma model among the models after comparing the Poisson, Negative Binomial and Zero Inflated Poisson model. Park et al. (2005) (Park & Saccomanno, 2020; Park & Saccomanno, 2005) presented a sequential modeling approach based on data mining and statistical methods to estimate the main and interactive effects of introducing countermeasures at individual grade crossings in Canada. Yan et al. (2010) used hierarchical tree-based regression (HTBR) to predict train vehicle crash frequency at passive highway-rail grade crossings in the United States. Lu and Tolliver (2016) examined the accident data in North Dakota, USA between 1996 and 2014 and proposed the use of Bernoulli, Conway-Maxwell-Poisson and Poisson Hurdle models to

Table 3
Filters Used on Grade Crossing Inventory Dataset.

Variable	Description	Filter	Description of Filter	Number of Crossings after filter (Illinois)
		None	Before any filters	26,089
TypeXing	Crossing Type	Select "3"	Select public crossings only	17,054
PosXing	Crossing Position	Select "1"	Select at grade crossing only	13,703
ReasonID	Reason for Update	Remove 16	Remove closed crossings	7925
TotalTrain	Total number of trains	>0	Select crossings with 1 or more trains operating per day	7183
TotalTrack	Total number of tracks	>0	Select crossings with 1 or more tracks at the crossing	7090
TraficLn	Number of highway lanes	>0	Select crossings with 1 or more highway lanes at the crossing	6774
Aadt	Annual average daily traffic count	>0	Select crossings with AADT > 0	6763
AadtYear	Annual average daily traffic Year	>2000	Select crossings with year of AADT > 2000	6673
HwySpeed	Posted highway speed limit	>0	Select crossings with posted speed limit > 0	6625
MaxTtSpd	Maximum timetable train speed	>0 and <=79	Select crossings with maximum timetable train speed between 0 and 79 mph	6624
WdCode	Warning Device Code	Select "3", "7", "8" and "9"	Select crossings with crossbucks, flashing Lights, four quad gates and all other gates	6476
XSurfaceID	Crossing Surface	Remove "17", "19", "20" and unknowns	Remove crossings with metal, unconsolidated, other or unknown crossing surfaces	5883

assessing grade crossing accident data with under dispersion. Khan et al. (2018) used binary logit regression model to analyze accidents in North Dakota, United States.

Borsos et al. (2016) developed negative binomial models for grade crossings in Hungary. Liang et al. (2016) developed accident prediction models for level crossings in France for active crossings with flashing lights and two barrier gates.

Studies were conducted to model accident severity as well. McCollister and Pflaum (2007) developed logistic regression models to predict the probability of accidents, injuries, and fatalities resulting from collisions between trains and vehicles at highway rail crossings in the United States. Hu et al. (2010) used a generalized logit model with stepwise variable selection instead to identify explanatory variables (factors or covariates) that were significantly associated with the severity. Eluru et al. (2012) modeled the driver injury severity at railroad grade crossing in the United States crashes using a latent segmentation based ordered response model. Hao and Daniel (2014) used ordered probit models to study the influence of time of day on driver injury severity. Liu et al. (2015) modeled injury severity of crashes at highway rail grade crossings with the objective of exploring the differences in crash outcomes at passive crossings (crossings with stop signs or crossbucks) and active crossings (crossings with flashing lights, gates, highway signals, audible warnings). Zhao and Khattak (2015) used random parameters logit model to identify factors associated with driver injuries after considering the ordered probit model, multinomial logit model, and random parameter logit model.

2.3. About ZINB models

Lord et al. (2005) argued in this paper that crash data characterized by a preponderance of zeros is not indicative of an underlying dual-state process. According to the authors, one or more of four conditions lead to excess zeros in crash data: (1) sites with a combination of low exposure, high heterogeneity, and sites categorized as high risk; (2) analyses conducted with small time or spatial scales; (3) data with a relatively high percentage of missing or mis-reported crashes; and (4) crash models with omitted important variables. In a later paper, Lord et al. (2007) further elaborates on the issues of using zero inflated models. The assumption in a zero inflated model is that an entity (highway segment) exists either in an inherently safe or non-safe state. Based on this, they ask the following questions: (1) What are the boundary conditions delimiting the two states? (2) If the site-specific traits that classify the two states are unobserved (i.e., not present in the observed data), what might they be? (3) Why use a single model if one could define the dual-state data generating process. A similar argument was also provided against the use of zero-inflated models by Warton (2005) in his study of ecological datasets.

The responses to these arguments are:

a. At crossings with very low exposure, (i.e., rural locations with very low number of daily trains and highway vehicles using the crossings), the opportunity for an interaction between a train and a highway vehicle may rarely arise. This is not saying that such crossings are inherently safe, but rather saying that the probability of such a crossing to have no accidents as a result of very low exposure is high. Therefore, the boundary condition is that a crossing may have no vehicle-train interaction, thus leading to zero accidents or may have interactions and the number of accidents could be modeled as a count process. This boundary is unobserved in the available data as the data does not provide information on interaction between a train and a highway vehicle at a crossing.
b. Previous studies (Oh et al., 2006) have concluded that the zero inflated models offer a better goodness of fit than traditional NB or Poisson models. Therefore, it is worth exploring if that is true in the context of crashes between highway vehicles and trains.
c. The zero inflated model is a parametric model and it is easily interpretable. There is a parametric expression for the expectation and variance using the model, which makes the model mathematically convenient.

2.4. Summary of literature review

In summary, several studies on accident prediction models at HRGC were identified in the literature review. Poisson regression model was commonly used as a starting point in these studies. In most of the studies, different models were developed based on the warning device types except, Park et al. (Park & Saccomanno, 2020; Park & Saccomanno, 2005) and Khan et al. (2018) (who used warning device type as an explanatory variable in the model that they developed), and Austin et al. Austin and Carson (2002) (who used the method of instrumental variables to develop new features [probability of gates, probability of flashing lights, probability of crossbucks, etc.]) in their developed model. Only a few models were identified that used accident history in their accident prediction models (the USDOT accident prediction formulae is one of them). One major shortcoming of the studies identified in the literature review was a lack of validation by comparing the developed models to the observed accident counts at the grade crossing locations. Other deficiencies identified in the past studies include the lack of categorization of the model based on the warning devices (highway traffic at crossings with active warning devices is expected to behave differently from highway traffic at crossings without active warning devices), age of the commonly used USDOT model, and absence of any adjustments to the model to account for the observed accident count.

In this study, we address the shortcomings identified from the literature review. Recent data are used to develop a new accident prediction model for highway rail grade crossings. Separate models are developed based on the warning device type used at the crossing. During the research, the authors were interested in questions like (1) is there a new model that is as good as, if not better than the USDOT model and the new FRA model in identifying high-risk grade crossing locations? (2) would the variables that were used in the USDOT model over 30 years ago still make sense now and are there variables that was not included in the USDOT model that are relevant to accident prediction? (3) Can a different model format and accident history adjustment procedure from the USDOT model be used to estimate expected accident count at railroad grade crossings? The new model developed in this paper was compared to the USDOT formula and the new FRA model and the comparisons are done to identify a better prediction model that offers a better selection of crossings in terms of the observed number of accidents. In this way, the paper compares the models in its ability to identify crossing with a high likelihood of accidents.

3. Data

The databases maintained by the Federal Railroad Administration (FRA) (FRA, 2019) were used in this study. Three separate databases used for this study are: (a) the Highway Rail Accident database, (b) the Grade Crossing Inventory database, and (c) the Grade Crossing Inventory History database.

The Highway Rail Accident database contains information about "any impact, regardless of severity, between a railroad on-track equipment consist and any user of a public or private crossing site"

(Federal Railroad Administration, 2011). All grade crossing collisions are reported to the FRA regardless of the monetary value of damage caused. The database contains a variety of information, including data about the type of highway vehicle involved, speed of the train at collision, and environmental factors such as time of day and weather conditions.

The Grade Crossing Inventory database includes information reported to the FRA by each state DOT about the condition of each crossing. This includes information about the highway (i.e., annual average daily traffic (AADT), number of traffic lanes, posted highway speed; and the rail line [i.e., timetable speed, daily number of trains]).

The Grade Crossing Inventory History database includes data about the changes to the crossing inventory database. This database was used to filter out the crossings that had a change in its warning device type during the analysis period.

The Crossing Inventory Database for Illinois had 26,089 records. This list contains crossings that are on both public and private highways, some crossings with old data that may not have been updated, crossings with missing or incomplete data, and so forth. Therefore, this database was filtered based on the filters given in the Table 3 below to obtain a meaningful dataset for at grade crossings on public roads. The researchers recommend the application of such filters before using the dataset for any analysis so that the analysis is done on a meaningful dataset.

During the filtering, it was also ensured that no crossing had any variables with missing entries in the dataset. After applying the filters in Table 3, there were 5,883 crossings remaining. Furthermore, the warning device in the crossing were compared to the warning device of the corresponding crossing as given in the Grade Crossing Inventory History dataset. This way, crossings that had a change in its warning device were also eliminated from the study. This removed 786 more crossings due to changes in the warning device type. All these efforts resulted in a data base that has 5,097 crossings that can be used in accident prediction modeling. The data for the state of Texas was used to validate the models built. The same filters were used on the crossings in Texas. The Texas dataset reduced from 27,023 to 5,195.

Using the crossing ID as the key, the filtered grade crossing inventory database and the grade crossing accident database were merged. Three separate databases were created, one for each warning device category. The number of crossings in Illinois (after the filters) and the number of accidents observed in the 5-year span (2012–2016) is given in Table 4.

4. Model building

4.1. Zero inflated negative binomial model format

Zero inflated negative binomial model format is used to build the accident prediction model for highway rail grade crossings. One reason for this selection was that the previous studies (Mathew et al., 2019; Medina & Benekohal, 2015) compared three different count models (Poisson, Negative Binomial (NB) and Zero Inflated Negative Binomial Models (ZINB)) and found a better goodness-of-fit with the ZINB model as compared to the Poisson or the NB models. Furthermore, the ZINB model is a parametric model giving parametric expressions for the expected accident counts and the variance of the expected accident counts. The last reason for selecting ZINB model was the convenience of calculating its parameters (the mean and variance) that are required for using Empirical Bayes method to account for accident history. In developing the models, a forward regression approach was used to select model variables that resulted in selecting some variables that are not included in the USDOT models or the New FRA model.

The zero inflated negative binomial model is a two-part model. The first part is the zero-inflation part that is based on the assumption that the possibility of accidents in certain locations is so close to zero that these locations would have zero accident counts. The second part is the count part of the model, which gives the distribution of the accident frequency as a count (Negative Binomial) process. The variables annual average daily traffic (Aadt) and Total Train were used as the variables representing the zero-inflation part of the ZINB model. It is reasonable to use the traffic variables (i.e., Aadt and Total Train) in the zero-inflation part of the model as a crossing with very low train and highway traffic has very low possibility of an accident between them. This goes hand in hand with the assumption that a crossing with low volume will have very low opportunities for a crash, which leads to the inflated number of zeros in the dataset. Therefore, the variables Ln(Aadt) and the Total Train variables were used in the zero-inflation part of the model. The log transformation of the variable Aadt is done as the variable is strictly positive and reduced the range of values within the variable. Furthermore, using the log transformation gave a better goodness of fit for the model in terms of Akaike Information Criteria (AIC) than models fitted without the log transformation. The remaining eight variables were used in all possible combinations in the count part of the model (resulting in 255 or 2^8-1 fitted models). This included models with only one variable, up to a model including all eight variables. These fitted models were sorted using AIC (Akaike, 1974; R-project.org) as the basis of their goodness of fit. The model with the lowest AIC value was the first choice.

Selecting the final model was based on three indicators:

(1) Select the model with the lowest AIC
(2) Check the coefficients of the variables in model with the lowest AIC to ensure they were reasonable.
(3) Compare the fit of this model with a model that would have one more (or one less) variable. These models were also considered before making the final recommendation as long as it didn't drastically increase the AIC values.

The model format for a ZINB model can be written as

$$E[a] = \mu(1 - p) \tag{6}$$

$$V[a] = \mu(1 - p)(1 + \mu(p + \alpha)) \tag{7}$$

where

E[a] is the expected value of accident count
V[a] is the variance of the expected value of accident count
μ is the mean of the negative binomial process
p is the probability of the entity being in the "always 0" case in the finite mixture model
α is the over dispersion parameter of the negative binomial model (=1/Θ, theta is an estimated parameter for the model)

Table 4
Number of Crossings and Accidents in Illinois & Texas (2012–2016).

	Warning Device Type	Number of Crossings	Number of Accidents (2012–2016)
Illinois	Gates	2755	234
	Flashing Lights	960	42
	Crossbucks	1382	52
Texas	Gates	3573	468
	Flashing Lights	346	60
	Crossbucks	1276	62

The models selected for each device will be discussed following the discussion of Empirical Bayes method which is given in the following section.

4.2. Empirical Bayes method

To improve the initial estimate, accident history is used. Accident history is used in additive format in several hazard models in the literature (Oregon, Utah, Detroit formulae) (Farr, 1981). However, the USDOT accident prediction formula employs a method that is a weighted average of the accident history and the initial model estimate. Another way to include the accident history in order to improve this initial estimate is Empirical Bayes method (Hauer et al., 2002). The Empirical Bayes method uses two clues to estimate the safety at railroad grade crossings. The first clue is the initial estimate of the expected number of accidents at the railroad grade crossing. This is estimated based on a reference population that shares the same traits as the crossing in consideration. "A reference population of entities is the group of entities that share the same set of traits as the entity in the safety of which we have an interest" (Hauer, 1997). The initial estimate of the expected number of accidents could be calculated based on the observed number of accidents at the grade crossings in the reference population. The second clue is the accident history (number of accidents recorded) at the railroad grade crossing.

The two clues are combined as follows (Hauer, 1986) to compute the adjusted accident prediction value (which is B).

$$B = k * E[a] + (1 - k) * N \tag{8}$$

$$k = \frac{1}{1 + \frac{Var[a]}{E[a]}} \tag{9}$$

where E[a] is the estimate of the expected number of accidents based on the reference population, Var[a] is the variance of this initial estimate. N is the number of accidents observed at the crossing. The duration for which the number of accidents (N) is observed at the crossing is equal to the duration of accident counts used to estimate E[a]. E[a] can be estimated for a crossing using the multivariate regression method and would depend on the traits of the crossing.

A few observations based on equation above can be made.

1. The adjusted accident prediction value is related to the number of observed accidents in the before period and the initial estimate of the expected accident count based on the crossing parameters.
2. The duration of the before period is the same as the duration of accident counts used in the estimation of E[a].
3. The adjusted accident prediction value depends on the variance of the initial estimate of the expected accident count Var[a].
4. If Var[a] is 0, the adjusted accident prediction value is equal to the estimated value for the accident count at the crossing. This means that, if the variance of the estimated expected accident count is 0, the expected number of accidents could be solely predicted based on the crossing parameters.
5. If Var[a] is very high, the adjusted accident prediction value for the crossing is influenced more by its accident history observed than the initial estimate based on crossing characteristics.
6. The Empirical Bayes method is very similar to the USDOT method of adjustment for accident history in the sense that they both involve the calculation of a weighted average of an initial accident prediction value and the recorded accident history over a given period of time. Even though the time parameter ("T") is not explicitly included in the Empirical Bayes equation, it should be noted that it is implicitly included as the number of recorded accidents is selected for the same duration as the years used in building the ZINB model.

The combination of the zero inflated negative binomial model with the Empirical Bayes accident history adjustment is called ZINEBS, which is short for Zero Inflated Negative Binomial Empirical Bayes System.

5. Description of the fitted models for each device type

5.1. Gates

Among the fitted models, the model with the lowest AIC (AIC = 1466.5) was the one involving four variables: total tracks, number of highway lanes, whether the highway was paved or not, and the angle of crossing. A smaller model with three out of the four variables (total tracks, number of highway lanes and the angle of crossing) had very similar AIC (1467.4), indicating that the variable indicating whether or not the highway is paved has a smallest contribution compared to other three variables. It should be noted that the USDOT model uses the variables total tracks and number of highway lanes, but not the others (angle of crossing and whether or not the highway is paved).

Since the smaller model doesn't cause a drastic change in the AIC, has more variables in common with the USDOT formula, and the simplicity that comes from having lesser variables, the smaller model is recommended as the ZINEBS model for gates. The coefficients of the count part and the zero-inflation part of the model are given in Table 5.

The equation for the model is given as

$$E[a] = \frac{e^{-2.47+0.27*TotalTrack+0.28*HwyLanes-0.66*Angle}}{\left(1+e^{4.97-0.05*TotalTrain-0.48*\ln(Aadt)}\right)} \tag{10}$$

Table 5
Zero Inflated Negative Binomial Coefficients for Model for Gates.

Table 5(a): Coefficients of the zero-inflation part of the model

	Estimate	e^Estimate	Std. Error	z value	Pr(>|z|)
Intercept	4.97	144.330	0.86	5.77	0e + 00
Total Train	−0.05	0.947	0.02	−3.48	5e-04
ln(Aadt)	−0.48	0.615	0.11	−4.36	1e-05

Table 5(b): Coefficients of the count part of the model

	Estimate	e^Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−2.47	0.084	0.37	−6.65	0.00000
Total Track	0.27	1.314	0.09	2.96	0.00306
Number of highway lanes	0.28	1.328	0.07	4.03	0.00006
Angle category>60	−0.66	0.515	0.16	−4.16	0.00003
Ln(theta)	0.56				

where

TotalTrack is the sum of the number of main tracks and number of other tracks at the crossing
HwyLanes is the number of traffic lanes at the crossing
Angle is 1 if the angle between the highway and the rail line is over 60 degrees
TotalTrain is the sum of the number of the daily thru trains, number of nighttime thru trains and the total number of switching trains at the crossing
Aadt is the annual average daily traffic at the crossing.

The model indicates that baseline odds of being among a crossing that wouldn't have an accident is 144.3 (which is given by $e^{4.97}$). The odds is decreased by 0.947 for every one unit increase in total train and it decreases by 0.615 for every one unit increase in ln(Aadt) at the crossing. The baseline number of accidents is 0.084 among those crossings that have a chance of accidents. A unit increase in total tracks increase it by 1.314 times. An increase in the number of highway lanes increase the baseline number of accidents by 1.328 times, whereas crossings with angle over 60 degrees decreases it by 0.515 times.

5.2. Flashing lights

Among the fitted models, the model with the lowest AIC (AIC = 320.32) was the one that had included the variables: posted highway speed limit and whether the highway was paved or not. Adding the variable angle category to this model slightly increases the AIC to 321.70.

Furthermore, on examination of the coefficient of angle category in the fitted model, crossings with angle over 60 degrees increases the baseline number of accidents, which is counter intuitive. A crossing with wider angle should have better visibility, therefore a lower accident count would be expected. The coefficient of the variable indicating if the highway was paved or not showed crossings on unpaved highways decreased the baseline number of accidents, which is also counter intuitive. This, however, may be because of the larger exposure between the trains and highway vehicles at crossings on paved highway.

A smaller model with the lowest AIC is the model that includes the variable posted highway speed limit (AIC = 320.66). Since the smaller model doesn't cause a drastic change in the AIC and has no variables with counter intuitive coefficients, it is chosen as the ZINEBS model for Flashing Lights. The coefficients of the count part and the zero-inflation part of the model are given in Table 6.

The equation for the model is written as

$$E[a] = \frac{e^{-3.59+0.04*HwySpeed}}{\left(1+e^{14.8944-0.253*TotalTrain-1.848*\ln(Aadt)}\right)} \tag{11}$$

where

HwySpeed is the posted highway speed limit
TotalTrain is the sum of the number of the daily thru trains, number of nighttime thru trains and the total number of switching trains at the crossing
Aadt is the annual average daily traffic at the crossing.

The model indicates that baseline odds of being among a crossing that wouldn't have an accident is 2941290.56. This may be because only 39 crossings had any accidents in the years 2012–2016 (years used in model development) among the 960 crossings with flashing lights. The odds are decreased by 0. 777 for every one unit increase in total train and it decreases by 0.158 for every one unit increase in ln(Aadt) at the crossing. The baseline number of accidents is 0.037 among those crossings that have a chance of accidents. A unit increase in posted highway speed increase it by 1.037 times.

5.3. Crossbucks

Among the fitted models, the model with the lowest AIC (AIC = 426.89) was the one that included the variables posted highway speed limit and the type of crossing surface. However, as per that model, the baseline number of accidents is reduced at a crossing on a highway at a higher speed limit, which is counter intuitive. A smaller model is the model including only the variable indicating the surface type at the crossing (AIC = 426.93) and the AIC of this model is not significantly different from the lowest value. Therefore, the smaller model is recommended as the ZINEBS model for crossbucks, and the coefficients are given in Table 7.

The equation for the model is

$$E[a] = \frac{e^{-2.34+S}}{1+e^{7.39-0.42*TotalTrain-1.07*\ln(Aadt)}} \tag{12}$$

where

S is the factor for type of surface and takes values as follows
Asphalt = 0
Concrete = 0.47
Rubber = 0.04
Timber = -0.83
Unconsolidated = -0.1

TotalTrain is the sum of the number of the daily thru trains, number of nighttime thru trains and the total number of switching trains at the crossing

Aadt is the annual average daily traffic at the crossing.

As per the fitted model, for crossings with crossbucks, baseline odds of being among a crossing which wouldn't have an accident is 1627.7 and this is reduced by 0.657 times for each unit increase in total number of trains and by 0.343 times each unit increase in in ln(Aadt). The baseline number of accidents expected based on the

Table 6
Zero Inflated Negative Binomial Coefficients for Model for Flashing Lights.

Table 6 (a): Coefficients of the zero-inflation part of the model

	Estimate	e^Estimate	Std. Error	z value	Pr(>|z|)
Intercept	14.8944	2941290.56	7.779	1.914	0.0556
Total Train	−0.253	0.777	0.185	−1.362	0.1730
ln(Aadt)	−1.848	0.158	1.066	−1.733	0.0830

Table 6(b): Coefficients of the count part of the model

	Estimate	e^Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−3.59	0.028	0.697	−5.142	2.72e-07
HwySpeed	0.04	1.037	0.016	2.200	0.0278
Ln(theta)	1.2060				

model is 0.097 accidents at a crossing. This number is increased by 1.605 at concrete surfaces and by 1.040 at rubber surfaces and is decreased by 0.437 at timber surfaces and by 0.909 at unconsolidated surfaces.

The variables Maximum timetable train speed and distance to nearby HW intersection were not selected in any of the model equations in the ZINEBS model.

6. Variables in ZINEBS model

The new ZINEBS model uses the following variable: (a) Total Tracks, (b) Angle Category, (c) Number of Highway Lanes, (d) Posted Highway Speed Limit, and (e) Crossing Surface. Some of the variables were also used in the USDOT model or the new FRA model, but not all of them. Table 8 shows the variables used in the three different models.

6.1. Total Track

This variable is obtained as the sum of the number of main tracks and the number of other tracks present at the crossing. The ZINEBS model uses this variable in its equation for gated crossings.

Fig. 1 shows the mean of the number of accidents recorded with respect to the number of tracks at a crossing. From Fig. 1(a) (crossings with Gates), we see an increase in accident count at gated crossings with increase in the number of tracks. This trend is not seen in Fig. 1(b) (crossings with Flashing Lights) and Fig. 1(c) (crossings with Crossbucks). This confirms that the variable Total Track should be included in the model for gates.

6.2. Angle category

The grade crossing inventory database provides the smallest angle between the rail tracks and the highway lane as a categorical variable divided into <30, 30–60, and >60. Due to limited number of entries in the category <30 (~3% of entries), it was combined with the 30–60 category. A crossing with a tight angle may create visibility issues for drivers and may lead to a higher proportion of accidents at the crossings with tight angle. Fig. 2 shows the mean of the number of accidents recorded with respect to the angle category.

As there are only two angle categories, a t-test was performed to verify if there is a significant difference in the mean accident count with respect to the angle category. Table 9 shows the results of the t-test.

From Table 9, it can be seen that the angle category is significant (p-value < 0.05) for gated crossings and not significant for the other two warning devices. This confirms the inclusion of angle category

Table 7
Zero Inflated Negative Binomial Coefficients for Model for Crossbucks.

Table 7(a): Coefficients of the zero-inflation part of the model

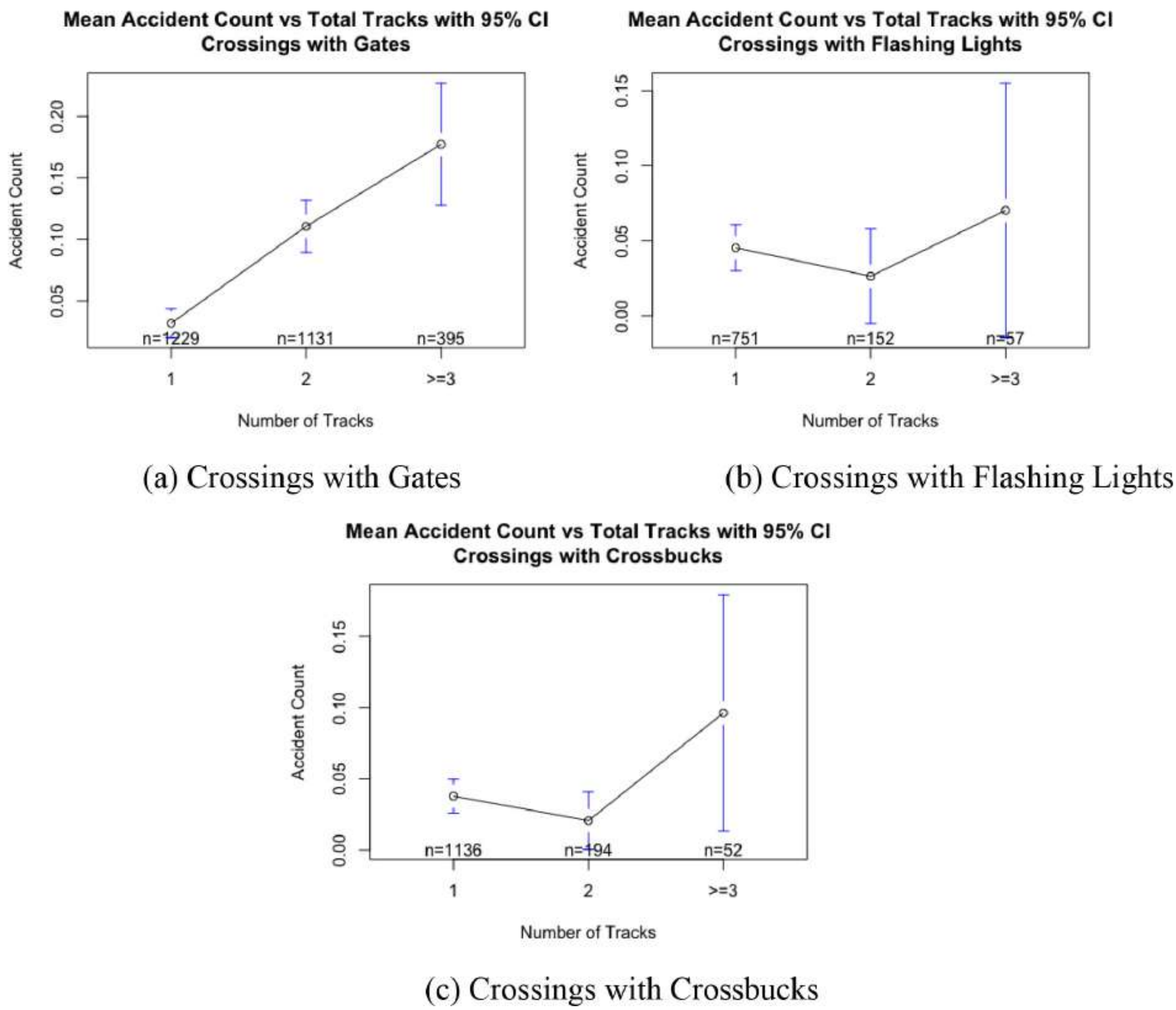
	Estimate	e^Estimate	Std. Error	z value	Pr(>|z|)
Intercept	7.39	1627.734	2.1	3.51	0.000441
Total Train	−0.42	0.657	0.18	−2.29	0.022248
ln(Aadt)	−1.07	0.343	0.38	−2.85	0.004397

Table 7(b): Coefficients of the count part of the model

	Estimate	e^Estimate	Std. Error	z value	Pr(>|z|)
Intercept	−2.34	0.097	0.28	−8.43	<2e-16
Surface Category = Concrete	0.47	1.605	0.42	1.13	0.2585
Surface Category = Rubber	0.04	1.040	1.04	0.04	0.9700
Surface Category =Timber	−0.83	0.437	0.38	−2.19	0.0287
Surface Category = Unconsolidated	−0.1	0.909	0.47	−0.2	0.8389
Ln(theta)	1.41				

Table 8
Variables used in USDOT model, new FRA model and ZINEBS model.

Variable Name	Comments on Variable	Is variable used in USDOT model?	Is variable used in new FRA model?	Is variable used in ZINEBS model
Annual Average Daily Traffic	Numeric Variable	Yes	Yes	Yes
Total Train	Sum of DayThru, NgthThru and TotalSwt	Yes	Yes	Yes
Maximum Timetable Train Speed	Numeric Variable	Yes	Yes	No
Posted Highway Speed Limit	Numeric Variable	No	No	Yes (Flashing Lights)
Surface Category	Data consolidated into 5 categories a) Timber b) Asphalt c) Concrete d) Rubber e) Unconsolidated	No	Yes	Yes (Crossbucks)
Angle Category	Data consolidated into 2 categories a) <=60 degrees b) > 60 degrees	No	No	Yes (Gates)
Number of Highway Lanes	Numeric Variable	Yes	No	Yes (Gates)
Total Track	Sum of MainTrk + OtherTrk	Yes	No	Yes (Gates)
Highway Paved?	Indicates whether the highway was paved or not	Yes	No	No



(a) Crossings with Gates

(b) Crossings with Flashing Lights

(c) Crossings with Crossbucks

Fig. 1. Accident Count vs Number of Tracks.

in the ZINEBS model equation for gates. Therefore, number of highway lanes should be included in the model for gates.

6.3. Number of highway lanes

The variable number of highway lanes is included in the ZINEBS model for gates. As seen in Fig. 3, at gated crossings, an increase in the number of accidents is seen with an increase in the number of highway lanes. This is in tune with the sign of the variable in the equation in ZINEBS model for gates.

6.4. Highway speed

The variable highway speed indicates the posted highway speed near the crossing. This variable is included in the ZINEBS model equation for crossings with flashing lights. The plot of the mean accident count given the highway speed is plotted in Fig. 4. The figure also shows the regression line obtained between the mean accident count and Highway Speed. The number adjacent to each point represents the number of crossings within that point.

Fig. 4 shows a decreasing relationship between the highway speed and accident counts for crossings with gates and crossbucks. On the other hand, accident count increases with highway speed for crossings with flashing light.

To test the significance of highway speed (a continuous variable), the regression line obtained between the accident count and highway speed is explored. Table 10 shows the coefficients of regression and their significance.

From Table 10, only the coefficient of highway speed for flashing lights is significant. The coefficient is not significant for gates and crossbucks. Therefore, the variable highway speed should be included in the equation for Flashing Lights.

6.5. Crossing surface

Crossing surface is divided into five categories (asphalt, concrete, rubber, timber, and unconsolidated). The ZINEBS model includes the crossing surface in its equation for crossbucks. Fig. 5 shows the mean accident count with respect to the type of crossing surface at crossings with different warning device categories.

Fig. 5(c) shows the trend of accident counts for crossbucks with respect to the surface category. This trend is captured in the ZINEBS model for crossbucks. Therefore, the variable Surface Category should be included in the model for crossbucks.

7. Agreement between predicted values and field data

One of the points raised in the new FRA model (2) is that separate models based on warning device types may result in inconsistent outcomes in the predicted values. The new FRA model incorporates the warning device type into its model, thereby ensuring the consistency in the predicted value outputs. This section checks if the consistency in model outputs is reflected in the field data.

To do that, the predicted values before a warning device upgrade is compared to the predicted values after the upgrade. This is done for two cases.

1. crossings with crossbucks when upgraded to flashing lights.
2. crossings with flashing lights when upgraded to gates.

7.1. Upgrade from crossbucks to flashing lights

Fig. 6 shows the new FRA model predicted value for crossbuck locations, as well as the same locations once it has been upgraded to Flashing Lights. The values are plotted against ln(AADT). As expected, the predicted values for crossbucks (given in blue triangle) are higher than the predicted values for flashing lights (given in orange circle).

In order to compare the predicted values from the new FRA model to the field data, Fig. 7 is plotted to show the field data versus log(AADT). The plot shows the average number of accidents at a location given the AADT, for crossbucks (blue) and flashing lights (orange).

As highlighted in Fig. 7, there are several locations with flashing lights that higher accident counts than locations with crossbucks. Several crossings, especially at higher values of AADT, show that the observed accident counts at flashing light locations are higher than the observed accident counts at crossbuck locations. This is not seen in the new FRA predicted model (Fig. 6). On the other hand, the predicted values from the ZINEBS model (Fig. 8) shows that there are several locations with flashing lights that have a higher predicted value than when the location had crossbucks. These locations are highlighted in Fig. 8. The predicted values from the ZINEBS model shows a closer agreement with the field data than the new FRA model.

A similar trend is seen if the predicted values are plotted against the total train counts. Fig. 9 shows the plot of the predicted accident count for crossings with crossbucks, and the crossings once they have been upgraded to flashing lights using the new FRA model. The predicted value for locations with crossbucks is higher than the predicted value for locations with flashing lights in all the cases, as seen in Fig. 9. This is expected as such a layering is incorporated into the new FRA model equation.

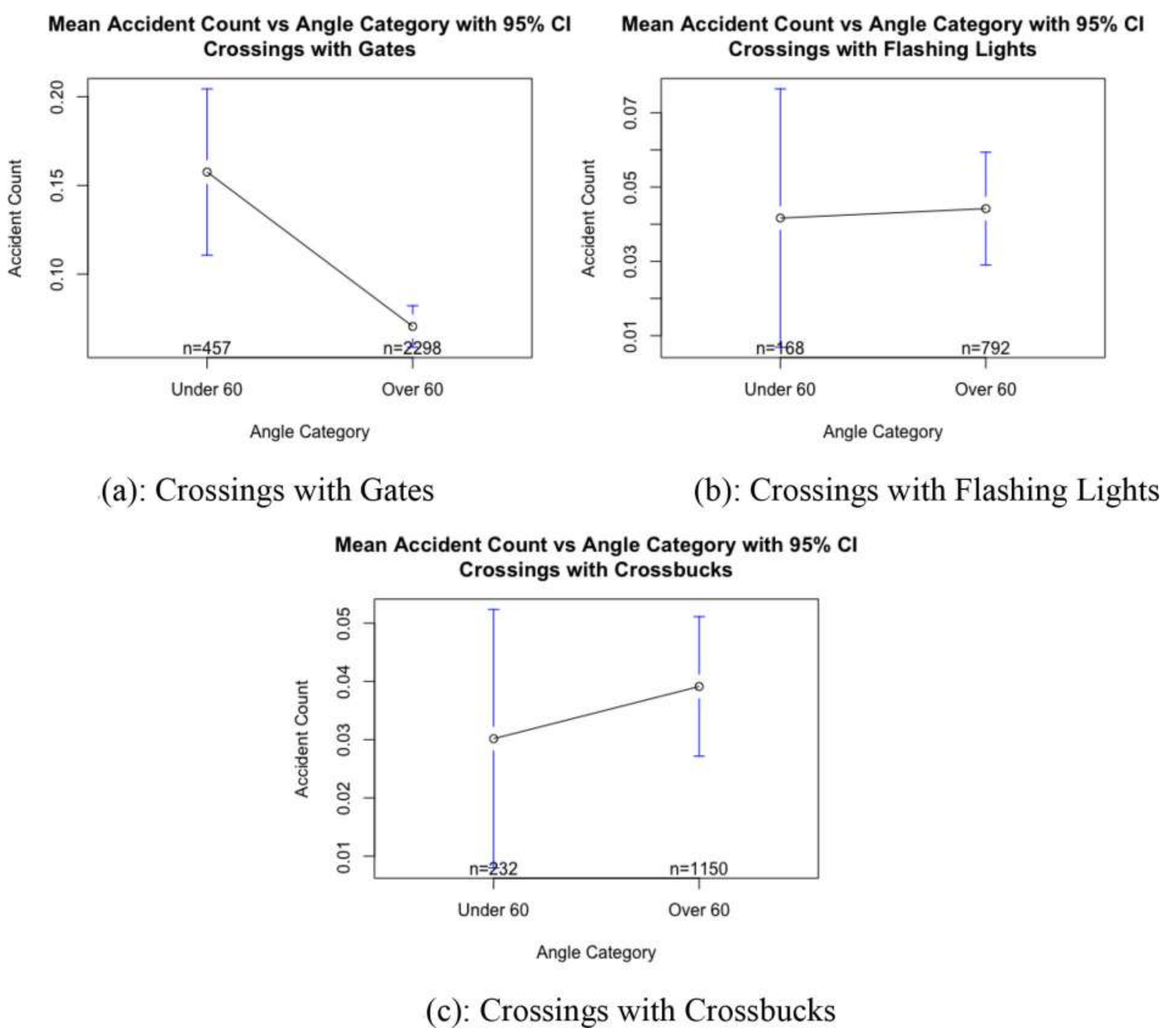


Fig. 2. Accident Count vs Angle Category.

Fig. 10 shows the plot of the field data vs log(AADT). The plot shows the average number of accidents at a location given the AADT, for crossbucks (blue) and flashing lights (orange). Please note that if both crossbuck locations and flashing light locations had no accidents, it isn't plotted in Fig. 10.

As highlighted in Fig. 10, there are several locations with flashing lights that had a higher accident count than locations with crossbucks. This trend is not seen in the new FRA predicted model (Fig. 9). On the other hand, the predicted values from the ZINEBS model (Fig. 11) shows that there are several locations with flashing lights that have a higher predicted value than when the location had crossbucks. These locations are highlighted in Fig. 11.

By comparing Figs. 10 and 11, predicted values from the ZINEBS model shows a closer agreement with the field data than the new FRA model.

Table 9
Result of t-test on Accident Count vs Angle Category.

Warning Device	t-statistic	df	*p*-value
Crossing with Gates	3.5389	514.62	0.0004382***
Crossing with Flashing Lights	−0.13125	235.68	0.8957
Crossing with Crossbucks	−0.69963	380.28	0.4846

Plots using the combination of AADT and Total Train values were also made to further show the similarity of the ZINEBS model to the field data. This is shown in Fig. 12.

The locations where the number of accidents at a flashing light location is higher than the number of accidents at a crossbuck location is highlighted using the red arrows in Fig. 12. In the plot for the predicted value using the new FRA model (Fig. 12(a)), the crossbuck locations consistently have a higher predicted value than the flashing light locations. This is not the case in the plot for the predicted value using the ZINEBS model (Fig. 12(b)) and field data (Fig. 12(c)).

7.2. Upgrade from flashing lights to gates

Fig. 13 shows the new FRA model predicted value for Flashing Light locations (orange circles), as well as the same locations once it has been upgraded to Gates (green diamonds). The values are plotted against log(AADT). Fig. 13 shows that the accident prediction value using the new FRA model for flashing lights is always higher than the accident prediction value for gates.

However, from Fig. 14, which shows the plot for the observed accident count for locations with flashing lights and gates, this trend (crossings with flashing lights have lower accident count than crossings with gates) is not consistently observed. In Fig. 14, several locations are highlighted where, for a given value for AADT,

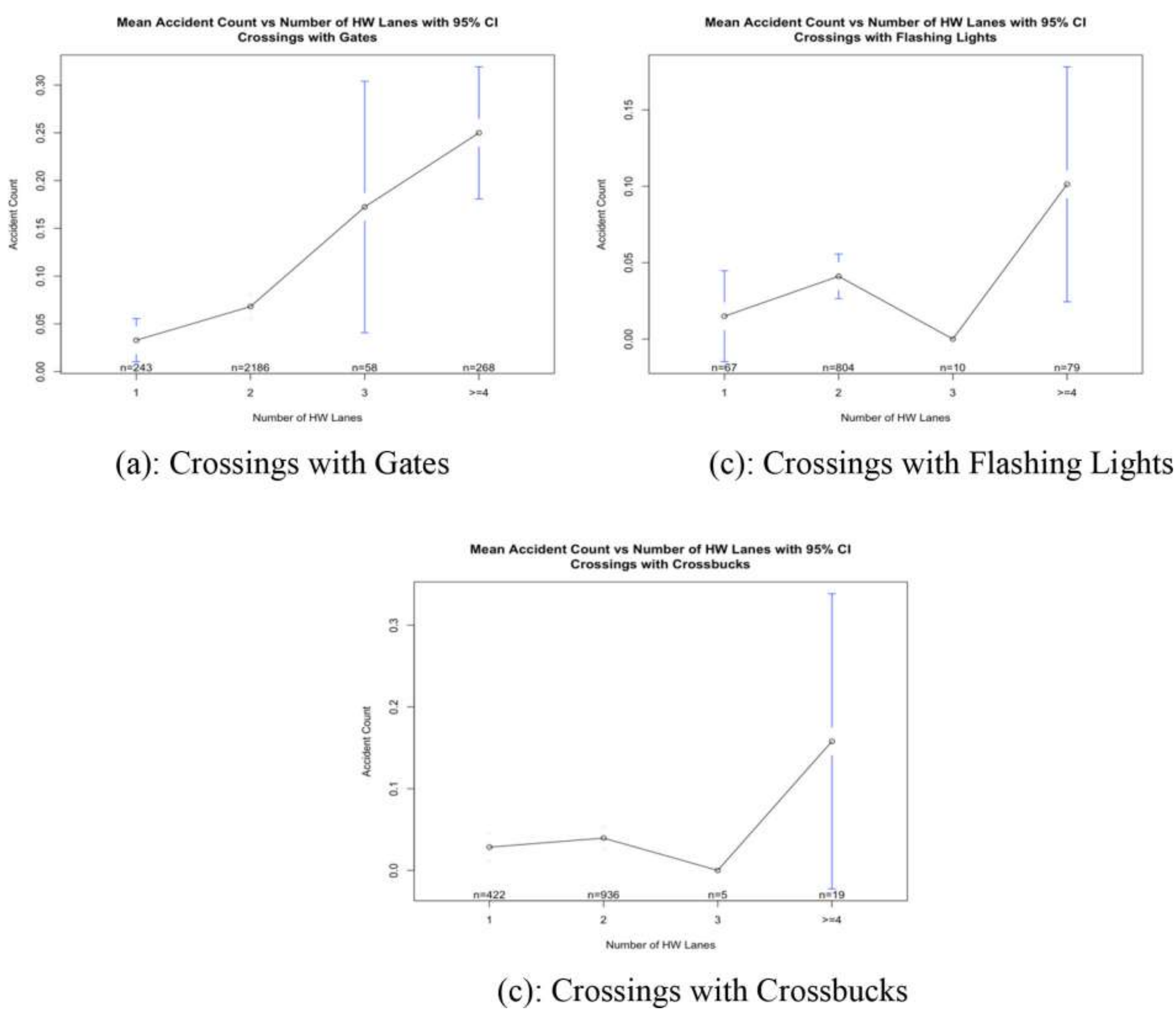


Fig. 3. Accident Count vs Number of HW Lanes.

the observed accident count for crossings with gates is higher than the observed accident count for crossings with flashing lights.

Fig. 15 shows the predicted values from the ZINEBS model. Fig. 15 shows that there are several locations with gates which has a higher predicted value than when the location had flashing lights, as highlighted using the red circles.

A similar trend is seen if the predicted values are plotted against the total train counts. Fig. 16 shows the plot of the predicted accident count for crossings with crossbucks, and the crossings once they have been upgraded to flashing lights using the new FRA model. The predicted value for locations with crossbucks is higher than the predicted value for locations with flashing lights in all the cases.

However, the plot for the observed accident count against total train values, as shown in Fig. 17, shows several locations where crossings with gates had more accidents than crossings with flashing lights. Fig. 17 highlights such locations in red circles.

Fig. 18 shows the predicted values from the ZINEBS model. Fig. 18 shows that there are several locations with gates that have a higher predicted value than when the location had flashing lights, as highlighted using the red circles.

Plots using the combination of AADT and Total Train values were also made to further show the similarity of the ZINEBS model to the field data when the warning device is upgraded from flashing lights to gates. This is shown in Fig. 19.

The locations where the number of accidents at a gated location is higher than the number of accidents at a flashing light location is highlighted using the red arrows in Fig. 19. In the plot for the predicted value using the new FRA model (Fig. 19(a)), the flashing light consistently has a higher predicted value than the gated locations. This is not the case in the plot for the predicted value using the ZINEBS model (Fig. 19(b)) and field data (Fig. 19(c)).

8. Validation of new model

The newly developed model was validated using (independent) Texas data. The model predicted value was compared to the accident data (or field data). Figs. 20–22 show the plot of the cumulative field data and the cumulative model predicted value. The predicted risk at a crossing is quantified by the model predicted output of the model for the crossing, and the field data (or observed accident count at the crossing) represents the actual risk at the crossing. The crossings are ranked based on the observed number of accidents at the location.

Fig. 20 shows the cumulative risk predicted by the ZINEBS model and the observed accident count for crossings with gates. Fig. 20(a) shows all the crossings within the state while Fig. 20 (b) shows only the crossings with accidents. The shape of the curve showing the cumulative predicted curve is similar to the shape of the curve showing the observed accident count with a significant rise in the cumulative risk predicted at crossings with accidents and only a slight rise among other crossings. The model predicts 57% of field data at the crossings that observed an accident in Texas with Gates.

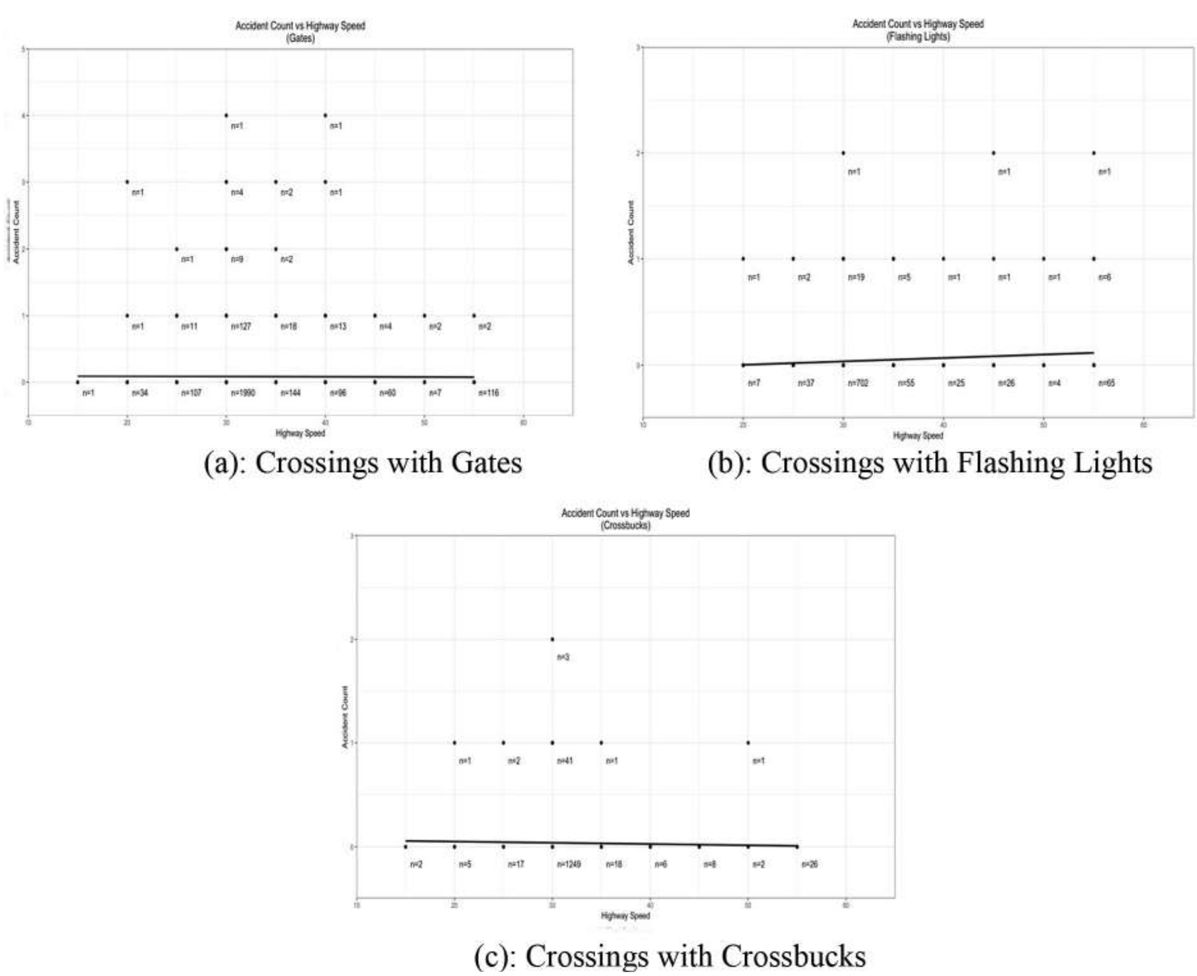


Fig. 4. Accident Count vs Highway Speed.

Fig. 21 shows similar observations for crossings with flashing lights and no gates. The model predicts 56% of field data at the crossings that observed an accident in Texas with flashing lights and no gates.

Crossings with crossbucks also show a similar observation as well. The model predicts 56% of field data at the crossings that observed an accident in Texas with crossbucks.

9. Comparison of new model to FRA models

The ZINEBS model is compared to the USDOT model (old) and the new FRA model. The comparison was done by comparing the cumulative risk at crossings as predicted by models.

The predicted risk at a crossing is quantified by the model predicted output of the model for the crossing, and the field data (or observed accident count at the crossing) represents the actual risk at the crossing. The crossings are ranked based on the observed number of accidents at the location. The cumulative predicted value given by each model for the crossings is plotted. A better model is the one that predicts accident counts closer to the actual cumulative risk.

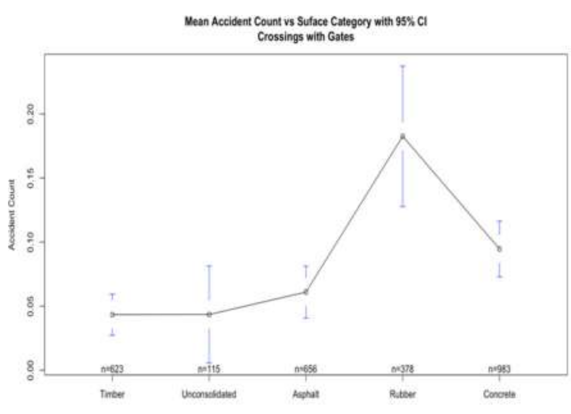
This comparison is done separately for crossings of each warning device types. The comparison is made for crossings in Illinois (model development dataset) and crossings in Texas (model validation dataset).

9.1. Crossings with gates

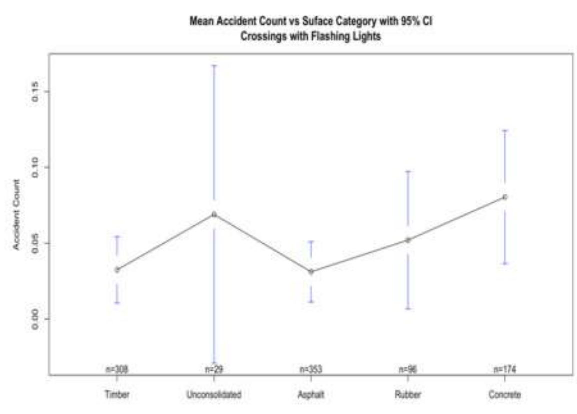
From the Fig. 23 (a and b), the cumulative risk calculated by the ZINEBS model can "pull" the model closer to the cumulative accident count values. There was a total of 234 accidents that were observed at gated crossings in Illinois in the period 2012–2016. The ZINEBS model estimated 233.877 as the cumulative risk at all gated crossings in Illinois. The new FRA model, on the other

Table 10
Regression coefficients of Highway Speed vs Accident Count.

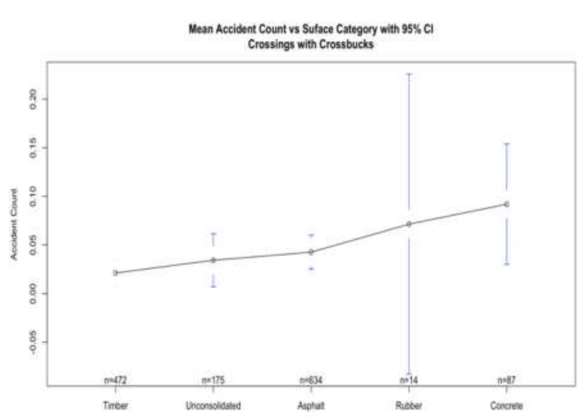
Warning Device	Coefficient for Highway Speed	Std. Error	t value	Pr(>|t|)
Crossings with Gates	−0.0004285	0.0010382	−0.413	0.67985
Flashing Lights	0.0031864	0.0009561	3.333	0.000893 ***
Crossbucks	−0.001174	0.001378	−0.852	0.3944



(a): Crossings with Gates



(b): Crossings with Flashing Lights



(c): Crossings with Crossbucks

Fig. 5. Accident Count vs Crossing Surface.

hand, estimated 176.198 as the cumulative risk over all gated crossings in Illinois. The cumulative estimate based on the USDOT model (old) was only 61.244. It is also noted that the ZINB model was fit to the field data, so the total sum of accidents is expected to be total actual observed accidents, as it is seen in Fig. 19(a). The 234 accidents at crossings in Illinois happened across 200 crossings. Looking at only the crossings with non-zero accidents (Fig. 23(b)), the ZINEBS model estimated a cumulative risk of 142.467 (60.88% of 234), while the new FRA model estimated 130.818 (55.90%) and the USDOT model (old) estimated 16.829 (7.19%).

For crossings in Texas, a similar result is obtained. There was a total of 468 accidents that were observed at gated crossings in Texas in the period of 2012–2016. The ZINEBS model estimated 358.836 as the cumulative risk at all gated crossings in Texas. The new FRA model estimated 299.984 as the cumulative risk over all gated crossings in Texas. The cumulative estimate based on the USDOT model (old) was only 76.065 (Fig. 24(a)). The 468 accidents in Texas happened across 350 crossings. Looking at only crossings that had a non-zero accident count, (Fig. 24(b)), the ZINEBS model estimated a cumulative risk of 266.790 (57.0% of 468), while the new FRA model estimated 252.548 (53.96%) and the USDOT model (old) estimated 25.415 (5.43%).

9.2. Crossings with flashing lights

From the Fig. 25(a and b), the cumulative risk calculated by the ZINEBS is closer to the cumulative accident count values than the other two models. There was a total of 42 accidents that were observed at crossings with flashing lights in Illinois in the period 2012–2016 across 39 crossings. The ZINEBS model estimated 42.032 as the cumulative risk at all flashing lights crossings in Illinois. The new FRA model estimated 31.780 as the cumulative risk over all flashing light crossings in Illinois, which is approximately 9 lower than ZINEBS model. The cumulative estimate based on the USDOT model (old) was only 10.360. At the 39 crossings which reported non-zero accident counts, (Fig. 25 (b)), the ZINEBS model estimated a cumulative risk of 23.235 (55.32% of 42), while the new FRA model estimated 22.414 (53.36%) and the USDOT model (old) estimated 1.632 (3.88%).

For crossings in Texas, a similar result is obtained. There was a total of 60 accidents that were observed at crossings with flashing lights in Texas in the period of 2012–2016. The ZINEBS model estimated 46.39 as the cumulative risk at all gated crossings in Texas. The new FRA model estimated 35.48 as the cumulative risk over all gated crossings in Texas. The cumulative estimate based on the USDOT model (old) was only 6.345 (Fig. 26(a)). The 60 accidents in Texas happened across 48 crossings. Looking at only crossings that had a non-zero accident count, (Fig. 26(b)), the ZINEBS model estimated a cumulative risk of 33.703 (56.17% of 60), while the new FRA model estimated 31.958 (53.326%) and the USDOT model (old) estimated 2.384 (3.97%).

9.3. Crossings with crossbucks

From the Fig. 27(a and b), a similar result as seen for crossings with Gates and crossings with Flashing lights is observed.

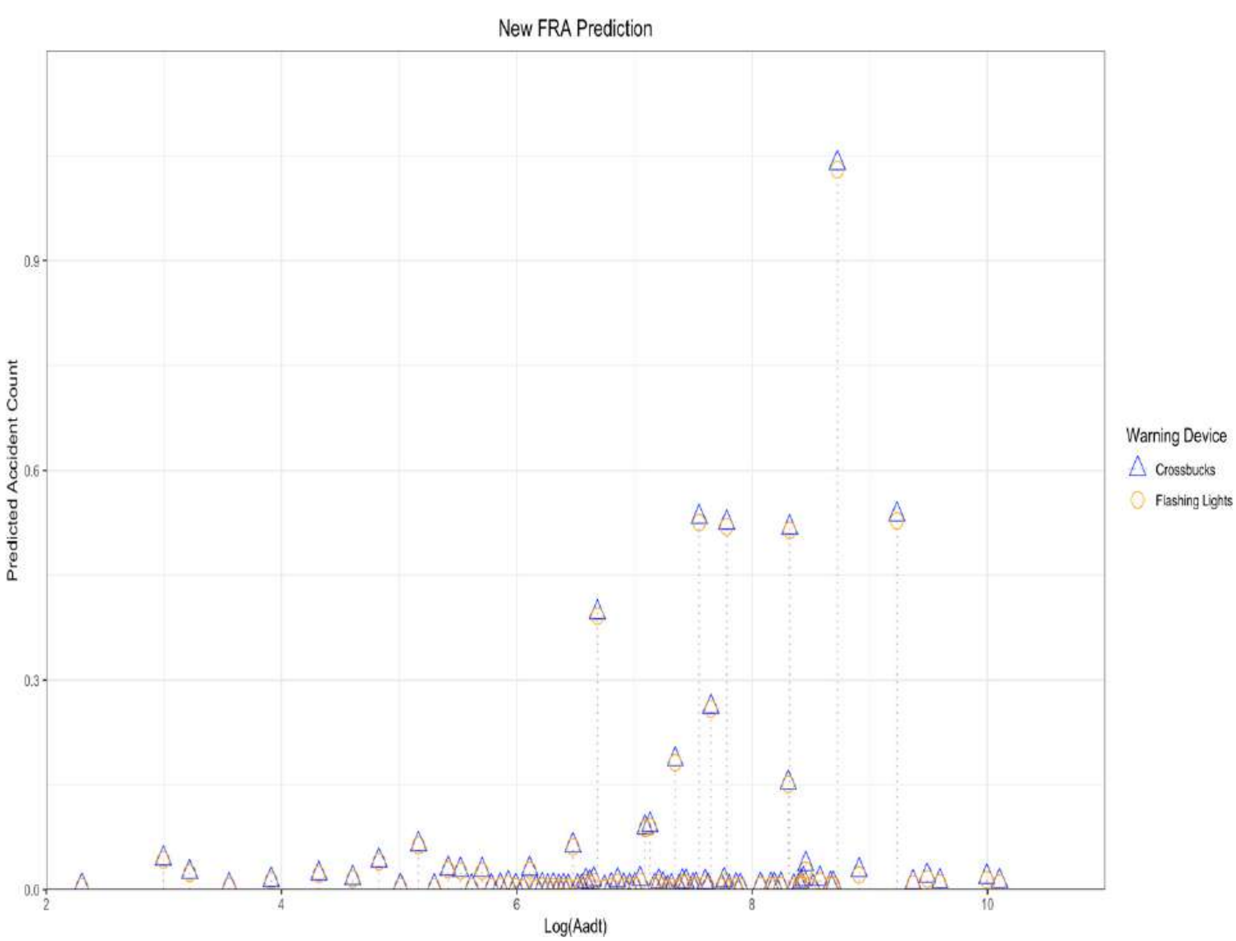


Fig. 6. Predicted accident count vs Ln(AADT) using the new FRA Model: Warning device changed from crossbucks to flashing lights.

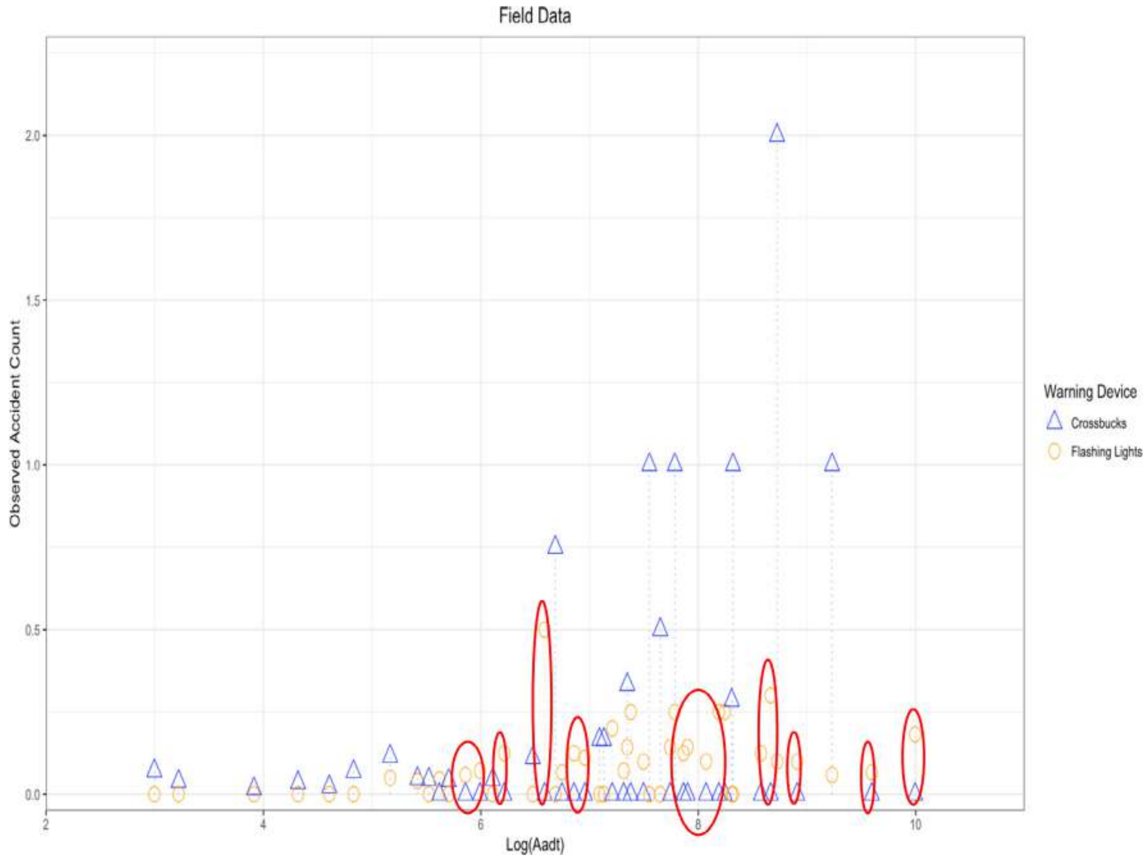


Fig. 7. Observed accident count vs Ln(Aadt): Warning device changed from crossbucks to flashing lights.

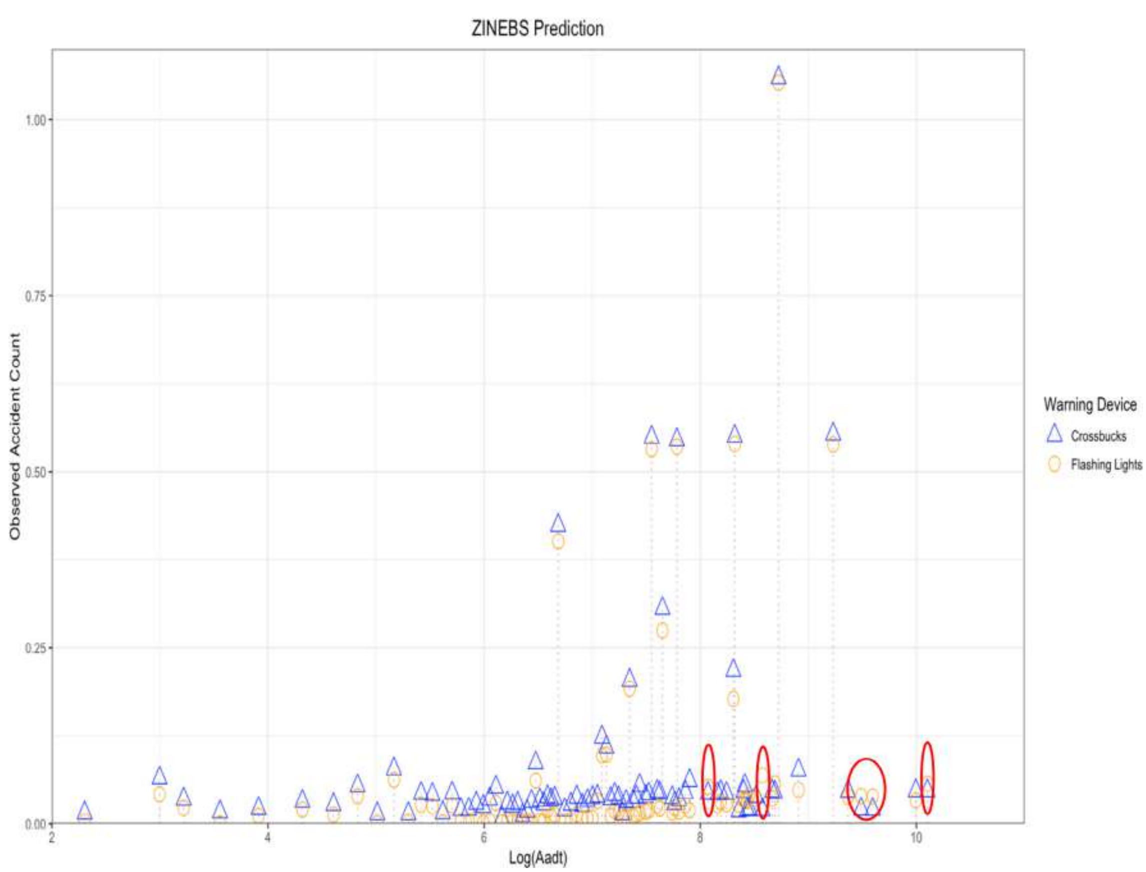


Fig. 8. Predicted accident count vs Ln(AADT) using the ZINEBS Model: Warning device changed from crossbucks to flashing lights.

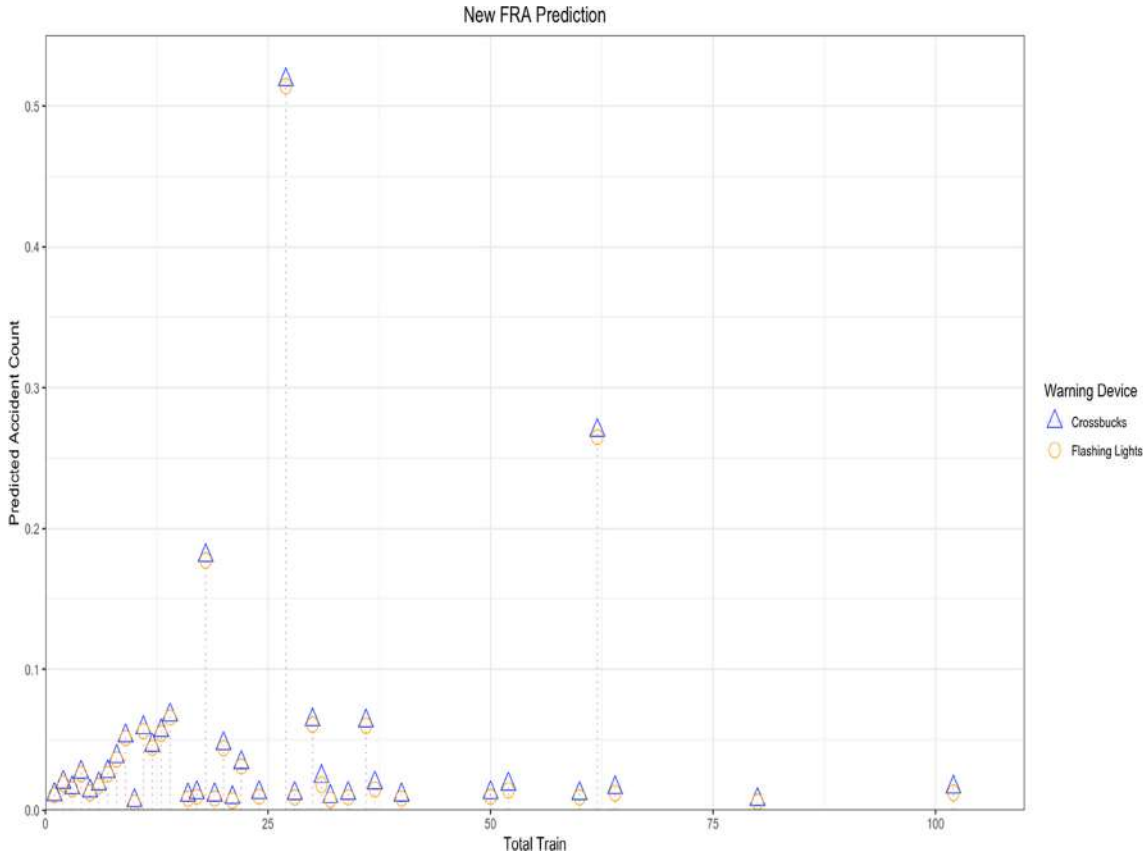


Fig. 9. Predicted accident count vs Total Train using the new FRA Model: Warning device changed from crossbucks to flashing lights.

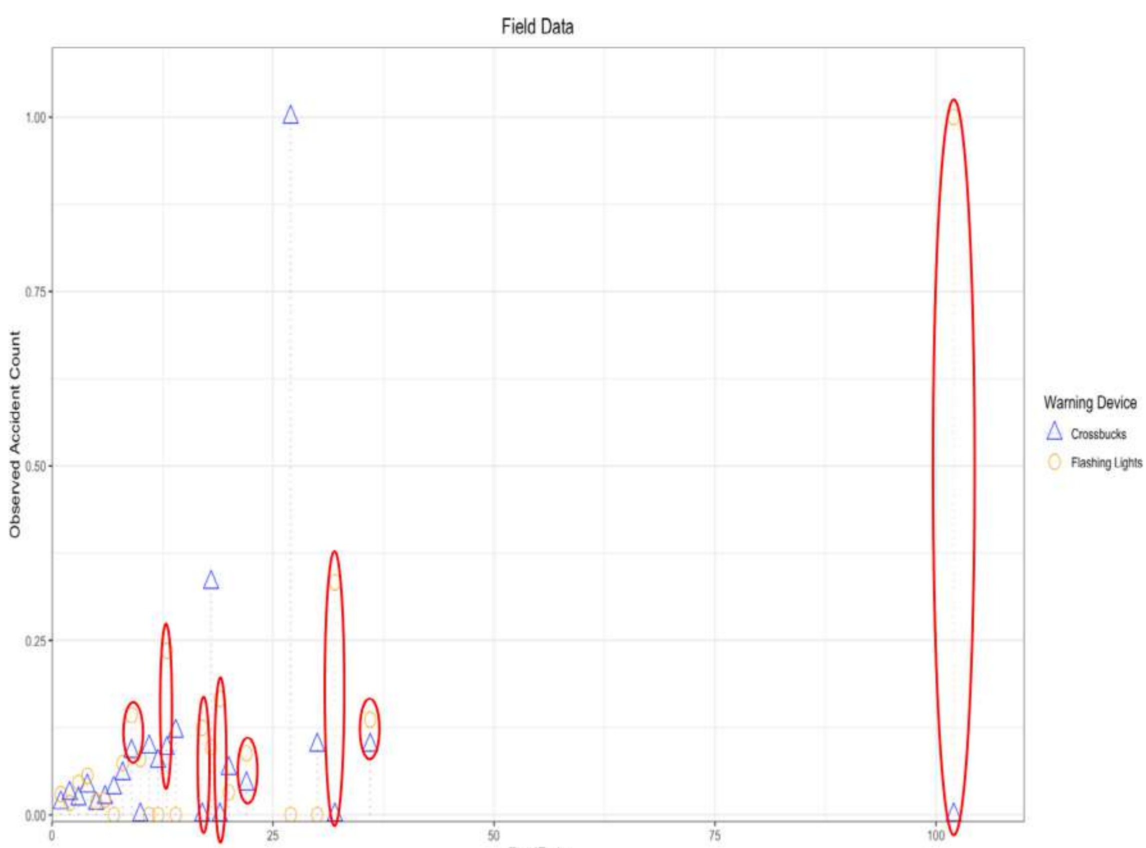


Fig. 10. Observed accident count vs Total Train: Warning device changed from crossbucks to flashing lights.

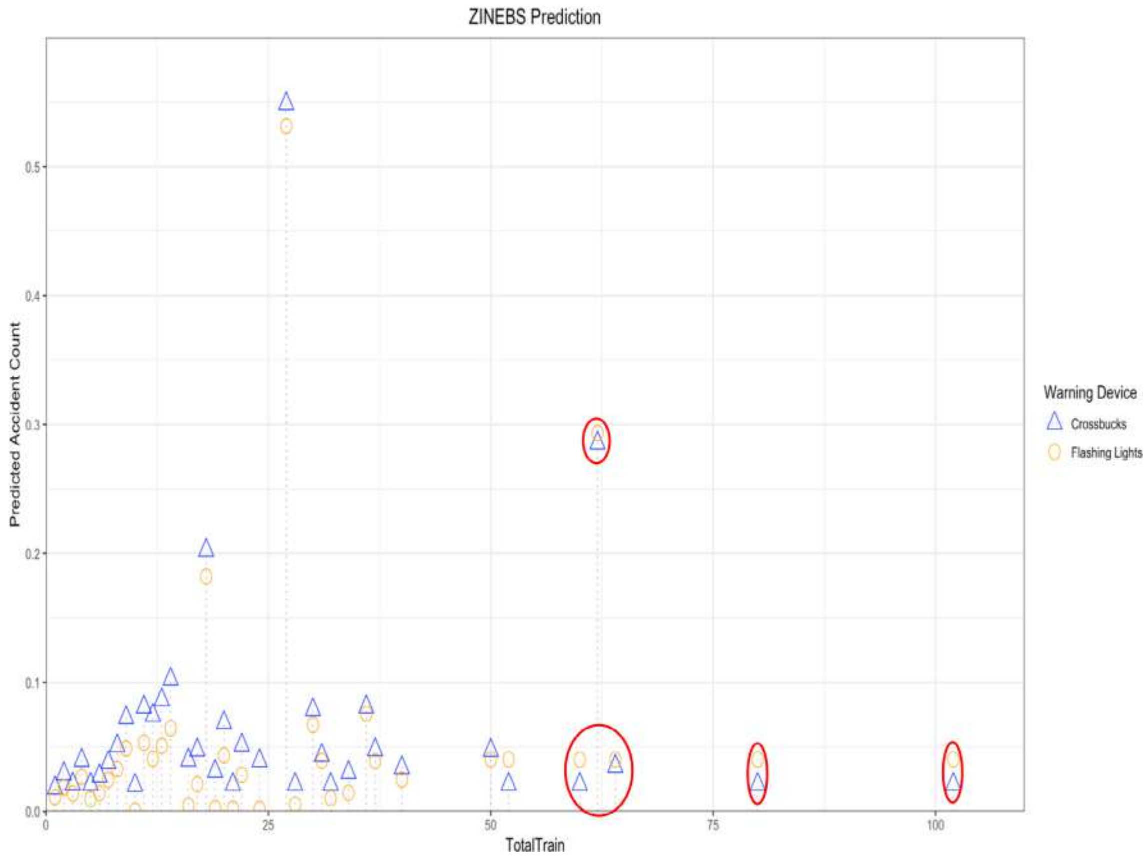


Fig. 11. Predicted accident count vs Total Train using the ZINEBS Model: Warning device changed from crossbucks to flashing lights.

The cumulative predicted risk calculated by the ZINEBS for crossbucks is closer to the cumulative accident count values than the other two models. There was a total of 52 accidents that were observed at crossings with crossbucks in Illinois in the period 2012–2016 across 49 crossings. The ZINEBS model estimated 52.003 as the cumulative risk at all crossings with crossbucks in Illinois. The new FRA model estimated 34.434 as the cumulative risk over all crossings with crossbucks in Illinois, which is approximately 18 lower than ZINEBS model. The cumulative estimate based on the USDOT model (old) was only 10.947. At the 49 crossings which reported non-zero accident counts, (Fig. 27(b)), the ZINEBS model estimated a cumulative risk of 28.2469 (54.32% of 52), while the new FRA model estimated 26.932 (51.79%) and the USDOT model (old) estimated only 2.0827 (4.00%).

For crossings in Texas, a similar result is obtained. There was a total of 62 accidents that were observed at crossings with flashing lights in Texas in the period of 2012–2016. The ZINEBS model estimated 63.757 as the cumulative risk at all crossings with crossbucks in Texas. The new FRA model estimated 40.32 as the cumulative risk over all gated crossings in Texas. The cumulative estimate based on the USDOT model (old) was only 14.025 (Fig. 28(a)). The 62 accidents in Texas happened across 57 crossings. Looking at only crossings that had a non-zero accident count, (Fig. 28(b)), the ZINEBS model estimated a cumulative risk of 33.844 (54.58% of 62), while the new FRA model estimated 32.278 (52.06%) and the USDOT model (old) estimated 2.384 (3.84%).

10. Discussion regarding USDOT model, new FRA model and ZINEBS model

The USDOT formula was developed over 40 years ago in the 1980s. This model used multiple logistic regression approach in developing the initial accident prediction value. The accident history adjustment procedure used is a weighted averaging method where the weights depend only on the initial accident prediction value. This model has not changed except for the normalizing constants that are updated every few years. Furthermore, from the comparisons made in the previous sections, it can be seen that the USDOT model underperforms in predicting the cumulative risk at crossings and also while ranking crossings when compared to the ZINEBS model.

The new FRA model adopted the ZINB methodology with EB adjustments. However, there are several key areas of differences when compared to the ZINEBS model.

1. The new FRA model is developed using national data. The authors found that while filtering the data based on the filters given in Table 3, several states lose a huge number of data points. Some states like Colorado, Washington, etc. are only left with 2% of the data after filtering is done. It is better to use states that have better data available to develop the models.
2. The data used in the new FRA model is not filtered as comprehensively as the filters used in the development of the ZINEBS model. The ZINEBS model development includes additional filters given below resulting in a more meaningful dataset.

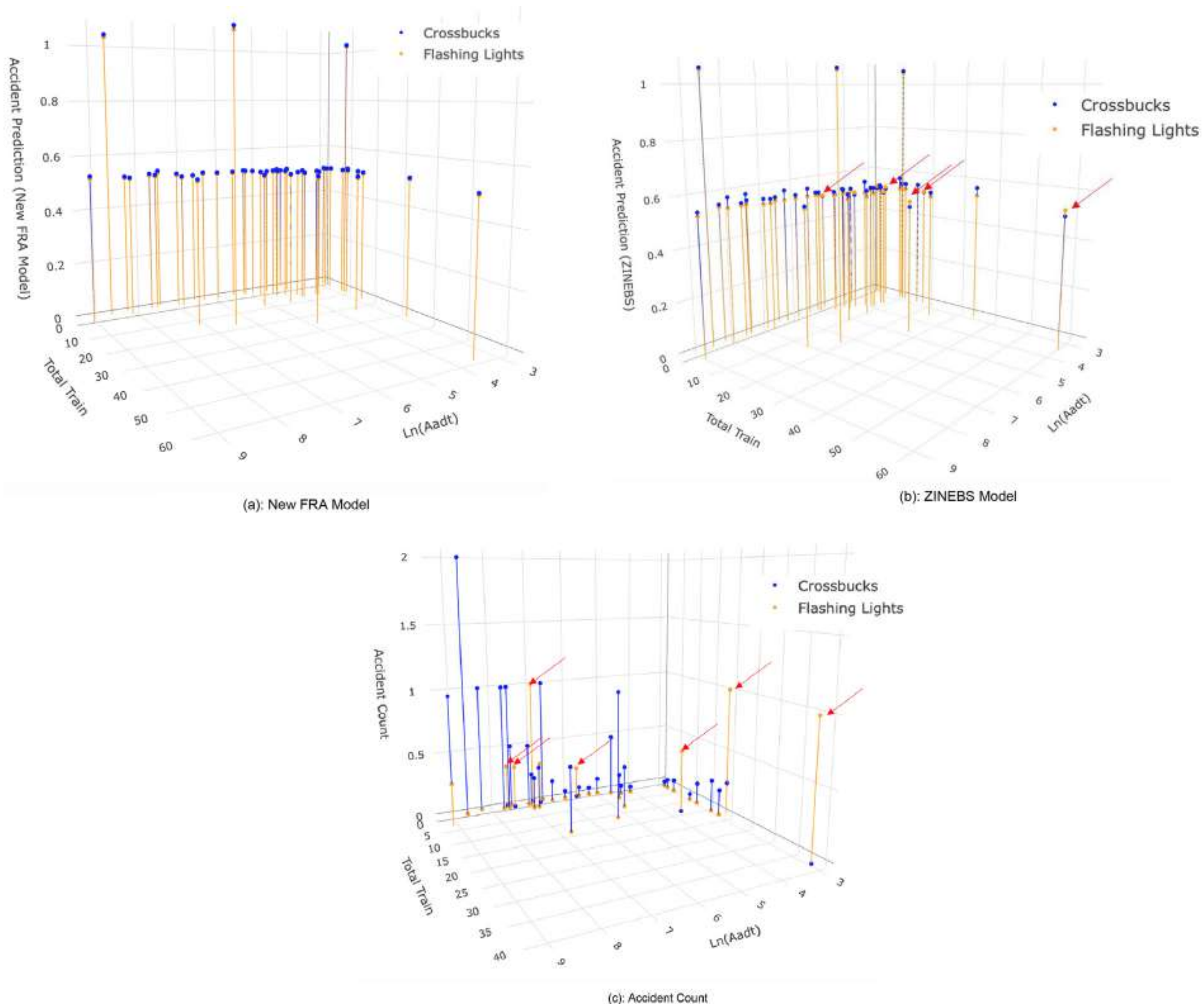


Fig. 12. Plot of Accident Count vs ln(AADT) and Total Train: Warning device changed from Crossbucks to Flashing Lights.

   i. Remove xings with AADT Year > year 2000
   ii. Remove xings where the warning device has been changed.
3. Variable selection in the new FRA model adopts a visual approach by plotting normalized accident counts against different variables to see if there is a difference in accident counts. The variables selected in the ZINEBS model were further analyzed to justify its incorporation in the appropriate model equation.
4. The new FRA model uses a single equation for all warning device types, while the ZINEBS model uses three separate equations for the three warning device types. Different warning devices offer different levels of protection. For this reason, the type of highway vehicle movement is expected to be different. It is therefore reasonable to adopt different equations for different warning device types, which also gives the flexibility of selecting different variables for each warning device type.
5. The new FRA model always predicts a higher accident count for crossbucks, followed by flashing lights and followed by gates. However, this trend is not seen in the field data. The ZINEBS model is more reflective of the field data.

11. Conclusion

The new FRA accident prediction model is based zero-inflated negative binomial approach that has been used by other researchers (Medina & Benekohal, 2015; Medina & Benekohal, 2015; Medina et al., 2016; Mathew & Benekohal, 2020). The unique feature of the new FRA model is that it has a single equation for all three traffic control devices (crossbuck, flashing light, and gates) and uses the same variables (AADT, Train Volume and Maximum timetable train speed, Crossing surface, and a variable indicating whether the crossing is located in a rural or urban setting) regardless of the traffic control devices at the crossing. While this model is significantly better than the old USDOT model, its shortcoming is that the single equation does not accurately represent the field condition. Since the New FRA model incorporates the warning device category as one of the variables in its model equation, the predicted accident frequency is higher when a crossing has crossbucks than flashing lights, and higher when it has flashing lights than gates. However, this outcome, even though true for some conditions, is not in general supported by field data.

This study developed different models for each type of warning device since the factors affecting accidents are not the same for all device types. The models are called ZINEBS (Zero Inflated Negative Binomial Empirical Bayes System). The model for gated crossing includes the variables, total train, AADT, total tracks, number of highway lanes, and the angle of crossing. The model for crossings with flashing lights includes the variables total train, AADT, and posted highway speed. For crossings with crossbucks, the model includes the variables total train, AADT, and type of crossing sur-

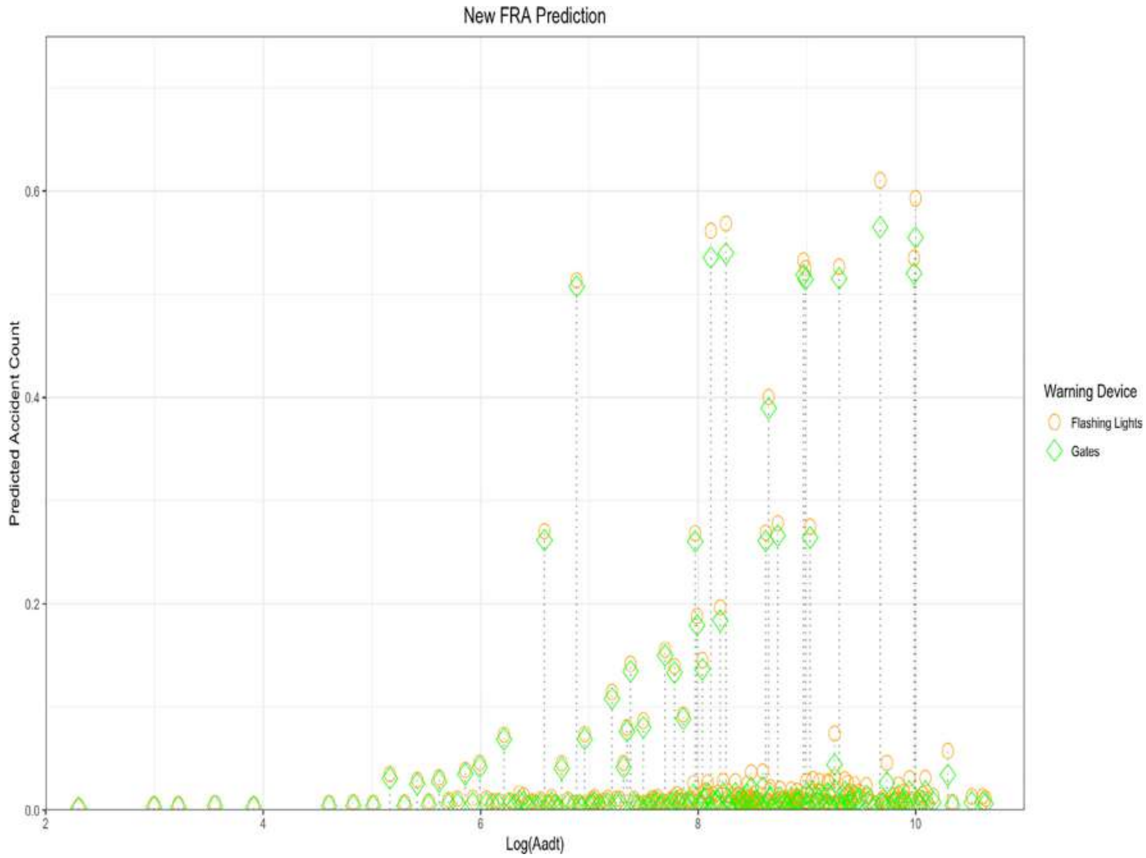


Fig. 13. Predicted accident count vs ln(AADT) using the New FRA Model: Warning device changed from Flashing Lights to Gates.

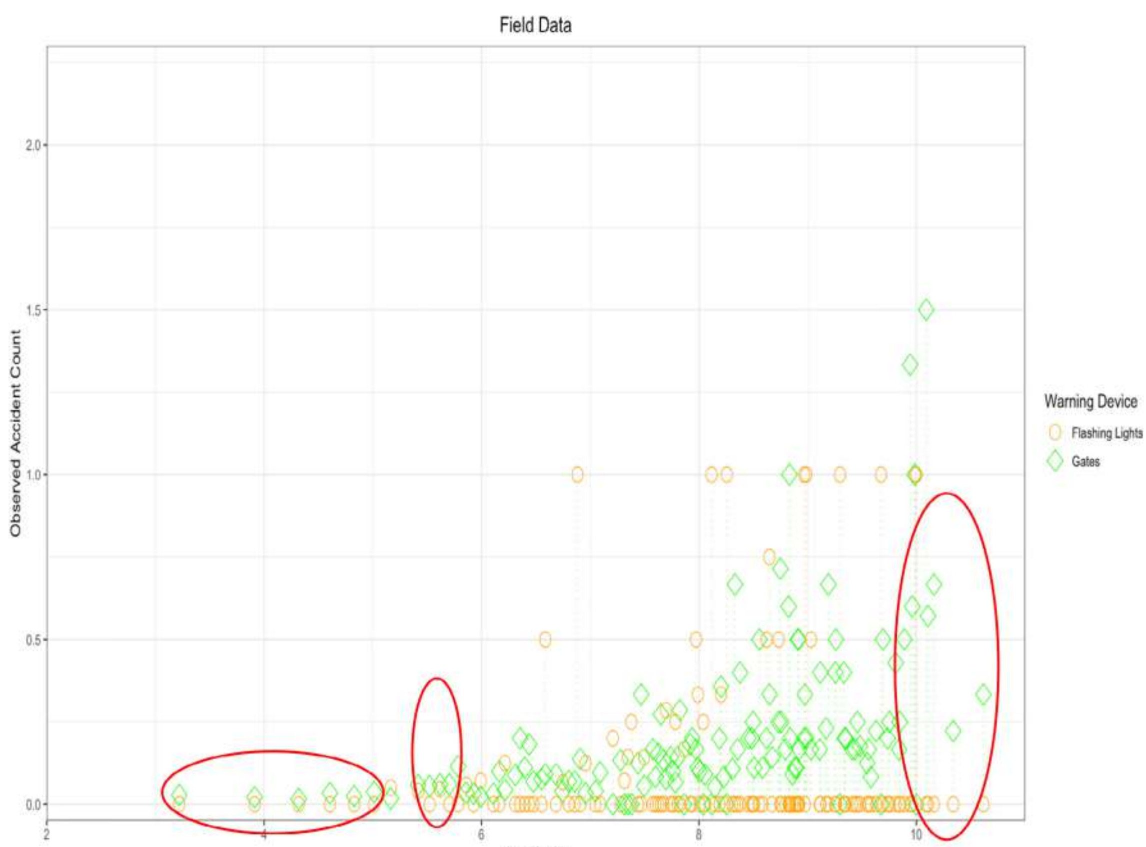


Fig. 14. Observed accident count vs ln(AADT): Warning device changed from Flashing Lights to Gates.

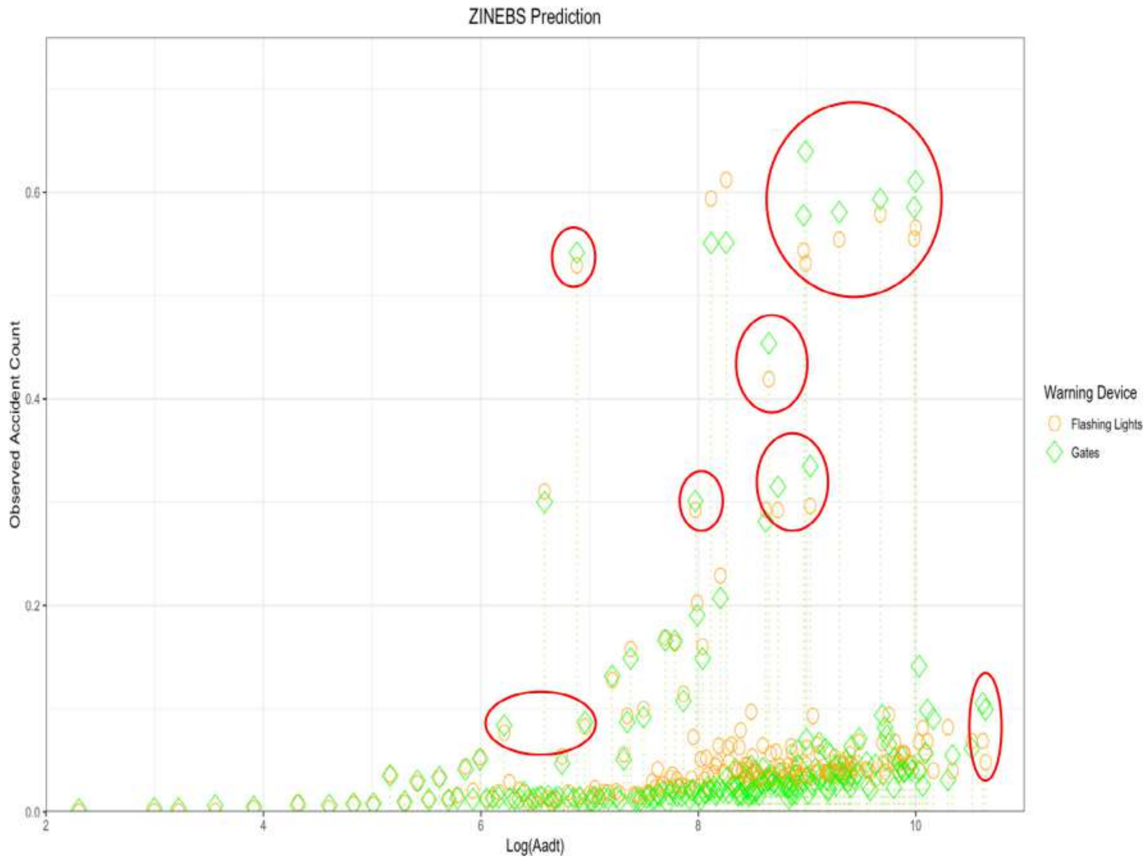


Fig. 15. Predicted accident count vs ln(AADT) using the ZINEBS Model: Warning device changed from Flashing Lights to Gates.

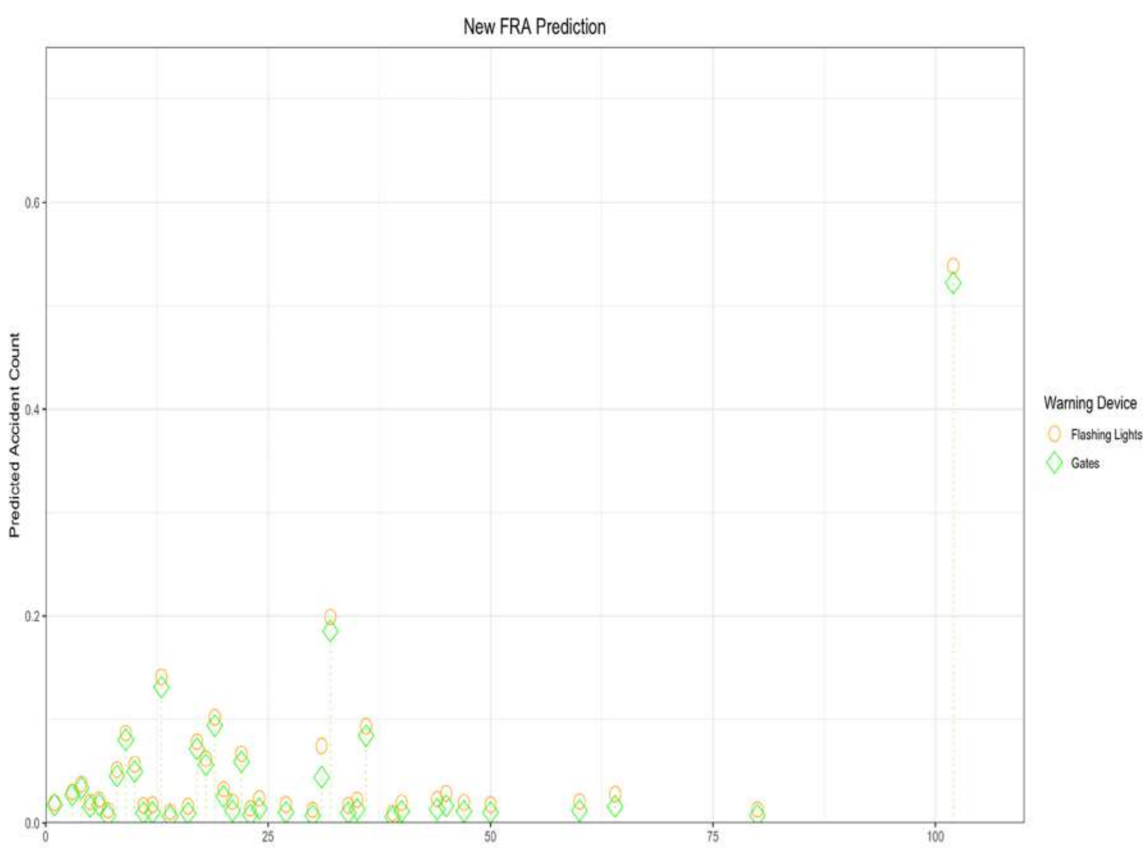


Fig. 16. Predicted accident count vs Total Train using the New FRA Model: Warning device changed from Flashing Lights to Gates.

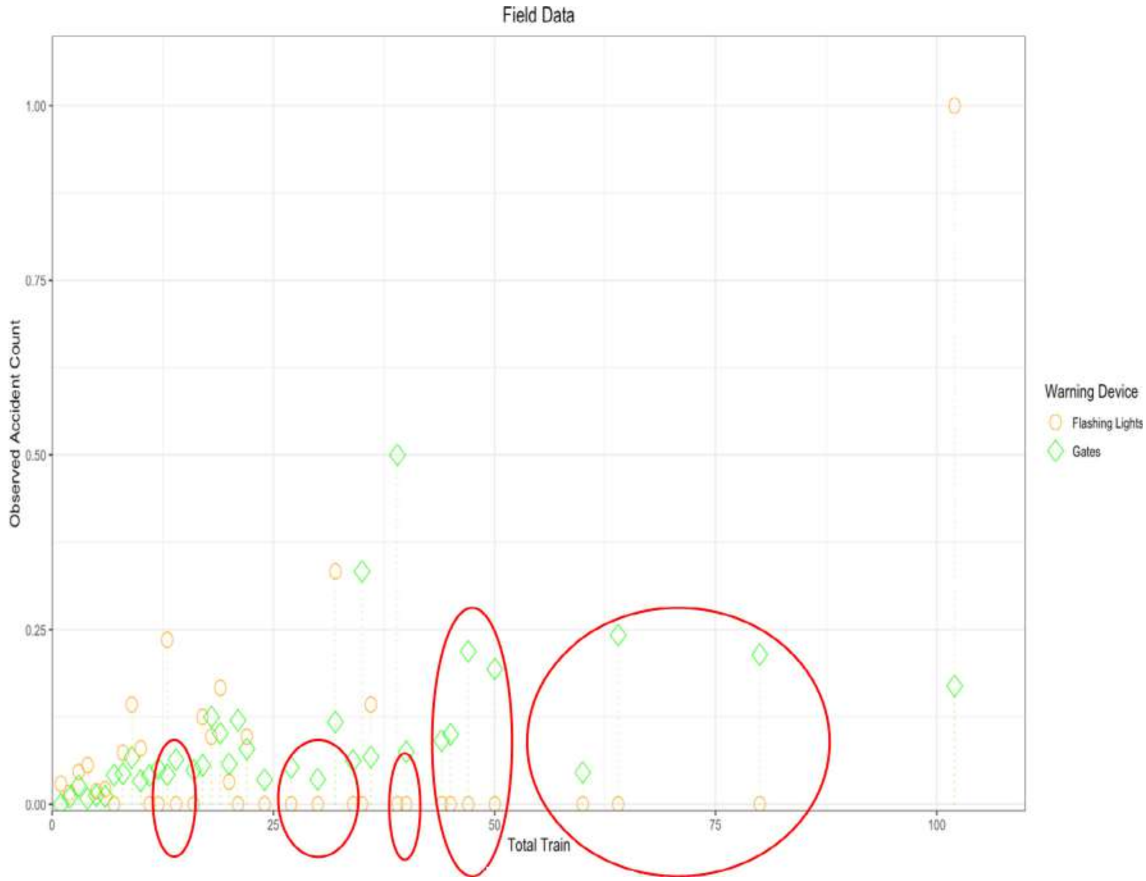


Fig. 17. Observed accident count vs Total Train: Warning device changed from Flashing Lights to Gates.

Fig. 18. Predicted accident count vs Total Train using the ZINEBS Model: Warning device changed from Flashing Lights to Gates.

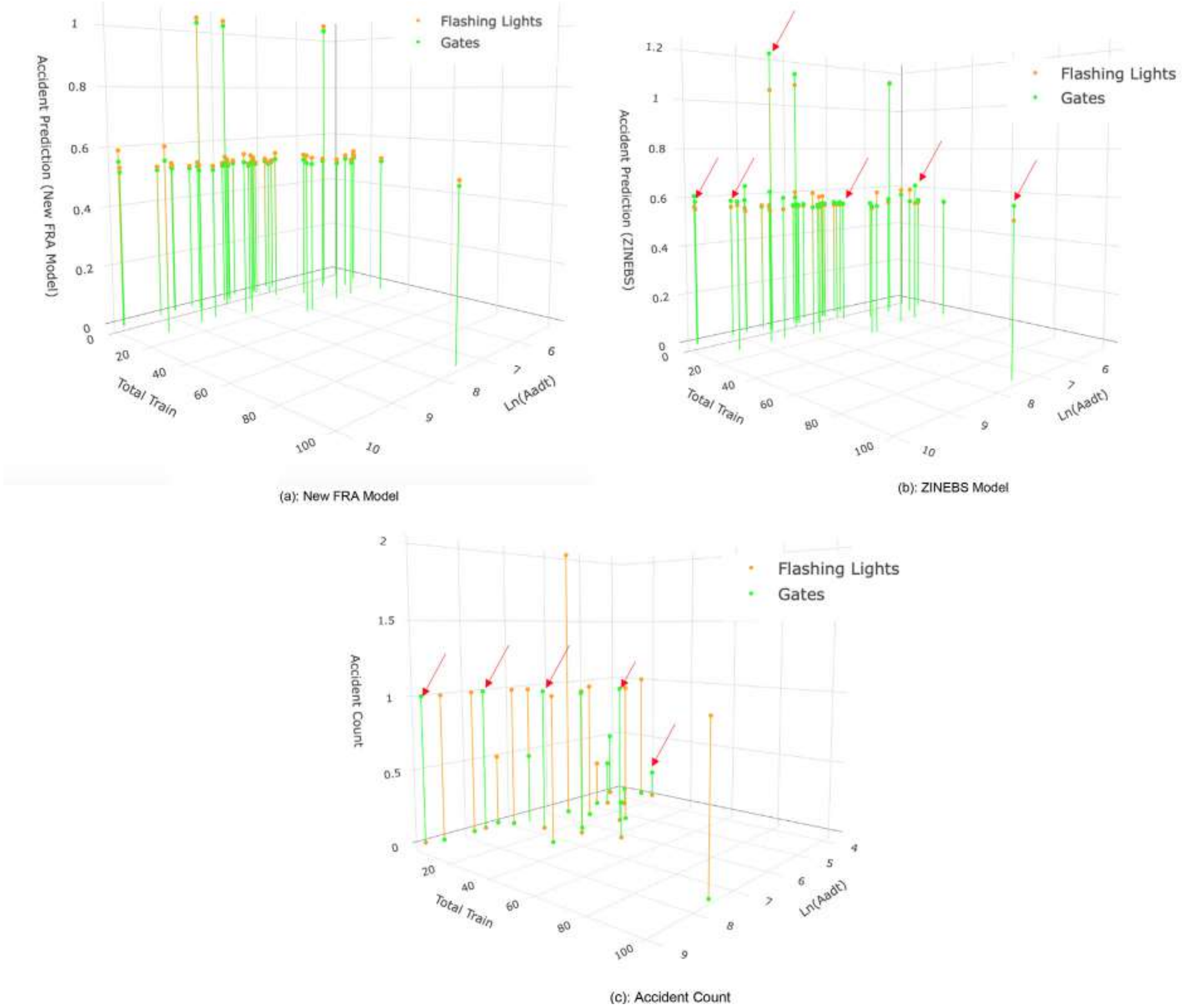


Fig. 19. 3D Plot of Accident Count vs ln(AADT) and Total Train: Warning device changed from Flashing Lights to Gates.

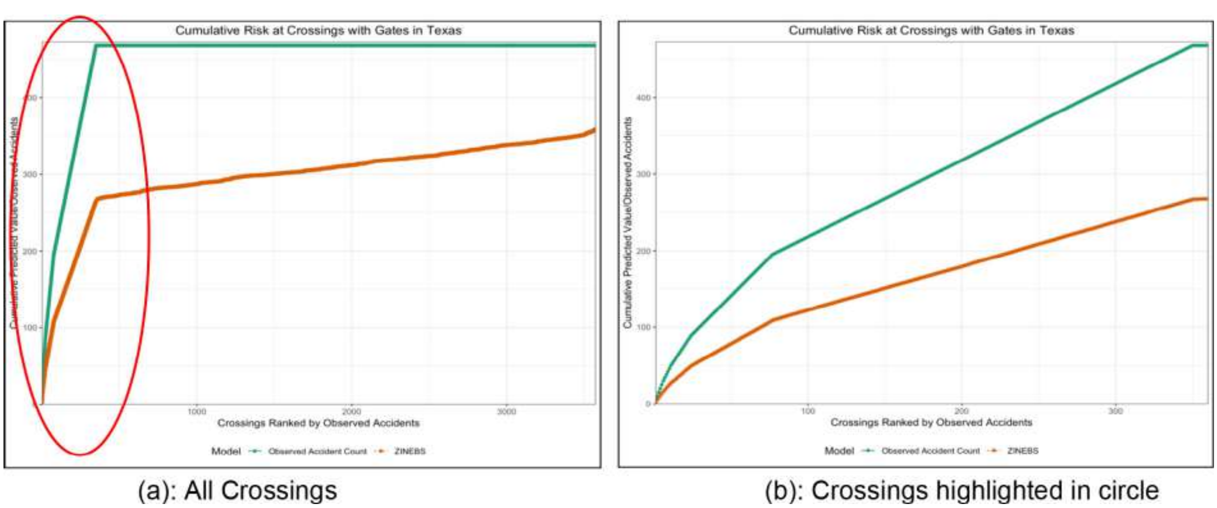
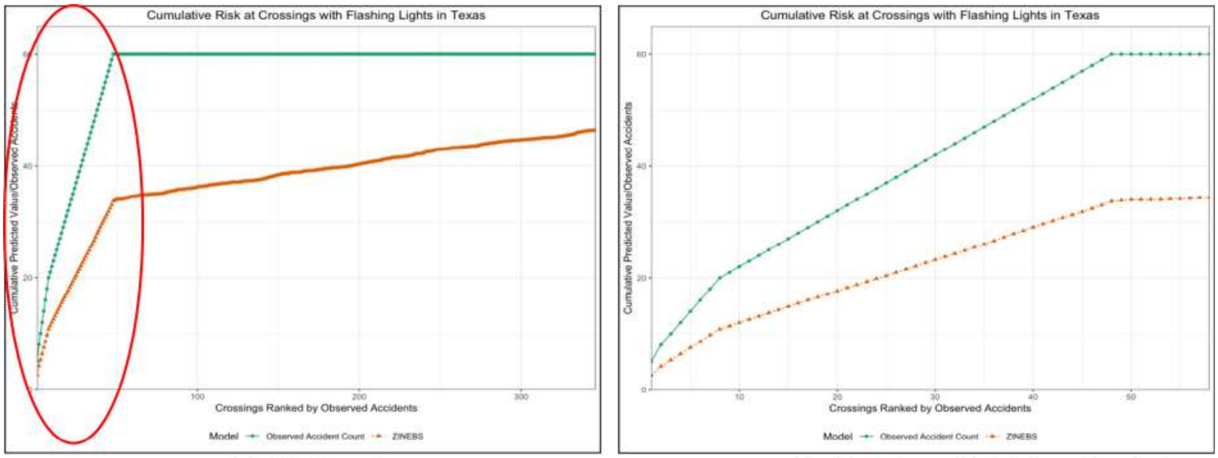
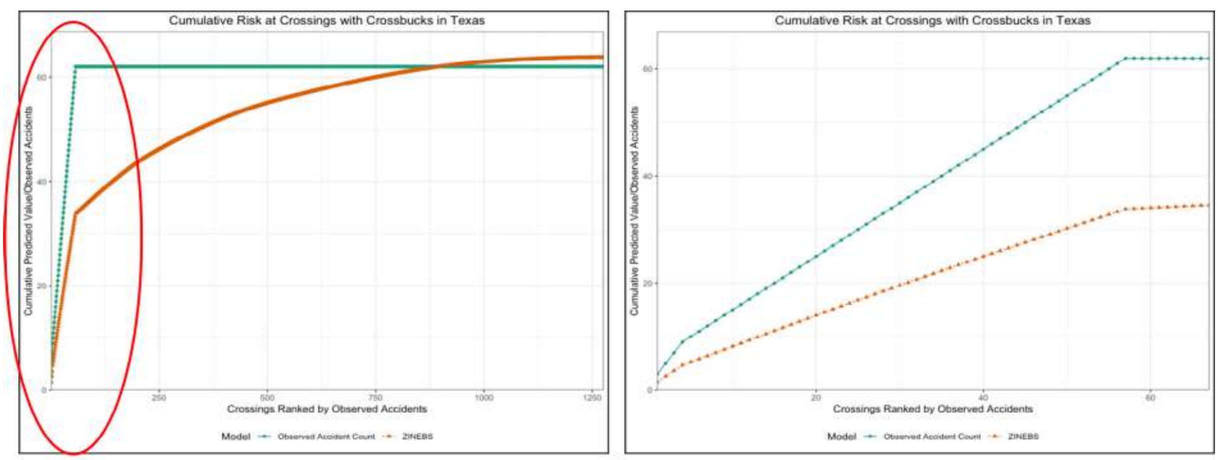


Fig. 20. Validating model by comparing cumulative risk to observed accident count in Texas (Gated Crossings).



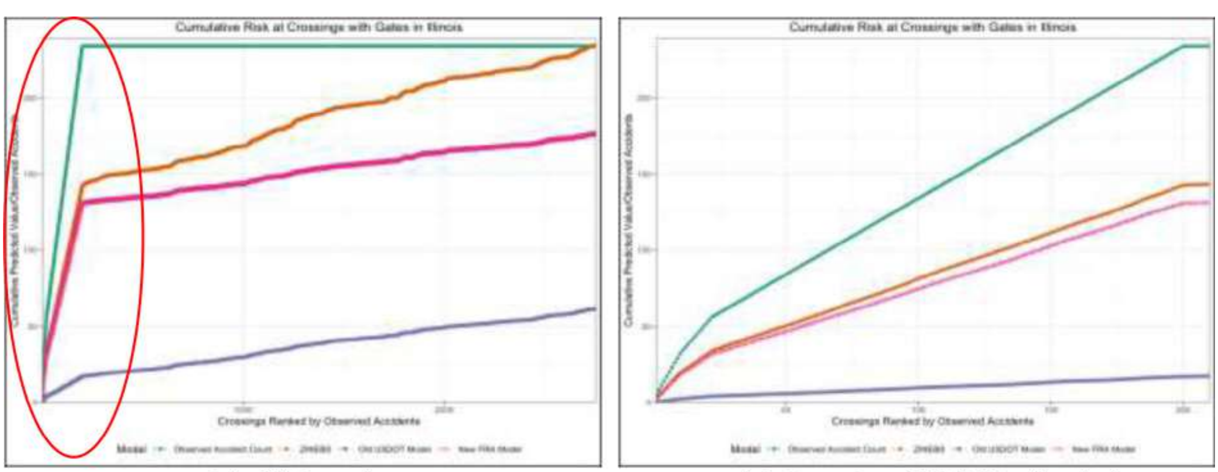
(a): All Crossings b): Crossings highlighted in circle

Fig. 21. Validating model by comparing cumulative risk to observed accident count in Texas (Crossings with Flashing Lights and No Gates).



(a): All Crossings (b): Crossings highlighted in circle

Fig. 22. Validating model by comparing cumulative risk to observed accident count in Texas (Crossings with Crossbucks).



(a): All Crossings (b): Crossings highlighted in circle

Fig. 23. Cumulative Risk at Crossings with Gates (Illinois).

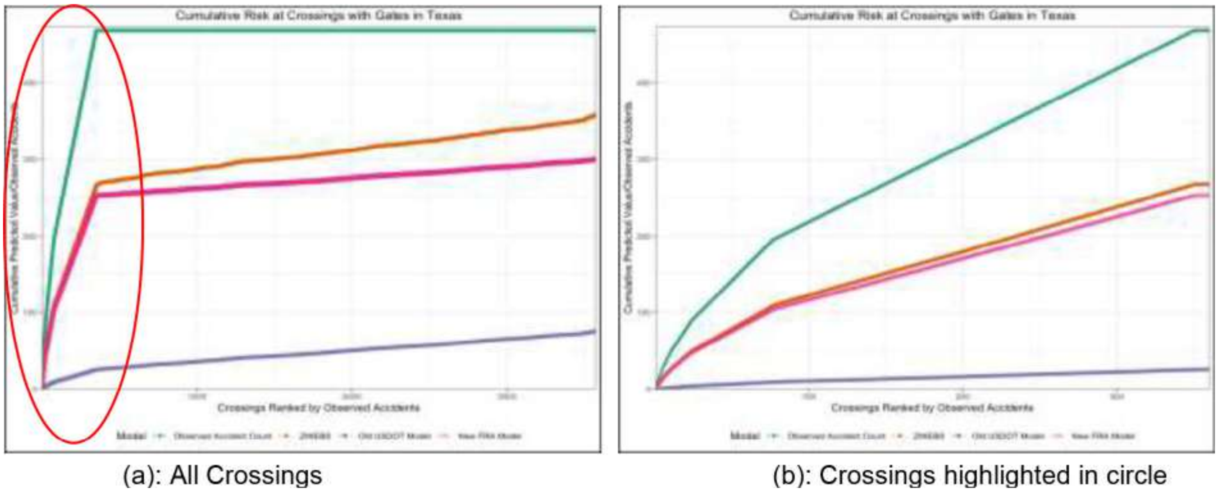


Fig. 24. Cumulative Risk at Crossings with Gates (Texas).

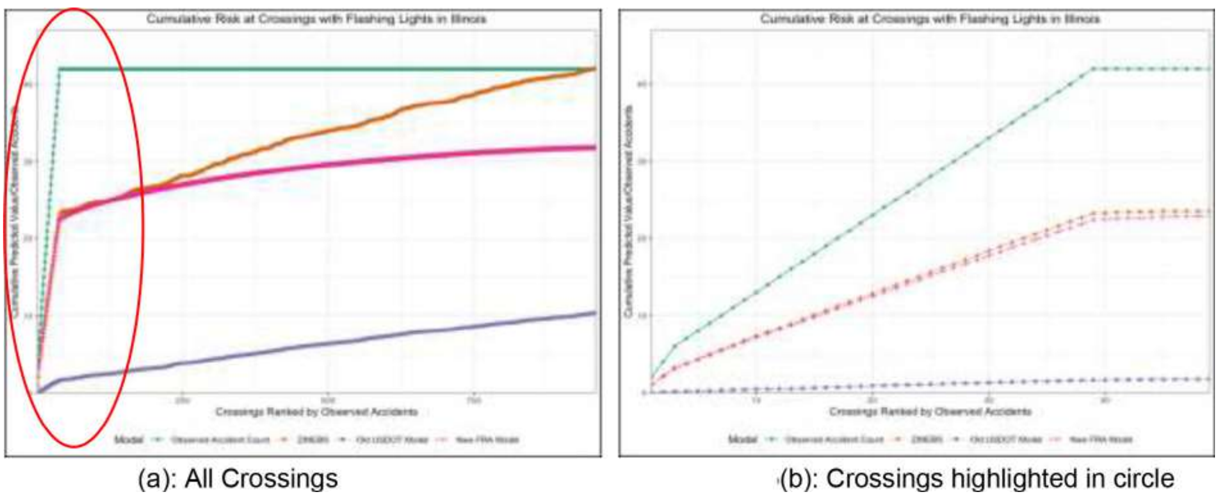


Fig. 25. Cumulative Risk at Crossings with Flashing Lights and no Gates (Illinois).

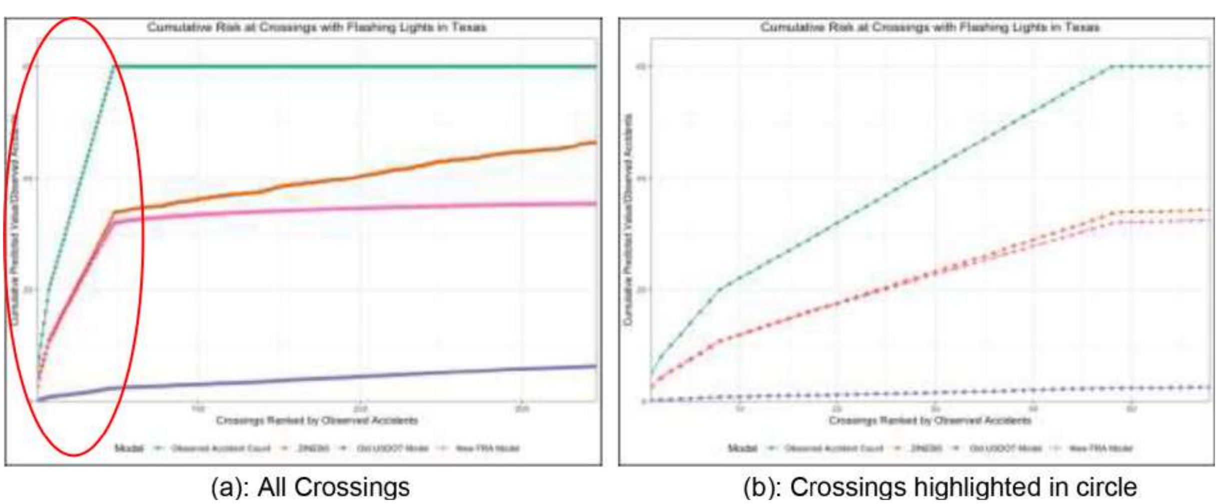


Fig. 26. Cumulative risk at crossings with Flashing Lights and no Gates (Texas).

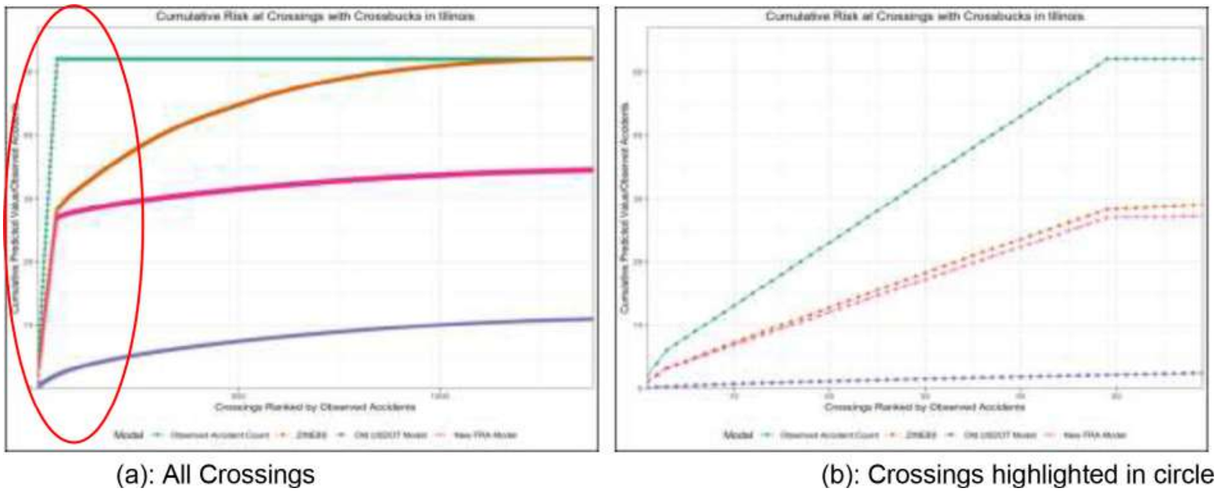


Fig. 27. Cumulative Risk at Crossings with Crossbucks (Illinois).

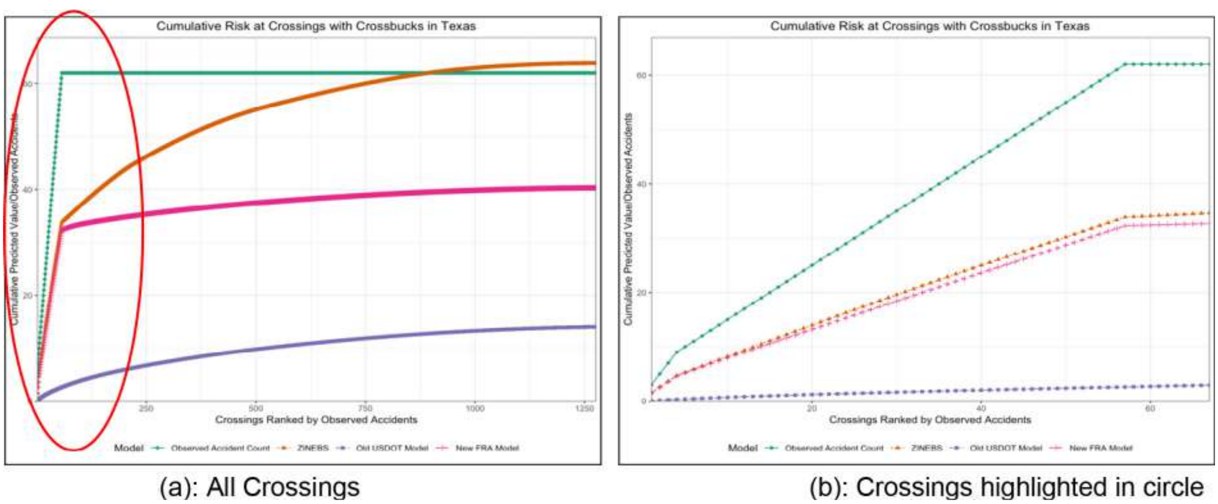


Fig. 28. Cumulative Risk at Crossings with Crossbucks (Texas).

face. The variables maximum timetable train speed and distance to nearby HW intersection were explored, but they were not selected by any of the models.

The models were developed using data from one state (Illinois) and were validated using data from another state (Texas results are included in this paper). The predicted values for the ZINEBS model show a closer agreement with the field data than the new FRA model. This observation was true for all three warning device types analyzed. This comparison indicates that the crossings selected using the ZINEBS model are more agreeable with an engineer charged with selecting "high-risk" locations. Based on the results of this study, the ZINEBS compliments the new FRA model and should be used when the single equation is not adequately representing the role of traffic control device types and relevant variables associated with that device type.

Conflict of interest

We confirm that this work is original and has not been published elsewhere, nor is it currently under consideration for publication elsewhere.

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Inclusion of phone use while driving data in predicting distraction-affected crashes

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ABSTRACT

Introduction: Given the tremendous number of lives lost or injured, distracted driving is an important safety area to study. With the widespread use of cellphones, phone use while driving has become the most common distracted driving behavior. Although researchers have developed safety performance functions (SPFs) for various crash types, SPFs for distraction-affected crashes are rarely studied in the literature. One possible reason is the lack of critical distracted behavior information in the commonly used safety data (i.e., roadway inventory, traffic, and crash counts). Recently, the frequency of phone use while driving (referred to as phone use data) is recorded by mobile application companies and has become available to safety researchers. The primary objective of this study is to examine if phone use data can potentially predict distracted-affected crashes. *Method:* The authors first integrated phone use data with roadway inventory, traffic, and crash data in Texas. Then, the Random Forest (RF) algorithm was applied to assess the significance of the feature - phone use while driving - for predicting the number of distraction-affected crashes on a road segment. Further, this study developed two SPFs for distraction-affected crashes with and without the phone use data, separately. Both SPFs were assessed in terms of model fitting and prediction performances. *Results:* RF results rank the frequency of phone use as an important factor contributing to the number of distraction-affected crashes. Performance evaluations indicated that the inclusion of phone use data in the SPFs consistently improved both fitting and prediction abilities to predict distracted-affected crashes. *Practical Applications:* The phone use data provide new insights into the safety analyses of distraction-affected crashes, which cannot be achieved by only using the conventional roadway inventory and crash data. Therefore, safety researchers and practitioners are encouraged to incorporate the emerging data sources in reducing distraction-affected crashes.

1. Introduction

As reported by the National Highway Traffic Safety Administration (NHTSA), 2,841 roadway users were killed, and distraction-affected crashes injured about 400,000 people on American roadways in 2018 (NHTSA, 2020). Further, the reported distraction-affected crashes account for 8% of fatal crashes and 15% of injury crashes (NHTSA, 2020). Hence, distracted driving is indeed a significant factor contributing to crashes. Distraction occurs when drivers divert their attention to a secondary task other than driving (NHTSA, 2020). Among all types of secondary tasks, a recent national-wide survey revealed that 52% of respondents reported talking on a hand-held cellphone, 41% reported reading texts or emails, and 32% reported typing texts or emails while driving (Arnold et al., 2019). The previous studies have pointed out that over 70% of those distractions are potentially preventable (Beanland et al., 2013), which means that it is possible to prevent distracted driving behaviors and reduce the number of distraction-affected crashes through implementing effective countermeasure (s). As such, distraction-affected crashes are identified as one of the seven emphasis areas in the Strategic Highway Safety Plan in Texas (TxDOT, 2019).

Safety researchers and roadway agencies have been making continuous efforts to understand the nature of distracted driving (Oviedo-Trespalacios et al., 2017, 2019; Iio et al., 2021) and the occurrence of distraction-affected crashes (Lym & Chen, 2020; Chen & Lym, 2021; Kong et al., 2021; Lym & Chen, 2021). Oviedo-Trespalacios et al. (2017) found that distracted drivers adapt their speed more in a complex road traffic environment. Lym and Chen (2020) first examined the spatial influence on the

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frequency and severity of vehicle crashes by driving in distraction, then analyzed the influences of the built environment on the frequency and severity of distracted-affected crashes (Chen & Lym, 2021) and evaluated the role of the built environment on the severity of vehicle crashes caused by distracted driving across 15 U.S. states (Lym & Chen, 2021). Although research and agencies have studied distracted driving and the occurrence of distraction-affected crashes, the annual number of distraction-affected crashes is still continuously increasing in recent years (NHTSA, 2020). It is necessary to conduct analytical studies on distraction-affected crashes to assist roadway agencies in effectively reducing fatalities, injuries, and property damage caused by distracted driving.

Statistical models are commonly used to predict roadway safety measures, identify hotspots, evaluate the effectiveness of treatments, and manage roadway network safety (Lord & Mannering, 2010). Although researchers have developed safety models for different roadway facilities and collision types (Caliendo et al., 2007; Montella et al., 2008; Wegman, 2014; Sohrabi & Lord, 2019), predictive models for distraction-affected crashes are rarely reported in the literature. To the best of the authors' knowledge, no safety prediction models have been developed specifically for distraction-affected crashes. The following two reasons could explain this. First, it is well known that distraction-affected crashes are underreported in crash records (e.g., drivers refuse to acknowledge that they had been distracted driving prior to or at the time of the crash; Hanley & Sikka, 2012; Regev et al., 2017). Second, the conventional safety data (i.e., roadway inventory, traffic, and crash counts) for developing safety performance functions (SPFs) may have missed important information associated with the occurrence of distraction-related crashes (e.g., phone use frequency and type).

The above two points bring challenges for developing a reliable distraction-affected crash model. Nevin et al. (2017) noted that officers were unlikely to get a warrant for drivers' phone records in minor crashes, and the drivers rarely admit to distracted driving. The underreporting of distraction-affected crashes is difficult to address in a relatively short period. However, with the development of advanced techniques (e.g., cellphones, precise locating systems, and fast mobile data bandwidth), emerging data sources are becoming available to transportation researchers for making inferences of distraction-affected crashes. Some private sectors tried to capture phone using events through built-in gyroscopes on cellphones (Root, 2019; Zendrive, 2019). This data collection approach is innovative, but reports from those private sectors are only descriptive statistics. For example, the Root insurance company published the Root Insurance Focused Driving Reports in 2019. The report documented that about 45 cities in Texas are with 10 or more distracted driving events per 100 miles (Root, 2019). In Zendrive's 2019 distracted driving study, their users spent 8.85% of their driving time on their phones per trip (Zendrive, 2019). Although the descriptive statistics provided by these reports are very informative and insightful, the reports lack a detailed description of methodologies.

A recent observational study (Iio et al., 2021) used phone use data collected from a mobile app and revealed a negative correlation between phone use events and driving speed. The study found that roadway users drove on average, 3.26 mph slower during distractions than that under undistracted conditions. Another study conducted by Kong et al. (2021) with a similar phone use while driving dataset identified the strong association between the frequency of a phone use event occurring and the distracted-crash counts on the road segments. Using the same phone use data source, this study examines the association between phone use while driving data and distracted-affected crashes. Intuitively, the phone use information while driving is closely related to the occurrence of distraction-affected crashes. However, this type of phone use data has not yet been used for predicting distraction-affected crashes.

Thus, the primary objectives of this study are as follows. This study (1) aims at examining if phone use frequency while driving is a significant factor contributing to distraction-affected crashes; (2) develops SPFs for distraction-affected crashes, and further investigates if the inclusion of phone use information improves the model performance. To achieve the objectives, this study first integrates phone use data with commonly used safety data (i.e., roadway inventory, traffic, and distraction-affected crash counts) in Texas; then deploys the random forest algorithm to identify the importance of phone use information as well as other roadway features on the number of distraction-affected crashes; finally, this study develops SPFs for distraction-affected crashes with and without phone use information separately, and compares the performance (model statistics fitting as well as prediction accuracy) of the two SPF models.

2. Methodology

SPF is a widely used approach to quantify the safety level of roadway entities (i.e., segments and intersections). It is one of the most important elements in roadway safety management (AASHTO, 2011). Many statistical models have been proposed as SPFs to estimate the average crash frequency by transportation safety analysts and practitioners (Das et al., 2021; Khodadadi et al., 2021). Among them, models based on negative binomial (NB) distribution (also known as Poisson-gamma) are commonly used for predicting crashes (Lord & Bonneson, 2007; Zou et al., 2015; Wu et al., 2020; Guo, Wu, et al., 2020), and are recommended in the first edition of the *Highway Safety Manual* (*HSM*) (AASHTO, 2011) for developing SPFs. The NB distribution is essentially a mixture of Poisson and gamma distributions. Assuming the number of crashes y at a road segment at a specific time is Poisson distributed with a Poisson mean λ, the probability mass function (PMF) is as follows:

$$f(y|\lambda) = \frac{\lambda^y \exp(-\lambda)}{y!}, \lambda > 0, and y = 0, 1, 2, \cdots, \tag{1}$$

where, the mean response of the observation crash count, λ, is assumed to be Gamma distributed with a mean $= \mu$, and a variance $= \mu^2\sigma^2$.

Then, following the Gamma distribution, the probability distribution of $\lambda$is:

$$f(\lambda|\mu,\sigma) = \frac{1}{(\mu\sigma^2)^{\frac{1}{\sigma^2}}} \times \frac{\lambda^{\left(\frac{1}{\sigma^2}-1\right)} \exp\left(-\frac{\lambda}{\mu\sigma^2}\right)}{\Gamma\left(\frac{1}{\sigma^2}\right)}, \tag{2}$$

where, $\Gamma\left(\frac{1}{\sigma^2}\right)$ is the gamma function with respect to $\frac{1}{\sigma^2}$, and $\frac{1}{\sigma^2}$ is the shape parameter of the Gamma distribution. Then, combining with Eq. (1), the PMF of the NB distribution is,

$$f(y|\mu,\sigma) = \int_0^\infty \frac{\lambda^y \exp(-\lambda)}{y!} \times \frac{1}{(\mu\sigma^2)^{\frac{1}{\sigma^2}}} \times \frac{\lambda^{\left(\frac{1}{\sigma^2}-1\right)} \exp\left(-\frac{\lambda}{\mu\sigma^2}\right)}{\Gamma\left(\frac{1}{\sigma^2}\right)} d\lambda, \tag{3}$$

which is equivalent to the following expression in terms of gamma function (curious readers are referred to Hilbe (2011) for a complete derivation of the NB model),

$$f(y|\mu,\sigma) = \frac{\Gamma\left(y+\frac{1}{\alpha}\right)}{\Gamma(y+1)\Gamma\left(\frac{1}{\alpha}\right)} \times \left(\frac{\alpha\mu}{1+\alpha\mu}\right)^y \times \left(\frac{1}{1+\alpha\mu}\right)^{\frac{1}{\alpha}}, \tag{4}$$

where, y is the response variable on a roadway segment during a time period (typically one year), μ is the mean response of crashes at the segment, and α is the dispersion parameter. The dispersion parameter can also be interpreted as the inverse of the shape parameter, as σ^2. The varying form of dispersion parameter, α, on crash estimation for roadway segments is recommended by the *HSM* (AASHTO, 2011). A commonly used function form (Cafiso et al., 2010; Geedipally & Lord, 2008) of the dispersion parameter is,

$$\alpha = \exp(\gamma + \log(L)) \tag{5}$$

where, γ is a model-specific parameter, a regression coefficient used to determine the overdispersion parameter; L indicates the length of the roadway segment in miles. Compared to the Poisson distribution, the NB distribution can allow for over-dispersion. If $\sigma \rightarrow 0$, the crash variance equals the crash mean, that is, the NB model converges to the Poisson model.

Research (Miaou & Lord, 2003; Meng et al., 2020) has shown that the functional form is very important for SPFs. Lord and Bonneson (2007) emphasized the significant characteristic associated with the development of statistical relationships is the choice of the function form linking the crashes to the variables (curious readers are referred to Chapter 6.5 of Lord et al. (2021) regarding the functional form and varying dispersion parameter). In this study, the authors intend to compare two SPFs for distraction-affected crashes. One (i.e., $\widehat{Y}*_i$) contains a phone use related variable and the other (i.e., $\widehat{Y}_i$) does not. The selected function form for the SPFs is,

$$\begin{cases} \widehat{Y}_i = \beta_0 L_i (AADT_i)^{\beta_1} exp\left(\sum_{i=2}^{i=n} \beta_i x_i\right) & (6) \\ \widehat{Y}*_i = \beta_0 L_i (AADT_i)^{\beta_1} exp\left(\sum_{i=2}^{i=n} \beta_i x_i + \beta_{PU} x_{PU}\right) & (7) \end{cases}$$

where $\widehat{Y}_i$ is a mean estimation, the estimated number of distraction-affected crashes by the SPF per year at segment *i*, L_i is the length of the segment *i* in miles, $AADT_i$ is the flow of segment *i*, x_i is a series of road inventory-related variables (e.g., lane width), x_{PU} is a dedicated phone use related variable, and $\beta_0, \beta_1, \cdots, \beta_n, \beta_{PU}$ are coefficients to be estimated. All β's in Eqs. (6) and (7) with the γ in Eq. (5) are estimated simultaneously using the method of maximum likelihood coded in R (Meng et al., 2020). The authors implemented a log-likelihood function specifically for the varying dispersion parameter crash model and used an R package "bbmle" to obtain the MLE estimates.

Moreover, the variable selection process is also important for SPFs. Mitra and Washington (2007) emphasized the negative influence of omitting significant variables in SPFs. Hence, it is important to select the right set of variables for x_i in Eqs. (6) and (7). Random forest (RF) algorithm is widely applied among scientists for variable selections, as it is a good indicator of the importance assigned to the features (Díaz-Uriarte & Alvarez de Andrés, 2006; Genuer et al., 2010; Han et al., 2016). In the field of transportation safety, researchers (Siddiqui et al., 2012; Pu et al., 2020; Guo, Peng, et al., 2020) adopted RF for variable selections. Guo et al. (2020) implemented the mean decrease impurity (MDI) measured by the Gini index from the RF model to select 13 key safety variables out of 111 variables in the Highway Safety Information System (HSIS) and the Highway Performance Monitoring System. In this study, a similar process is taking place to check the importance of phone use variable and select road inventory-related variables, x_i in Eqs. (6) and (7). However, RF in this study is used as a regression model for distracted-affected crashes, instead of a classifier. The MDI for regression is still the total decrease in node impurities for splitting on the variable averaged over all trees. Instead of Gini index, the total decrease in node impurities is measured by residual sum of squares. Then, the MDI is as the mean square error defined in Eq. (8).

$$Mean\ Decrease\ Impurity = \frac{1}{N}\sum_{i=1}^{N}(p_i - \overline{p})^2 \tag{8}$$

where N is the total number of instances, p_i means one instance, $\overline{p}$ indicates the mean given by $\frac{1}{N}\sum_{i=1}^{N} p_i$. MDI is a measure of variable importance. A higher MDI indicates higher variable importance.

Lastly, in this study, the Akaike information criterion (AIC) and Root Mean Square Error (RMSE) are used as the measures of effectiveness (MOE) for model fitting and model evaluation. The AIC is commonly used by researchers to measure how well a model fits the data (Akaike, 1974). AIC could locate the best-fit model if the model explains the largest variation by using the fewest independent variables. The best-fit model has the smallest AIC value.

$$AIC = 2K - 2\ln(L) \tag{9}$$

where, K indicates the number of independent variables, and L is the log-likelihood estimate of the model.

RMSE is a widely accepted method of measuring the difference between the predicted values and actual observations (Hyndman & Koehler, 2006). RMSE is an indicator of the accuracy of the model predictions.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}\left(\widehat{y_n} - y_n\right)^2}{N}} \tag{10}$$

where, $\widehat{y_n}$ is the predicted distracted crash count of each road segment; y_n represents the actual distracted crash count of each road segment; N is the total number of road segments in this study.

3. Data integration

In this section, two sets of data are first introduced, separately. Dataset 1 contains the roadway inventory and distraction-affected crash counts. It is extracted from the Roadway Highway Inventory Network Offload (RHiNO) database managed by the Texas Department of Transportation (TxDOT). Dataset 2 is phone use events. It is extracted from a commercial mobile app. These two sets of data from different data platforms are then integrated into a master dataset for the development of SPF. Then, the master dataset is presented. Lastly, the selected variables are tabulated with their descriptive statistics.

3.1. Roadway inventory and distraction-affected crash counts – dataset 1

Conventionally, safety analysts develop SPFs using roadway inventory and historical crash data. This study also collected both of them. The TxDOT's RHiNO (2018 Version) is used to gather the segment layer dataset. The RHiNO database contains a variety of roadway features, including traffic volume, truck percentage, function class, lane, shoulder, median, k-factor, speed limit, area type, and so forth. Curious readers are referred to the TxDOT's website for a full list of the variables (https://www.txdot.gov/inside-txdot/division/transportation-planning/roadway-inventory.html). To fulfill the objective of this study, the authors selected rural and urban on-system roadways separately. Each roadway is divided into a number of homogenous segments based on roadway features included in the RHiNO data.

For crash counts, this study collected distraction-affected crashes from the TxDOT's Crash Records Information System (CRIS) in the most recent three years (i.e., 2017–2019). A distraction-affected crash is defined as when the contributing factor description associated with the primary person is "*distraction in vehicle*," "*driver inattention*," or "*cell/mobile phone use*." This definition is consistent with the Texas Strategic Highway Safety Plan (TxDOT, 2019).

3.2. Phone use events – dataset 2

To develop a SPF with phone use events, the authors examined a pseudonymized dataset through a mobile app, SAFE 2 SAVE. This mobile app was launched in 2016 with the motivation of encouraging people in a positive way to stay off their phones while driving. By the end of February 2020, the app had been downloaded more than 340,000 times. The following is how the mobile app works while its user is driving at a speed more than 15 mph:

- When the user handles a cellphone (e.g., texting, answering phone calls with a hand-held cellphone), a phone use event is recorded along with the user's current geocoordinates (i.e., longitude and latitude in degrees), user's pseudonymized ID, and event time.

For this study, the authors studied 11,385,092 phone use events from 29,620 users in Texas from January 1, 2019, to December 31, 2019. Since users are recorded by a pseudonymized user ID (random integers), personal detail cannot be identified.

The critical step of data preparation is to count the total number of phone use events per RHiNO segment ID, so that this phone use dataset (i.e., Dataset 2) can be integrated with data (i.e., Dataset 1) from the RHiNO database. As mentioned above, the mobile app collected phone use events when a user handles a cellphone in a moving vehicle. The geocoordinates are recorded in each phone use event, and they served as the key for spatially joining functions from PostGIS to conflate with the RHiNO database. After conflation, phone use events were snapped into the nearest roadway segment. One problem with this conflation is that all points in the database were snapped to their nearest roadways, even for these points far from the on-system roadways. To eliminate these inaccurate conflations, points with a distance from the nearest snapped roadways greater than 9 ft are excluded from the dataset. This conflation and cleaning process generated an event-based dataset containing the occurrence of a phone use event and its corresponding RHiNO segment ID. Then, the total number of phone use events per segment can be obtained by aggregating all events within the same RHiNO segment ID. This aggregated segment-based dataset contains phone use event counts over unique RHiNO segment IDs.

3.3. Master dataset for SPF development

After converting Dataset 2 from an event-based to a segment-based dataset, it was then integrated with Dataset 1 by matching the unique RHiNO segment IDs. This integrated segment-based dataset is then called the master dataset. Each row of the dataset represents a roadway segment. The variables are the number of distraction-affected crashes, number of phone used while driving, and selected roadway features at each column. There are 72 variables in the master dataset. Some selected variables are listed in Table 1. A number of 5,082 segments are filtered using the length of segment length and frequency of phone use as criteria. To ensure that the segments are neither too long nor too short, the authors conducted re-segmentation work on the original RHiNO data, such that each segment is between 0.1 mi and 2 mi (i.e., segments shorter than 0.1 mi are excluded from the dataset; segments greater than 2 mi are split into equal length sub-segments). In order to get the most reasonable phone use event counts per segment, this study only kept those segments with phone use event counts larger than 30 per year but smaller than 200 per year. Further, in order to eliminate outliers with extremely wide lanes, the authors only kept the number of lanes from 2 to 6. Moreover, outliers in truck percentage and lane width are removed. Thus, on 4,983 segments, there was an average of 1.43 distraction-affected crashes (in three years) and an average of 74.88 phone use events.

Table 1
Summary statistics of distraction-affected crash counts, phone use frequency and selected observations (4,983 segments).

Variable	Min	Max	Mean (SD)
3-yr Distraction-affected Crash Count	0	10	1.43 (2.30)
Phone Use Frequency	30	200	74.88 (43.16)
AADT (veh/day)	70	99,537	11,550 (12,383.07)
Segment Length (ft)	0.10	2.00	0.72 (0.55)
Truck Percentage (%)	0	42.5	11.10 (7.68)
Peak Hour Factor (%)	6.40	29.20	10.19 (2.03)
Outside Shoulder Width (ft)	0	44	6.18 (5.84)
Inside Shoulder Width (ft)	0	25	4.92 (4.16)
Lane Width (ft)	9	18	11.95 (1.31)
Number of Lanes (#)	2	6	2.93 (1.21)
Posted Speed Limit (mph)	25	75	56.33 (10.07)
Urban Segment Indicator	Urban: 55.7%; Rural: 44.3%		

Note: SD = standard deviation. Many unselected variables are not listed in this table.

The maximum number of distraction-affected crashes in the dataset is 10, and the maximum number of phone use events is 200, while the minimum numbers are 0 and 30, respectively.

4. Results

This section first introduces how the roadway variables are ranked and selected using MDI. Then, roadway variables associated with relatively higher MDI values are considered as those selected variables for developing SPFs. Further, two SPFs, one without (i.e., SPF_{woPU}) and the other with phone use data (i.e., SPF_{PU}), are developed using NB distribution with varying dispersion parameters for the number of distraction-affected crashes. Their regression results are compared and discussed. Finally, the mean estimations from SPF_{woPU} and SPF_{PU} are generated, and their values are compared using two MOEs (i.e., AIC and RMSE) for the purposes of model statistical fitting and prediction accuracy.

A series of data cleansing and correlation tests were taken place. The number of variables in the master dataset was decreased from 72 to 22. Furthermore, the MDI values of these 22 variables from RF are ranked as shown in Fig. 1. A larger MDI value of a roadway feature indicates that this feature plays a relatively more important role in predicting observed distraction-affected crashes on a segment.

Phone use while driving events rank as number four. This indicates that the phone use data demonstrate the potential to benefit from the development of SPFs for distraction-affected crashes. This result met authors' expectations, as it shows that the phone use event is a significant factor in predicting distraction-affected crashes. Moreover, this encourages authors to further investigate the possibility of developing a SPF for distraction-affected crashes by including the phone use event as a variable.

AADT and segment length ranked first and second in Fig. 1. These agree with the variable selection recommended in *HSM* (AASHTO, 2011) when modeling a segment SPF. Furthermore, truck percentage, peak hour factor, and the speed limit are ranked third, fifith and sixth, respectively, as shown in Fig. 1. These are also commonly used roadway features when researchers developed segment SPFs (Lord & Bonneson, 2007; Guo et al., 2019). In addition to the above six top-ranked variables in MDI, other values with MDI values larger than 500 are included to develop SPFs. Thus, a total of 11 variables, including the frequency of phone use, are selected using the MDI value to develop SPFs for the distraction-affected crashes in this study. Their descriptive statistics are documented in Table 1.

Although the ranking of MDI has revealed the possible relationship between phone use events and distraction-affected crashes, it

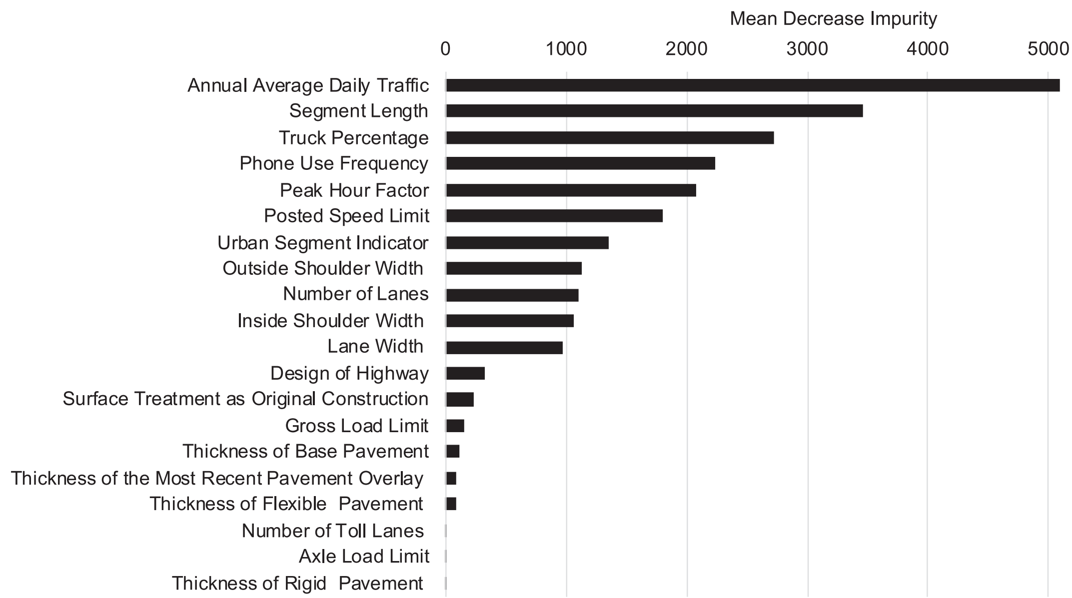

Fig. 1. Variable Selection for Developing Safety Performance Function.

is not obvious whether the inclusion of phone use events will improve the SPF model performance. Hence, two NB-based SPFs are developed with varying dispersion parameters. The SPF for distraction-affected crashes without phone use event as a variable is abbreviated as SPF_{woPU}, and its regression results are tabulated in Table 2. The SPF for distraction-affected crashes with phone use event is abbreviated as SPF_{PU}, and its regression results are tabulated in Table 3.

As the models in Tables 2 and 3 are performed on a randomly selected training dataset (i.e., containing 3,239 segments out of 4,983 segments), the results may be different depending on the selected training and test sets. In order to further verify the consistency of results, this study repeated the process a total of 100 times. The MOE, AIC is applied to compare the goodness of fit for these two SPFs, while the other MOE, RSME is used to compare the performance of these two SPFs in terms of accuracy in prediction. A summary of the AIC and RMSE values in the 100 experiments is presented in Table 4.

5. Discussion

A few interesting observations are revealed from the regression results of SPF_{woPU} in Table 2.

From Table 2, the variables for AADT and urban segment indicator showed significant impacts on the number of distraction-affected crashes with positive estimates. That is, an increased value of these variables is associated with an increase in the number of distraction-affected crashes. For instance, the estimated coefficient for the urban segment indicator is 0.8539, statistically significant at the 99.9% level. This means that the predicted number of distraction-affected crashes is higher when a segment is urban than that of a rural segment with similar characteristics. This same finding is also observed in existing literature (Chen & Lym, 2021). On the other hand, the posted speed limit is significant with a negative estimate. This indicates that the predicted number of distraction-affected crashes is relatively higher on those segments with a lower speed limit. Although when the speed limit is low, the predicted number of distracted-affected crashes is high, existing studies (Lym & Chen, 2021) found that the severity was also low.

Four variables (i.e., number of lanes, peak hour factor, outside shoulder width, and inside shoulder width) are not significant at the 95% level, but they are still kept in the model as the primary purpose of the distraction-affected crash SPFs in this study is not for prediction. Some variables, such as inside shoulder width and outside shoulder width, may be correlated, making the parameter estimates relatively unstable.

Table 2
Regression results of SPF without phone use data.

Variable	Estimate	Std. Error	*z* value	Pr(>|z|)	Significance
Intercept	−5.0607	0.6468	−7.8244	<0.0001	99.9%
Log (AADT)	0.7967	0.0580	13.7292	<0.0001	99.9%
Lane Width	0.0643	0.0275	2.3347	0.0196	95%
Truck Percentage	1.1719	0.4744	2.4704	0.0135	95%
Number of Lanes	−0.0645	0.0397	−1.6236	0.1045	–
Peak Hour Factor	−0.0060	0.0234	−0.2549	0.7988	–
Outside Shoulder Width	−0.0127	0.0089	−1.4229	0.1548	–
Inside Shoulder Width	−0.0004	0.0122	−0.0304	0.9757	–
Posted Speed Limit	−0.0447	0.0040	−11.0779	<0.0001	99.9%
Urban Segment Indicator	0.8539	0.1139	7.4952	<0.0001	99.9%
Parameter of Dispersion Function	−0.7784	0.0736	−10.5820	<0.0001	99.9%
AIC			5,283.38		

Note: "–" indicates not significant at 95% level.

Table 3
Regression Results of SPF with Phone Use Data.

Variable	Estimate	Std. Error	z value	Pr(>|z|)	Significance
Intercept	−2.6224	0.5579	−4.7003	<0.0001	99.9%
Phone Use Frequency*	0.3375	0.0123	27.4734	<0.0001	99.9%
Log (AADT)	0.4520	0.0501	9.0259	<0.0001	99.9%
Lane Width	−0.0040	0.0220	−0.1797	0.8574	–
Truck Percentage	0.2518	0.4080	0.6170	0.5372	–
Number of Lanes	−0.1040	0.0321	−3.2348	0.0012	99.0%
Peak Hour Factor	−0.0080	0.0207	−0.3861	0.6994	–
Outside Shoulder Width	−0.0035	0.0075	−0.4675	0.6401	–
Inside Shoulder Width	0.0099	0.0103	0.9614	0.3363	–
Posted Speed Limit	−0.0300	0.0034	−8.7566	<0.0001	99.9%
Urban Segment Indicator	0.6003	0.1033	5.8093	<0.0001	99.9%
Parameter of Dispersion Function	−1.8913	0.1012	−18.6979	<0.0001	99.9%
AIC			4,414.52		

Note: Phone Use Frequency is the annual frequency of phone use while driving per segment; "–" indicates not significant at 95% level.

Table 4
Evaluation results in AIC and RMSE.

Experiment No.	AIC			RMSE		
	SPF without Phone Use	SPF with Phone Use	Difference	SPF without Phone Use	SPF with Phone Use	Percentage Difference
1	5,280.03	4,382.24	897.79	11.10	7.95	28.37%
2	5,304.02	4,405.87	898.15	12.23	7.89	35.46%
3	5,308.71	4,275.50	1,033.20	12.03	8.53	29.12%
...	...	...	...	...	...	...
99	5,292.75	4,425.62	867.13	10.95	7.50	31.49%
100	5,283.38	4,414.52	868.86	11.48	7.99	30.43%
Maximum	–	–	1,033.20	–	–	36.22%
Minimum	–	–	775.03	–	–	20.75%

Moreover, as expected, the phone use variable has a 99.9% significant level with a positive estimated coefficient of 0.3375 in Table 3. The magnitude of the phone use variable is also relatively large in Table 3. This indicates that the phone use variable is significant in the SPF model for distraction-affected crashes. Further, such a significant contribution is with a positive coefficient, meaning a segment with larger phone use is associated with a higher number of distraction-affected crashes. Consistent with those results in the SPF_{woPU} model (see Table 2), AADT and urban segment indicator again show significant positive impacts, while the posted speed limit is significant with negative impacts on the number of distraction-affected crashes.

Another interesting finding is the dispersion parameter (i.e., α in Eqs. (4) and (5)). In the two SPFs with and without phone use information, the dispersion parameters are $\exp(-1.8913+\log(L)) = L/6.63$, and $\exp(-0.7784+\log(L)) = L/2.18$, respectively. For a segment with a certain length, the dispersion parameter in the former SPF is significantly smaller than the latter (the ratio between the two is 1:3). A smaller dispersion parameter indicates a smaller variance of the predicted distraction-affected crash number and higher accuracy. Additionally, the dispersion parameter plays a significant role in the process of the empirical Bayes (EB) estimate. Smaller dispersion parameter leads to more reliable EB estimates. Hence the safety analyses (e.g., hotspot identification, safety effectiveness evaluation) based on the SPF_{PU} are superior to those based on the SPF_{woPU} model. From this perspective, phone use data greatly improves the performance of distraction-affected SPFs.

The comparison between the two SPFs (i.e., SPF_{woPU} in Table 2 and SPF_{PU} in Table 3) demonstrates that: (1) the phone use frequency variable has a significantly positive impact on predicting distraction-affected crashes; (2) the significant variables have the same signs in SPF models with and without phone use. In addition to the comparison between the regression results of the two models, the data fitting measurement (i.e., AIC) and the prediction accuracy measurement (i.e., RMSE) are computed for the two models. The SPF_{woPU} has an AIC value of 5,283.38, while the SPF_{PU} has an AIC value of 4,414.52. AIC estimates the relative amount of information lost in a given model. The less information a model loses, the higher the quality of that model contains. This difference of 868.86 in AIC clearly indicates that the SPF_{PU} provides a better model statistical fit than the SPF_{woPU}. However, researchers (Meng et al., 2020) pointed out that some functional forms that provided a better model statistical fit do not guarantee better model prediction performance. In order to examine if the SPF_{PU} also has a better performance in model prediction, the RMSE values of both SPF models are computed by measuring the differences between the distraction-affected crash means predicted by SPF models and the actual number of distraction-affected crashes observed in the test set. The RMSE of SPF_{woPU} is 11.48, and the RMSE of SPF_{PU} is 7.99. As the RMSE is a measurement of prediction accuracy, a smaller RMSE indicates a better model in prediction. The RMSE of SPF_{PU} is 30.43% smaller than the RMSE of SPF_{woPU}. This indicates that the SPF_{PU} model owns a higher prediction accuracy than the SPF_{woPU} model.

Lastly, to verify the consistency of the above findings, this study repeated the process, computed AIC and RMSE values for a total of 100 times with different random seeds. The AIC value of SPF_{PU} in every experiment is observed to be always smaller than the AIC value of its corresponding SPF_{woPU}. The smallest difference in AIC is 775.03, and the largest difference in AIC is 1,033.20. These demonstrated that a SPF_{PU} model always provides a better model statistical fit than a SPF_{woPU} model for distraction-affected crashes. Similarly, the observation on RMSE at the specific experiment has been consistently observed in the 100 experiments. The RMSE value of SPF_{PU} in every experiment is smaller than the RMSE value from its corresponding SPF_{woPU}. The minimum percentage difference is 20.75%, and the maximum percentage difference is 36.22%. These results reveal that a SPF_{PU} model always has a higher prediction accuracy than a SPF_{woPU} model for distraction-affected crashes.

6. Conclusions and future research

Distracted driving is one of the most significant factors contributing to crashes. However, out of the various safety models for different roadway facilities and collision types (Caliendo et al., 2007; Montella et al., 2008; AASHTO, 2011; Wegman, 2014), models for distraction-affected crashes are rarely reported in the literature. Therefore, in this study, the authors integrated the following two datasets at the segment level: (1) user-generated phone use events collected by a mobile phone app; (2) roadway inventory and reported distraction-affected crash counts from RHiNO and CRIS, both managed by TxDOT. In this study, the authors first examined and demonstrated that phone use information is an important factor affecting the number of distraction-affected crashes. Then, this study further developed two SPFs for distraction-affected crashes with and without phone use information. Two measures of effectiveness, AIC, and RMSE, were computed to compare the SPFs from the perspective of model fitting and prediction accuracy. Results showed that a distraction-affected crash SPF model with phone use information always provides a better model statistical fit than a distraction-affected crash SPF without phone use information. Out of 100 experiments with 100 different random seeds, the AIC value of the SPF model without phone use information was consistently larger than that with phone use information. A minimum difference in AIC is 775.03, and a maximum difference in AIC is 1,033.20. Not only in model fitting, by including the phone use information, the prediction accuracy was also increased. The RMSE value of the SPF model with phone use information in every experiment is smaller than that without phone use information. The minimum percentage difference in RMSE is 20.75%, and the maximum percentage difference is 36.22%.

There are a few limitations in this study, which call for potential future studies:

- Since the phone use events are only collected when app users drive while using a hand-held mobile phone, distracted driving while using a hands-free mobile phone is not included in this study. Nevertheless, studies (Oviedo-Trespalacios et al., 2018) have shown that the distraction with a hands-free mobile phone is less significant than with a hand-held mobile phone.
- Considering the mobile app launched with the motivation of encouraging people in a positive way to stay off their phones while driving, the phone use data collected by the app may be to some extend biased. However, we would like to point out that the app contains a relatively large user size (i.e., 29,620 unique users' pseudonymized IDs) and a fairly large phone use events out of those users (i.e., 11,385,092 points). That is, an average of 384 phone use events per user during a year. The authors believe that studied data could well capture phone use distractions from the users and represent the general driver population in the study area.
- Some secondary tasks (e.g., tapping a phone screen on a stable phone holder or eating), which may result in distracted driving, are not included in this study.
- Types of phone use (e.g., talking, texting) and the durations are unavailable from the dataset.

Based on the findings from this study, the authors concluded that the inclusion of phone use data in a SPF for predicting distraction-affected crashes yields a better model statistical fit and higher prediction accuracy. The authors would recommend phone use data be included for safety analysis and predicting distraction-affected crashes. Future studies that consider any interactive effect between an environmental variable and phone use would make the prediction of the SPF model even better.

Declaration of interest

None.

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Influence of built environment and roadway characteristics on the frequency of vehicle crashes caused by driver inattention: A comparison between rural roads and urban roads

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ABSTRACT

Introduction: With prevalent and increased attention to driver inattention (DI) behavior, this research provides a comprehensive investigation of the influence of built environment and roadway characteristics on the DI-related vehicle crash frequency per year. Specifically, a comparative analysis between DI-related crash frequency in rural road segments and urban road segments is conducted. *Method:* Utilizing DI-related crash data collected from North Carolina for the period 2013–2017, three types of models: (1) Poisson/negative binomial (NB) model, (2) Poisson hurdle (HP) model/negative binomial hurdle (HNB) model, and (3) random intercepts Poisson hurdle (RIHP) model/random intercepts negative binomial hurdle (RIHNB) model, are applied to handle excessive zeros and unobserved heterogeneity in the dataset. *Results:* The results show that RIHP and RIHNB models distinctly outperform other models in terms of goodness-of-fit. The presence of commercial areas is found to increase the probability and frequency of DI-related crashes in both rural and urban regions. Roadway characteristics (such as non-freeways, segments with multiple lanes, and traffic signals) are positively associated with increased DI-related crash counts, whereas state-secondary routes and speed limits (higher than 35 mph) are associated with decreased DI-related crash counts in rural and urban regions. Besides, horizontal curved and longitudinal bottomed segments and segments with double yellow lines/no passing zones are likely to have fewer DI-related crashes in urban areas. Medians in rural road segments are found to be effective to reduce DI-related crashes. *Practical Applications:* These findings provide a valuable understanding of the DI-related crash frequency for transportation agencies to propose effective countermeasures and safety treatments (e.g., dispatching more police enforcement or surveillance cameras in commercial areas, and setting more medians in rural roads) to mitigate the negative consequences of DI behavior.

1. Introduction

Driver inattention (DI) has been a pervasive issue since people have been driving cars (Caird and Dewar, 2007). It is reported that DI is a major contributing factor in approximately 25%-35% of all actual crashes on roadways (Campbell, Smith, & Najm, 2003; Wang, Knipling, & Goodman, 1996). According to the National Highway Traffic Safety Administration (NHTSA, 2001), the primary factor (sole) and the primary factor (in combination) of DI account for 16.7% and 5.2% in the total crash contributions, respectively. DI-related crash counts increased by 8.40% from 2013 to 2017 in North Carolina (NHTSA, 2014; NHTSA, 2018). The prevalence and continuous increase in vehicle crashes caused by DI behavior has posed a great potential threat to the health and safety of road traffic participants. As a result, DI-related crashes have become a major concern to national and local traffic agencies and policymakers.

DI behavior is defined as insufficient, or no attention, to activities critical for safe driving (Regan, Hallett, & Gordon, 2011). DI can be divided into five subtypes: (a) driver restricted attention (DRA), (b) driver misprioritized attention (DMPA), (c) driver neglected attention (DNA), (d) driver cursory attention (DCA), and (e) driver diverted attention (DDA) (Beanland, Fitzharris, Young, & Lenné, 2013; Regan et al., 2011; Wundersitz, 2019). Note that driver distraction (i.e., cellphone use, reading, eating, and chatting) is just a subtype of DI, and it belongs to one type of DDA (Pettitt, Burnett, &

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Stevens, 2005; Regan et al., 2011). DRA describes circumstance where attention is limited due to physical or biological factors, such as drowsiness and glare. DMPA occurs when the driver is excessively focused on less safety–critical aspects of driving. DNA occurs when the driver fails to attend to activities critical for safe driving, such as failing to look for oncoming vehicles. DCA occurs when the driver attends superficially to activities critical for safe driving and sometimes related to cognitive distraction (Beanland et al., 2013). Several studies have investigated the driving performance and environmental factors of DI (Beanland et al., 2013; Campbell et al., 2003; Klauer et al., 2006; Sundfør, Sagberg, & Høye, 2019; Wundersitz, 2019), especially for distracted driving (Chen & Lym, 2021; Gershon et al., 2019; Lym & Chen, 2020, 2021; Tivesten & Dozza, 2014). However, a comprehensive understanding of the linkages between built environment/roadway characteristics and DI-related crashes remains inadequate. To this end, it is necessary to investigate the DI-related crashes from a post-accident perspective based on a sufficient police-report crash database, thus generating reliable results and conclusions.

The objective of this research is to improve our understanding of the influence of built environment and roadway characteristics on the frequency of vehicle crashes mainly contributing to DI from a post-accident perspective. Specifically, the following three research questions are addressed:

(1) To what extent the crash frequency of DI varies among various built environment and roadway characteristics on road segments?
(2) What are the differences between the influence of built environment and roadway characteristics on DI-related crash counts in rural and urban road segments?
(3) How do built environment and roadway characteristics influence annual DI-related crash frequencies by using a hurdle methodological framework?

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 and 4 introduce the data and methodology. Section 5 presents the research results and discussion. Section 6 concludes and summarizes.

2. Literature review

2.1. General description of DI studies

A significant number of studies have concentrated on the investigation of the relationship between drivers' characteristics, environmental factors, and DI-related crash risks. Table 1 presents a summary of recent studies on DI.

In terms of data source, most studies collected police-report crash data (Campbell et al., 2003; Chen & Lym, 2021; Hendricks, Fell, & Freedman, 2001; Lym & Chen, 2021), naturalistic driving data (Gershon et al., 2019; Klauer et al., 2006; Tivesten & Dozza, 2014), and in-depth crash data (Beanland et al., 2013; Sundfør et al., 2019; Wundersitz, 2019) to investigate DI behavior. Klauer et al. (2006) analyzed crash risks of DI by collecting 100-cars naturalistic driving data for one year, which captured drivers' real-time behavior, detailed pre-crash/crash information, and vehicle dynamics. Tivesten and Dozza (2014) analyzed drivers' eye glance behavior in different contexts and phone tasks based on 1 million kilometers' naturalistic driving data. Although the main advantage of using naturalistic driving data is the realistic information regarding DI behaviors, naturalistic driving data are often costly, time-consuming, and geographically biased (Beanland et al., 2013; Tivesten & Dozza, 2014). Instead, in-depth crash data can provide significant detailed information about pre-crash circumstances and detailed subtypes of inattention by drivers' recall. Wundersitz (2019) investigated the contribution of driver inattention within fatal and injury crashes by using 186 in-depth crash data from South Australia. They found that driver inattention contributed to 31.3% of crashes and the most common types of DI were distractions and mispriortized attention (Wundersitz, 2019). However, the data size of in-depth crash data is usually relatively small (less than 2,000). Another limitation of in-depth crash data is that it relies on subjective reports, which cannot be validated by using external data sources (Beanland et al., 2013). Police-reported crash data has the advantage of low costs and large crash datasets. Many current studies of DI are based on crash records. For example, Lym and Chen (2021) analyzed the influence of built environments on the severity of distraction-related crashes based on distraction-related crash data from 15 U.S. states.

As for methods of DI studies, several studies applied simple statistical analysis for comparisons (Campbell et al., 2003; Klauer et al., 2006; Wundersitz, 2019). Surveys and questionnaires towards DI are also effective methods to obtain valuable information (Beanland et al., 2013; Klauer et al., 2006; Sundfør et al., 2019). In recent years, logistic regression with mixed effects (Gershon et al., 2019) and generalized ordered logit models (Chen & Lym, 2021; Lym & Chen, 2021) were applied to model crash severities of distraction-related crashes. To investigate the frequency of distraction-related crashes, negative binomial regression and Bayesian multivariate conditional autoregression models were applied (Lym & Chen, 2020, 2021). However, the frequency analysis of DI-related crashes (including all subtypes of inattention) on segment-level, especially for annual counts, seems to be inadequate so far.

2.2. Influence of built environment and roadway characteristics on DI

Previous studies have investigated the effects of some environmental and roadway characteristics on the crash risk of DI behavior. Klauer et al. (2006) assessed the near-crash/crash risk of DI in different environmental conditions (such as lighting, weather, road types, road alignments, traffic density, and surface condition). They showed that drowsy drivers (one type of inattention) are over six times as likely to be involved in a crash or near-crash as an alert driver on a straight roadway. Similarly, Tivesten and Dozza (2014) revealed that drivers' glance behavior may be sensitive to weather conditions, and drivers exhibited shorter off-road glances in rainy weather than in clear weather. Chen and Lym (2021)'s study showed that the frequency of distracted driving crashes tends to be much higher than that of non-distracted driving crashes in the urbanized road environment. Roadways with medians and shoulders with an asphalt pavement were significantly negatively associated with the distraction-related crash counts. A rise in commercial land use would lead to an increased risk of all severity levels of distraction-related crashes at census-tracts level (Lym & Chen, 2020). These studies provide a solid understanding of DI behavior in various environments. However, there is limited understanding on the extent that crash frequency (as a result of DI behavior) varies among built environment and roadway characteristics on road segments. In addition, differences in the influence of built environment and roadway features on DI-related crashes in rural and urban regions need to be addressed because overall environment of rural and urban regions are quite different.

2.3. Methods of handling excess zeros and unobserved heterogeneity in crash frequency analysis

One methodological challenge often faced in analyzing crash frequency is the presence of a large number of zeros. Due to rare events and the random nature of DI-related crashes, the datasets

Table 1
Summary of the studies of DI.

Authors	Types of inattention	Region	Data	Method	Major findings
Hendricks et al. (2001)	Non-specified	US	Serious crash data selected using the National Automotive Sampling System (NASS) protocol	Clinical analysis method and a multivariate analysis sequence	Driver inattention was the most dominant component of the causal factor pattern in unsafe driving acts and this factor should receive high priority with respect to countermeasure.
Campbell et al., (2003)	Non-specified	US	Crash data from National Automotive Sampling System's 1997–2000 Crashworthiness Data System (CDS) and 2000 General Estimates System (GES)	Comparison analysis and cross-correlation analysis	Driver inattention was the top primary contributing factor for single-vehicle off-road collisions, rear-end collisions, and lane change collisions.
Klauer et al. (2006)	Secondary tasks, driving-related inattention, drowsiness, non-specific eyeglance	US	Naturalistic driving data. Crashes and near-crashes were collected from 100 drivers of instrumented vehicles driving for 12 months	Comparison of baseline database, surveys, questionnaires, and performance-based tests	Drivers engaging in visually and/ or manually complex tasks have a three-times higher crash risk than attentive drivers.
Regan et al. (2011)	Driver restricted attention (DRA), driver misprioritised attention (DMPA), driver neglected attention (DNA), driver cursory attention (DCA), driver diverted attention (DDA)	France	A review of existing definition and taxonomies of driver distraction and driver inattention	Literature review and comparison analysis	Driver distraction is just one form of driver inattention, and driver inattention means insufficient or no attention to activities critical for safe driving
Beanland et al. (2013)	DRA, DMPA, DNA, DCA, and DDA	Australia	Crash data from the Austrian National Crash In-depth Study (ANCIS)	Statistical analysis and survey	Over a half of crashes showed evidence of driver inattention and the most frequent subtype of inattention was DRA, followed by DDA
Tivesten and Dozza (2014)	Distracted driving (visual-manual phone tasks)	Sweden	Naturalistic driving data of 100 cars for one year	Statistical analysis and glance metrics	Driving context (i.e. turning maneuvers, presence of lead or oncoming vehicles, vehicle speed) influenced drivers' glance behavior
Gershon et al. (2019)	Distracted driving	US	Naturalistic driving data collected from 82 newly licensed teenagers	Mixed-effects logistic regression models and mediation analyses	Manual cellphone uses and reaching for objects were associated with increased crash risk
Sundfør et al. (2019)	Non-specified	Norway	In-depth crash data from Norwegian Public Roads Administration	Statistical analysis and survey	Inattention among at-fault drivers of motor vehicles contributed to one out of three fatal road crashes, failure to check for information in blind spots or behind other sight obstruction is a typical form of inattention
Wundersitz (2019)	DMPA, DNA, DCA, DDA, and unspecified inattention (U)	Australia	In-depth crash data from fatal and injury crashes in South Australia	Statistical analysis and comparison between inattention and non-inattention crashes	The most common subtype of inattention was distractions, and inattention crashes were most likely to involve right turn/angle or rear-end crash types and occur at intersections, in metropolitan areas, and lower speed zones
Chen and Lym (2021)	Distracted driving	US	Crash data from the Ohio Department of Transportation (ODOT)	Negative binomial regression model and generalized ordered logit model	The frequency of distracted driving crashes tends to be much higher than that of non-distracted driving in the urbanized road environment
Lym and Chen (2021)	Distracted driving	US	Crash data from fifteen states of Department of Transportation (DOT)	Generalized ordered logit regression model	A state-specific variability of the influence of the built environment on the severity of distracted driving crashes

contain excessive zero counts at the segment-level. However, the standard count models (such as Poisson and negative binomial) are often insufficient to account for the preponderance of zeros, leading to biased model results (Cai, Lee, Eluru, & Abdel-Aty, 2016). Therefore, zero-altered models (namely zero-inflated (ZI) model and hurdle model) are widely adopted to deal with the excessive zeros in crash frequency analyses (Cai et al., 2016; Dong, Clarke, Yan, Khattak, & Huang, 2014; Hosseinpour, Yahaya, & Sadullah, 2014; Huang & Chin, 2010; Lee & Mannering, 2002; Qiu, Logan, Oxley, & Lowe, 2020; Son, Kweon, & Park, 2011; Yu, Wang, Quddus, & Li, 2019). In essence, the biggest difference between the two zero-altered models is the generation process of zeros. ZI models assume the zero counts are arising from both structural zeros and sampling zeros. Structural zeros indicate that the roadway segments are inherently safe, and sampling zeros indicate that no crash occurred in the observation period (Shankar, Milton, & Mannering, 1997). However, the assumption of structural zeros of ZI models has been criticized by some scholars (Lord, Washington, & Ivan, 2005; Lord, Washington, & Ivan, 2007). Conversely, the hurdle model assumes that all zeros in the dataset are all sampling zeros. That is, it assumes that every road segment is not inherently safe and has the probability of having crashes, which is more consistent with realistic situations. Additionally, hurdle models displayed good fit and provide reliable results in current traffic safety studies (Hosseinpour et al., 2014; Qiu et al., 2020; Yu et al., 2019).

It is also noted that the DI-related crash frequency data exhibit a typical panel data structure, which calculated crash observations at segment level every year. This suggests that there may be potential heterogeneity (i.e., caused by spatiotemporal correlations) in the crash data, which is frequently discussed in previous studies (Mannering, Shankar, & Bhat, 2016; Mannering & Bhat, 2014). To deal with the unobserved heterogeneity, models with random parameters (Hou, Tarko, & Meng, 2018; Huo, Leng, Hou, Zheng, & Zhao, 2020) and random effects (Qiu et al., 2020; Yu et al., 2019) are recommended to be applied. Thus, random intercept models were introduced in this study as they allow for a site-specific disturbance term.

As previously discussed in the literature review, studies on DI have been dominated by investigations in inattention subtypes, drivers' characteristics, and distraction-related crashes. Hence, this research aims to fill the gaps in knowledge from a different perspective by adopting a hurdle framework to improve our understanding of DI-related crashes.

3. Data

Data used in this study were obtained from the Highway Safety Information System (HSIS) in North Carolina between 2013 and 2017. This study defined the DI-related crash as a crash caused by at least one driver exhibiting inattention (i.e., the first contributory factor is DI). The database includes 29,539 and 60,569 DI-related crashes between light vehicles (i.e., passenger cars, pickups, sports utility, and taxicabs) on rural and urban road segments, respectively. Fig. 1 presents the comparison of DI-related crashes in all road types in this dataset. Overall, the share of DI-related crashes that happened on road segments is much higher than other road types. This finding is supported by a report of DI-related crashes (Klauer et al., 2006). It is also clear that DI-related crashes that occurred on road segments are annually increasing from 2013 to 2017.

After that, road segments with short lengths (less than 0.08 miles) and missing values of useful variables are deleted. Finally, DI-related crash counts of 1,327 and 4,914 road segments from rural and urban regions in each year from 2013 to 2017 are used for the later modeling (Fig. 2 shows the road lengths of selected rural and urban segments in this study). Approximately 78% and 74% of annual DI-related crash frequency of road segments are zeros in the rural dataset and urban dataset, respectively, which reflects the presence of excessive zeros. This is consistent with the nature of DI-related crashes due to the strong randomness of this type of crash happening on road segments (Wundersitz, 2019). However, DI-related crashes are also significantly influenced by environmental factors (i.e., traffic density, road types, and road alignments; Chen & Lym, 2021; Hosseinpour et al., 2014; Klauer et al., 2006). Thus, various types of explanatory variables that represent different built environments and roadway characteristics of road segments are considered in this study. Additionally, the same classification of built environment variables and roadway features can be found in Song, Li, Fan, and Wu (2020) and Song and Fan (2020). The statistic descriptions of the explanatory category variables are shown in Table 2.

4. Methodology

4.1. Standard count models

The Poisson model is the fundamental model for crash frequency analysis (Lord & Mannering, 2010). In a Poisson regression model, the probability of roadway segment i having y_{it} DI-related crashes in the t year $P(y_{it})$ is given by:

$$P(y_{it}) = \frac{EXP(-\lambda_{it})\lambda_{it}^{y_{it}}}{y_{it}!} \tag{1}$$

$$\lambda_{it} = EXP(\boldsymbol{\beta_i x_i}) \tag{2}$$

where λ_{it} is the expected DI-related crash number of road segment i in the t time period, $\boldsymbol{x_i}$ is a set of explanatory variables, and $\boldsymbol{\beta_i}$ is a vector of estimated parameters. However, Poisson models can not handle the over-dispersion problem in crash counts (i.e., variance significantly exceeds the mean).

The negative binomial (NB) model is proposed to handle the over-dispersion by adding an error term ε_{it} to the mean of the Poisson model as:

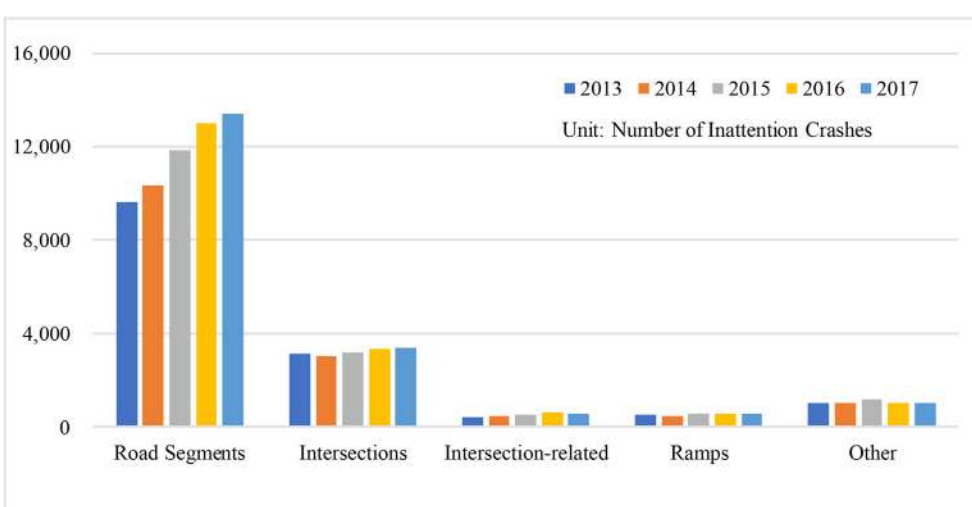
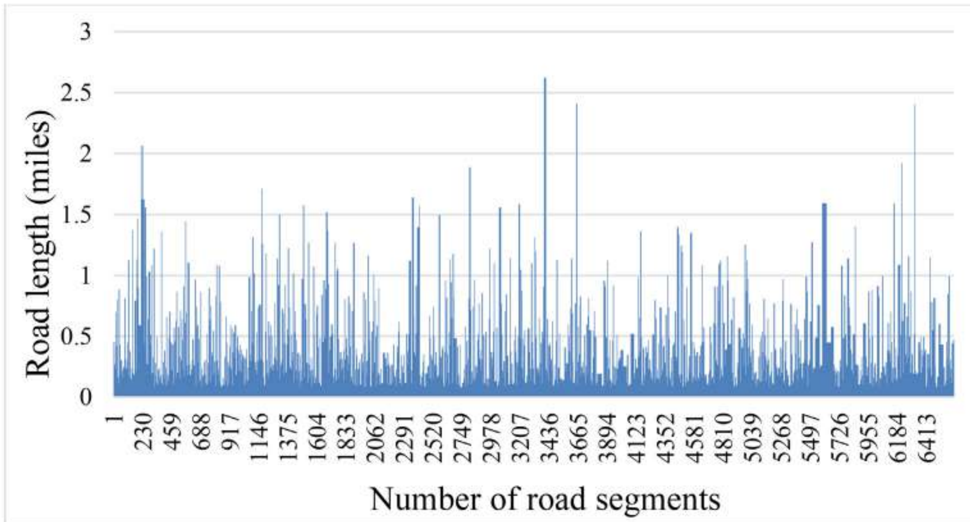
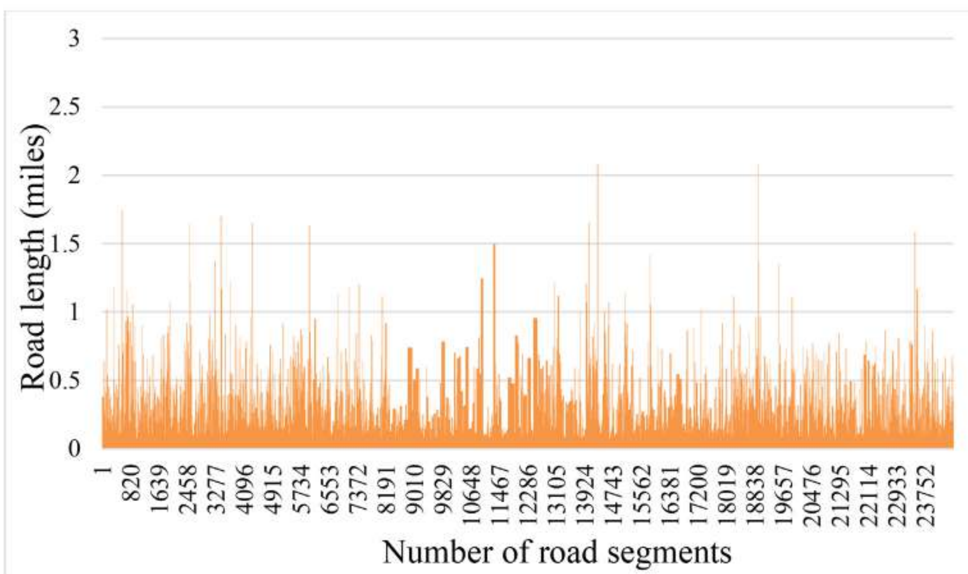


Fig. 1. Annual DI-related crashes by different road types (North Carolina, 2013–2017).



(a) Lengths of rural road segments



(b) Lengths of urban road segments

Fig. 2. Lengths of selected rural and urban road segments for DI-related crash frequency modelling during 2013–2017.

$$\lambda_{it} = EXP(\boldsymbol{\beta_i x_i} + \varepsilon_{it}) \tag{3}$$

where $EXP(\varepsilon_{it})$ is a Gamma-distributed disturbance term with mean 1 and variance α. The probability of roadway segment i having y_{it} DI-related crashes can be given by:

$$P(y_{it}) = \frac{\Gamma\left[\left(\frac{1}{\alpha}\right) + y_{it}\right]}{\Gamma\left(\frac{1}{\alpha}\right) y_{it}!} \left(\frac{\frac{1}{\alpha}}{\left(\frac{1}{\alpha}\right) + \lambda_{it}}\right)^{\frac{1}{\alpha}} \left(\frac{\lambda_{it}}{\left(\frac{1}{\alpha}\right) + \lambda_{it}}\right)^{y_{it}} \tag{4}$$

where $\Gamma(\cdot)$ is a Gamma function. α is the over-dispersion parameter of the NB model.

4.2. Hurdle models

Traditional standard count models (i.e., Poisson and NB models) have limited capabilities in dealing with excessive zeros (Dong, Richards, Clarke, Zhou, & Ma, 2014; Hosseinpour et al., 2014). Instead, zero-altered models (i.e., ZI and hurdle models) are commonly applied to handle excess zero counts (Lee & Mannering, 2002; Qin, Ivan, & Ravishanker, 2004; Hosseinpour et al., 2014; Cai et al., 2016; Yu et al., 2019).

The hurdle model was introduced by Cragg (1971) and then developed by Mullahy (1986). It is a two-state model with a zero state and a non-zero positive state. The first part of the model can be modeled by a binary regression, such as logit or probit models. The second part is modeled by a left truncated Poisson or NB distribution. The density function of a hurdle Poisson (HP) model is given as follows:

$$P(Y = y_{it}) = \begin{cases} P_{it} & y_{it} = 0 \\ (1 - P_{it}) \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{(1 - e^{-\lambda_{it}}) y_{it}!} & y_{it} > 0 \end{cases} \tag{5}$$

Table 2
Descriptive statistics of explanatory variables.

Variables		Description	Rural	Urban
Exposure variables				
Log of VMT		Log of VMT (vehicle miles traveled per million)	Mean: 0.183 S.D.: 0.630	Mean: 0.292 S.D.: 0.484
Built environment variables				
Locality	1	Farms, woods and pastures*	659 (49.66%)	200 (4.07%)
	2	Residential	296 (22.31%)	1,120 (22.79%)
	3	Commercial	360 (27.13%)	3,512 (71.47%)
	4	Institutional	9 (0.68%)	38 (0.77%)
	5	Industrial	3 (0.23%)	44 (0.90%)
Road curve	1	Straight*	1,075 (81.01%)	418 (8.51%)
	2	Curve	252 (18.99%)	4,496 (91.49%)
Road gradient	1	Level*	971 (73.17%)	4,098 (83.39%)
	2	Grade	310 (23.36%)	646 (13.15%)
	3	Hillcrest	33 (2.49%)	149 (3.03%)
	4	Bottom	13 (0.98%)	21 (0.43%)
Route type	1	Interstate*	254 (19.14%)	306 (6.23%)
	2	US route	295 (22.23%)	495 (10.07%)
	3	State route	240 (18.09%)	447 (9.10%)
	4	State secondary route	382 (28.79%)	140 (2.85%)
	5	Local street	153 (11.53%)	3,442 (70.04%)
	6	Public vehicular area	3 (0.23%)	70 (1.42%)
Functional class	1	Principal arterial*	621 (46.80%)	2,824 (57.47%)
	2	Minor arterial	380 (28.64%)	1,626 (33.09%)
	3	Collector	225 (16.96%)	384 (7.81%)
	4	Local	101 (7.61%)	80 (1.63%)
Traffic control	1	No control present*	715 (53.88%)	3,169 (64.49%)
	2	Signs	35 (2.64%)	229 (4.66%)
	3	Signals	99 (7.46%)	1,321 (26.88%)
	4	Double Yellow Line, no passing zone	474 (35.72%)	187 (3.81%)
	5	Human control	4 (0.30%)	5 (0.10%)
Speed limit	1	≤35 mph*	268 (20.20%)	1,779 (36.20%)
	2	36–55 mph	759 (57.20%)	2,898 (58.97%)
	3	56–70 mph	300 (22.61%)	237 (4.82%)
If freeways	1	Freeways*	324 (24.42%)	418 (8.51%)
	2	Non-freeways	1,003 (75.78%)	4,496 (91.49%)
No. of lanes	1	≤2*	719 (54.18%)	1,331 (27.09%)
	2	3 and 4	476 (35.87%)	2,641 (53.74%)
	3	>4	132 (9.95%)	942 (19.17%)
Median type	1	Undivided roadway*	895 (67.45%)	3,458 (70.37%)
	2	divided roadway	432 (32.55%)	1,456 (29.63%)
Other environmental variables				
Terrain	1	Flat*	184 (13.87%)	506 (10.30%)
	2	Rolling	953 (71.82%)	4,275 (87.00%)
	3	Mountainous	190 (14.32%)	133 (2.71%)

Note: * denotes the base of the explanatory variables.

where P_{it} is the probability of being zero counts of DI-related crashes for road segment i in the t year, $(1 - P_{it})$is the probability of non-zero DI-related crash counts for road segment i in the t year, and λ_{it} is the average DI-related crash counts derived from the left-truncated Poisson regression model.

To handle the over-dispersion in the crash frequency, hurdle negative binomial (HNB) models can be used. Based on the hurdle framework, the density function of HNB model is given as:

$$P(Y = y_{it}) = \begin{cases} P_{it} & y_{it} = 0 \\ (1 - P_{it})\left(1 - \frac{1}{(1+\alpha\lambda_{it})^{\left(\frac{1}{\alpha}\right)}}\right)\left(\frac{\Gamma\left(y_{it}+\left(\frac{1}{\alpha}\right)\right)}{\Gamma(y_{it}+1)\Gamma\left(\frac{1}{\alpha}\right)}\right)\left(\frac{(\alpha\lambda_{it})^{y_{it}}}{(1+\alpha\lambda_{it})^{y_{it}+\left(\frac{1}{\alpha}\right)}}\right) & y_{it} > 0 \end{cases}$$

where α is the over-dispersion parameter, $\Gamma(\cdot)$ is a Gamma function, and λ_{it} is the average DI-related crash counts derived from the left-truncated NB model.

In the first state (i.e. zeros) of the HP and HNB model, a logistic regression is adopted, as shown in:

$$P_{it} = logit(\pi_{it}) = \boldsymbol{x}_{1i}^T\delta \tag{7}$$

where $\boldsymbol{x}_{1i}^T$ is a vector of explanatory variables for the fixed parameter δ in the binary part.

In the second state (i.e. non-zeros) of the HP model, a Poisson regression model is used, as shown in:

$$\lambda_{it} = EXP(\boldsymbol{\beta}_{2i}\boldsymbol{x}_{2i}) \tag{8}$$

where $\boldsymbol{x}_{2i}$ is a vector of explanatory variables for the fixed parameters $\boldsymbol{\beta}_{2i}$ in the count part. The NB regression model also can be used in the second state, as shown in:

$$\lambda_{it} = EXP(\boldsymbol{\beta}_{2i}\boldsymbol{x}_{2i} + \varepsilon_{it}) \tag{9}$$

where $EXP(\varepsilon_{it})$ is a Gamma-distributed term in the count part of the HNB model.

4.3. Hurdle models with random intercepts

The random intercepts hurdle model accounts for site-specific factors and can provide better goodness-of-fit than the hurdle model (Yu et al., 2019). It captures unobserved heterogeneity of road segment i, which is constant within each roadway segment and different across roadway segments. Based on the formulation of HP and HNB models, the site-specific random intercepts of the count part of hurdle models are considered as follows:

$$\lambda_{it} = EXP(\boldsymbol{\beta}_{2i}\boldsymbol{x}_{2i} + b_{ip}) \tag{10}$$

$$\lambda_{it} = EXP(\boldsymbol{\beta}_{2i}\boldsymbol{x}_{2i} + \varepsilon_{it} + b_{inb}) \tag{11}$$

where b_{ip} is the random intercepts in the HP model, and b_{inb} is the random intercepts in the HNB model. The random effects are both assumed to be independent to each other and follow a normal distribution with mean zero and variance σ_b^2.

4.4. Model comparison and selection

To verify the existence of overdispersion in the DI-related crash counts of urban road segments, a likelihood ratio test (LRT) is conducted to compare the NB model and its Poisson counterpart, then z-statistics test of the overdispersion parameter in the NB model is also performed. Results of both LRT (χ^2 = 17285.2, df = 1, p < 0.0001) and z-statistics (z = 41.65, p < 0.0001) confirm the presence of overdispersion in the DI-related crash counts in the urban dataset. Thus, the NB model is preferred in the urban crash datasets of DI.

For non-nested models (i.e., Poisson, HP, RIHP, NB, HNB, and RIHP), comparisons are performed using the Vuong test (Vuong, 1989). Given that $P_1(y_{it}|x_i)$ and $P_2(y_{it}|x_i)$ are the predicted probabilities of model A and model B, respectively. The Vuong test can be given as:

$$V = \frac{\overline{m}\sqrt{n}}{SD(m)} \tag{12}$$

$$m_{it} = \ln\left(\frac{\sum_i\sum_t P_1(y_{it}|x_i)}{\sum_i\sum_t P_2(y_{it}|x_i)}\right) \tag{13}$$

where $\overline{m}$ is the mean of m_{it}, and $SD(m)$ is the standard deviation of m_{it}. The V follows a standard normal distribution. If V is greater than 1.96, then it favors the model B, and if V is lower than -1.96, it favors model A. Otherwise, neither model is preferred over the other.

To this end, the Akaike Information Criterion (AIC), the McFadden pseudo R^2 and the Chi-square χ^2 test are also used to evaluate the statistical fit of candidate models (i.e., Poisson, HP, RIHP, NB, HNB, and RIHNB models) of DI-related crash counts:

$$AIC = -2LL(\beta) + 2K \tag{14}$$

$$R^2 = 1 - \exp[-2(LL(\beta) - LL(0)/N] \tag{15}$$

where LL(β) is the log-likelihood at convergence, K is the number of parameters and $LL(0)$ is the log-likelihood with only the intercept term. N is the total number of observations. The smaller AIC value indicates a better fitted model. A simulation-based maximum likelihood method is implemented in the LIMDEP software (Greene, 2016) and Halton draws are employed to estimate parameters of RIHP and RIHNB models (Bhat, 2003; Train, 2009).

5. Results and discussions

5.1. Model evaluation

In this study, DI-related crashes from rural road segments are selected for Poisson, HP, and RIHP model estimation. DI-related crashes from urban road segments are selected for NB, HNB, and RIHNB model estimation. A backward stepwise regression technique is used and only variables with at least 90% confidence level are kept in the model. Then, a correlation analysis for independent variables is conducted. Most pairwise correlation coefficients were less than 0.70 and no multi-collinearity among the included variables. The goodness-of-fit measures of the estimated models are displayed in Table 3. First, across rural and urban road segments, the hurdle models (i.e., HP, HNB, RIHP, and RIHNB) offer better goodness-of-fit when they are compared with standard count models (i.e., Poisson and NB) in terms of log-likelihood and AIC. This result indicates the good performance of hurdle models in fitting datasets with excessive zeros, which is consistent with previous studies (Son et al., 2011; Yu et al., 2019; Qiu et al., 2020). Second, the RIHP and RIHNB model are the best model of goodness-of-fit across all model structures based on the Macfadden R^2. Among these models, the RIHP and RIHNB models have the highest R^2 (0.161 and 0.472) indicating the strong explanatory ability of hurdle models with random intercepts. The Vuong test also shows the RIHP and RIHNB models distinctly outperform the standard count models (the Poisson and NB model) at the 95% significant level. Therefore, in terms of our results, we can conclude that the RIHP and RIHNB model offer the best statistical fit for DI-related crashes in rural and urban road segments, respectively.

Tables 4 and 5 present the estimation results of three models of DI-related crashes on rural and urban road segments, respectively. Statistically significant variables are grouped into four categories: exposure, built environment, roadway characteristics, and other environmental variables. It can be seen that there are more significant variables of DI-related crashes in urban road segments than those in rural road segments. This outcome reflects the complex effects of land use and roadway characteristics in urban roads on the occurrence of DI-related crashes. Two significant parameters (the mean and variance σ_b of intercepts in the count part) in the RIHP and RIHNB model indicate that unobserved location-specific heterogeneity indeed exists.

The marginal effects of the RIHP model and RIHNB model for rural road segments and urban road segments are presented in Table 6. Note that marginal effects are the average effects of a unit increase in an independent variable on the annual crash counts on an average segment mainly caused by DI in this study. For brevity, the following section analyzes the modeling results of the RIHP and RIHNB model and discusses the similarities and differences between DI-related crashes in rural and urban road segments.

Table 3
Comparison of goodness-of-fits between different models.

Measures	Rural			Urban		
	Poisson	HP	RIHP	NB	HNB	RIHNB
No of parameters	11	13	14	24	31	32
Log-likelihood with constant only	−4842.7	−4738.1	−5236.8	−32779.1	−32779.1	−44764.7
Log-likelihood at convergence	−4738.1	−4431.7	−4393.1	−24136.4	−23630.3	−23630.5
Macfadden R^2	0.022	0.065	0.161	0.264	0.279	0.472
AIC	9498.2	8889.4	8814.2	48320.9	47322.6	47325.1
Vuong test (p value)	2.55 (<0.05)[a]	2.66 (<0.05)[b]	11.83 (<0.05)[c]	0.79[d]	1.21[e]	15.86 (<0.05)[f]

Note: [a]Vuong test for HP vs. Poisson, [b]Vuong test for RIHP vs. HP, [c]Vuong test for RIHP vs. Poisson, [d]Vuong test for HNB vs. NB, [e]Vuong test for RIHNB vs. HNB, and [f]Vuong test for RIHNB vs. NB.

5.2. Binary part

The binary part of the RIHP model and the RIHNB model identified significant factors that influence the possibility of having crashes caused by DI on rural road segments and urban road segments each year. A positive regression coefficient implies an increase in the probability of DI-related crashes occurring. The estimation results in the binary part of the final models are displayed in Tables 4 and 5.

5.2.1. Traffic exposure

The log of VMT is found to have positive and statistically significant associations with DI-related crashes in the urban dataset. This result reveals that higher VMT is associated with a higher probability of DI-related crashes occurring in urban regions. The VMT variable is often a measure of vehicle exposure and, as expected, increases the likelihood of vehicle crashes (Cai et al., 2016; Chen & Lym, 2021). This is probably because the likelihood of DI-related crashes occurring increases with the likelihood of total crashes occurring in the large exposure of vehicles and roadway length.

5.2.2. Built environment

Among different built environments (i.e., residential, commercial, institutional, and industrial land uses), the presence of commercial areas is highly associated with the increased probability of DI-related crashes happening in both rural and urban roads. This finding is consistent with many previous studies (Kim & Yamashita, 2002; Merlin, Guerra, & Dumbaugh, 2020; Ukkusuri, Miranda-Moreno, Ramadurai, & Isa-Tavarez, 2012; Yang & Loo, 2016) because commercial areas are likely to have a large number of passing vehicles, pedestrians, and non-motorized vehicles (i.e., bicycles, scooters, e-bikes). This complicated traffic environment may increase the possibility of DI behavior. For example, vehicle drivers may have more eyeglance of external traffic environment and divert their attention from safe driving in commercial areas. Drivers engaging in visually complex tasks have a three-times higher near-crash/ crash risk than drivers who do not engage in visually complex tasks (Klauer et al., 2006).

5.2.3. Roadway characteristics

Road characteristics are only found to have significant effects on the occurrence of DI-related crashes in urban areas. Non-freeways and roadways with multiple lanes (number of lanes is more than three) are more likely to have a higher possibility of DI-related crashes occurring in urban regions. This is expected because non-freeway segments per kilometer have more access points than freeway segments per kilometer, and these access points may disturb the attention of drivers. Additionally, the study of distraction-related crashes also found that roadways with relatively more lanes would increase the crash risk (Chen & Lym, 2021).

5.2.4. Other environmental factors

Road segments in rolling terrains are expected to increase the likelihood of DI-related crashes occurring in the urban regions. This finding is slightly counterintuitive to our expectations. This could be interpreted from two aspects: (i) DI-related crashes are likely to happen in the road segments of the rolling terrain because 87% of selected urban road segments are located in rolling terrains; (ii) rolling terrains possibly have unobserved natural environmental factors that easily cause the driving-related inattention behavior of drivers.

5.3. Count part

The count part of the RIHP model and the RIHNB model reveals the influencing factors for the DI-related crash frequency, where positive regression coefficients indicate the increasing number of DI-related crashes (non-zero crashes). The estimation results in the count part of the final models are displayed in Table 4 and Table 5.

5.3.1. Traffic exposure

The log of VMT is significant with a positive sign in both DI-related datasets of rural and urban road segments. It indicates that

Table 4
Estimation results for DI-related crash counts of rural road segments per year.

Variables	Poisson		HP		RIHP	
	Estimate	Z-stat	Estimate	Z-stat	Estimate	Z-stat
Count part						
Intercept	−1.243***	−13.80	−0.806***	−5.75	−1.013***	−6.09
Exposure variables						
Log of VMT (vehicle miles traveled per million)	0.388***	7.27	1.315***	14.12	1.452***	12.48
Built environment variables						
Commercial areas presence	0.239***	4.13	0.473***	4.35	0.441***	3.38
Roadway characteristics variables						
State secondary route	−0.881	−1.31	−1.039***	−5.42	−0.954***	−4.43
Signals	0.142*	1.79	0.234**	2.25	0.255**	2.00
Speed limit of 36–55 mph	−0.315***	−5.08	−0.808***	−8.78	−0.965***	−7.94
Speed limit of 56–70 mph	−0.430***	−4.09	−1.19***	−7.62	−1.323***	−6.30
No. of lanes (>4)	0.313***	4.01	0.614***	5.40	0.593***	4.37
Median presence	−0.127*	−1.82	−0.463***	−4.06	−0.543***	−4.02
Other environmental variables						
Rolling terrain	0.164**	2.26	0.508***	3.29	0.399**	2.40
Mountainous terrain	0.123	1.32	0.395**	2.07	0.318	1.53
Binary part						
Intercept	–	–	−1.318***	−37.25	−1.318***	−37.33
Built environment variables						
Commercial areas presence	–	–	0.138**	2.06	0.138**	2.08
σ_b	–	–	–	–	0.810***	17.54

Note: ***, ** and * denote significant at 1%, 5% and 10% level, respectively.

Table 5
Estimation results for DI-related crash counts of urban road segments per year.

Variables	NB		HNB		RIHNB	
	Estimate	Z-stat	Estimate	Z-stat	Estimate	Z-stat
Count part						
Intercept	−2.224***	−13.38	−2.606***	−15.06	−2.634***	−15.32
Exposure variables						
Log of VMT (vehicle miles traveled per million)	0.644***	19.45	1.164***	37.36	1.165***	39.90
Built environment variables						
Residential areas presence	0.135	1.20	0.393***	3.42	0.396***	3.40
Commercial areas presence	0.336***	3.11	0.676***	6.10	0.680***	6.07
Industrial areas presence	0.092	0.44	0.480**	2.31	0.479**	2.26
Roadway characteristics variables						
Roads horizontal alignment (curved)	−0.152	−1.34	−0.387***	−3.55	−0.388***	−3.50
Roads longitudinal alignment (bottom)	−0.311	−0.97	−0.632**	−2.05	−0.636**	−2.03
State route	0.082	1.03	0.240***	3.37	0.242***	3.32
State secondary route	−0.033	−0.23	−0.268*	−1.90	−0.265*	−1.85
Local street	0.327***	5.35	0.509***	9.44	0.511***	9.32
Public vehicular area	0.309**	2.00	0.438***	3.26	0.438***	3.19
Minor arterial	−0.179***	−4.13	−0.255***	−6.76	−0.256***	−6.65
Collector	−0.290***	−3.11	−0.603***	−5.95	−0.603***	−5.88
Local	−0.488***	−2.64	−0.852***	−3.79	−0.853***	−3.76
Signals	0.130***	3.32	0.166***	4.83	0.168***	4.78
Double yellow line, no passing zone	−0.199*	−1.65	−0.512***	−4.10	−0.514***	−4.07
Speed limit of 36–55 mph	−0.050	−1.24	−0.124***	−3.33	−0.124***	−3.26
Speed limit of 56–70 mph	−0.285**	−2.06	−0.526***	−4.27	−0.530***	−4.24
Non-freeways	0.493***	4.85	0.745***	8.43	0.745***	8.31
No. of lanes (3 and 4)	0.172***	3.53	0.231***	5.17	0.234***	5.15
No. of lanes (>4)	0.286***	4.50	0.382***	6.64	0.388***	6.64
Other environmental variables						
Rolling terrain	0.545***	7.48	0.976***	11.49	0.980***	11.40
Mountainous terrain	0.281**	1.99	0.619***	4.23	0.623***	4.21
Binary part						
Intercept	–	–	−1.465***	−18.72	−1.465***	−18.73
Log of VMT (vehicle miles traveled per million)	–	–	0.061*	1.78	0.061*	1.77
Built environment variables	–	–				
Commercial areas presence	–	–	0.080**	2.29	0.080**	2.29
Roadway characteristics variables	–	–				
Non–freeways	–	–	0.146**	2.47	0.146**	2.48
No. of lanes (3 and 4)	–	–	0.114***	3.00	0.114***	3.00
No. of lanes (>4)	–	–	0.119**	2.36	0.120**	2.36
Other geographic variables						
Rolling terrain	–	–	0.133***	2.95	0.133***	2.95
Over-dispersion parameter α	4.007***	41.65	0.567***	13.41	1.671***	39.46
σ_b	–	–	–	–	0.055***	3.58

Note: ***, **, and * denote significant at 1%, 5% and 10% level, respectively.

DI-related crash counts increased with the VMT, which agrees with our expectations and similar studies (Cai et al., 2016; Chen & Lym, 2021; Qiu et al., 2020). Large exposure of vehicles is significantly correlated with high crash frequency, and the frequency of DI-related crashes follows the same pattern as well. Besides, it has been found that drivers who engage in secondary tasks are more dangerous in the high traffic density environment (Klauer et al., 2006). The coefficient of log VMT is larger than 1.0, indicating that the increasing vehicle miles traveled can lead to more DI-related crashes in the rural and urban environment at a higher rate than linear growth. This result is also consistent with previous studies of the relationship between VMT and crash counts (Xie, Ozbay, & Yang, 2019).

5.3.2. Built environment

The built environment variable used the presence of farms, woods, and pastures as a reference, and the presence of commercial areas is statistically significant with positive coefficients in the rural dataset. In contrast with the rural dataset, the presence of residential areas, commercial areas, and industrial areas are all significant with positive coefficients in the urban dataset. Additionally, the presence of commercial areas holds the largest estimated coefficient in urban roads. These results indicate that the frequency of DI-related crashes is highly associated with roads with commercial areas in both rural and urban environments, and DI-related crashes are easily influenced by more land-use types in urban regions than rural regions. Kim and Yamashita (2002) found that the majority of vehicle-to-vehicle crashes happened along with residential lands and commercial lands. Several studies have also concluded the high crash risk of commercial, residential, and industrial land uses (Huang, Wang, & Patton, 2018; Kim & Yamashita, 2002; Lizarazo & Valencia, 2018; Merlin et al., 2020; Xie et al., 2019). The increase in DI-related crashes in urban road segments could reflect the increased traffic exposure, conflicts between road users, and other visual interference of drivers around commercial areas, residential areas, and industrial areas.

5.3.3. Roadway characteristics

The influence of road geometric alignments on DI-related crash counts is also investigated. Interestingly, horizontal curved and longitudinal-bottomed road segments are found to have decreased the frequency of DI-related crashes in urban regions. The marginal

Table 6
Marginal effects of significant variables of DI-related crashes in rural road segments and urban road segments of the RIHP and the RIHNB model, respectively.

Variables	Rural		Urban	
	Average (|t|)	S.E	Average (|t|)	S.E
Exposure variables				
Log of VMT (vehicle miles traveled per million)	0.138 (9.40)	0.015	0.450 (20.20)	0.022
Built environment variables				
Residential areas presence	–	–	0.175 (2.82)	0.062
Commercial areas presence	0.077 (3.40)	0.023	0.231 (7.13)	0.032
Roadway characteristics variables				
Roads horizontal alignment (curved)	–	–	−0.114 (4.41)	0.026
Roads longitudinal alignment (bottom)	–	–	−0.161 (3.07)	0.053
State route	–	–	0.100 (2.92)	0.034
State secondary route	−0.060 (6.42)	0.009	−0.829 (2.18)	0.038
Local street	–	–	0.162 (9.98)	0.016
Public vehicular area	–	–	0.208 (2.50)	0.083
Minor arterial	–	–	−0.087 (6.96)	0.012
Collector	–	–	−0.159 (8.32)	0.019
Local	–	–	−0.194 (6.51)	0.030
Signals	–	–	0.063 (4.56)	0.014
Double yellow line, no passing zone			−0.140 (5.57)	0.025
Speed limit of 36–55 mph	−0.092 (6.88)	0.013	−0.047 (3.14)	0.015
Speed limit of 56–70 mph	−0.135 (4.60)	0.029	−0.144 (5.76)	0.025
Non-freeways	–	–	0.231 (10.03)	0.023
No. of lanes (3 and 4)	–	–	0.130 (5.82)	0.022
No. of lanes (>4)	0.070 (3.43)	0.020	0.220 (5.55)	0.040
Median presence	−0.052 (3.70)	0.014	–	–
Other environmental variables				
Rolling terrain	0.034 (2.62)	0.013	0.263 (14.79)	0.018
Mountainous terrain	–	–	0.334 (3.00)	0.112

effect of the roadway characteristics' variables is summarized in Table 6. A one-unit increase in the road horizontal alignment (curved) and road longitudinal alignment (bottom) are associated with the average crash frequency decreased by 0.114 and 0.161 if the cause of crashes were caused by DI. The explanation can be that road segments with curves and bottomed grades usually increase the complicity of driving tasks of drivers, and drivers are likely to be more focused on safe driving. It is reported that the frequency of drowsiness-related and secondary task-related crashes on roads with straight-levels are dramatically higher than that of other road alignment types (Klauer et al., 2006).

Road classes are also found to have significant influence on the frequency of DI-related crashes. State secondary routes have fewer expected DI-related crashes than other classes of roads in both rural and urban regions. Conversely, other classes of roads (i.e., state routes, local streets, and public vehicular areas) significantly increased the frequency of DI-related crashes in urban road segments. As shown in Table 6, state secondary routes have fewer DI-related crashes (-0.829), and state routes, local streets, and public vehicular areas have more DI-related crashes (+0.100, +0.162, and +0.208, respectively). One possible reason for this might be local streets and public vehicular areas in urban regions tend to have more pedestrians and lower speed limits, which possibly increases the frequency of non-specific eyeglance and secondary-task behavior of drivers. This explanation has been supported by Klauer et al. (2006) work, the odds ratio for engaging in complex secondary tasks in a parking lot is very high and has increased near-crash/crash risk.

In addition, principal arterials are used as the reference of functional class of roads, minor arterials, collectors, and local roads are all statistically significant with negative coefficients in the urban dataset. In particular, minor arterials, collector, and local roads are expected to have fewer DI-related crashes (−0.087, −0.159, and −0.194, respectively) than principal arterials in Table 6. This result is consistent with our intuition because minor arterials, collectors, and local roads have lower traffic volumes than principal arterials, which might decrease the frequency of DI-related crashes. Similar results can also be reached in Chen and Lym (2021) and Ukkusuri et al. (2012).

In terms of traffic control and management facilities, signals are significant with a positive coefficient both in rural and urban datasets, which indicates that segments with traffic signals are more likely to incur more crashes caused by DI. The positive estimated coefficients indicate that the inattention behavior of drivers may be generated in the complicated traffic environment (e.g., passing vehicles and pedestrians) with signal control presents. On the contrary, road segments with double yellow lines and no passing zones are found to incur fewer DI-related crashes in urban regions in this study. Marginal effects in Table 6 indicate that segments with double yellow lines or no-passing zones significantly decrease the frequency of DI-related crashes by 0.140. This finding reflects the significant and necessary set of double yellow lines and no passing zones on certain road segments, and these yellow traffic lines and signs may effectively improve the alertness of drivers.

The coefficient of speed limits of roadways larger than 35 miles per hour would have a lower expected crash frequency caused by DI in both rural and urban regions. This result is supported by a recent study of DI-related crashes (Wundersitz, 2019); DI-related crashes are likely to occur on roads with lower speed limits. A possible explanation for this might be that high speed limits probably make drivers more focused on the primary driving task than when they drive on roads with low speed limits. Similarly, non-freeways are found to have a significantly positive effect on the DI-related crash counts in urban regions.

More than four lanes of roadway are found to have a positive relationship with DI-related crashes in both rural and urban areas, which agrees with our expectations. Besides, urban roadways with three or four lanes are also found to have a positive relationship with DI-related crashes. This is related to risk exposure determinants such as high traffic volumes. Similar results could also be found in previous studies (Chen & Lym, 2021; Ukkusuri et al., 2012).

Interestingly, it is found that fewer DI-related crashes are expected in rural road segments with a median presence. As shown in Table 6, the average DI-related crash frequency in rural areas is significantly associated with 5.2% lower than if the road segment has a median. This indicates that medians are an effective measure for reducing the risk of crashes related to DI. One possible reason could be that medians can decrease the visual disturbance from the opposing direction of traffic, thus improving the safe driving performance of drivers. This interpretation is supported by a study that investigated the effect of the oncoming vehicles on drivers' glance behavior. Drivers' glance behavior is more sensitive to the presence of oncoming vehicles on rural roads without a median barrier (Tivesten & Dozza, 2014). Chen and Lym (2021) also confirmed the effectiveness of medians that can reduce the distraction-related crash counts.

5.3.4. Other environmental factors

With regard to terrain types, rolling terrains and mountainous terrains are highly associated with the increased DI-related crash frequency both in rural and urban roads. Undulating terrains have been found to be positively associated with head-on crash counts as well (Hosseinpour et al., 2014). A possible explanation for this result is that rolling and mountainous terrains may bring drivers with some visual obstructions in their sight distances, which is harmful to safe driving.

6. Conclusion

The prevalence of DI in vehicle crashes has received rising attention from transportation agencies and policymakers. The understanding of the influence of the built environment and roadway characteristics on the frequency of DI-related crashes remains limited. This study fills this gap by conducting an empirical assessment using official crash records in North Carolina for the period 2013–2017 as an example. The relationship between built environments and the frequency of DI-related crashes in rural and urban road segments is examined by using three types of models: Poisson/NB, HP/HNB, and RIHP/RIHNB. The comparison of these models indicates that RIHP and RIHNB models distinctly outperform other models in terms of goodness-of-fit.

The results of the binary part of RIHP and RIHNB models reveal that the presence of commercial areas increases the probability of DI-related crash occurrence in rural and urban regions. Non-freeways, multiple lanes (more than three), and rolling terrains have significant positive associations with the increase in DI-related crashes' occurrence in urban segments. The outcomes of the count part of RIHP and RIHNB models suggest that a large amount of VMT, commercial areas' presence, signals, multiple lanes (more than four), and rolling/mountainous terrains tend to have more DI-related crash counts in both rural and urban segments. However, the DI-related crash frequency is likely to be lower when the crashes occur in rural/urban state-secondary routes with speed limits higher than 35 mph. Built environment (including residential areas' presence and industrial areas' presence) and roadway characteristics (such as state routes, local streets, public vehicular areas, and non-freeways) positively contribute to increasing DI-related crash counts. However, curved/bottomed road segments and double yellow lines/no passing zones are negatively related to DI-related crash counts in urban regions. It is interesting to find that road segments with medians are expected to reduce DI-related crashes in rural regions.

Overall, the research findings provide the following policy implications for improving traffic safety of DI behavior. Firstly, a possible solution for improving roadway safety is dispatching more police enforcement or surveillance cameras in commercial areas of rural and urban regions with high DI-related crash frequency. Making traffic signs more attractive is another possible solution because disregarding signs and signals would also increase crash injury severity (Song et al., 2020; Song & Fan, 2020). Second, the removal of advertisements is suggested on roadway segments with multiple lanes (more than three), large VMT, and signals because of the negative influence of advertisements on attracting drivers' attention (Hughes & Cole, 1986; Topolšek, Areh, & Cvahte, 2016; Young et al., 2009). In addition, a driver assistance system (i.e., drivers' behavior real-time surveillance, safety voice alert, and speed modification) could be applied to vehicles when they drive on these segments with high DI crash risks. Third, improving road designs and traffic managements, such as setting medians double yellow lines/no passing zones, and variable speed limits could also effectively reduce the frequency of DI-related crashes. Lastly, regional safety education (e.g., higher-order driving instructions) toward drivers should be further enhanced in certain areas (e.g., counties with a high proportion of rolling and mountainous terrains), which has the potential to reduce inattentive driving behavior (Beanland et al., 2013; Watson-Brown, Scott-Parker, & Senserrick, 2019; Zhao & Khattak, 2017).

One should note that this study has several limitations that should be further improved in future research. It is worth noting that DI behavior tends to be underreported in police-report crash data. This study only reveals the statistical association between crash frequency and the built/roadway environment factors based on police-report crash data. Future research may consider incorporating different data sources, such as naturalistic driving data and in-depth crash data, to further validate the conclusions in this study.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Investigating the relationship between person–environment fit and safety behavior: A social cognition perspective

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ABSTRACT

Introduction: This study explored the relationship between person–job fit and safety behavior, as well as the mediating role played by psychological safety, from the perspective of social cognitive theory and person–environment fit theory. *Method:* A total of 800 employees from petroleum enterprises were recruited, with cluster random sampling used to collect data in two stages. *Results:* The results showed that employees' safety behavior is higher under the condition of "high person–job fit—high person–organization fit" than under that of "low person–job fit—low person–organization fit." In other words, the more congruent the level of person–job fit and person–organization fit for a given employee, the higher their level of safety behavior. *Practical Applications:* Psychological safety plays a mediating role between the congruence of both person–job fit and person–organization fit and employees' safety behavior.

Although occupational safety protocols have improved in recent decades (Guo & Yiu, 2015), accidents and casualties still occur from time to time in the workplace (Smith et al., 2018). Workplace safety accidents are characterized by high mortality and disability rates (Christian et al., 2009), which can have detrimental consequences for both employees and their organizations. According to the U.S. Bureau of Labor Statistics (BLS, 2017), 5,190 fatal workplace safety accidents were reported in the United States in 2016 alone. Although most safety accidents were caused by the interaction of multiple factors, individual behavior often plays a significant role. According to a workplace survey, over 70% of safety accidents were caused by individual mistakes or unsafe behavior, resulting in tens of billions of economic losses every year (Christian et al., 2009). Accordingly, improving employees' understanding of safety protocols and reducing their risky behavior in the workplace is an urgent issue for many enterprise managers.

According to Lewin's field theory (Lewin, 1951), the life space includes the individual and his or her psychological environment. A person's behavior (B) depends on the interaction between the person (P) and his or her environment (E), that is, behavior depends on the individual's life space (B = f(P, E)). The idea of person––environment fit (P–E fit) has always been regarded as an important factor to explain and study employees' behavior and performance within organizations (Kristof-Brown, Zimmerman, & Johnson, 2005; Lv & Xu, 2018). It embodies the idea of "the interaction between individuals and the environment." According to the theory of P–E fit (Kristof-Brown et al., 2005), working behavior and employees' working attitudes are influenced by the degree of consistency between employees' internal characteristics and the characteristics of their organizations. In other words, when the support of the environment is consistent with employees' needs, their motivation and engagement at work can be stimulated (Lv & Xu, 2018). P–E fit also has a positive impact on employees' innovation behavior (Afsar, Badir, & Khan, 2015), voice behavior (Cheng et al., 2013), organizational citizenship behavior (Cheng et al., 2013) and other desirable behaviors. Thus, P–E fit is consistently recognized as an important factor in improving employees' behavior (e.g., safety behavior) and organizational performance (e.g., safety performance; Edwards, 2008).

Research has shown that the key dimensions at play in P–E fit include job, organization, occupation, group, and person (Kristof-Brown et al., 2005). Person–job fit (P–J fit) emphasizes the consistency between individual characteristics (e.g., knowledge, personality traits), personal expectations and job requirements, reflecting the complementary fit between individuals and job requirements at the micro-level. Person–organization fit (P–O fit) indicates whether individuals and organizations have similar characteristics or complementary needs, reflecting a similarity fit at the

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macro-level (Kristof-Brown et al., 2005). Existing literature on the relationship between P–E fit and safety behavior is still relatively lacking. However, relevant studies have shown that both P–J fit and P–O fit impact employees' behavior and attitudes. For example, a study by Afsar et al. (2015) demonstrated that high levels of P–J fit and P–O fit promote innovative behavior among employees. Accordingly, we hypothesize that P–J fit and P–O fit will have the same effect on safety behavior. P–J fit and P–O fit have, however, different mechanisms. Lauver and Kristofbrown (2001) compared the effects of these two fit types on job satisfaction, job performance, turnover intention, and peripheral performance, and found that P–O fit better predicted job performance, turnover tendency and peripheral performance, but did not predict job satisfaction better than P–J fit. In short, although the relationship between the two types of fit is close, and both are related to employees' work behavior, they are different in concept, measurement, scope of application, and mechanism. Edwards (2008) posits that although there are differences in the effects of P–J fit and P–O fit on employees' behavior and attitudes, there are situations in which they work together. In light of this, the present study takes P–J fit and P–O fit as two subordinate concepts of P–E fit to explore the effects of the (in)congruence of the two P–E fit types on safety behavior.

According to social cognitive theory, behavior is influenced by the interaction of individual factors and environmental factors, with cognitive factors representing an important part of personal traits. Existing research has tended to focus on external factors such as organizational support or other work-related factors (Warr & Inceoglu, 2012) when exploring the mediating mechanisms of P–E fit on employees' behavior, while paying less attention to individuals' subjective cognitive factors. Relevant studies have shown that employees' work behavior is affected by their subjective cognitive feelings (Egan, Zigarmi, & Richardson, 2019), and these subjective cognitive feelings are also influenced by the fit between individuals and their environment (Cheng et al., 2013). Psychological safety, for example, is an individual's belief and perception of safety in the face of a risky environment (Edmondson, 1999). When individuals perceive that their safety is guaranteed, they may interact more with the environment or with others, and perform behaviors with high aspirations that might be outside of their roles (Men et al., 2020), which are consistent with the requirements of safety behavior. The present study explores the mediating role of psychological safety in the relationship between P–E fit and safety behavior.

In summary, the present study uses social cognitive theory and P–E fit theory (Kristof-Brown et al., 2005) to explore the mechanism by which P–J fit and P–O fit affects employees' safety. Specifically, this study positions P–J fit and P–O fit into a P–E fit congruent condition (four kinds of fit conditions are shown in Table 1), used to explore the effect of the congruence between P–J fit and P–O fit on employees' safety behavior. First, we examine the impact of congruence (high and low) on safety behavior where the two types of P–E fit are congruent. Second, we examine which one ("high P–J fit, low P–O fit" or "low P–J fit, high P–O fit") affects safety behavior when they are not congruent. Finally, the study examines psychological safety as a potential mediating variable underlying the mechanism by which P–E fit affects employees' safety behavior.

Table 1
P–E Fit conditions.

P–E fit		P–J fit	
		low	high
P–O fit	low	congruent	incongruent
	high	incongruent	congruent

1. Literature review and hypothesis

1.1. P–E fit and safety behavior

Safety behavior refers to behavior that employees perform to comply with safety regulations and achieve an organization's safety objectives (Griffin & Neal, 2000). The generation of personal safety behavior is not only related to an individual's characteristics but also closely related to their environment. If the environment is consistent with individuals' behavior, it will often promote generation of that behavior. In general, the consistency or compatibility between individuals and their environment is defined as P–E fit. P–E fit theory posits that people are born to adapt to the environment, and strive to find the environment that conforms to their characteristics (Kristof-Brown et al., 2005).

In essence, P–E fit theory holds that there are potential similarities between organizational characteristics and personal characteristics, and that individuals' attitudes and behavior are affected by the similarity or degree of fitting between themselves and their organizations (Edwards, 2008). According to social cognitive theory (Lewin, 1951) and fit theory (Kristof-Brown et al., 2005), individual behavior is affected by the environment. When there is a good fit between employees and their organization, employees experience certain emotional tendencies and attitudes towards it which naturally affect their behavior. As shown by previous studies, P–O fit has a significant impact on important work attitudes such as job satisfaction (Rauvola et al., 2020), organizational commitment (Kooij & Boon, 2018), and turnover intention (Abdalla et al., 2018). If employees realize that there is a good fit between themselves and their workplace, meaning that the organization is able to meet their needs, desires, and preferences (Kristof-Brown et al., 2005), they will produce good results (e.g., trust, creativity, job involvement, job commitment, and job satisfaction). These results can be converted into a sense of belonging, or psychological contract, which in turn will encourage employees to engage in behaviors that are beneficial to their organizations. Previous studies have shown that the higher the P–O fit, the more positive the work outcomes, such as higher job involvement (Lv & Xu, 2018), higher organizational commitment (Kooij & Boon, 2018), better work attitude (Mehlika et al., 2018), and lower turnover intention (Abdalla et al., 2018). Meanwhile, research has shown that higher P–O fit can increase employees' intrinsic motivation and job involvement, thus enhancing their organizational citizenship behavior (Kim & Gatling, 2019). As mentioned above, safety behavior is similar to organizational citizenship behavior, except with a particular focus on safety (Griffin & Neal, 2000; Smith et al., 2018). Thus, we hypothesize that P–O fit has a similar effect on safety behavior as on organizational citizenship behavior.

When employees' values, goals, personality, attitudes, knowledge, skills, and abilities are fitted with factors related to an organization's culture, climate, values, goals, norms, organizational resources, and tasks, the degree of P–O fit is relatively high (Griffin & Neal, 2000; Smith et al., 2018). If the degree of fit between employees and organizations that emphasize safety is high, meaning that they have consistency on safety issues, the safety values and targets of the organization will have a positive impact on employees' safety behavior. Such consistency is conducive to promoting the exchange of safety information between employees and their organizations, increasing the likelihood of employees complying with safety rules and regulations, enhancing the internal safety motivation of employees (Panuwatwanich et al., 2017), and reducing the possibility of being misunderstood by leaders and colleagues, as well as reducing inner uncertainty when performing out-of-role behavior such as making safety-related suggestions. All of these will lead to greater participation in safety-related activities. Accordingly, this study advances the following hypothesis:

H1: P–O fit is significantly positively correlated with safety behavior.

P–O fit explains the fit between employees and the environment at the macro level, whereas P–J fit explains the fit between employees and the environment at the micro level (i.e., in terms of fitting an individual's skills, knowledge, and abilities to the particular characteristics of a job) (Edwards, 2008). The micro-working environment in which individuals work and perform their duties plays a crucial role in predicting work behavior. In the micro-working environment, position has a stronger impact on employees than the organization, and the fit between positions and employees can be directly perceived by employees. Their suitability to the work environment and work assignments can be compared against their values, knowledge, skills, and needs (Cable & Judge, 1997; Arieli, Sagiv, & Roccas, 2020). Research has shown that employees' work behavior and attitudes are directly affected by the fit between personal interests and their attitudes towards work assignments and the work environment (De Beer et al., 2016). When P–J fit is high, it means that job characteristics, organization demands, and resource availability are matched with employees' ability and internal demands. This leads employees to be satisfied with their positions and naturally comply with the company's rules and regulations regarding job safety. If the company's protocols emphasize the importance of safety, employees will perform more safety behavior. However, it also means that employees' knowledge, skills, and abilities meet the job needs, and they can respond more appropriately to the external environment (Kristof-Brown et al., 2005; Kim & Gatling, 2019). When employees are satisfied with their jobs, they are likely to perform more out-of-role safety behavior, such as proposing new ideas for safety management. Accordingly, we advance the following hypothesis:

H2: P–J fit is significantly positively correlated with employees' safety behavior;

As mentioned above, P–O fit and P–J fit belong to the macro and micro levels of P–E fit, respectively, with both of them having a certain impact on employees' attitudes and behavior. Some studies have found situations where they work together (Cai et al., 2018). The question thus arises as to whether a joint effect between them affects employees' safety behavior, and whether there might be a situation in which the two types of fit are incongruent as regards this joint effect. In other words, given the four different fit permutations, which is more important to safety behavior? As mentioned previously, the micro-environment is more likely to affect employees' perceptions of fit. Therefore, the following hypotheses are proposed in this study from the perspective of P–E fit:

H3: Employees' safety behavior is higher under the congruence condition of "high person–job fit—high person–organization fit" than it is under that of "low P–J fit—low P–O fit."

H4: Employees' safety behavior is higher under the congruence condition of "high P–J fit—low P–O fit" than it is under that of "low P–J fit—high P–O fit."

H5: The more congruent P–J fit and P–O fit are, the higher employees' safety behavior will be.

1.2. Mediating role of psychological safety

Psychological safety is a necessary condition for people to feel supported and engaged in their work, thereby enabling them to fully display their talents without worrying about a negative impact on their image, status, or career (Kahn, 1990). This study follows Kahn's (1990) definition of psychological safety as a positive individual psychological trait that refers to the perception of one's own safety when a member of an organization contributes beneficial actions or suggestions. According to social cognitive theory (Lewin, 1951), the behavior of individuals is affected by their cognitive factors. Psychological safety is the perception of interpersonal risk. Before reaching a decision to act, individuals in the workplace will first deliberate on the potential responses of leaders and team members to their behavior (Cai et al., 2018). When individuals perceive that their behavior may invite negative reactions from others, they may choose not to engage in that behavior. However, when individuals believe that their safety is guaranteed, and they have a sense of psychological safety, they may interact more with the environment or others (Singh, Winkel, & Selvarajan, 2013; Hu, Zhu, et al., 2018), engaging in high-aspiration or extra-role behavior (Cheng et al., 2013), both of which are consistent with the requirements of safety behavior. When employees' psychological safety is high, and their enterprise emphasizes safety, they will abide by the appropriate safety rules and regulations. Furthermore, if individuals have a high level of psychological safety, supervisors and colleagues will encourage and support employees in taking risky, extra-role behavior, which motivates them to contribute further safety advice.

From a fitting perspective, ensuring a fit of values enables individuals in a group to hold similar beliefs and norms, which in turn promotes the loyalty of team members and trust in each other (Arieli et al., 2020). In other words, employees are more likely to experience friendliness and trust from managers and colleagues when their values and needs are fitted to that of the organization. In such trusting relationships, individuals perceive their work environment as a safe environment where they can express their true selves and promote their own psychological safety (Kahn, 1990; Men et al., 2020). In contrast, individuals with incompatible values, or those experiencing a mismatch between supply and demand in the group, may experience psychological pressure, negative emotions, and broken interpersonal relationships, thus reducing their psychological safety (Men et al., 2020). Previous studies have shown that P–E fit is positively correlated with the quality of the working relationship (Liang et al., 2012). High-quality relationships can increase trust and reduce fear and embarrassment among people (Tepper et al., 2018). Meanwhile, research conducted by Jiang et al. (2019) found that when individuals have confidence in their team, they have reduced fears about the possible negative consequences of their actions, thus increasing their psychological safety. Given that P–E fit has a positive effect on individual psychological safety, we propose the following hypothesis:

H6: Psychological safety plays a mediating role between the congruence of person–job fit and person–organization fit and employee' safety behavior.

2. Measures

2.1. Procedure and participants

The current study investigating employees' safety behavior was conducted with the employees of a large national oil enterprise. We collected data in two stages. With the help of the human resources department, we used a whole group random sampling method to select 800 participants out of 1309 employees at the organization for a questionnaire survey. All participants took part in our study voluntarily and signed an informed consent form at the beginning of the process. Additionally, all procedures conformed to the ethical standards of the research committee of

Shandong Normal University and the 1964 Helsinki Declaration, and other similar ethical standards.

The questionnaire presented at stage 1 included demographic information (number, name of sub-unit, gender, age, marital status, education level, position, working years, etc.), as well as the person–job fit scale, person–organization fit scale and psychological safety scale. Twenty days later, the questionnaires at stage 2 were collected, which included demographic information and the safety behavior scale.

At stage 1, we distributed 800 questionnaires; 737 were returned, comprising 698 valid questionnaires. At stage 2, we distributed 698 questionnaires and all were returned (including blank questionnaires that were not filled out), comprising 636 valid questionnaires. This resulted in a total response rate of 79.5%. Fifty-three percent of the employees were males; 36.6% had a junior college degree, and 34.0% had an undergraduate degree; 95.9% were married. Sample respondents were on average 39.58 years old (*SD* = 6.38), and had worked at the company for an average of 17.78 years (*SD* = 8.51). Front-line employees (construction staff, business organizers, etc.) accounted for 75.4%.

To explore whether the respondents who participated in stage 1 and stage 2 (group 1) and those who only participated in stage 1 (group 2) were homogeneous, we conducted nine independent sample *t*-tests to compare the differences between the two groups. The results showed that the two groups were generally homogeneous.

2.2. Measures

2.2.1. Person–job fit

Some researchers have asserted that the measurement of person–job fit should be measured locally: the working environment should be divided into different aspects so as to enable comparison of the consistency between different aspects of the working environment and individuals' requirements of that environment (e.g., Ironson, Smith, Brannick, Gibson, & Paul, 1989). This kind of measurement, however, could lead to omission and bias due to variation of environments between different employees, thus failing to accurately reflect the generalized phenomenon. An alternative global form of measurement allows employees to evaluate how well they fit with the overall working environment based on how they feel about it (Cable & Judge, 1997). Existing studies have shown that this global measurement provides a better prediction of person–job fit (Lauver & Kristofbrown, 2001).

In light of this, person–job fit was measured by global measurement using the 4-item questionnaire developed by Singh and Greenhaus (2004), and revised by Weng (2010). Employees rated these items on a 5-point Likert scale ranging from 1 (completely disagree) to 5 (completely agree). The higher the score, the higher the degree of person–job fit. One sample item was "The requirements of my new job match my experience, specific talents and skills." The Cronbach's alpha for this scale in the study was 0.88.

2.2.2. Person–organization fit

Person–organization fit was measured using the 7-item questionnaire developed by Cable and Judge (1997), and revised by Huang and Cao (2008). Items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating a higher degree of person–organization fit. One sample item was "I think my personality traits match the company's image traits well." The Cronbach's alpha for this scale in the study was 0.91.

2.2.3. Psychological safety

Psychological safety was assessed using a three-item scale adapted by He (2010) from the instrument developed by Edmondson (1999). The second and third items were reverse-coded. Employees rated items on a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree), with higher scales indicating a higher level of psychological safety. One sample item was "Working with members of this team, my unique skills and talents are valued and utilized." The Cronbach's alpha for this scale in the study was 0.78.

2.2.4. Safety behavior scale

Safety behavior was assessed using an 11-item questionnaire developed by Neal and Griffin (2006), and revised by Ye et al. (2014). Employees rated items on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), with higher scales indicating a higher level of safety behavior. One sample item was "I strictly abide by the safety rules and regulations in my work." The Cronbach's alpha for this scale in the study was 0.96.

2.3. Analysis and design

Polynomial regression was used in the current study to test the hypotheses. This included linear terms (e.g., X and Y), n-degree polynomial terms (e.g., X^2 and Y^2), and interaction terms (e.g., $X \times Y$) that could test not only the linear effects of variables, but also the non-linear relationships (e.g., quadratic, cubic nonlinearities). According to Edwards and Cable (2009), applying difference scores may cause spurious correlations, as well as low reliability and validity. Hence, we tested the consistency in fit by using quadratic polynomial regression and response surface methodology. The steps were as follows:

First, following the method of Edwards and Parry (1993), we established the regression equation: $Z = b_0 + b_1X + b_2Y + b_3X^2 + b_4X \times Y + b_5Y^2 + e$, where Z represents safety behavior; X and Y respectively represent person–job fit and person–organization fit; e is a random disturbance term; b_0 is the constant term, and b_1 to b_5 are the regression coefficients of each item respectively.

Second, the independent variables were standardized or centralized to construct the product term ($X \times Y$) and quadratic term (X^2 and Y^2) of the regression equation.

Next, we calculated the coefficients of regression equation (b_1 to b_5), the slope ($a1 = b_1 + b_2$) and curvature ($a2 = b_3 + b_4 + b_5$) of the congruence line ($X = Y$), and the slope ($a3 = b_1 - b_2$) and curvature ($a4 = b_3 - b_4 + b_5$) of the incongruence line ($Y = -X$).

If the slope of the congruence line is significant and the coefficients are positive, it indicates that safety behavior is higher in the case of "high P–J fit—high P–O fit" than for "low P–J fit—low P–O fit." In contrast, if the slope of the incongruence line is significant and the coefficients are positive, it indicates that safety behavior is higher in the case of "high P–J fit and low P–O fit" than for "low P–J fit—high P–O fit." Moreover, if the curvature of the congruence line is significantly positive and the curvature of the incongruence line is significantly negative, it indicates that the higher the degree of person–job fit and person–organization fit, the higher the level of employee's safety behavior.

Finally, as regards mediation, we explored the relationship between psychological safety on person–environment fit and safety behavior. The independent variable was conceptualized as the interaction between person–job fit and person–organization fit. It would be inappropriate to directly analyze the moderating effects of the two variables separately. Instead, a block variable should be constructed to represent person–environment fit. Following the standard recommended by Edwards and Cable (2009), we multiplied the regression coefficients of the equation with the original values of the corresponding variables (i.e., X, Y, X^2, $X \times Y$, and Y^2) and then added them to obtain the block variable and evaluate the hypotheses via path analysis.

3. Results

3.1. Validity of measures

To obtain discriminant validity, we used Mplus 8.0 to conduct a confirmatory factor analysis (CFA) on the self-reported questionnaires of person–job fit, person–organization fit, psychological safety, and safety behavior. We compared the hypothesized four-factor model, three-factor model, and two-factor model. The results of a Chi-square difference test indicated that the four-factor model displayed a better model fit ($\chi^2/df = 4.46$, RMSEA = 0.07, CFI = 0.93, TLI = 0.92, SRMR = 0.04) than the alternative models (see Table 2). All results showed that the other three models provided a worse fit than the four-factor model, suggesting that our measures had desirable discriminant validity. Based on Podsakoff, MacKenzie, Lee, and Podsakoff's (2003) standard, the one-factor model displayed the worst fit, indicating that there was no serious problem with common method biases.

3.2. Descriptive statistics

Table 3 displays the means, standard deviations, and intercorrelations of the four main variables and demographic variables, from which we observed that person–job fit and person–organization fit are positively correlated with safety behavior ($r = 0.26$, $p < 0.01$; $r = 0.14$, $p < 0.01$), and psychological safety also correlates positively with safety behavior ($r = 0.33$, $p < 0.01$). This analysis thus supports hypothesis 1 and hypothesis 2.

3.3. Hypothesis testing

Polynomial regression was used to test hypotheses 3 to 5, combined with response surface methodology to analyze the curvatures and slopes. Before the polynomial regression analysis, the pairing condition of the samples was tested (Shanock et al., 2010); that is, the consistent and inconsistent proportions of P–O and P–J were counted. If the proportions are greater than the threshold value of 10%, it indicates that further analysis is necessary; if less, it indicates that polynomial regression is not required. Since person–job fit and person–organization fit belong to two different scales, it is not possible to compare them directly. Therefore, z-score conversion was carried out for the scores of the two scales, and then the degrees of consistency of the z-scores were compared. The specific results are shown in Table 4.

As shown in Table 4, the consistent sample proportion of person–job fit and person–organization fit is 59.43%; samples involving a higher person–job fit than person–organization fit account for 24.37% of the total, while samples involving a higher person–organization fit than person–job fit account for 16.19%. The data threshold of this study is greater than the threshold standard provided by Shanock et al. (2010). Therefore, further polynomial regression analysis can be conducted, with the results shown in Table 5.

In model 1, the direct impact of person–job fit on safety behavior is not significant ($b_1 = 0.41$, *n.s.*), but person–organization fit significantly predicts safety behavior ($b_2 = 0.12$, $p < 0.05$). At the same time, compared with model 1, in model 2, person–job fit has a significant direct impact on safety behavior ($b_1 = 0.09$, $p < 0.1$), as does person–organization fit ($b_2 = 0.12$, $p < 0.01$). However, the square of person–job fit has no significant direct impact on safety behavior ($b_1 = -0.08$, *n.s.*). The interaction of person–job fit and person–organization fit has a significant predictive effect on safety behavior ($b_4 = 0.33$, $p < 0.05$), as does the square of person–organization fit ($b_5 = -0.14$, $p < 0.1$). Additionally, compared with model 1, which includes only linear terms, the second-order polynomial terms explain significant incremental variance in safety behavior ($\Delta R^2 = 0.03$, $p < 0.001$), indicating that response surface analysis can be conducted in the next step (Edwards & Parry, 1993). Following up on these results, we used Origin Pro 2018 software to plot a three-dimensional response surface graph in order to more intuitively present the relationships between person–job fit, person–organization fit, and safety behavior. This surface is shown in Fig. 1.

From Table 5 and Fig. 1 we can see that the response surface is roughly concave. Under the condition of the consistency of person–job fit and person–organization fit, the slope of the surface along the congruence line is significantly positive ($a1 = 0.21$, $p < 0.001$). This means that the level of safety behavior is higher in the condition of "high P–J fit and high P–O fit" than in the condition of "low P–J fit and low P–O fit," thus supporting Hypothesis 3. When there is incongruence between person–job fit and person–organization fit, the slope of the surface along the incongruence line is not significant ($a3 = -0.03$, *n.s.*), indicating that there is no difference in the level of safety behavior between "high P–J fit and low P–O fit" and "low P–J fit and high P–O fit," a finding that opposes our Hypothesis 4. Moreover, the curvatures of the congruence line and incongruence line are significantly positive and negative, respectively ($a2 = 0.12$, $p < 0.05$; $a4 = -0.55$, $p < 0.001$), demonstrating that the more consistent person–job fit and person–organization fit, the higher the level of employee's safety behavior. This finding thus supports Hypothesis 5.

To explore why Hypothesis 4 was not supported, we used the results of the response surface analysis and plotted a two-dimensional graph depicting inconsistencies between person–job fit and person–organization fit, as shown in Fig. 2. From this figure it can be seen that when the score of either person–job fit or person–organization is low, the corresponding level of safety behavior is not high. As long as both parties maintain a high level, the level of employees' safety behavior will be high. These results correspond precisely with Hypothesis 5.

Note: Z-score is used for conversion, with 0 representing the average score of person–job fit and person–organization fit. A score of 2 means that the score is 2 standard deviations above the mean; a score of −2 represents two standard deviations below the mean.

For Hypothesis 6, we used SPSS's PROCESS macro to test the mediating effect of psychological safety. Following previous findings related to safety behavior (Christian et al., 2009), we con-

Table 2
Models ft results for confirmatory factor analyses ($N = 636$).

Models	χ^2	*df*	$\Delta\chi^2$	RMSEA	CFI	TLI	SRMR
four-factor model a	1172.72	263	–	0.07	0.93	0.92	0.04
three-factor model b	2290.68	272	1117.96***	0.11	0.85	0.83	0.05
two-factor model c	2972.99	274	1800.27***	0.12	0.80	0.78	0.08
one-factor model d	6789.50	275	5616.78***	0.19	0.51	0.46	0.23

Note: a: hypothesized model; b: pooling person–job fit and person–organization fit into a single factor; c: pooling person–job fit, person–organization fit, and psychological safety into a single factor; d: pooling all four factors into a single factor.
*** $p < 0.001$, two-tailed test.

Table 3
Descriptive statistics and intercorrelations among study variables.

Variable	Mean	*SD*	1	2	3	4	5	6	7	8	9	10
1. Gender	–	–	1									
2. Age	39.58	6.38	0.03	1								
3. Education	–	–	0.01	−0.46**	1							
4. Marital status	–	–	−0.01	−0.07	0.06	1						
5. Position	–	–	−0.05	−0.07	−0.24**	0.01	1					
6. Working years	17.78	8.51	0.08	0.88**	−0.52**	−0.05	−0.06	1				
7. Safety behavior	6.28	0.86	0.12*	0.09	−0.06	0.01	−0.02	0.18**	(0.96)			
8. Person–organization fit	3.73	0.67	0.11*	−0.01	0.07	0.01	−0.02	−0.02	0.14**	(0.91)		
9. Person–job fit	3.64	0.70	0.07	−0.02	−0.01	−0.08	0.01	−0.02	0.26**	0.52**	(0.88)	
10. Psychological safety	4.72	0.78	0.15**	0.06	0.03	0.04	−0.09	0.05	0.33**	0.52**	0.47**	(0.78)

Note. $N = 636$; gender coded as (1 = male, 2 = female); education coded as (1 = junior high and below, 2 = high school or technical school, 3 = junior college, 4 = undergraduate, 5 = master or above); marital status coded as (1 = married, 2 = unmarried, 3 = others [divorce, etc.]); position coded as (1 = senior management, 2 = middle management, 3 = first-line management, 4 = first-line employees, 5 = others [labor dispatch, etc.]).
* $p < 0.05$.
** $p < 0.01$.

Table 4
Frequency table of the congruence between person–job fit and person–organization fit.

Categories	P–J < −1	−1 ≤ P–J < 0	0 ≤ P–J < 1	1 ≤ P–J	Proportion%
P–O < −1	54(8.49%)	21	7	1	13.05
−1 ≤ P–O < 0	26	92(14.47%)	94	4	33.96
0 ≤ P–O < 1	8	31	175(27.52%)	28	38.05
1 ≤ P–O	0	3	35	57(8.96%)	14.94
Proportion%	13.84	23.11	48.90	14.15	100%

Note: $N = 636$; P–J means person–job fit; P–O means person–organization fit. This classification is based on the *Z*-score of each case across the two variables. The diagonal presents the number and proportion (59.43% in total) with the same P–J and P–O scores.

Table 5
Polynomial regression results for safety behavior.

Variables	Safety behavior	
	Model 1	Model 2
Intercept (b_0)	6.34***	6.34***
P–J fit (b_1)	0.41	0.09+
P–O fit (b_2)	0.12*	0.12*
The square of P–J fit (b_3)		−0.08
P–J fit × P–O fit (b_4)		0.33**
The square of P–O fit (b_5)		−0.14+
R^2	0.04***	0.07***
ΔR^2		0.03***
Congruence line		
Slope (*a*1)		0.21***
Curvature (*a*2)		0.12*
Incongruence line		
Slope (*a*3)		−0.03
Curvature (*a*4)		−0.55***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$, two-tailed test.

P- J fit: person–job fit.

P–O fit: person–organization fit.

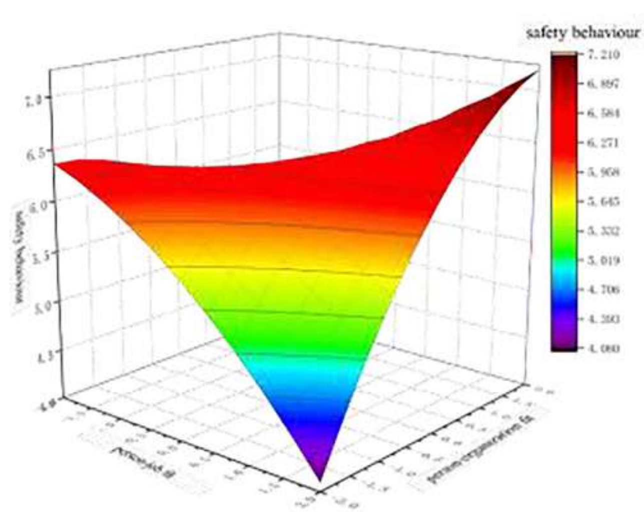

Fig. 1. Congruence of person–job fit and person–organization fit on safety behavior.

trolled for two variables related to safety behaviors: gender ($r = 0.12$, $p < 0.05$) and working lifetime ($r = 0.18$, $p < 0.01$). We used 5,000 bootstrap samples to examine all paths of mediation, with specific results shown in Table 6. The results show that block variable (i.e., person–environment fit) plays a significant and positive role in psychological safety ($\beta = 0.92$, $p < 0.001$, 95% CI = [0.65, 1.20]). In addition, when person–environment fit and psychological safety were both added to the regression equation, psychological safety emerged as having a significant positive influence on safety behavior ($\beta = 0.25$, $p < 0.001$, 95% CI = [0.18, 0.32]). Furthermore, person–environment fit still had a significant and positive impact on safety behavior ($\beta = 0.61$, $p < 0.001$, 95% CI = [0.35, 0.88]), indicating that psychological safety played a partial mediating role in the relationship between person–environment fit and safety behavior. Finally, the mediation effect size value of the person–environment fit on safety behavior through psychological safety was 0.23 (95% CI = [−0.322, −0.013]), which accounted for 27.47% of the total effect.

4. Discussion

This study has empirically examined the potential impact of two fit types, namely person–job fit and person–organization fit, on safety behavior. The results have shown that both person–job fit and person–organization fit are significantly and positively related to employees' psychological safety and safety behavior. In addition, we found that when person–job fit and person–organiza-

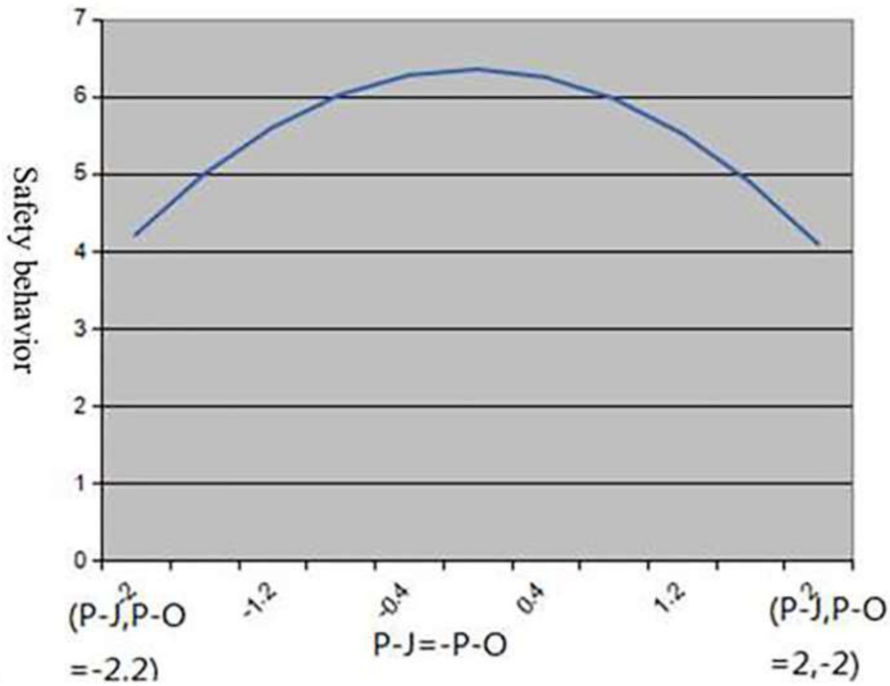

Fig. 2. Incongruence of person–job fit and person–organization fit on safety behavior.

Table 6
Results of mediating effect analysis.

Variables	Model 1 psychological safety			Model 2 safety behavior		
	β	SE	95% CI	β	SE	95% CI
Gender	0.21**	0.07	[0.08,0.34]	0.05	0.06	[−0.07,0.18]
Working years	0.01	0.01	[0.00,0.01]	0.01***	0.00	[0.01,0.02]
person–environment fit	0.92***	0.14	[0.65,1.20]	0.61***	0.14	[0.35,0.88]
psychological safety				0.25***	0.04	[0.18,0.32]
R^2	0.08			0.15		

Note: 95% CI means 95% confidence interval. *** $p < 0.001$, ** $p < 0.01$, two-tailed test.

tion fit are consistent, employees show more safety behavior in the case of "high P–J fit — high P–O fit" than in the case of "low P–J fit — low P–O fit." The greater the degree of matching between the two, the higher the safety behavior of employees. Moreover, when the two fit types are not congruent, no significant difference is found for the impact of "low person–job fit and high person–organization fit" or "high person–job fit and low person–organization fit" on safety behavior.

4.1. Theoretical implications

According to social cognitive theory (Lewin, 1951), an individual's behavior is influenced by the environment and arises as a result of the interaction between an individual's internal characteristics and their environment. Safety behavior, such as complying with safety rules and regulations or making safety recommendations, is a matter of individual choice, a process whose intrinsic mechanism is often influenced by the environment (Christian et al., 2009). Our study, which is the first to examine the relationship between person–environment fit and employees' safety behavior, has shown that both person–job fit and person–organization fit are positively related to employees' safety behavior. If employees perceive that they fit their organizational environment well, they naturally develop a sense of belonging or dependence on the organization. This belonging may be transformed into organizational commitment or a psychological contract, resulting in the generation of behaviors that are permitted and supported by the organization (e.g., safety behavior; Kim & Gatling, 2019). If the organization advocates safety behavior, employees will be prepared to obey the associated arrangements, abide by the organization's safety rules and regulations, and engage in extra-role behaviors that benefit the safety procedures, such as actively participating in making safety-related suggestions (Pei, Sparrow, & Cooper, 2016). Person–job fit provides another important perspective in explaining employees' safety behavior. If employees believe that they are very compatible with the position they hold, they will tend to have a strong sense of satisfaction and be full of enthusiasm for work, giving full play to their work abilities, completing their work to a higher standard, and performing more safety behaviors (Tims, Derks, & Bakker, 2016). The current study has contributed to a further understanding of the antecedent variables of employees' safety behavior, while at the same time helping to extend the research on person–environment fit and safety behavior.

Looking back on previous related studies, researchers have mostly focused on the influence of one particular aspect of person–environment fit on employee behavior, such as person–job fit, person–organization fit, or other types of fit, but rarely has the role of both person–job fit and person–organization fit been considered together. Even studies that have integrated multiple types of fit have only examined their linear relationship, ignoring any joint effect (Cai et al., 2018). This has resulted in an incomplete understanding of the relationship and internal mechanism connecting person–environment fit and safety behavior. Our findings have demonstrated that although person–job fit alone does not necessarily have a significant direct effect on safety behavior, it can indeed affect safety behavior through comparison and interaction with person–organization fit. Person–job fit reflects how employees evaluate their own competencies and needs next to those required for the position, whereas person–organization fit reflects how employees evaluate their own values and goals next to those of the organization (Kristof-Brown et al., 2005). Previous research has confirmed that the closer the psychological distance between environment and individual, the greater the impact of the environment on the individual. For example, Huang et al. (2017) found that supervisors have a greater influence on employees' safety behaviors than seniors. Some researchers, however, have argued that organizational culture and organizational climate are guiding norms that can have a more profound impact on employees. Christian et al. (2009), for example, confirmed that organizational environment plays a greater role in employees' safety behavior. The results of our study thus provide an explanation for the divergence between the two perspectives, namely, that P–O fit and P–J fit are linked and need to be combined in order to explore their common influence. People seek verification of their own abilities and needs (i.e., person–job fit) and hope to maximize consistency in all aspects of the self, such as attitudes, beliefs, and behaviors (Kim & Gatling, 2019). In addition, individuals strive to obtain certainty and predictability. When their own beliefs, attitudes, and behaviors align with those of others in the social environment (i.e., person–organization fit), individuals will realize that they share common characteristics and achieve a sense of belonging (i.e., fit; Arieli et al., 2020). When the two types of fit work together, employees are able to exert control over their own lives, reduce uncertainty, achieve a sense of belonging, and lead happy and fulfilling lives (Afsar et al., 2015), thereby promoting greater safety behavior. This study used polynomial regression to simultaneously examine the linear relationship, curvilinear relationship, and interaction between the two types of fit. Combined with response surface analysis, this permitted an in-depth analysis of the mechanism by which person–job fit and person–organization fit influence safety behavior. As well as revealing a joint influence of person–job fit and person–organization fit on safety behavior, the results have contributed to a deeper understanding of the relationship between the congruence of person–environment fit types and safety behavior.

Finally, this study has explored the mediating effect of employees' psychological safety on the relationship between person–environment fit consistency and employees' safety behavior. In previous related studies, researchers focused on organizational support or other work-related factors (Warr & Inceoglu, 2012), yet overlooked the role of individual cognition, an important individual characteristic. According to social cognitive theory, individual characteristics and the social environment are important factors that interact to influence individual behavior. The previous lack of exploration of individual cognition has therefore counted against the development of a deeper understanding of how person–environment fit relates to safety behavior. Supportive organizational measures (e.g., person–environment fit) enhance employees' perceptions of psychological safety, thereby increasing their organizational commitment and performance. For example, research has found that employees' perceptions of organizational support (Singh et al., 2013) can enhance their psychological safety. Person–environment fit reflects the support of an organization for its employees. When a team's organizational characteristics match those of its employees, psychological safety is enhanced. This cognitive state is necessary for learning and change, on which many behavioral outcomes depend, such as learning behavior, shared behavior, organizational citizenship behavior, and creativity. Several studies have shown that psychological safety has a direct impact on task performance (Schaubroeck et al., 2011). It also reduces the potential negative factors of making mistakes, thus enabling employees to focus on tasks that enhance performance (Faraj & Yan, 2009). In addition, psychological safety creates an environment that encourages risk-taking behaviors among people. Employees are more likely to feel that it is safe to voice opinions, make suggestions, and challenge current ways of doing things (Walumbwa & Schaubroeck, 2009). In the context of rapid economic and social changes in China today, employees' perceptions of their job security (e.g., psychological safety) are having a strong influence on their psychology and behavior (Morrow et al., 2010). Integrating environmental factors with individual cognitive factors thus offers a novel and potentially informative direction for future safety behavior research.

4.2. Management recommendations

Based on the results of our study, we propose the following recommendations for improving safety behavior in the workplace. First, organizations and managers need to improve the degree of fit between employees and their workplace. Person–organization fit is primarily a fit of values. Therefore, organizations should regard the fit of values between employees and the workplace as an important screening criterion in the recruitment process. In addition, when considering the appointment and promotion of staff to important positions, companies should choose managers with a high degree of organization fit in order to maximize the impact of such leaders on their subordinates (Hu, Wu et al., 2018). Companies can also enhance employees' participation in decision-making, thus fostering a sense of belonging and commitment, which ultimately serves to enhance the level of fit between them and their organization.

Second, when the congruence of the person–environment fit types is high, it can lead to improvements in employees' safety behavior. Companies can use psychological measurement methods to develop effective tools for evaluating person–job fit during the process of selection and placement, so as to ensure that employees are well adapted to their positions. Furthermore, organizations should guide their employees' interests and strengths and help them to develop detailed career plans. Such measures can ensure that employees have a clear understanding of themselves and experience a high level of person–job fit. Through job rotation, job enrichment, job redesign, and other approaches, companies can help employees to develop deeper interest and understanding of their positions, thereby enhancing their level of fit with the job.

Finally, enterprises and managers should pay more attention to employees' psychological feelings. When employees are in a positive corporate atmosphere, they experience a higher level of psychological safety. Once they have a sense of security and responsibility for the company, they are more likely to identify with the organization's values and rules, and exhibit behavior conducive to the development of the enterprise. Leaders should be expected to care about others and establish a safe working environment through active communication with employees (Liu, Liao, & Wei, 2015), thus enabling them to feel safe at work and demonstrate the behaviors expected by the organization.

4.3. Limitations and directions for future research

Although the current study has yielded informative results, there are several limitations that might by addressed by future research. First, all of the data in this study are drawn from a single state-owned petrochemical company in China, which happens to place great emphasis on employees' safety at work. All of the employees involved in this study would have had a high level of safety awareness. Such attention to safety might not be replicated within other petrochemical companies or other industries. Future research should extend the scope of the investigation to encompass a more diversified sample of companies, thus improving the level of ecological validity.

Second, to avoid the problem of common method bias, we collected employee self-reported data at two separate points in time. Although we emphasized authenticity and confidentiality during the reporting process, issues such as social desirability and employees' concerns may have influenced the data collected on safety behavior. Future research might aim to simultaneously evaluate employees' safety behavior from the perspective of their leaders or colleagues. The current study is essentially just a cross-sectional study, meaning that causality cannot be inferred. Future cross-lagged analyses and longitudinal investigations would help to address these limitations.

Third, although this study investigated the relationship between the congruence of person–environment fit types and safety behavior, as well as its mediating mechanism, there may well be other mechanisms involved in this relationship, or boundary conditions that make it stronger. While this study used two representative categories, namely person–job fit and person–organization fit, there are other potential classifications of person–environment fit (e.g., person–team fit, person–career fit, person–leader fit). The relationship between the consistency of these two types of fit and other unstudied types of fit and safety behavior, as well as the mechanism underlying them, could prove to be a fruitful avenue of future research. Subsequent studies might also aim to incorporate variables specifically related to social cognition into the research framework.

Finally, whereas the current study explored the moderating mechanism of psychological safety at the individual level, it has been noted that psychological safety can be aggregated at the group level (Singh, Winkel, & Selvarajan, 2013). Safety perceptions at the group level might also have an influence on employees' behavior. Future research could adopt multi-level approaches to explore the effects of psychological safety at the group level.

5. Conclusion

The study found that the more consistent the match between person–job fit and person–organization fit, the higher employees' level of safety behavior. Employees showed more safety behavior in the situation of "high person–job fit - high person–organization fit" than they did in the situation of "low person–job fit - low person–organization fit." Finally, psychological safety has been shown to play a mediating role between the congruence of person–job fit, person–organization fit and employees' safety behavior.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability statement

Research data are not shared.

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Investigation of occupant kinematics and injury risk in a reclined and rearward-facing seat under various frontal crash velocities

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Introduction: The availability of highly automated driving functions will vastly change the seating configuration in future vehicles. A reclined and rearward-facing seating position could become one of the popular seating positions. The occupant safety needs to be addressed in these novel seating configurations, as novel occupant loading conditions occur and the current standards as well as regulations are not fully applicable. *Method:* Twelve finite element simulations using a series production seat model and a state of the art 50th percentile male human body model were conducted to investigate the influences of various parameters on the occupant kinematics and injury risk. The varied parameters included the seatback angle, impact speed, and seatback rotational stiffness. *Results:* The seat model shows a large seatback rotation angle during the frontal crash scenario with high impact speed. A reclining of the seatback angle leads to no significant increase of the injury risk for the assessed injury values. However, the reclining does affect the interaction among the occupant, seatbelt, and seatback. An increase of the seatback rotational stiffness helps reduce brain and chest injury metrics, while neck injury values are higher for the stiffer seatback.

1. Introduction

Highly automated vehicles (HAVs) of SAE Level 4 or 5 (SAE International, 2018) become realistic with advanced technologies and are able to perform the driving task independently. This allows occupants to do various activities during the drive. The common vehicle interior equipped with steering wheel, dashboard, and forward-facing seats can be adapted accordingly. In a voluntary research on future driving scenarios, the participants frequently mentioned a so-called "living room" seating configuration with rotatable seats in the front-row facing rearward as one of the most preferred configurations in HAVs (Jorlöv et al., 2017). Nie et al. (2020) conducted a national survey in China regarding seating preferences in HAVs. It was found that for specific travelling purposes (i.e., long drives with family or excursion) front-row seats facing rearward seats obtained as high percentage as front-row seats facing rearward. Regarding user acceptance, a rearward-facing seat is the second highest, right after the conventional forward-facing seating position (Köhler et al., 2019). In addition to the seat rotation, a reclined seating position is highly expected in HAVs (Jorlöv et al., 2017). In these new seating configurations, state-of-the-art occupant protection systems face new challenges and their applicability is questionable. An analysis of the German In-Depth Accident Study data found five cases involving rearward-facing seats, all of which were in an upright position, without proof of the influence of the rearward-facing configuration on the occupant injury risk (Zellmer et al., 2018).

A frontal impact with a rearward facing seat configuration makes the occupant experience rear impact dynamics. Current regulations for rear impacts only focus on low-speed tests (below 25 km/h (EuroNCAP; NHTSA), while those for frontal impacts conduct much higher impact speed tests (above 50 km/h (EuroNCAP; Hollowell et al., 1998). This raises a concern about occupant safety in rearward-facing seats, when frontal crashes and therefore high impact speeds are applied. The new concept of seat design for HAVs must consequently incorporate the protection of occupants.

Jin et al. (2018) studied occupant biomechanics in various seat orientations under high-speed frontal impacts and reported the lowest injury risk in rearward-facing seats due to a distributed load

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on the seatback. Zellmer and Manneck (2019) conducted sled tests using a Hybrid III dummy in a rearward-facing position under severe frontal crash pulses. All reported injury measures were below the injury reference assessment values. However, the above-mentioned studies did not consider a highly reclined seating position (≥45°). Kitagawa et al. (2017) investigated various non-standard seating positions in frontal crashes, including a rearward-facing seat with a reclined seatback, using THUMS and a rigid series production seat model. They initially found higher displacement of the first thoracic vertebra (T1) and belt force but lower seat force in reclined seating. Neck Injury metrics (Nij) and Brain Injury measure (BrIC) were reported to be highest in a rearward-facing seat. Hasija et al. (2019) also performed a simulation analysis on future driving, including a reclined and rearward-facing seat. They found an upward trend of the BrIC with a more reclined seatback angle, while the chest deflection decreased with an increase of the seatback angle.

The above-mentioned studies usually made use of either a rigid seat or an experimental seat (Jin et al., 2018; Zellmer and Manneck, 2019; Kitagawa et al., 2017). An experimental seat setup has a different geometry compared to a series production seat and the means of controlling its seatback rotational stiffness with, for example, spring and cable, might alter the test outcomes (Kang et al., 2012). The series production seat in one study could not withstand highly severe rear-loadings (Zellmer and Manneck, 2019). Some studies used a constant seatback rotational stiffness of 65 Nm/deg (Hasija et al., 2019) (Kang et al., 2012). The value itself, reported firstly in 1998 (Molino, 1998), is lower compared to series production seats in today's vehicles (Bridges et al., 2019). It is questionable whether the reported results still hold for a series production seat in a HAV.

The review of literature shows that especially the reclined and rearward-facing seat has not been investigated in detail and only few comparable examples from accident statistics exist. Especially in frontal collisions where high impact velocities can be expected, the performance of the seat structure is uncertain. Particularly, the seatback rotational stiffness as well as the restraint capability in reclined positions of series production seats have not been broadly investigated. Consequently, the effect on occupant safety and appropriate injury measures also need to be discussed in this context.

The focus of this study is on the occupant behavior in a reclined and rearward-facing series production seat when different full-frontal impact velocities are applied, whereas specifically the interaction of occupant and reclined seatback is investigated in a parametric study. In order to identify possible challenges for seat manufacturers and restraint system suppliers, the occupant kinematics and injury risks are assessed.

2. Method

2.1. Preparation of the seat model

The geometry and material characteristic of the FE seat model are based on the publicly available Toyota Yaris FE seat model (NHTSA, 2010). It is a plain geometric model, which is not capable to withstand any direct load. Hence, the model was modified to obtain a seatback behavior corresponding to a typical series production seat. A revolute joint was created at the recliner position, analytically constraining the seatback to the seat base. The seat frame was rigidified to eliminate any influences by material failure that is not validated. The seatback rotation hence depends only on the stiffness of the recliner, which is represented by the joint. The rotational stiffness curve of the recliner was extracted from a NHTSA report in which pull tests were conducted on a Honda Accord's seatback to develop a detailed FE model for rear impact crashes (Bridges et al., 2019). The stiffness curve was derived by combining the moment and seatback rotation profiles from the report, as shown in Fig. 1 where collapsing of the seatback occurs at a relative rotation angle of 26°. The seatback angle was adjusted to 22° and 45° from the vertical axis to represent an upright and a reclined seating position, respectively. A seat-integrated belt system with a retractor, a pre-tensioner of 3.5 kN, and a load limiter of 4 kN was added. As needed for studying the effect of the seatback rotational stiffness on the occupant injury risks, the seatback rotation was constrained by scaling up the stiffness curve of the recliner joint to an extreme value. The seat model with constrained seatback rotation is hereafter referred to as the rigid seat.

2.2. Preparation of the human body model

A 50th percentile male THUMS v4.0.2 with a height of 178 cm and a weight of 74.3 kg was used in this study. THUMS original posture is in a driving state. It was positioned into a relaxed posture in the upright (22°) and reclined (45°) for this study. The Oasis Primer was utilized as a pre-processing tool for repositioning THUMS. The two postures were obtained by applying prescribed motion on the T1 vertebra in pre-simulations. Afterwards, the arms were pulled to the thighs by assigning displacement to the tip of the ulna bones. The head was put into contact with the headrest in both seats, according to a "good" rating of the Insurance Institute for Highway Safety (IIHS, 2019). Lastly, THUMS was settled by gravitational load until an equilibrium state was reached between THUMS and the seat foam. The final upright posture was not much different from the original THUMS. For the reclined posture, the spine angles of THUMS were compared with those calculated from the posture-prediction model of Reed et al. (2019). Overall, good comparison was seen in most regions. Discrepancy in some areas were within the root mean square error of the regression model. The two seating postures are shown in Fig. 2a. Two database historic nodes were mounted at the head and pelvis center of gravity (CG) to measure their displacement. The head rotational velocities were also obtained at the same node as the head displacement. A cross-section was created at the intervertebral disc between the second (C2) and the third cervical vertebra (C3) to record the neck forces and moments as practiced in Arosio et al. (2017). Chest deflections were measured through spring elements at the mid-sternum position (as in a conventional dummy) and at four local areas (see Fig. 2b) as practiced in Kitagawa and Yasuki (2013).

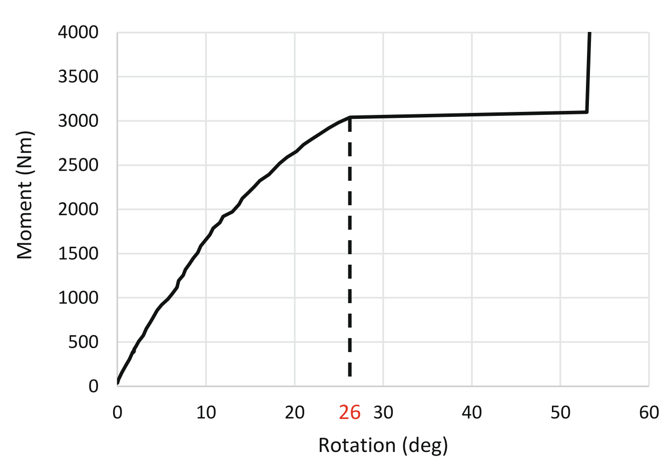


Fig. 1. The seatback rotational stiffness derived from NHTSA report (Bridges et al., 2019).

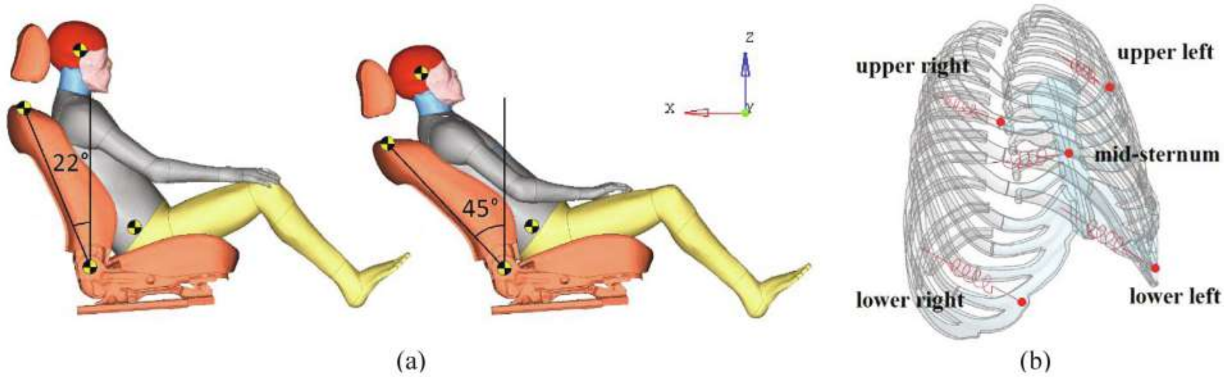


Fig. 2. Occupant position in an upright and a reclined seat (a). Locations of chest deflection measurement (b).

2.3. Frontal impact simulation conditions and injury measures

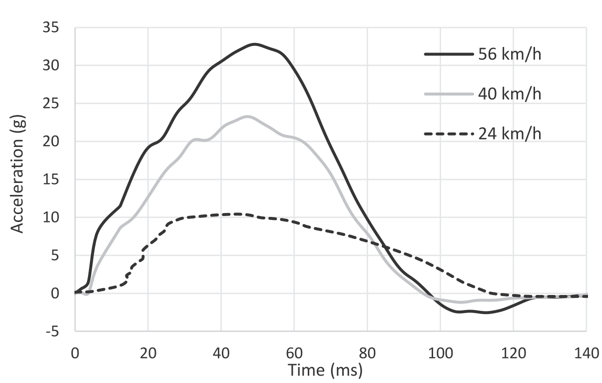
The model is used to simulate the frontal collision with three impact speeds, including 24 km/h, 40 km/h, and 56 km/h (see Fig. 3a). Whereas the acceleration pulse of the 24 km/h impact speed was taken from a cadaveric rear impact test of Kang et al. (2012). The acceleration curve for an impact speed of 56 km/h was derived from a frontal impact of a compact car against a rigid barrier (crash scenario according to UNECE R94 (UNECE, 2017). The 40 km/h impact speed represents a median speed in an urban area and the acceleration pulse was obtained by generating the average acceleration pulse of two compact cars from a rigid barrier crash test. Each crash pulse is applied to the seat base in longitudinal direction. In total, 12 simulations were conducted, including three impact speeds, two seatback angles (22°, 45°), and two seatback rotational stiffness (series production/compliant, rigid) (see Fig. 3b). All simulations were run using LS-DYNA Version 971 (Livermore Software Technology Corporation, US).

The following output responses were obtained from the simulations: seatback rotation; head longitudinal and vertical displacement; pelvis longitudinal and vertical displacement; and contact forces of the human body model (HBM) to the seat and seatbelt. Injury indices considered in this study include BrIC and brain's Cumulative Strain Damage Measure (CSDM) for the head; Neck Injury metrics (N_{ij} and N_{km}); and chest deflection. The BrIC was calculated from rotational velocities of the head center of gravity. CSDM with the strain limit of 0.25 was recorded for the brain to verify the reliability of the BrIC calculation and to preliminarily study the risk of brain neurological injury (Takhounts et al., 2013). N_{ij} was introduced for the assessment of severe neck injuries in frontal impacts and is based on axial force and lateral moment (NHTSA, 1999). Meanwhile, N_{km} was used for the assessment of neck injuries in rear-end impacts (Schmitt et al., 2002) based on shear force and lateral moment. Chest deflections were considered to assess the risk of thorax injury. The evaluation of injuries only serves as relative assessment among the shown cases and does not necessarily indicate actual injury risks.

3. Results

3.1. Model validation and robustness

The FE seat model was compared with experimental data from Edwards et al. (2019) using the Hybrid III 50th percentile male dummy model, where a 36.5 km/h rear impact was applied to different series production seats in an upright seatback position. Similar test conditions were set up for the FE simulation. Good comparison can be seen with slight discrepancy. The result of the FE simulation is within the average range of series production seats reported by Edwards et al. (2019) as shown in Fig. 4. The overall kinematics of the dummy is comparable. The slight discrepancy



(a)

Speed [km/h]	Seatback angle [°]	Seatback rot. stiffness [-]
24	22	compliant
		rigid
	45	compliant
		rigid
40	22	compliant
		rigid
	45	compliant
		rigid
56	22	compliant
		rigid
	45	compliant
		rigid

(b)

Fig. 3. The three generic acceleration pulses (a) and the simulation matrix (b).

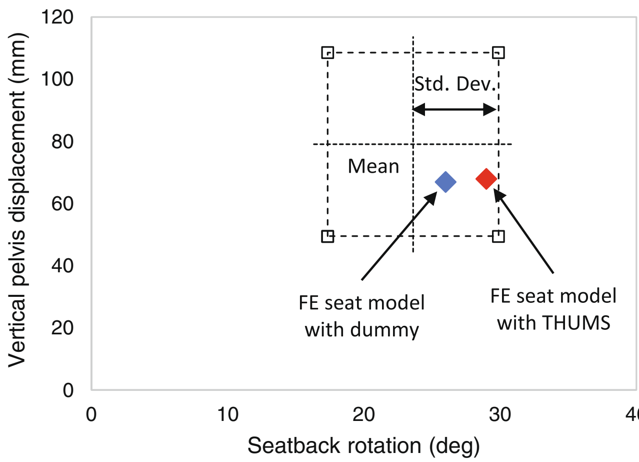


Fig. 4. Vertical pelvis displacement and seatback rotation of the FE seat model compared to the average range of series production seats.

can be explained by differences in seat geometries of the Honda Accord seat (tested seat) and the Toyota Yaris seat (simulated seat). The Hybrid III dummy was then replaced by THUMS and the simulation was performed under the same conditions. The overall kinematics of THUMS and Hybrid III dummy in the FE seat model were similar with minor difference at local regions (e.g., neck and feet). The maximum seatback rotation and the vertical pelvis displacement of THUMS are within the tests' average range (Fig. 4). In conclusion, the simulation setup has a good correlation with the reported data in terms of the kinematics.

To check the model robustness, perturbation in parameter values (e.g., small changes in seatback angle as well as with and without belt pretension) were performed. An overall good mesh quality was observed. There was no such mesh distortion, irregular element shape, or poor element aspect ratio. The mesh sizes were also quite uniform. In addition, the resulting change of kinematics was minimal as expected and calculation time remained consistent as shown in Fig. 5. Moreover, every simulation in this paper took around 6.5 h using 48 cores MPP processing. They terminated normally without critical warnings. The calculation converged uniformly for all values of parameters.

3.2. Results of the series production seat model

The kinematics of the occupant with an upright posture and a reclined posture on a series production (compliant) seat are shown in Figs. 6 to 8 for different impact speeds and several time steps. Under the rear impact load, the occupant moves rearward relative to the seat. When the buttock hits the seatback, the whole body ramps upwards along the seatback, while the seat belt restrains the body downwards on the shoulder and lap. The back of the occupant loads the seatback resulting in the rotation of the recliner joint. The lower legs contact the seat base's cushion on the rear side of the tibia (fibula bone).

For a 24 km/h impact speed, the upper body reaches maximum rearward excursion before the seatback collapses. Afterwards the upper body rebounds forward. For the 40 km/h and 56 km/h impact speeds, the seatback rotates largely from its initial position, leading to the collapsing of the seatback, which is defined at a rotation angle of 26° relative to the initial seatback angle (see Fig. 1). Consequently, the seatback is not rebounding for these two impact speeds. The whole body slides upward along the seatback, causing an excessive head displacement behind the headrest. These kinematics are similar for the two investigated seatback angles. For the lower body the kinematics differs between upright and reclined posture. After losing contact with the seatback during the ramping, the lower body in the upright seat is restrained by the lap belt and drops down. In the reclined seat, the lap belt slips off the thighs due to the higher seatback angle. This leads to a higher displacement of the occupant in the reclined position, especially when a high impact speed (56 km/h) is applied.

The seatback rotation angles plotted against time for three impact speeds and two initial seatback angles are illustrated in Fig. 9. For all cases, the dynamic seatback rotation increases with the impact speed. While the reclined cases reach a higher absolute seatback rotation than the upright cases, the rate of change of seatback rotation is higher for the upright seats. The simulations with impact speed of 56 km/h display the belt slipping in both seatback angles (Fig. 8 at 140 ms). For an impact speed of 40 km/h, the belt slipping only occurs in the reclined seat (Fig. 7d at 140 ms). The lap belt slips off the thighs when the absolute seatback rotation reaches an average angle of 73°.

The occupant's head and pelvis displacement trajectories are displayed in Fig. 10. For both cases, an upright and reclined seatback

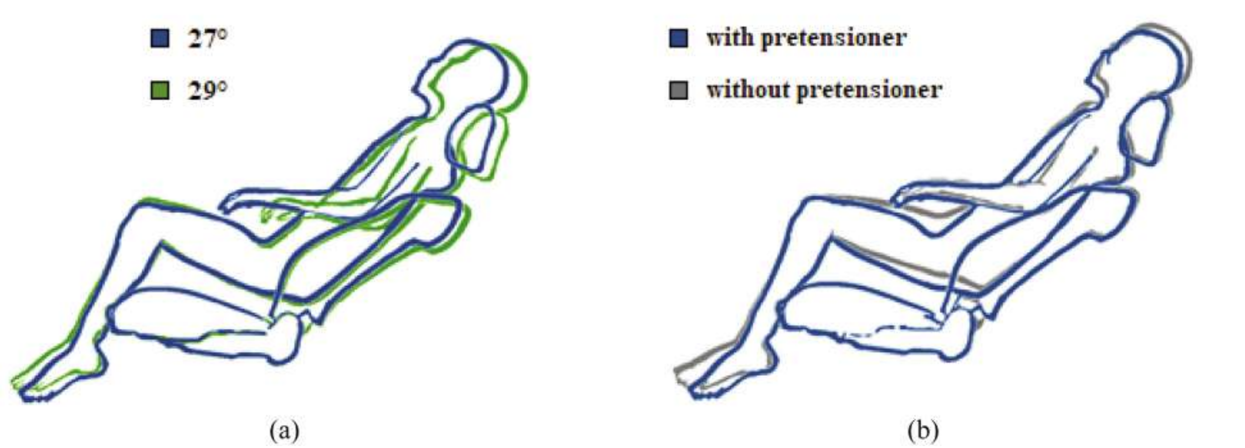


Fig. 5. Comparisons of THUMS kinematics obtained from the models with seatback angles of 27° and 29° (a). with pretensioner and without pretensioner (b).

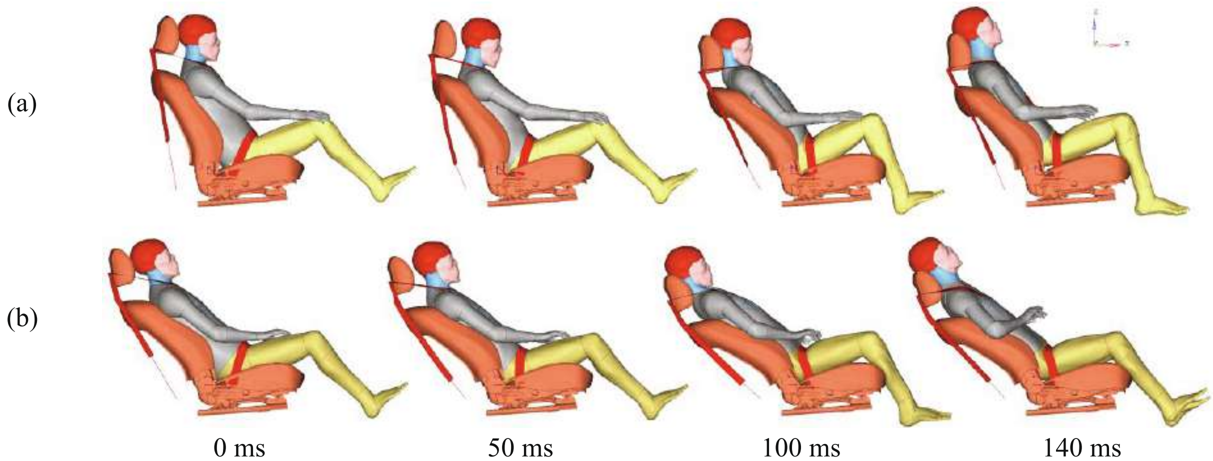


Fig. 6. Occupant kinematics in an upright (a) and a reclined compliant seat (b) under 24 km/h impact.

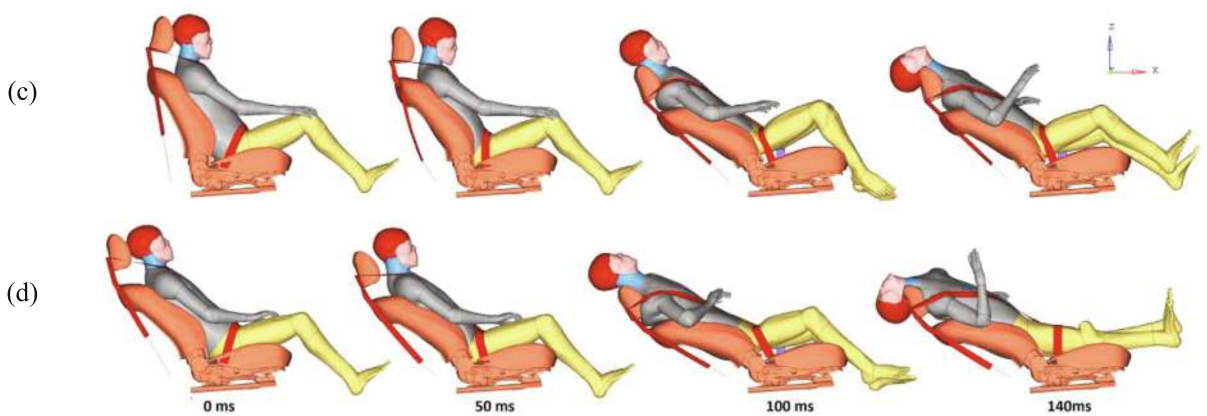


Fig. 7. Occupant kinematics in an upright (c) and a reclined compliant seat (d) under 40 km/h impact.

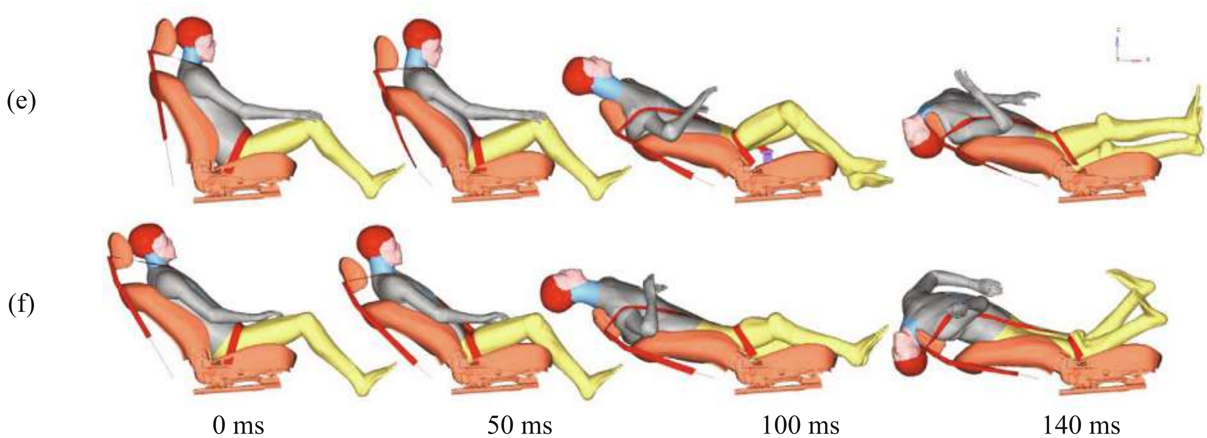


Fig. 8. Occupant kinematics in an upright (e) and a reclined compliant seat (f) under 56 km/h impact.

angle, the resulting head trajectories have similar trends but are different in their magnitudes. For both seatback angles in the low impact speed case (24 km/h), the head rebound is visualized in the trajectories. The maximum head displacement for this crash speed is 50 mm vertically and 300 mm longitudinally. Cadaver experiments with a comparable impact speed show similar results (Kang et al., 2019). As the seatback collapses in higher impact speed, excessive head excursions, ranging from around 700 mm to 900 mm, appear. The head excursion increases with the impact speed. Longitudinal head displacement relative to the initial head position is higher for the upright seat, while the vertical displacement is higher for the reclined seat in all three investigated impact speeds.

For the pelvis, until the buttocks are constrained by the seatback, the pelvis slides downwards along the cushion slope. After-

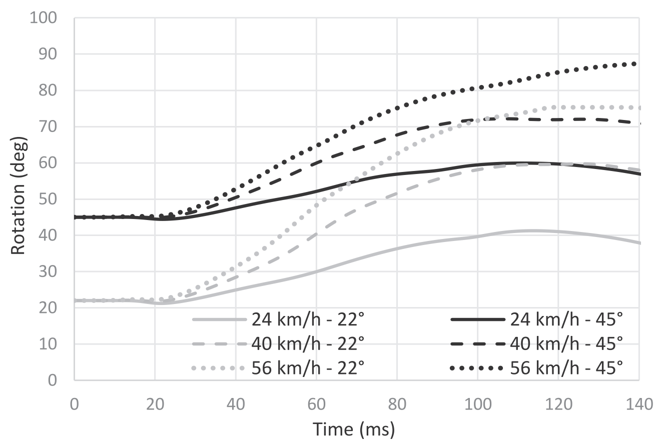


Fig. 9. Seatback rotation of the compliant seat.

wards the pelvis starts to move upward along the seatback. Due to the rebound of the seatback in 24 km/h impacts, the pelvis translates forward for both seatback angles. Contrarily, in the higher impact cases (40 km/h and 56 km/h), the higher absolute seatback angle leads to a shallow slope in the cushion surface, allowing the pelvis to ramp up and move further rearward.

In Fig. 11, the seat contact force as a function of time for each simulation case is shown. Mainly the seatback cushion contributes the seat contact force. For 24 km/h impact speeds, the curve of the seat contact force is comparable for the upright and reclined seatback angle. With higher impact speeds, the effect of the reclined seatback on the contact force becomes more significant. There are three simultaneous impacts, leading to the first peak force in the graph. These impacts are between the head and the headrest, the buttock and the stiff structure behind the seatback foam and between the legs and the seat base. The second peak in the graph for 40 km/h – 22° and 56 km/h – 22° is due to the lower body dropping down (see Fig. 7c and Fig. 8e). In the high-speed tests (40 km/h and 56 km/h), the upright seat leads to higher contact forces than the reclined seat. Due to the reclining, the effective restraint area, which is the contact area between the occupant and the seat normal to the load direction, is reduced.

The belt contact force in dependency of the time is shown in Fig. 12. The belt force increases with the seatback angle as well as the impact speed and displays two peaks in all cases. Due to the belt pre-tensioning the first peak occurs at around 20 ms. The second peak is reached when the belt restrains the ramping occupant. As the occupant excursion is opposite to the designed restraint direction of the belt system, the maximum belt force is mainly contributed by the lap belt. The second peak of the belt force obtained from the simulations with 40 km/h and 56 km/h speed are quite high due to excessive body excursion along the seatback (see Figs. 6 and 7). It is found that the maximum pelvis strain is around 0.06 for both high impact speeds. This implies possible risk of pelvis fracture as it exceeds 3% strain criteria of bone fracture. However, for 24 km/h impact speed, the belt force is low, and the pelvis strain is lower than 0.03. The belt force of the case 56 km/h – 45° increases at around 135 ms as the excessive rearward body motion causes the belt to contact the kneecaps when the legs overstretch.

The injury values of the various seatback angles and impact speeds with the series production seat are summarized in Table 1. BrIC and CSDM show a correlated trend and increase with the impact speed for both seatback angles. For 56 km/h, the BrIC and the CSDM decrease significantly with a higher seatback angle. In lower impact speed cases, BrIC and CSDM are mainly induced by the rebound of the seatback, leading to a head rotation mainly around the lateral axis (y-axis) as shown in Fig. 13. Under higher-speed impacts, not only the head angular velocity around the lateral axis (ωy) but also around the longitudinal axis (ωx) increases. In these cases, the *x*-rotation is induced by the shoulder belt engagement, which pulls the upper body asymmetrically downwards. The *y*-rotation is caused by the neck impact to the headrest followed by the head wrapping around the headrest (see Fig. 8).

Brain injury risks predicted by BrIC and CSDM are also consistent for all cases. For 24 km/h, both metrics have low values, indicating no risk of brain injury. For 40 km/h and 56 km/h impact speed, BrIC is above 1.0 and CSDM is higher than the 54% criteria for 50% risk of AIS 3 diffuse axonal injury (Takhounts et al., 2008). Fig. 14 exemplarly shows the contour plot of the brain strain for the upright seatback angle in the 56 km/h test, where the elements in red color experience strain above 0.25.

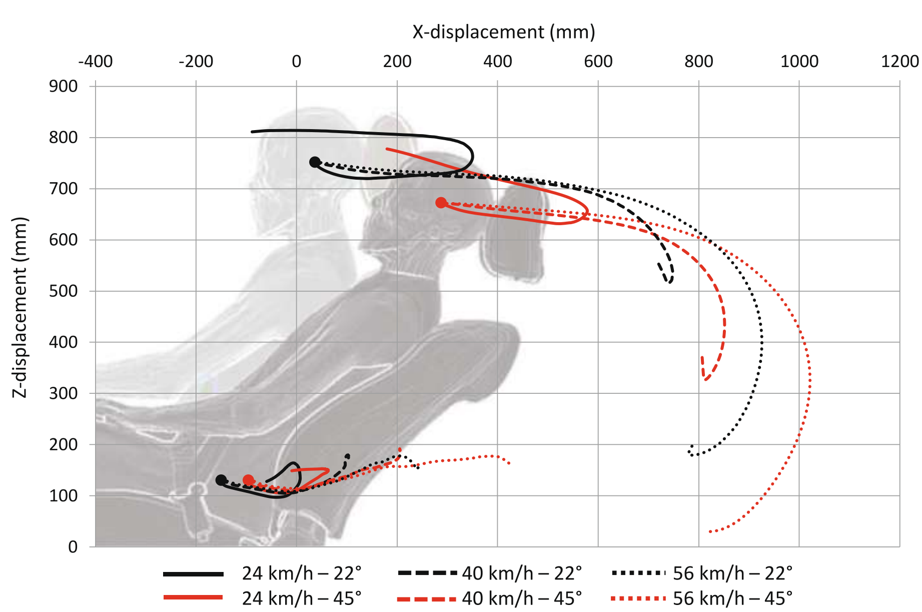


Fig. 10. Head and pelvis displacement trajectory in the compliant seat.

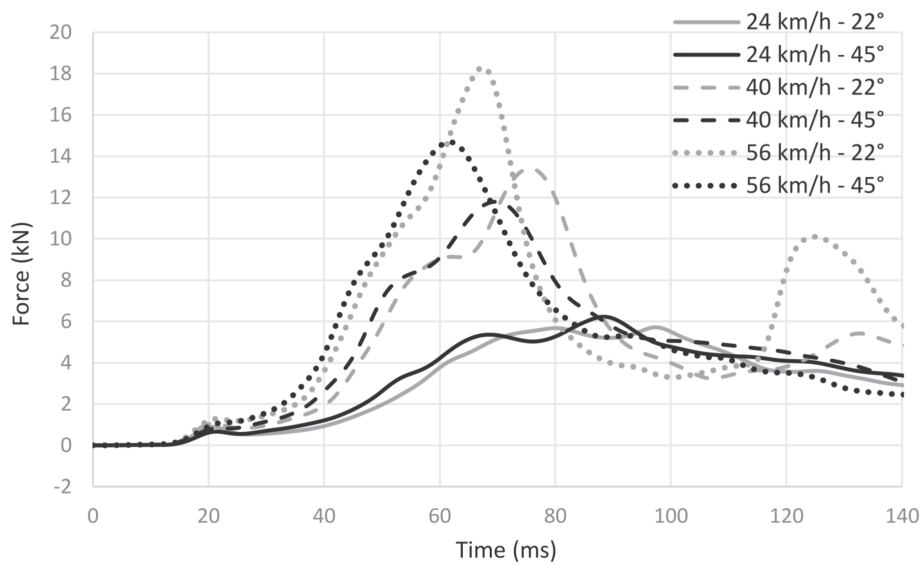


Fig. 11. Seat to occupant contact force of the compliant sea.

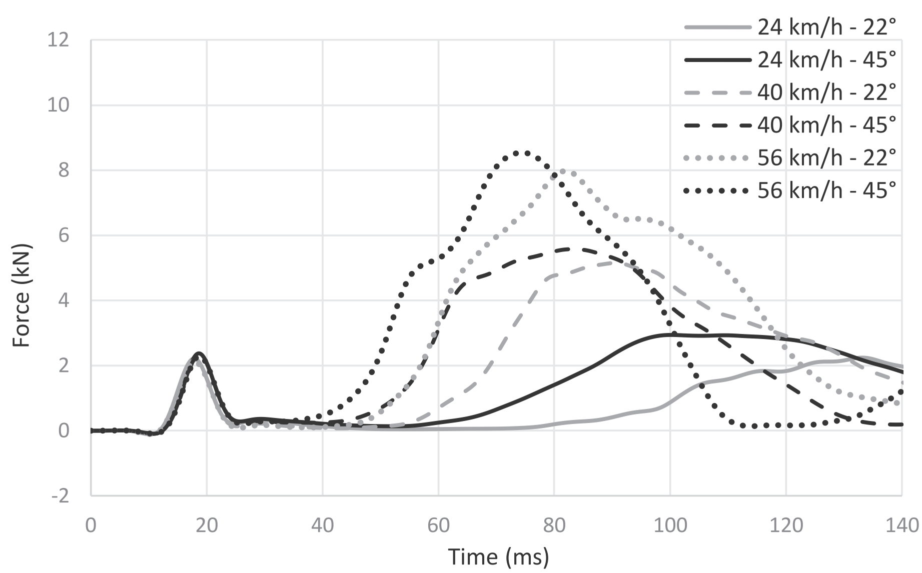


Fig. 12. Belt contact force in the compliant seat.

Table 1
Summary of injury metrics for the compliant seat.

Speed [km/h]	Seatback angle [°]	BrIC [-]	CSDM [%]	Nij [-]	Nkm [-]	Chest deflection [mm]				
						Mid-sternum	Upper right	Upper left	Lower right	Lower left
24	22	0.50	3	0.06	0.06	21.0	12.4	9.7	21.4	25.2
	45	0.57	6	0.04	0.05	21.1	14.0	7.8	23.1	24.7
40	22	1.48	60	0.16	0.17	31.8	16.5	12.7	27.2	30.2
	45	1.40	63	0.13	0.12	26.8	19.1	13.1	27.4	31.2
56	22	1.92	88	0.20	0.30	33.6	27.5	12.7	27.3	23.8
	45	1.56	62	0.07	0.04	21.1	22.4	11.2	27.3	29.8

Nij and Nkm show similar values and a decreasing trend with an increase of the seatback angle for all impact speeds. The loading mode of the neck is not influenced significantly by the seatback angle but by the impact speed. For Nij, compression-flexion is the dominant mode in low-speed cases while tension-extension and tension-flexion are dominant in moderate- and high-speed cases, respectively. For Nkm, posterior shear-flexion is the dominating mode in the low impact speed cases. Whereas anterior shear combined with extension and flexion is the main loading mode in 40 km/h and 56 km/h impact speed cases, respectively.

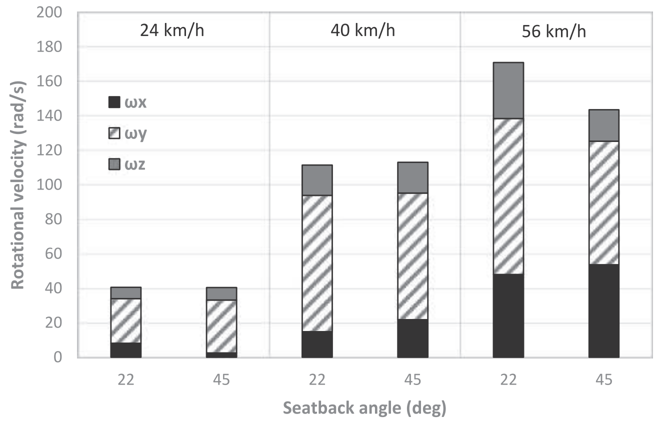


Fig. 13. Head rotational velocity for the compliant seat.

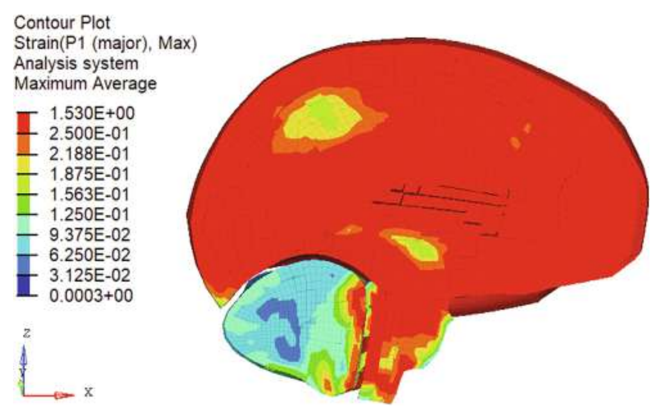


Fig. 14. Contour plot of brain strain with the limit of 0.25 for the case 56 km/h – 22°.

Dominant load of the neck occurs at around 70 ms in low impact speed cases. Whereas in higher impact speed cases, the dominant load occurs at the end of the crash (140 ms).

The neck compression load is caused by the contact of the head with the headrest as the seat is still in the rebound range, enabling full restraint of the occupant for the 24 km/h impact speed cases. This headrest-induced force poses posterior shear load to the upper neck. Meanwhile, under higher impact speeds, the head ramped over the headrest, resulting in tension/positive shear load to the neck. For the reclined seating position, which leads to higher absolute seatback rotation during the crash event, the upper body moves simultaneously with the neck, reducing the relative head-to-neck movement and hence the forces and moments compared to the upright seating position. With respect to the rotational loading condition, the flexion moment is more significant than the extension moment in all cases. From the perspective of injury metrics, the moment is inferior to the force component. Note that the recorded moments do not always reflect the observed kinematics. For instance, the neck flesh motion cannot be captured by the accelerometer at the upper cervical spine.

The mid-sternum chest deflection (CD) is comparable for both seatback angles in the low impact speed cases. For higher impact speed cases, mid-sternum CD decreases with seatback angle, which correlates well with the seat contact force. The highest mid-sternum CD value is 33.6 mm at an impact speed of 56 km/h with upright seatback angle. This value is below the threshold of 42 mm for a Hybrid III dummy (UNECE,2017). However, the maximum rib strain for this case is 5.6%, which exceeds the rib fracture criteria of 3% strain (Kemper et al., 2005), at the rib number 1, which implies the possibility of rib fracture. In the other cases with lower impact speed and reclined seatback, the maximum rib strain is below the fracture strain. For all cases, CD is relatively higher at mid-sternum, lower left and lower right thorax locations. These locations are within the effective restraint area of the seatback. The CD at the upper left and upper right area of the thorax is below 20 mm, as the upper ribcage moves between the seatback and the headrest. Only for the 56 km/h cases, the ribcage contacts the headrest causing higher CD at the upper thorax areas.

3.3. Results of the constrained seatback rotation seat model

The kinematics of the occupant in an upright posture and a reclined posture on a constrained seatback rotation (rigid) seat under 24 km/h and 56 km/h impact speeds are shown in Fig. 15 and Fig. 16. For the 40 km/h impact speed, the occupant kinematics is comparable to the 56 km/h impact case and therefore the 40 km/h case is not analyzed in detail here. In all investigated impact velocities, the body moves rearward and upward into the seatback, followed by a forward rebound of the upper body. The headrest maintains contact with the head during all time steps. For all cases, both head and pelvis displacements increase in the reclined posture. Due to the fixed seatback angle, no belt slipping occurs for the lap as well as the shoulder belt. This kinematics are similar to that of the compliant seat in the low impact speed cases. Compared to the compliant seat, a rigid seatback offers more occupant retention and reduces the head and pelvis displacement significantly for medium and high impact speed cases.

Fig. 17 shows the seat contact force for the rigid seat. The seat force decreases with a higher seatback angle in higher impact speed cases and is correspondent with the occupant kinematics. Compared to the compliant seat the maximum force level appears in a defined timeframe, when the main contact between occupant and seat appears. The peak force is on a higher value than for the compliant seat (see Fig. 11), which indicates that the rigid seat has a higher occupant retention.

Fig. 18 shows the belt contact force for the rigid seat. The belt force shows high sensitivity for the seatback angle, as it increases significantly in the reclined cases. Comparable to the series production seat, the belt pre tensioning causes the first peak force. The second peak belt force is due to the lap belt restraining the occupant ramping and occurs near the time of maximum pelvis excursion. Generally, the belt forces measured in the rigid seat are lower compared to the compliant seat cases. The maximum pelvis strain is around 0.02, 0.04, and 0.06 for impact speeds of 24, 40, and 56 km/h, respectively. Considering the typical bone fracture strain of 3%, the high impact speed of 40 and 56 km/h possibly leads to high risk of pelvis fracture for the high impact speed of 40 and 56 km/h.

The injury values for the various seatback angles and impact speeds with the constrained seatback rotation (rigid) seat are summarized in Table 2. It can be observed that injury metrics increase with the impact speed for all cases. BrIC and CSDM continue to correlate as in the compliant seat cases. While at low impact speeds, the brain injury metrics vary slightly between the two seatback angles, in higher impact speeds, both BrIC and CSDM increase significantly with a higher seatback angle. The occupant ramps up more in the reclined seat than in the upright one, consequently the head passes the top of the headrest. Both BrIC and CSDM values in all cases, except for the reclined seat with 56 km/h impact speed, are lower than the neurological injury threshold (1.0 for BrIC and 54% for CSDM) indicating possible no risk of neurological injury. However, injury values reading from the reclined seat with 56 km/h impact speed are 1.05 (BrIC) and 66% (CSDM). This implies possibility of neurological injury. Neck injury values decrease with higher seatback angle for all impact speeds. In all tests, the domi-

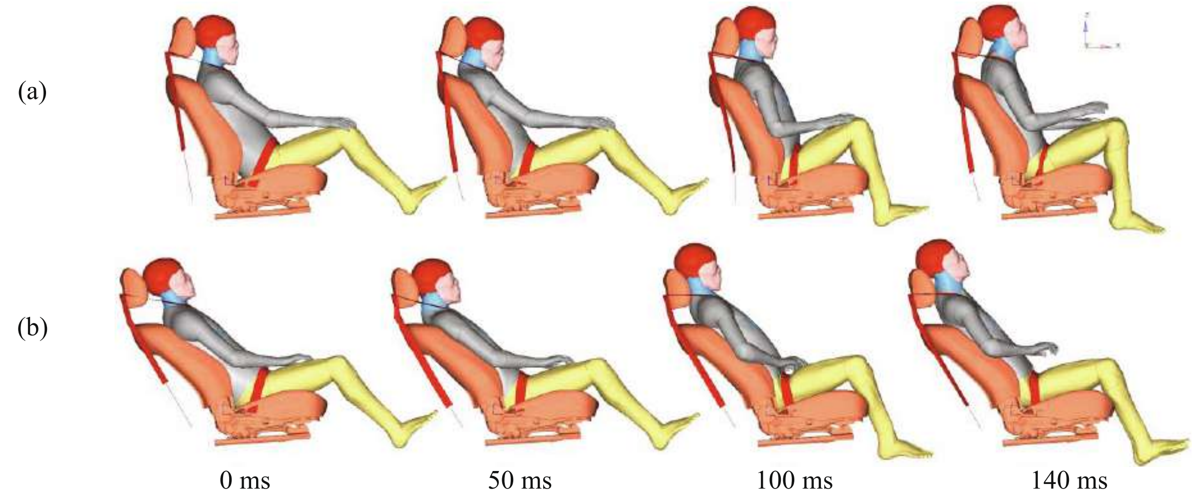


Fig. 15. Occupant kinematics in an upright (a) and a reclined (b) rigid seat under 24 km/h impact.

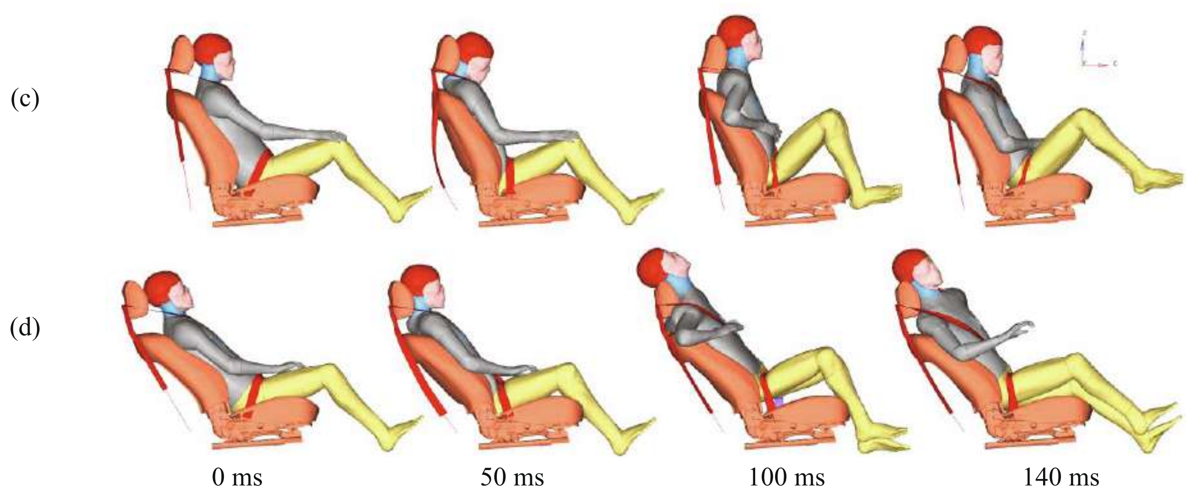


Fig. 16. Occupant kinematics in an upright (c) and a reclined (d) rigid seat under 56 km/h impact.

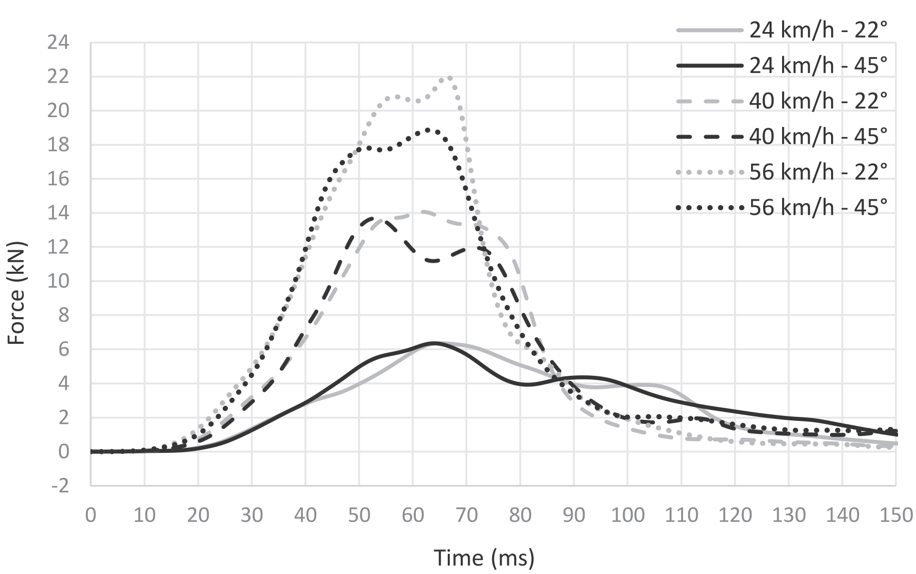


Fig. 17. Seat contact force of the rigid seat.

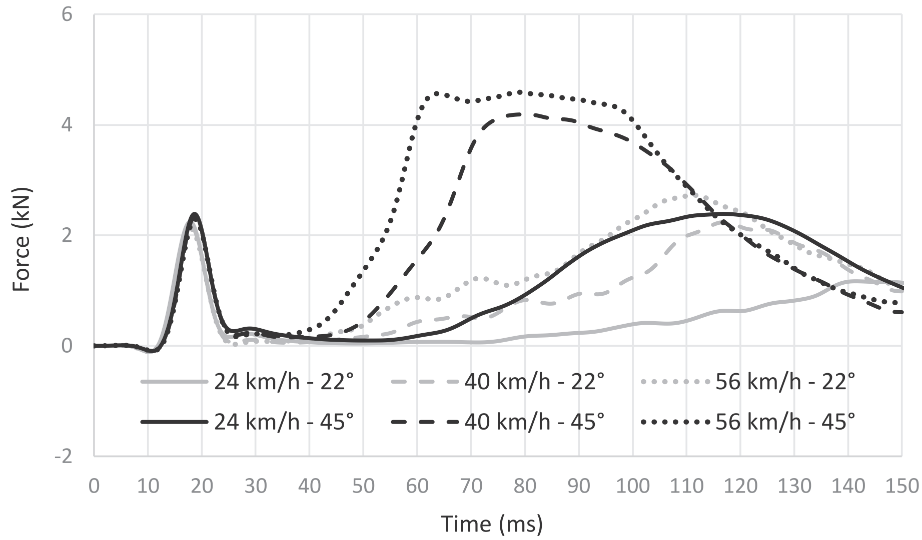


Fig. 18. Belt contact force for the rigid seat.

Table 2
Summary of injury metrics for the rigid seat.

Speed [km/h]	Seatback angle [°]	BrIC [-]	CSDM [%]	Nij [-]	Nkm [-]	Chest deflection [mm]				
						Mid-sternum	Upper right	Upper left	Lower right	Lower left
24	22	0.46	2	0.12	0.11	15.1	11.7	10.1	16.5	17.4
	45	0.38	1	0.07	0.06	19.5	9.1	7.6	14.0	17.1
40	22	0.54	7	0.19	0.15	21.3	12.9	12.2	22.0	28.4
	45	0.80	45	0.11	0.06	24.0	15.3	10.8	20.0	31.1
56	22	0.55	11	0.22	0.11	26.4	14.0	13.8	23.6	32.3
	45	1.05	66	0.15	0.06	28.2	15.7	17.7	29.2	44.9

nant loading mode of Nij and Nkm is compression-flexion and posterior shear-flexion, respectively.

Mid-sternum CD increases with higher seatback angle, which is opposite to the trend of seat contact force. The occupant's ribcage in an upright seating posture impacts the middle area of the seatback cushion. The highest mid-sternum CD value is 28.2 mm, which is below the 42 mm threshold for Hybrid III dummy (UNECE,2017). However, the CD occurs at the lower left location for the 56 km/h impact speed with reclined seat is as high as 44.9 mm. As the seat model used in this study does not have any structure behind the seatback foam, the occupant pockets into the soft seat foam for the upright seatback angle. In the reclined seat, the ribcage of the occupant hits into the rigid frame on the top of the seatback, resulting in an increase of the mid-sternum CD values. The local CD values show no clear trend for the two investigated seatback angles. The chest areas in contact with the seatback structure show higher CDs compared to other areas, where the ribcage is only in contact with the seat foam. However, the maximum rib strain for high impact speed cases (40 and 56 km/h) exceeds the typical rib fracture criteria of 3% strain (Kemper et al. 2005), which implies possibility of rib fracture.

4. Discussion

The occupant kinematic response is almost identical across the investigated impact speeds for the rigid seat. For the compliant seat more significant differences occur among the test speeds, depending on whether the seatback rebound limit is reached or not. The compliant seat that is used in this study only retains the occupant in the 24 km/h impact speed cases. For higher impact speeds of 40 km/h and 56 km/h, the seatback collapses and the occupant moves excessively rearward. The seatback recliner stiffness (according to (Bridges et al., 2019) that is used in this study cannot withstand the rearward loading of a 50th percentile male occupant caused by high impact speeds as applied in current frontal crash tests regulations. The requirements for the seat structure, and especially the recliner stiffness, shall be increased when novel rearward facing seating positions are introduced in HAVs.

When the seatback collapses under the occupants loading, consequently the rearward movement of the occupant increases. In this case, even the belt system does not prevent the occupant from moving excessively out of the seating area and an occupant ejection becomes likely. The lap belt slips off the thighs once the absolute seatback rotation reaches an average value of 73°. An initially reclined seatback reduces the amount of relative seatback rotation to reach this threshold angle. An increase of the recliner stiffness needs to be taken into account when high loadings are applied to the seatback in future seating configurations. Additionally, the lap belt can play an important role when the occupant's ramping along the seatback becomes critical. For highly reclined seats, further restraint strategies need to be discussed and investigated.

The rigid seat shows lower brain injury measures compared to the compliant seat in almost all test cases. This is due to the seatback and headrest maintaining their restrain capability, which reduces unfavorable rotations of the head as it can be observed in the compliant seat. An exceptional case is the case 56 km/h – 45°, where CSDM increases. Contrarily, Nij reduces in one case (reclined seat in 40 km/h) while it increases in all other cases with the rigid seat. The rigid seatback, which acts as a hard impact surface, makes the head bounce off the headrest and thus creates a higher compression load to the neck than a yielding seatback does. Accordingly, the flexion moment of the upper neck increases significantly. In contrast, the shear force decreases as the discrepancy in the head and neck motion in the longitudinal direction decreases. This reduces the Nkm in some of the investigated cases. Generally, the Nij and Nkm for the rigid seat remain on a low level (relative to the threshold of 1.0). Regarding thorax injuries, the rigid seat shows lower CD in almost all areas of the ribcage. The CD is sensitive to the impact location and remains low when the ribcage contacts the seatback cushion. Meanwhile, CD increases when the ribcage contacts the rigid frame due to the occupant ramping. Risk of rib fracture at high-speed impact is possible for both compliant and rigid seats.

The influences of the seatback angle on the injury values depends on the seatback rotational stiffness, as the head and thorax injury trends in the compliant seat are different for the rigid seatback cases. Meanwhile, the assessment of neck injury remains consistent regardless of the seatback rotational stiffness.

For the protection of vehicle occupants in a rearward-facing and reclined seat under frontal impacts, not only the seatback rotational stiffness but also the geometry of the headrest and seatback needs to be re-evaluated. Additionally, the injury measures, which address the standardized injury mechanism in a whiplash situation, are not verified for the novel seating and loading condition of the occupant. Consequently, the injury evaluation is challenging.

The presented study has the following limitations. No interior parts are considered, although their existence can alter the simulation outcomes and lead to contacts with the occupant. In addition, the application of THUMS and the seat model in a high-velocity rear impact has not been validated by physical tests. THUMS is positioned into a reclined posture and it is uncertain whether its performance remains reliable. Additionally, THUMS v4.0.2 is a passive model and cannot replicate any muscle activities of the occupant. Current crash scenarios and velocities are used in this study, without any pre-crash manoeuvers (e.g., autonomous emergency braking or steering), which are likely to become standard in HAVs. Lastly, the calculations of the injury values in this study are based on standards developed for dummies as well as standard seating positions and might not reflect the true values for HBMs. Therefore, these values are only used to show trends when comparing the presented simulation runs and a severity rating of the injury values is not considered.

5. Conclusion

In total, 12 simulations were conducted with the variation of three parameters (seatback angle, impact speed, and seatback rotational stiffness) to investigate the occupant kinematics and injury risk in a rearward facing and reclined seating position. Regarding the occupant kinematics, the seatback rotational stiffness, which defines the collapse angle of the recliner, is the most influencing among the investigated parameters. The occupant displacement increases and the restraint function of the seatback as well as the lap belt decreases when the collapse angle of the seatback is exceeded. For the investigated speeds of 40 km/h and 56 km/h, this threshold is reached for a series production seat. With a high seatback rotational stiffness (e.g., a rigid seat), the occupant's kinematics is almost identical across all impact speeds. A reclined seatback leads to ramping and increases the displacement of the occupant. In addition, a higher seatback angle makes the lap belt more prone to slipping off the thighs. With respect to the injury assessment in the low impact speed cases, no significant differences with subject to the seatback rotational stiffness and seatback angle are found. Meanwhile, under higher impact speeds, the higher seatback angle yields lower head and neck injury measures for the compliant seatback rotational stiffness. For the rigid seatback rotational stiffness, the reclined seat shows increased head injury values but lower neck injury measures. The chest deflection is sensitive to the contact location between the occupant and the structure of the seat frame. Generally, an increase of the seatback rotational stiffness helps reduce brain and chest injury metrics, but neck injury values are higher for the stiffer seatback. An optimization of the seatback rotational stiffness for seats in HAVs can be considered from several perspectives. To prevent a seatback collapse and an occupant ejection in high impact velocities and especially in reclined positions, the backrest stiffness needs to increase compared to current production seats. In addition, geometric adjustments and an integrated restraint strategy, which addresses not only upright but also reclined seats, may become necessary.

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Modelling the relationship of driver license and offense history with fatal and serious injury (FSI) crash involvement

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ABSTRACT

Introduction: Previous research has indicated that increases in traffic offenses are linked to increased crash involvement rates, making reductions in offending an appropriate measure for evaluating road safety interventions in the short-term. However, the extent to which traffic offending predicts fatal and serious injury (FSI) crash involvement risk is not well established, prompting this new Victorian (Australia) study. *Method:* A preliminary cluster analysis was performed to describe the offense data and assess FSI crash involvement risk for each cluster. While controlling demographic and licensing variables, the key traffic offenses that predict future FSI crash involvement were then identified. The large sample size allowed the use of machine learning methods such as random forests, gradient boosting, and Least Absolute Shrinkage and Selection Operator (LASSO) regression. This was done for the 'all driver' sample and five sometimes overlapping groups of drivers; the young, the elderly, and those with a motorcycle license, a heavy vehicle license endorsement and/or a history of license bans. *Results:* With the exception of the group of drivers who had a history of bans, offense history significantly improved the accuracy of models predicting future FSI crash involvement using demographic and licensing data, suggesting that traffic offenses may be an important factor to consider when analyzing FSI crash involvement risk and the effects of road safety countermeasures. *Conclusions:* The results are helpful for identifying driver groups to target with further road safety countermeasures, and for showing that machine learning methods have an important role to play in research of this nature. *Practical Application:* This research indicates with whom road safety interventions should particularly be applied. Changes to driver demerit policies to better target offenses related to FSI crash involvement and repeat traffic offenders, who are at greater risk of FSI crash involvement, are recommended.

1. Introduction

The effectiveness of new sanctions and other behavioral road safety countermeasures is largely determined by their impact on fatal and serious injury (FSI) crashes. Due to the relative rarity of FSI crashes, it may be many years before the impact of reforms and interventions can be reliably observed. Changes in offending patterns post-intervention have been postulated to reflect the specific effects of interventions. As traffic offenses are much more frequent compared with FSI crashes, earlier evaluation of interventions can perhaps be carried out using a reduction in offending as a proxy measure for success (Australian Bureau of Statistics, 2019; BITRE, 2017). However, the extent to which traffic offending increases FSI crash involvement risk is not well established, prompting the need for this investigation.

Offense history (i.e., the number of traffic infringement convictions) and crash history (i.e., the number of crashes a driver has been involved in) have frequently been found to be useful predictors of future FSI crashes (DeYoung & Gebers, 2004; Elliott, Waller, Raghunathan, & Shope, 2007; Rezapour, Wulff, & Ksaibati, 2018). Previous research has also indicated that increases in offending patterns are linked to increased crash involvement rates

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(e.g. Cooper, 1997), while the increase in crash involvement risk is particularly high when repeated violations lead to license suspension or ban (revocation). A previous traffic offense increases the likelihood of having a crash for one, two, and multi-vehicle crashes (Kim, Kim, & Son, 2006), while speeding violations and a license suspension, rather than any other type of offense, are associated with increased injury severity (Hamzeie, Thompson, Roy, & Savolainen, 2017). Leal and Watson (2011) have reported that 3.7% of illegal street racing offenses brought to police attention resulted in crashes. This and other research by Palk, Freeman, Kee, Steinhardt, and Davey (2011) has suggested that the driving records of 'hoons,' who are most likely to be young males aged 16–24 years, are more likely to include traffic infringements, license sanctions, and crashes than other drivers. But there are of course many other factors that are associated with crashes. Environmental factors (e.g., weather conditions), road conditions (e.g. road geometry), legal factors (e.g., extant law, law enforcement strategy), licensing factors (e.g., licensing status), and driver characteristics (e.g., age and years of driving experience) may all contribute to FSI crash involvement (Asbridge et al., 2017; Asgarian, Namdari, & Soori, 2019; Bingham & Ehsani, 2012; Chen, Liu, Zhang, & Hou, 2017; Moradi, Saeed, Nazari, & Rahmani, 2018; Salmon et al., 2019; Wali, Ahmed, Iqbal, & Hussain, 2017; Yang, Liu, Chan, Xu, & Guo, 2019).

Much of the research considering the relationship between offense history and crash risk has been conducted in the United States, with very little research exploring such trends using Australian crash data. The most comprehensive analysis using Victorian crash data was published over 20 years ago (Diamantopoulou, Cameron, Dyte, & Harrison, 1997) and Victoria's licensing system, road safety legislation, and regulations have changed significantly over the last 20 years. More recently a Victorian study has shown that the odds of receiving an infringement notice were greater in the 30 days prior to a crash, suggesting that infringement notices may not be encouraging safer driving as much as expected (McDonald, Berecki-Gisolf, Stephan, & Newstead, 2020). The objective of this study is therefore to quantify the relationship between the various types of traffic offense and the risk of future FSI crashes and crash involvements, while controlling for licensing and demographic risk factors using Victorian data. This will be achieved through exploring two research questions. Firstly, what combinations of driver characteristics, license and offense histories are associated with the greatest levels of future FSI crash involvement risk? And secondly, what is the relationship between offense history and crash involvement after controlling for driver characteristics and license history? These research questions were addressed by first considering the Victorian driving population ('all driver' population) and then considering particular groups of interest; namely young drivers, older drivers, drivers who have motorcycle licenses, drivers who have heavy vehicle license endorsements, and drivers who have recently been banned from driving.

A systematic review of the literature, considering the types of statistical model used to predict FSI crashes using driver crash and offense history data (Slikboer, Muir, Silva, & Meyer, 2020), has found that, as yet, the use of machine learning methods is uncommon, despite large sample sizes and large numbers of highly correlated predictor variables for crash involvement. Furthermore, there has seldom been an attempt to validate models using fresh data that has not been used to train these models, although this is the standard approach with machine learning methods. These methods are therefore utilized in this study, with the intention of validating the final models for FSI crash involvement risk that will be used to identify suitable interventions for the reduction of crash occurrences.

2. Materials and methods

2.1. Data preparation

A two-year predictor period (1 July 2013–30 June 2015) was used to predict FSI crashes and crash involvements in the following three-year crash outcome period (1 July 2015–30 June 2018). The three-year outcome period ensured a large sample of crash-involved drivers whereas the two-year predictor period ensured that only recent relevant driver history was included for prediction purposes. Victorian drivers involved in FSI crashes between July 2015 and June 2018 were identified from the Victorian Road Crash Information System (RCIS) ($N = 22{,}641$). The proportion of drivers involved in FSI crashes was less than 1% of the total number of drivers, making it necessary for only a random sample of drivers who were not involved in FSI crashes in the same period to be used for modelling purposes. A sample consisting of a randomly selected 1% of all drivers not involved in FSI crashes between July 2015 and June 2018 ($N = 57{,}742$) was therefore selected. This better balancing of the number of drivers involved and not involved in FSI crashes was previously done in similar studies conducted by Taamneh, Alkheder, and Taamneh (2017) and Peng, Li, Wang, Gao, and Yu (2020) in order to obtain reliable models for predicting the probability of future crash involvement. Licensing details and offense history convictions were then extracted from the Victorian Driver Licensing System (DLS) for the period between July 2013 and June 2015 for all the above drivers ($N = 22{,}641 + 57{,}742$). Driver license numbers were required to link the DLS and crash data, and this was the only form of driver identification information used, apart from gender and date of birth.

In order to make the comparison as reliable as possible, the random sample of drivers not involved in FSI crashes needed to be representative of this driver population in terms of demographics and licensing history. Chi-squared goodness of fit tests were used to confirm that the sample was representative of this population in terms of driver age, gender, region of residence, licensing proficiency, and licensing status distributions. Licensing data and age were recorded as of 30th June 2015 and a decision was taken to exclude drivers over the age of 90, as well as drivers with surrendered licenses. This was done on the grounds that these people were unlikely to still be driving, and may be deceased because date of death is not well recorded in the DLS.

Demographic data included each driver's age, gender, and Accessibility/Remoteness Index of Australia (ARIA), which was coded as major city, inner regional, outer regional, or remote. Also, Socio-Economic Indices for Areas (SEIFA) quintiles (range 1 –5), where low quintiles indicate poorer socio-economic residency areas, were included.

Licensing data included each driver's license status (current, cancelled, disqualified, expired, or suspended), proficiency (full license, probationary license), possessing a motorcycle license, having a heavy vehicle license endorsement, medical condition license flag (yes or no), history of an overseas or interstate license, and number of attempts needed to pass driving tests**.** A Victorian probationary license is applied to drivers 18 years or older after completing the requirements of the Graduated Driver Licensing System (VicRoads, 2019). The restrictions for P1 licenses, required for one year if aged under 21 at licensing, are slightly stricter than for P2 licenses in that only one passenger aged between 16 and 22 years of age is allowed, and applicants must complete 120 hours of supervised practice. However, there are many other restrictions that apply for the probationary period of four years (VicRoads, 2019). Offense data included each driver's frequency for each type of offense committed. These offenses included speeding offenses of increasing severity, failure to wear a seat belt, traffic light offenses, and many more. The number of court and traffic infringement notices and license bans were also collated for each driver.

2.2. Statistical analysis

As illustrated in Fig. 1 and explained below, two separate analyses were performed, the first a cluster analysis and the second the development of models to predict FSI crash involvement. The cluster analysis was conducted with the offense data, using an initial hierarchical clustering with Ward's method as described by Murtagh and Legendre (2014). Cluster analysis is commonly used for the clustering of road traffic crashes (e.g., Taamneh, Taamneh, & Alkheder, 2016) but we have yet to find an example where drivers have been clustered based on their traffic offense history. The resulting dendrogram plot suggested six clusters and provided initial cluster means for all the offense variables, allowing a final fine-tuned K-means cluster analysis as conducted by Li, Chihuri, and Brady (2017) for fatal crashes. The resulting six driver clusters were compared in terms of their demographic and licensing characteristics as well as future FSI crash involvement risk.

In the second analysis, FSI crash involvement was recorded as a binary variable for the three-year crash outcome period and was modelled with demographic variables, license characteristics, and offense history data for the predictor period. This was done for the "all driver" sample and the five sub-groups defined above. Only four demographic variables were considered (age, gender, region and socio-economic advantage of residential area) but there were numerous licensing history variables (e.g., car/motorcycle license status, license proficiency, heavy vehicle endorsement, medical condition license flag, previous interstate/overseas license, ages at which license testing and license acquisition were accomplished and number of license test attempts). There were also numerous offense history variables (e.g., numbers of speeding, seat belt and traffic light offenses, as well as the total number of offenses and ban types). This analysis was conducted for the entire sample and then separately for the five sub-groups, which were not always mutually exclusive; probationary drivers, older drivers (60–90 years of age), heavy vehicle license endorsed drivers, motorcyclists, and drivers who had received at least one license ban (suspension, cancellation or disqualification) in the predictor period (i.e. July 2013–June 2015). These five sub-groups were identified by the funders of this research as being of high importance for interventions designed to reduce crash risk.

Three machine learning classification models (random forest, gradient boosting, and penalized logistic regression models; James, Witten, Hastie, & Tibshirani, 2013; Williams, 2011), were developed for each sample in order to predict the probability of FSI crash involvement in the following three years. Random forests consist of a random sample of tree models which segment the data into non-overlapping regions and then classify all the drivers in the same segment according to the most common class (FSI crash involved – yes or no). The data segments for each tree are defined using a randomly chosen small sample of variables. For any driver a prediction for the probability of FSI crash involvement is obtained by combining the classification results from all the trees in the forest. Random forests were used successfully by Mafi, AbdelRazig, and Doczy (2018) and by Iranitalab and Khattak (2017) to predict level of injury for drivers involved in crashes. Boosting also considers a random sample of tree models but these trees are grown sequentially, using the information available from previously grown trees within the gradient boosting algorithm. Like random forests, boosting models provide a single consensus prediction for the probability of FSI crash involvement.

Both these methods have been previously used by Wang, Liu, Xu, and Lv (2019) to predict the future driving risk of crash-involved drivers. They provide measures of importance for each

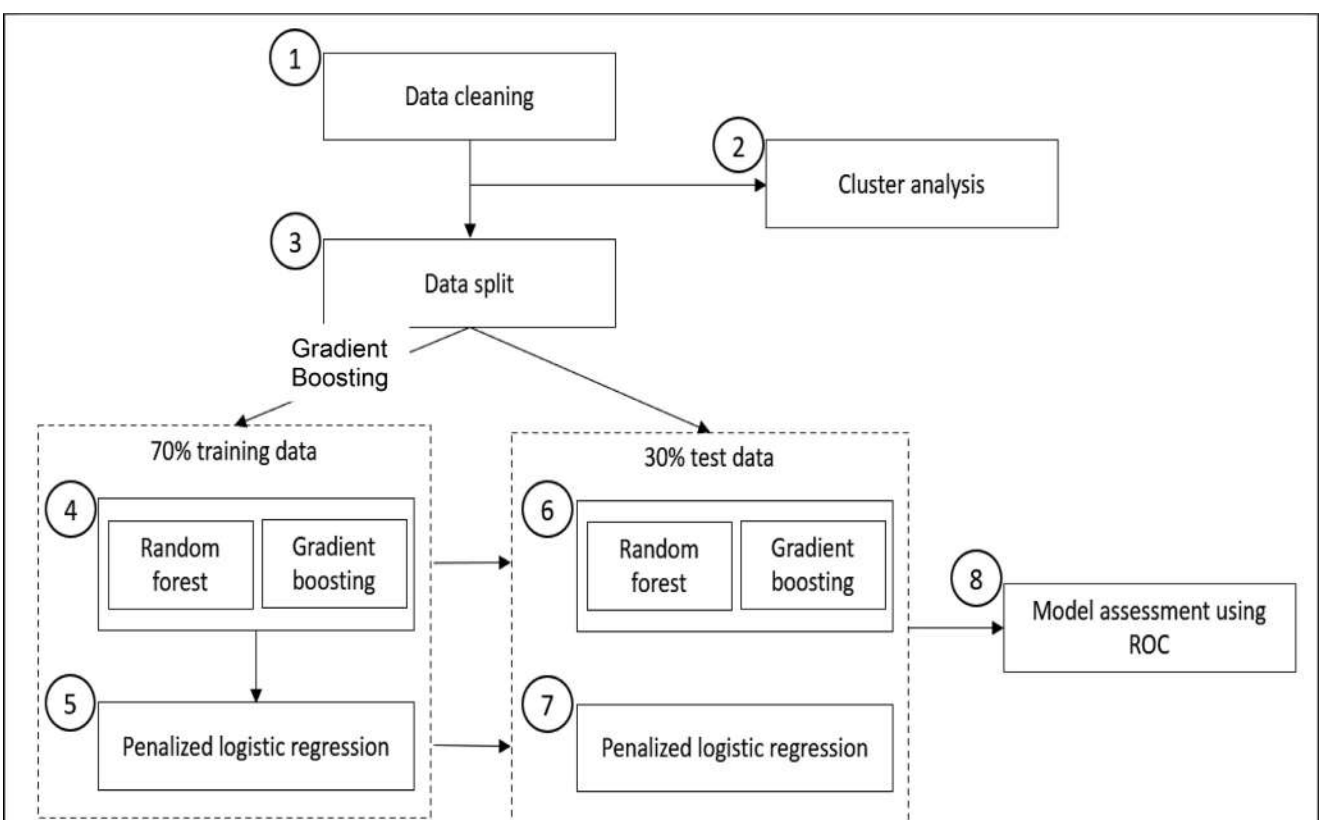

Fig. 1. Flowchart for cluster analysis and the development of a model to predict FSI crash involvement.

of the predictor variables as explained by James et al. (2013). **F**or the random forest these measures are calculated using the mean decrease in prediction accuracy (for new test data) when the data for each variable is permuted in turn. For the (eXtreme) gradient boosting these variable importance measures are calculated using improvement in classification accuracy achieved by each predictor variable in each tree, averaged over all the decision trees within the model.

In contrast to these two methods penalized logistic regression provides a single model. The Least Absolute Shrinkage and Selection Operator (LASSO) penalties were used in this analysis to ensure that only *one* of two or more highly correlated predictor variables were kept in the model, with only the significant predictor variables retained. This LASSO method produced more accurate predictions than other penalty approaches considered (utilizing Elastic Net Regularisation), and has been previously used by Bui et al. (2018) to identify driving behaviors associated with crashes in the fire services.

These three modelling techniques (random forests, gradient boosting and LASSO regression) all accommodate variable selection as well as providing importance measures for each of the explanatory variables considered. Each model was trained on a randomly chosen 70% of the data and their classification accuracy was assessed on the remaining 30% of the data. Basing model accuracy on the remaining 30% of the data rather than the 70% training data provides levels of accuracy that are indicative of the future performance of the model when applied with new data. The performance of these models was compared using the area under the Receiver Operating Characteristic (ROC) as done by Wang et al. (2019), with a minimum of 70% accuracy required to identify individuals at risk of future FSI crash involvement. The results were similar for all three methods but the small number of predictors retained in the logistic regression model, and the odds ratios provided for each of these variables, made it the stand-out model. The adjusted odds ratios from the logistic regression model were used to quantify the magnitude of the effects of each explanatory variable on the risk of future FSI crash involvement, while controlling for the other variables included in the model. The 95% confidence intervals are provided for these odds ratios rather than p-values because these are more meaningful, allowing an assessment of the accuracy of the odds ratios. The excluded variables differed for each sub-group sample, with the license testing data found to be unhelpful for all but the probationary drivers.

3. Results

3.1. Cluster analysis

Six driver clusters were identified using the cluster analysis. Clusters were named according to the offense severity and frequency of offenses. For example, "mild" offenders were those drivers who committed less severe offenses (e.g., <10 km/h excess speed), while "severe" offenders were those who committed more serious offenses (e.g., $\geq$10 km/h excess speed). Table 1 shows that as the offender clusters escalate in their level and severity of offending, so do their numbers of demerit points, court and traffic infringement notices (TINs), and license bans, with the very frequent severe offenders displaying very high levels of these behaviors in comparison with the other offender clusters.

Table 1 demonstrates that a high rate of reoffending particularly distinguishes a driver most likely to become involved in an FSI crash within the next three years, with more detail provided in Supplementary Tables 1–3. However, there were also some significant demographic and licensing differences between the clusters as reported in Supplementary Tables 4 and 5. In particular the last two clusters in Table 1 included a high percentage of males (75% and 73%) and novice drivers aged 18–25 (25% and 21%), many with P2 probationary licenses (15.7% and 17.9%) and license bans. Although the probationary, older, and banned sub-groups show clear cluster patterns linked to expected FSI risk profiles, this is not as clear for the heavy vehicle and motorcyclist sub-groups. This confirms that FSI crash models are particularly required for these two sub-groups in order to identify appropriate crash interventions.

3.2. Models for future FSI crash involvement

Random forests, gradient boosting, and penalized logistic regression were used to model the risk of FSI crash involvement for the drivers in the whole sample ('all driver') and in the five sub-group samples. As shown in Supplementary Table 6, the non-linear random forest and gradient boosting models provided markedly different measures of importance for the predictor variables. The penalized logistic regression was validated by these methods in that, although it assumed linearity (with a logit link) and included only a relatively small number of predictor variables, it achieved similar levels of prediction accuracy (AUR = 0.620–0.664) as these more complex "non-linear" methods. Indeed, as shown in Table 2 the random forest models produced worse predictive accuracy for all the sub-groups (AUR = 0.584–0.649), while the gradient boosting models produced only slightly better predictive accuracy than the penalized logistic regression for the overall sample and two of the five sub-groups (AUR = 0.628–0.671).

However, none of these models achieved an area under the Receiver Operating Curve (ROC) of 0.7, indicating that none of these models should be used for predicting FSI crash involvement risk for individual drivers. With the exception of the group of drivers who had a history of bans, offense history significantly improved the accuracy (area under the ROC) of models predicting future FSI crash involvement using only demographic and licensing data. Table 2 also reports the rates of FSI crash involvement showing that all the sub-groups (except the older subgroup, 60–90 years) are at greater FSI crash involvement risk than the 'all driver' population.

The odds-ratios from the parsimonious penalized logistic regression models were more informative than the variable importance measures provided by the random forest or gradient boosting, in that their interpretation related directly to FSI crash risk as demonstrated below.

3.2.1. Demographic predictor variables for penalized logistic regression models

Table 3 provides the odds ratios for the statistically significant demographic variables included in the penalized logistic regression models. In the following summary odds ratios are provided in brackets only for the 'all driver' model. Table 2 indicates that the odds of FSI crash involvement declined with increasing age in most cases; however, there was an increase in FSI crash involvement risk in the case of the 80–90 year age group (OR = 1.54) and the 18–25 year age group (OR = 1.22). This piecewise linear approach for the modelling of age allowed for the non-linear relationship between age and the risk of FSI crash involvement. The risk was generally higher for males than females (OR = 1.28), higher in the major cities than inner regional areas (OR = 1.26), and lower in outer regional areas (OR = 0.72). Finally, the risk was generally lower for people living in higher socio-economic postcodes (4th and 5th SEIFA quintile: OR = 0.82 and 0.68 respectively) than for people living in middle level socio-economic postcodes (3rd SEIFA quintile).

Table 1
Offense characteristics summary for the six offender clusters.

	Mean offense characteristics (1 July 2013 to 30 June 2015 – predictor period)					
	Never and seldom offender (63.8%)	Occasional mild offenders (16.0%)	Occasional severe offenders (10.3%)	Repeat mild offenders (5.9%)	Repeat severe offenders (3.5%)	Very frequent severe offenders (0.4%)
Sample size	40,377	10,103	6528	3719	2237	274
No. offenses	0.11	1.41	1.63	4.13	4.60	17.15
No. demerit points	0.26	1.69	4.10	6.00	9.17	26.52
No. court hearings	0.02	0.04	0.10	0.11	0.61	2.24
No. traffic infringement notices	0.09	1.37	1.53	4.01	3.97	14.54
No. bans	0.01	0.01	0.09	0.04	0.38	1.35
Future FSI crash involvement rates[1] per 1000 drivers per annum	1.28	1.83	2.54	2.62	4.29	7.76
% males	51.6	58.3	65.4	63.0	75.4	73.4
% major city	73.3	80.6	75.2	87.2	79.3	88.0
% 18–25 years	12.4	10.4	16.6	9.9	25.2	20.8
% P1 probationary license	2.1	0.6	1.6	0.5	3.0	3.6
% P2 probationary license	6.8	5.4	9.7	4.6	15.7	17.9
% older drivers (60–90 years)	25.4	18.4	12.4	13.2	6.4	0.4
% heavy vehicle endorsements	13.0	14.2	17,0	15.5	16.5	15.7
% motorcycle license	10.9	13.2	16.9	14.7	16.5	10.2
% drivers with bans	0.6	0.9	7.4	3.4	21.2	42.7

[1] Calculated based on July 2015 to June 2018 data.

Table 2
Evaluation of the predictive accuracy of the machine learning models for each sample.

Model	Area under ROC curve					
	All driver	Probationary	Older	Heavy vehicle	Motorcycle	Banned
Random forest	0.649	0.616	0.602	0.602	0.622	0.584
Gradient Boosting	0.671	0.620	0.639	0.639	0.628	0.639
Penalized logistic regression	0.664	0.622	0.641	0.659	0.627	0.620
Future FSI Crash Involvement risk[1] per 1000 drivers pa	1.62	2.98	1.21	2.51	3.00	5.36

[1] Calculated based on July 2015 to June 2018 data using the same method used for the clusters in Supplementary Table 1.

Table 3
Penalized logistic regression results for each sample: Demographic predictor variables, controlling for licensing and offense variables.

Predictor	Adjusted Odds Ratios (95% confidence intervals)					
	All driver	Probationary	Older	Heavy Vehicle	Motorcycle	Banned
Age (continuous)						
Age (years)	0.99 (0.99, 1.00)		1.01 (1.00, 1.02)	0.99 (0.98, 0.99)	0.99 (0.98, 0.99)	0.98 (0.97, 0.99)
Age (categorical)						
Age group 26–79	1.00		1.00	1.00		
Age group 18–25	1.22 (1.12, 1.34)		NA			
Age group 80–90	1.54 (1.34, 1.76)		1.26 (1.04, 1.52)	1.60 (1.15, 2.23)		
Female	1.00	1.00	1.00	1.00	1.00	
Male	1.28 (1.22, 1.34)	1.20 (1.05, 1.37)	1.22 (1.10, 1.35)	1.53 (1.20, 1.94)	1.28 (1.05, 1.55)	
ARIA region						
Inner regional	1.00		1.00	1.00	1.00	
Major city	1.26 (1.19, 1.33)		1.23 (1.11, 1.37)	1.37 (1.22, 1.55)	1.31 (1.15, 1.49)	
Outer regional	0.72 (0.64, 0.81)			0.68 (0.55, 0.84)	0.68 (0.52, 0.88)	
SEIFA quintile						
3rd SEIFA quintile	1.00	1.00	1.00	1.00	1.00	
4th SEIFA quintile	0.82 (0.78, 0.87)			0.82 (0.72, 0.94)		
5th SEIFA quintile	0.68 (0.64, 0.71)	0.68 (0.58, 0.80)	0.86 (0.77, 0.96)	0.70 (0.59, 0.82)	0.72 (0.63, 0.82)	

Note: The "age (years)" variable is a continuous variable (in years). The "age group" variables are categorical; Predictor variables that were not included in any final model are excluded in this table; Cells = 1.00 indicate that this category is the reference group for the indent categories below it.

3.2.2. License history predictor variables for penalized logistic regression models

Table 4 provides the odds ratios for the significant licensing variables in the penalized logistic regression models. In the following summary, odds ratios are again provided in brackets for the 'all driver' model unless indicated otherwise. Overall, the odds of FSI crash involvement were higher for drivers with record of a motorcycle license (OR = 1.75), but lower for motorcyclists who also had a car license (OR = 0.46). Also, the FSI crash involvement risk was higher for drivers with a heavy vehicle license endorsement, particularly when this was for a multi-combination heavy vehicle license endorsement (OR = 2.21). The withdrawal of a license due to cancellation, disqualification, or expiration reduced the risk of FSI crash involvement (OR = 0.45, 0.43, and 0.23, respectively). However, probationary drivers who had previously had their licenses suspended were at high FSI crash involvement risk (OR = 1.70) as were probationary drivers who needed to attempt their learner permit knowledge test more than once to pass (OR = 1.19). In addition, probationary drivers in their first year (P1) were more at risk of FSI crash involvement (OR = 1.45) than in the following three years of their probationary driving period (P2). A medical condition license flag indicated significantly greater risk of FSI crash involvement only in the case of heavy vehicle license endorsed drivers (OR = 1.48), perhaps because these drivers are required to have more frequent medical tests than other drivers. A previous interstate or overseas license indicated greater risk of FSI crash involvement only in the case of motorcyclists (OR = 1.14). Finally, for the banned group, drivers with a motorcycle license were more likely to be FSI crash involved (OR = 2.53), as were drivers with a heavy rigid endorsement (OR = 2.03). However,

Table 4
Penalized logistic regression results for each sample: License history predictor variables controlling for demographic and offense variables.

Predictor	Adjusted Odds Ratios (95% confidence intervals)					
	All driver	Probationary	Older	Heavy vehicle	Motorcycle	Banned
Motorcycle license						
No record of a motorcycle license	1.00		1.00	1.00	NA	1.00
Record of motorcycle license	1.75 (1.64, 1.87)		1.70 (1.45, 1.99)	1.52 (1.35, 1.70)	NA	2.53 (1.76, 3.64)
Car license						
No record of a car license	1.00			NA	1.00	
Record of car license	0.48 (0.30, 0.78)			NA	0.46 (0.28, 0.78)	
Heavy vehicle license endorsement						
No heavy vehicle license endorsement	1.00	NA	1.00	NA	1.00	1.00
Light rigid endorsement		NA		1.00††		
Medium rigid endorsement	1.20 (1.05, 1.36)	NA		0.87 (0.75, 0.99)		
Heavy rigid endorsement	1.45 (1.33, 1.59)	NA	1.25 (1.05, 1.49)			2.03 (1.20, 3.45)
Heavy combination endorsement	1.46 (1.31, 1.62)	NA	1.38 (1.15, 1.64)		1.24 (1.05, 1.48)	
Multi-combination endorsement	2.21 (1.85, 2.66)	NA	1.95 (1.17, 3.24)	1.75 (1.44, 2.13)	2.00 (1.52, 2.64)	
License proficiency						
Full license†	1.00	NA		NA		
P1 license	2.02 (1.72, 2.38)	1.45 (1.22, 1.69)		NA		
P2 license	1.40 (1.27, 1.54)	1.00		NA		
License status						
Current license	1.00	1.00	1.00	1.00	1.00	1.00
Cancelled license	0.45 (0.29, 0.70)					0.57 (0.37, 0.90)
Disqualified driver	0.43 (0.30, 0.62)		0.03 (0.00, 0.18)	0.19 (0.07, 0.55)		
Expired license	0.23 (0.19, 0.29)		0.02 (0.01, 0.07)	0.28 (0.16, 0.49)	0.24 (0.13, 0.45)	
Suspended license		1.70 (1.05, 2.77)	0.34 (0.16, 0.75)			
Medical condition flag						
No flag				1.00		
Flag				1.48 (1.07, 2.04)		
Previous Interstate or overseas license						
No		NA			1.00	
Yes		NA			1.14 (1.01, 1.28)	
Knowledge test						
No. of knowledge test attempts	NA	1.19 (1.06, 1.34)	NA	NA	NA	NA

Note: Predictor variables that were not included in any final model are excluded in this table; NA = this predictor variable was not included in the analysis for this sample; Cells = 1.00 indicate that this category is the reference group for the indent categories below it. †Full license holders were merged with Learner drivers; ††"Light rigid" was the reference category for license endorsement for the heavy vehicle license endorsed sample.

Table 5
Penalized logistic regression results for each sample: Offense history predictor variables controlling for demographic and licensing variables.

Predictor	Adjusted Odds ratios (95% confidence intervals)					
	All driver	Probationary	Older	Heavy vehicle	Motorcycle	Banned
No. of high speed (≥10 km/h) offenses	1.15 (1.09, 1.21)					
No. of failure to wear seat belt offenses	1.24 (1.02, 1.50)					
No. of disobey traffic light offenses	1.14 (1.07, 1.22)					
No. of offenses		1.12 (1.08, 1.16)	1.26 (1.21, 1.32)	1.18 (1.14, 1.23)		
No. of traffic infringement notices	1.11 (1.05, 1.16)				1.16 (1.11, 1.21)	
No. of bans				1.35 (1.05, 1.75)		
No. of suspension bans					2.39 (1.61, 3.56)	1.28 (1.09, 1.51)
Max. ban duration						
No bans	1.00					
Less than 3 months	1.56 (1.26, 1.93)					
Between 3 and 6 months	1.56 (1.02, 2.39)					
More than 6 months	1.48 (1.17, 1.87)					

Note: Predictor variables that were not included in any final model are excluded in this table; Cells = 1.00 indicate that this category is the reference group for the indent categories below it.

after license cancellation the risk of FSI crash involvement was reduced for the banned group (OR = 0.57). Although license suspension did not feature in the 'all driver' model, this was addressed in Table 5 where ban duration was found to be very important.

3.2.3. Offense history predictor variables for penalized logistic regression models

Table 5 identifies the offense variables that contribute significantly to predictions of FSI crash involvement. In the 'all driver' sample these factors include higher numbers of offenses involving excess speeds of ≥10 km/h (OR = 1.15), seat belt offenses (OR = 1.24), and traffic light offenses (OR = 1.14). For probationary, older drivers (60–90 years), and heavy vehicle license endorsed drivers the number of traffic offenses is an important predictor of FSI crash involvement risk (OR = 1.12, 1.26, and 1.18, respectively). For motorcyclists and banned drivers with a larger number of suspension bans in the last two years, FSI crash involvement risk is higher (OR = 2.39 and OR = 1.28, respectively). For heavy vehicle endorsed drivers with a higher number of bans, FSI crash involvement risk is also greater (OR = 1.35). However, for the 'all driver' group the maximum license ban duration provided a more nuanced indication of FSI crash involvement risk (OR = 1.48–1.56) than the number of bans. Finally, the total number of traffic infringement notices provides a good indication of future FSI crash involvement risk in the case of motorcyclists (OR = 1.16).

4. Discussion

4.1. Cluster analysis

Six distinct groups of drivers were identified based on their offending levels in the two-year predictor period. The two groups with the highest offending rates were found to have FSI crash involvement rates (per 1,000 drivers) of 4.3 and 7.8 per annum in the following three years, confirming the link between traffic offending and FSI crashes. The link between traffic offending and future crashing has been documented elsewhere. For example, McDonald and colleagues (2020) reported the odds of receiving an infringement in the month prior to a crash were 35% higher than receiving an infringement in the same month the year prior. A 2015 Queensland study found drivers had a 32% increased crash risk after receiving traffic infringements, with a 41% increased crash risk for crashes in which the offender was at fault (Walter & Studdert, 2015). In the United States, 40% of drivers injured in crashes while under the influence of alcohol had a previous history of alcohol offenses (Lapham, Baum, Skipper, & Chang, 2000).

4.2. Models for future FSI crash involvement

After controlling for demographic and licensing characteristics significantly related to FSI crash involvement (namely gender, socio-economic level, urban/rural residence, license status and endorsements), it was found that drivers receiving more traffic infringement notices for seat belt, disobeying traffic lights, and speeding offenses were at increased risk of FSI crash involvement. This supports the work of Factor (2014) who found that the probability of involvement in an FSI crash was more than 11 times higher for drivers with six traffic infringements per year compared to those with one infringement per year.

Separate analyses for five important driver sub-groups indicated the following: first year probationary drivers (P1) were more at risk than second to fourth year probationary drivers (P2), those aged over 80 were at greater risk than drivers aged 60–79, drivers with a multi-combination heavy vehicle license endorsement were more at risk than other heavy vehicle license endorsed drivers, motorcyclists were more at risk if they did not have a car license. The higher FSI crash involvement risk of these sub-groups is common knowledge amongst road safety professionals.

Victorian probationary drivers have the highest risk of crashing in their first year of driving and this group has more crashes than any other road user type (VicRoads, 2017, 2019). Indeed, young drivers (18–25 years) are overrepresented in crashes and resulting casualties across Australia (Senserrick & Williams, 2015) and Victorian novice drivers have higher casualty and FSI crash involvement rates compared with Victorian experienced drivers (Catchpole, 2020). Regarding older drivers, the increased FSI crash involvement risk found here also matches past research. Studies in Australia and worldwide show that, for crash rates per distance driven, younger and older drivers have higher crash rates compared with middle-aged drivers (Baldock, Thompson, Dutschke, Kloeden, Lindsay, & Woolley, 2016).

The finding that drivers with a multi-combination heavy vehicle license endorsement were more at risk than other heavy vehicle license endorsed drivers has been found in another Victorian study where articulated truck crashes were more severe than rigid truck crashes (Haworth & Symmons, 2003). As multi-combination heavy vehicles are larger than articulated trucks resulting in more severe outcomes during a crash, this finding would be expected. The finding that having a car license is protective for motorcyclists was also not unexpected. In 2017, for every mile travelled, U.S. motorcyclist fatalities occurred nearly 27 times more frequently than passenger car occupant fatalities (NHTSA, 2019). In 2019, Victorian motorcyclists had a much higher fatality crash rate per billion vehicle kilometers travelled – 84.9 versus 2.4 for vehicle occupants (BITRE, 2020).

Also, drivers who had received a traffic ban in the last two years were particularly at risk of future FSI crash involvement in the following three years if they were younger, a motorcyclist, or heavy vehicle license endorsed driver. Finally, the study found that FSI crash involvement risk increases for all license ban durations, with bans less than three months and bans three to six months having a slightly higher crash involvement risk compared with bans greater than six months. The FSI crash involvement risk occurs as some banned drivers continue to drive unauthorized and the banned drivers in this study were compared with drivers with a current license who are inherently safer drivers. It should be noted that other research with Victorian drink-drivers and Victorian speeders has found license cancellation and suspension to be effective sanctions in reducing offending and crashing (Imberger, Watson, & Kaye, 2019; VicRoads, 2016).

4.3. Practical applications

This research has identified five groups of driver who are at risk of involvement in FSI crashes, suggesting that road safety interventions need to target these groups. Successful interventions for some of the above high risk groups are well established. Castellucci, Bravo, Arezes, and Lavalliere (2020) have provided a review of interventions that are tailored to improving driving in older healthy individuals by working on components of safe driving such as self-awareness, knowledge, behavior skills, and reducing crash/collision rates, while many other studies have focused on developing screening tools to identify medically at-risk drivers (Bédard, Weaver, Dārzin, & Porter, 2008; Dickerson & Bedard, 2014). Our research suggests that older people with a higher number of recent traffic offenses and with heavy vehicle endorsed licenses or motorcycle licenses need to be particularly targeted in these ways.

Similarly, there has been considerable research investigating the effectiveness of interventions designed to improve safety of probationary drivers (Pressley, Fernandez-Medina, Helman, McKenna, Stradling, & Husband, 2016). Interventions that maximize maturity and on-road experience before licensure, and limiting exposure to risky situations such as night-time driving and carrying peer-age passengers, have all been shown to be successful (VicRoads, 2017). Other interventions that have shown promise include engaging parents in managing post-test driving in specific risky situations, utilizing technology such as in-vehicle data recorders to monitor driver behavior (e.g., speeding and use of mobile phones), and to provide feedback to the driver, banning of distracting devices and training in hazard perception skills. Our research shines a light on the need for interventions with young drivers who have had license suspensions in the past, who have battled to pass their learner driving knowledge test, and those who have had a high number of traffic offenses.

Similar interventions have been suggested for motorcyclists (Haworth, Rowden, Wishart, Buckley, & Watson, 2012). Our research indicates that motorcyclists that receive traffic infringement notices or suspension bans should be specifically targeted with interventions that will reduce unsafe attitudes and behavioral intentions, particularly if they hold a license with a heavy vehicle endorsement. Mooren, Grzebieta, Williamson, Olivier, and Friswell (2014) have suggested that safety training, management commitment, worker participation, incentives, work scheduling, vehicle technologies, and pay levels can all affect the safety of heavy vehicle drivers. Our research suggests that drivers with a multi-combination license endorsement and those with high numbers of previous traffic offenses and bans need to be especially targeted in this way. However, medical flags were also seen to be reflected in higher FSI crash involvement, indicating that medical testing of drivers of heavy vehicles is also an important priority.

Finally, drivers who have a history of bans are usually handled through the courts, but there is also some research regarding post-court safety interventions for convicted traffic offenders. Wright, Ayton, Rowe, and Pligt (2007) have recommended interactive, certificated, classroom-based interventions focusing on the consequences of illegal driving behavior for the drivers themselves and other drivers (often perceived as being less able drivers). Research also indicates that such courses should be 'behavior change' based to have an impact, targeting items such as beliefs about peer acceptability, the commonness of the undesirable behavior, driver responsibility, perceptions of the likelihood of detection, and providing alternative safe behaviors and strategies for managing triggers and relapses of unsafe behavior (Fylan, Hempel, Grunfeld, Conner, & Lawton, 2006). Our research suggests that banned drivers with motorcycle licenses and/or heavy vehicle endorsed licenses should be specifically targeted with 'behavior change' strategies.

It is particularly important to consider interventions for repeat offenders in any of the above categories, because these drivers are more likely to be involved in future FSI crashes. In addition, this research indicates which offense categories should be monitored when evaluating interventions designed to change risky driving behaviors. These offense variables include high excess speed ($\geq$10 km/h), failure to wear seatbelts, and disobeying traffic lights. Allowing greater penalties (e.g., demerit point penalties) for these particular offenses is another response that may be helpful.

4.4. Limitations

This analysis was not without its limitations. Firstly, the way the outcome variable (FSI crash involvement) has been defined may be a limitation. This variable does not consider whether a driver was at fault (Victorian crash data does not indicate driver fault), rather, just that the driver was or was not involved in an FSI crash. Further, potential predictor variables such as crash history were not explored in our analysis as too few drivers had experienced multiple FSI crashes in the period of interest. However, it can be argued that the offense data included in this analysis would capture previous crash involvement when the driver was at fault, so this may not be a serious omission. A driver who causes a FSI crash is likely to be convicted of an offense of some nature.

Further, potential predictors (e.g., kilometers travelled) and traffic variables (e.g., traffic volumes) were not included in this analysis because the data were not available. This means that the results for drivers that travel large distances, particularly drivers with heavy vehicle license endorsements, should be interpreted with caution. However, some of the variables included in the analysis are directly related to driving exposure (e.g., heavy vehicle endorsement) and some are likely to be indirectly related to driving exposure (e.g., number of offenses). Also, it should be noted that it is not known in which vehicle offenses were committed. For example, the number of bans was found to be positively associated with FSI crash involvement risk for the heavy vehicle license endorsed driver subgroup; however, it is not known if these bans were imposed as a result of driving offenses committed in heavy vehicles, cars, or on motorcycles. Another important variable not captured in our data is police enforcement practices (e.g., technology such as speed cameras) and policing intensity, which relate to both detection levels for offending and the likelihood of FSI crashes (Bates, Soole, & Watson, 2012).

Finally, although insights regarding the relationship between offense history and future FSI crash involvement have been gleaned from the machine learning methods employed in this study, none of our models are sufficiently powerful to be able to provide estimated probabilities of future crash involvement for individual drivers. This is because there are many driver specific variables (such as personality and cognition variables) that were not included in this study. The inclusion of such variables would be required to produce models with sufficient accuracy as to allow individual predictions of future FSI crash involvement. The collection of such data would be very costly, making this an unachievable goal at this time.

5. Conclusions

The use of machine learning methods in this study has shown that these methods, used in tandem, can be successfully used in this context and can therefore be recommended for the future modelling of crash data. The first of these methods, a two-stage cluster analysis, has shown that the nature of offending and reoffending can be captured from large numbers of offending statistics, allowing the relationships between offense patterns and future FSI crash involvement risk to be better understood, while identifying population sub-groups that need further investigation. The next two methods, random forests and gradient boosting, have shown that it is possible to identify the variables that are most predictive of future FSI crash involvement risk, without making assumptions about the nature of these relationships. Finally, this study has shown that penalized logistic regression can be used to provide a more parsimonious model for FSI crash involvement risk. This has been done by using the LASSO algorithm to select a more parsimonious model with predictive accuracy similar to that obtained with random forests and gradient boosting, while allowing the use of familiar odds ratios for condensing the critical modelling information in a format that facilitates policy decision-making.

To conclude, the models produced provide significant insights regarding the predictors associated with FSI crash involvement for at-risk driver groups but cannot be used to predict the circumstances for an individual driver. This study has shown the efficacy of machine learning methods for the prediction of future FSI crash involvement risk with the most useful models derived using penalized logistic regression. The large numbers of observations and the large numbers of highly correlated variables makes these machine learning methods more appropriate than conventional statistical modelling for these data, allowing the best models to be chosen for describing the data. It is therefore recommended that such methods be considered for future studies of this nature.

The results of this study show that demographics and licensing history do explain, to a large extent, the types of drivers who are more at risk of involvement in FSI crashes. However, traffic offense history is also important, significantly improving the accuracy of five of the six models considered. The results provide up-to-date insights into the driver characteristics most associated with FSI crash involvement risk. This information will help better target road safety interventions and provide indications of which offense variables should be monitored when evaluating interventions.

Declaration of Competing Interest

Kelly Imberger and Victoria Pyta are employed by the Victorian Department of Transport (Road Safety Victoria), which funded this work. They declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Denny Meyer, Reneta Slikboer, Samuel Muir and Sampathawaduge Sandun Malpriya Silva were employed by the Swinburne University of Technology to complete this project. The Swinburne University project team has no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsr.2021.08.008.

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Nighttime effectiveness of the pedestrian hybrid beacon, rectangular rapid flashing beacon, and LED-embedded crossing sign

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A B S T R A C T

Introduction: A large majority of pedestrian fatal crashes occurred during the nighttime. The focus of this research was to identify if the following pedestrian crossing treatments were more or less effective at night: pedestrian hybrid beacon (PHB), rectangular rapid flashing beacon (RRFB), or LED-embedded crossing warning sign (LED-Em). *Method:* For each treatment, two statistical evaluations were used on the staged pedestrian data: ANCOVA models that considered per site mean yield rates and logistic regression that considered the individual driver response to the crossing pedestrian. *Results:* For the PHB, essentially no difference was found between the very high daytime and nighttime driver yielding values. The research found RRFBs to be more effective at night, and the LED-Em to be more effective during the day. Using the results from the logistic regression evaluation, higher driver yielding was observed at LED-Em sites in the lower speed limit group (30 or 35 mph (48.3 or 56.3 kph), with 2 lanes (rather than 4 lanes), with narrow lanes of 10.5 or 11 ft (3.2 or 3.4 m) widths (rather than 11.5 or 12 ft (3.5 or 3.7 m) widths), and lower hourly volumes. The results from the ANCOVA model for LED-Ems also showed a statistically significant difference for yield lines (higher yielding when present). *Conclusions:* This analysis represents the only known study to date on the effectiveness of pedestrian crossing treatments at night. *Practical Applications:* This study provides additional support for the PHB as a treatment because the PHB was found to be highly effective during the nighttime as well as the daytime. The value of using advance yield lines was also demonstrated. The findings offer a caution regarding the use of the LED-Em treatment on higher speed, higher volume, or wider roads.

1. Introduction

One reason that motor vehicle-crashes with pedestrians are a concern is because pedestrians are more likely to sustain fatal or severe injuries compared to vehicle occupants. In Texas between 2010 and 2016, pedestrian crashes accounted for 3,434 fatal crashes representing 16% of all fatal crashes (Texas Strategic Highway Safety Plan, 2020). A large majority of those pedestrian fatal crashes occurred during the nighttime (79%).

Several traffic control device treatments aimed at improving crossing opportunities for pedestrians have been installed including the following:

- Pedestrian hybrid beacon (PHB) (see example in Fig. 1a).
- Rectangular rapid flashing beacon (RRFB) (see example in Fig. 1b).
- Light emitting diode embedded (LED-Em) pedestrian/school crossing sign (see example in Fig. 1c).

The PHB uses typical traffic and pedestrian signals, but with a different configuration and sequence of operations (see Fig. 2). The PHB was developed in Tucson, Arizona starting about 2000 with changes reflecting feedback from the traffic engineering community. The PHB was included in the 2009 Manual on Uniform Traffic Control Devices (MUTCD) (FHWA, 2009). The RRFB currently has Interim Approval for optional use (Knopp, 2018). The RRFB is a pedestrian-actuated conspicuity enhancement to supplement standard pedestrian and school crossing warning signs at uncontrolled marked crosswalks. It uses rectangular-shaped LEDs, flashes rapidly in a combination wig-wag and simultaneous flash pattern, and is mounted immediately adjacent to the crossing sign. LEDs are embedded in traffic signs to enhance drivers' awareness of the signs and can outline either the sign itself or the words and symbols on the sign. For this study, LED-Em sites were only considered if the LEDs were pedestrian activated (as opposed to flashing continuously) and the sign had the LEDs in the border.

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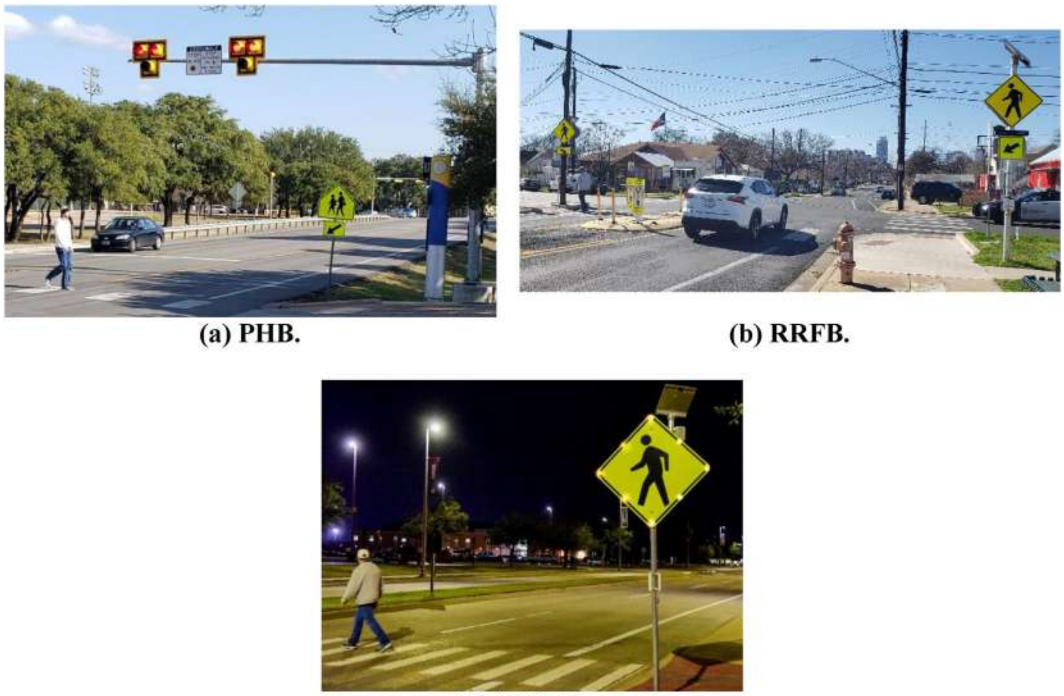

(a) PHB. (b) RRFB.

(c) LED-Em.

Fig. 1. Examples of Treatments.

While the effectiveness of the PHB, RRFB, and LED-Em have been examined in previous studies, whether these treatments have a similar effectiveness at night needs to be explored. For this activity, researchers sought to evaluate and compare the day and night operational performance of the PHB, RRFB, and LED-Em treatments.

2. Previous research

Several studies have examined the performance of pedestrian traffic control device crossing treatments including a 2019 Texas Department of Transportation (TxDOT) study that summarized the findings for these three treatments (Finley et al., 2020; Rista & Fitzpatrick, 2020). Most of these studies used a study approach of counting the number of drivers that did and did not yield to a crossing pedestrian. In many cases a staged pedestrian, who is a researcher trained to cross in a similar manner for all locations and crossings, was used. A summary of key findings for each of the treatments follow.

2.1. PHBs

Several studies have evaluated the PHBs and have reported high yielding rates varying from 75% to 97% (Fitzpatrick et al., 2006; Turner, Fitzpatrick, Brewer, & Park, 2006; Fitzpatrick, Avelar, et al., 2016). A comprehensive study for FHWA (Fitzpatrick & Pratt, 2016) identified an overall average driver yield rate of 96% for sites with posted speed limits between 30 and 45 mph (48.3–72.4 kph). An Arizona Department of Transportation study (Fitzpatrick, Cynecki, Pratt, Park, & Beckley, 2019) utilized 10 locations in Arizona for which operating speeds ranged between 44 mph (70.8 kph) and 54 mph (86.9 kph) to evaluate the driver yielding rates for facilities with higher posted speed limits. The researchers found that the average yield rate across the sites was 97%, thus concluding that PHBs are equally effective on facilities with higher posted speed limits.

2.2. RRFBs

A 2016 Texas A&M Transportation Institute (TTI) report (Fitzpatrick, Brewer, et al., 2016) that evaluated the effectiveness of RRFBs provides a detailed summary of various studies that investigated the effectiveness of RRFBs utilizing the measure of driver yield rates. The TTI study (Fitzpatrick, Brewer, et al., 2016) combined previous data from TxDOT and Federal Highway Administration (FHWA) studies and through a series of statistical models, identified factors associated with driver yielding at the RRFB. Those factors included intersection configuration (number of legs), presence of median, crossing distance, and direction of travel (one-way vs. two-way traffic). For a subset of data that included one-minute vehicle counts for each crossing, the statistical model showed a number of significant factors contributing to driver yielding such as, intersection configuration, crossing distance, one-minute traffic count, posted speed limit, location of the beacons (overhead or roadside), sign face (e.g., pedestrian, trail, etc.), and presence of yield line, school, or transit stop.

Before-and-after studies for the RRFB reported increased yielding rates although with large variability in the magnitude of the increase. Other more recent studies (Fitzpatrick et al., 2015; Fitzpatrick, Avelar, et al., 2016; Morrissey, 2013; Potts et al., 2015) examined the yield rate at treated sites with either staged or non-staged pedestrian observations, also found a wide range of effectiveness, varying by time of day, treatment activation, and beacon location. A 2020 study (Monsere, Kothuri, & Anderson, 2020) in Oregon found higher yielding rates with the presence of beacons in the median; however, the increase was not large (<5%) and was not statistically significant.

2.3. LED-Ems

Most previous studies on the LED-Em pedestrian/school crossing signs only included a few locations (Hawkins & Bektas, 2012; Ellis & Tremblay, 2014; Hourdos, 2018). These studies found, in

Drivers See...	Appropriate Action	Pedestrians See...	Appropriate Action
	Proceed with caution. The signal rests in dark mode		Push the button to cross street.
	Slow down, prepare to stop. Pedestrian has activated the push button		Wait as traffic is preparing to stop.
	Stop if safe to do so.		Continue waiting as traffic is beginning to stop
	Stop, remain stopped.		Start Crossing, look for traffic from both directions prior to crossing.
	Stop, then proceed with caution if crosswalk is clear.		Continue crossing, the countdown indicates how much time is left to finish crossing the street.
	Proceed with caution.		Push the button to cross street.

Note: images are from 2009 MUTCD where R = red lens, Y = yellow lens, FY = flashing yellow indication, SY = steady yellow indication, SR = steady red indication, and FR = alternating flashing red indication.

Fig. 2. Pedestrian hybrid beacon sequence along with appropriate actions for driver and pedestrian.

general, low driver yielding. At a crosswalk with an LED-Em in Des Moines (Hawkins & Bektas, 2012), motorist yielding observed was highest in the morning at 46%, followed by lower yielding rates of 40% at noon, and 30% in the afternoon. A Vermont case study (Ellis & Tremblay, 2014) noted that overall yield rate decreased at the site from year one to year four of installation, but still remained 12% higher than the yield rate before installation. Observations at a Minnesota (Hourdos, 2018) site included no improvement in driver yield rates after the installation of the LED-Em with less than 20% of pedestrians activating the treatment during crossings.

A Texas study (Finley et al., 2020; Rista & Fitzpatrick, 2020) collected data at several LED-Em installations. Higher hourly volumes, speeds 45 mph (72.4 kph) and greater, lack of sidewalks, and 12-ft (3.7 m) lanes (no deviation from baseline 12-ft (3.7 m) lane width) were found to adversely affect yield probability. The authors concluded that based on the findings, LED-Em would be a suitable candidate treatment at sites with sidewalks, lower operating speeds and traffic volumes, and narrow lanes.

2.4. Key findings from literature

The main findings from the literature review included the following:

- None of the previous research efforts included nighttime data collection.
- PHBs have been found to have very high driver yielding rates including sites with wider crossing distances and operating speeds up to 54 mph (86.9 kph), making PHBs a preferred treatment for higher speed or multilane roadways.
- While RRFBs have been shown to be an effective treatment, several studies have demonstrated a wide range of effectiveness. The treatment was found to be more effective for crossings with shorter crossing distance and presence of a median, presence of yield lines, and near a school or transit stop.
- Most of the studies on the effectiveness of LED-Ems only included a few locations. The 2019 TxDOT study (Finley et al., 2020) collected data at 13 locations and found an average driver yield rate of 40%.

These findings suggested that in the examination of nighttime conditions, study site selection should consider a range of geometric conditions including number of lanes (crossing distance), median presence, and speed (operating or posted).

3. Study approach

Researchers employed a staged pedestrian crossing study approach in this study. The intent was to collect data at 30 sites during both daytime and nighttime conditions; however, equipment malfunctions and in a few cases, concerns with the available nighttime street lighting conditions, limited nighttime data collection. The following sections describe site selection, site characteristics, data collection methodology, and data reduction processes.

3.1. Site selection

The goal was to select 10 sites for each of the treatments of interest. Sites were selected with consideration of having a range of posted speed limits and median type represented. In addition, sites were selected to represent either 2- or 4-lane roads. Data collection efficiency was the final consideration in site selection. For the LED-Em treatment, all feasible sites were considered. The sites with PHBs were concentrated in Austin, which reflects the city with the most PHB installations in Texas. More regions within Texas have installed the RRFB (and the LED-Em) and the site selection reflected that diversity with sites being in or near the three major population regions of Texas (Houston, Dallas/Fort Worth, and San Antonio).

3.2. Site characteristics

Researchers collected data at 10 PHB sites, 12 RRFB sites, and 8 LED-Em sites. In addition, the daytime data collected at 12 LED-Em sites in the late spring of 2019 (Finley et al., 2020) were also used in the analysis. Researchers used aerial photographs to identify the roadway geometric characteristics and these characteristics were confirmed in the field as needed. Table 1 lists the variable descriptions considered in the statistical analysis. Additional variables were collected for each site, such as presence of bike lane or on-street parking, crosswalk pavement marking pattern type, and distance to streetlight; however, those variables were either uniform for all sites or were determined in the preliminary analyses to be not influential with respect to driver yielding.

Table 2 lists the site characteristics for the sites and Table 3 provides the summary statistics or number of sites by treatment type. All PHB sites had an advance stop line and continental crosswalk pavement markings. Most had an advance warning sign. For motorists, the PHB rests in the dark mode and when activated transitions to flashing yellow, steady yellow, steady red, and then flashing red. The flashing yellow provides an additional warning to the drivers that the device will soon be transiting to red. For these 10 sites the flashing yellow lasted between 4 and 9 s. The flashing red ranged between 24 and 35 s.

One of the RRFB sites had diagonal crosswalk pavement markings with all remaining sites having continental pavement markings at the crosswalk. The length of time the device was active (i.e., flashing yellow) ranged between 25 and 35 s. Researchers did not collect nighttime data at one location because the equipment had malfunctioned, and the device would not activate when the pedestrian pushed the button.

Because of challenges during data collection for the LED-Em sites, attempts to collect data between November 2019 to February 2020 occurred at 8 rather than the preferred 10 sites. The daytime data collected at 12 sites during the May 2019 study (Finley et al., 2020) were included in the analysis to expand the sample size. Additional challenges were faced with regards to the nighttime data collection for the LED-Em sites. At two of the sites, the data collectors did not feel comfortable with the combination of operating speed, available streetlight levels for both sides of the street, type of development, and/or lack of general pedestrian activity level; therefore, nighttime data collection was stopped at those two sites. Table 2 Indicates if the data available for analysis represented: (a) daytime data collected in spring of 2019, (b) daytime

Table 1
Variable Descriptions.

Variable Name, Variable	Description	Levels/Range
ActiveSLGroup, Active Speed Limit Group	Speed limits groups	Low: 35 mph and less (56.3 kph and less) High: 40 mph and more (64.4 kph)
ActiveSL, Active Speed Limit	Speed limit active during data collection (mph). Variable used as a surrogate for typical operating speeds.	20 mph (32.2 kph) to 50 mph (80.5 kph)
AdvSign, Advance Sign	Is an advance warning sign present for the site?	Yes = advance sign present No = no advance sign present
HourlyVol, Hourly Volume	Estimated hourly volume just prior to the staged pedestrian crossing based on 1-min count	Day: 118 to 3741, average 754 veh/hr Night: 88 to 3287, average 596 veh/hr
LnWdGroup, Lane Width Group	Lane width groups	Narrow: 10.5 or 11 ft (3.2 or 3.4 m) Typical: 11.5 or 12 ft (3.5 or 3.7 m) Wide: 13 ft (4.0 m) or more
LnWd, Lane Width	Lane width	9 to 14 ft (2.7 to 4.3 m), average 11.3 ft (3.4 m)
Legs, Legs	Number of legs	2 legs = midblock crossing 3 legs = T-intersection 4 legs = cross intersection.
LightLevel, Light level	Natural light level during data collection	Day Night
MedType, Median Type	Type of median	raised, two-way left turn lane (TWLTL), or none
Develop, Develop	Type of land development	Com = commercial Hos/Uni = hospital/university (Hos/Uni) Res = residential Mix = mix of land uses
#Thru, Number of Through Lanes	Number of through lanes on the major road, total of both directions	2 to 4 lanes with one site having 5 lanes
PSL, PSL	Posted speed limit	30 mph (48.3 kph) to 50 mph (80.5 kph)
Site, Site	Pedestrian treatment (PHB, RRFB, or LED-Em), two-letter city code, three-digit site number.	Unique for each site
TreatType, Treatment Type	Type of treatment	PHB, RRFB, or LED-Em
Line, Yield or Stop Line	Presence of a stop or yield line prior to the crosswalk	Stop (only PHBs) Yield (for RRFBs or LED-Ems) None

Table 2
Site characteristics.

Site[1]	Data[2]	#Thru	Ln Wd[3]	PSL[4]	Legs	Med Type	AdvSign	Line	D-HV[5]	N-HV[5]
PHB-AU-001	B, C	5	10	40	3	Raised	Yes	Stop	1739	1001
PHB-AU-013	B, C	4	11	40	2	TWLTL	Yes	Stop	488	261
PHB-AU-014	B, C	2	10	35	2	None	Yes	Stop	613	239
PHB-AU-027	B, C	2	10	30	3	TWLTL	Yes	Stop	1231	896
PHB-AU-035	B, C	4	9.5	35	2	None	Yes	Stop	1759	1802
PHB-AU-042	B, C	2	10	35	2	TWLTL	Yes	Stop	484	570
PHB-AU-045	B, C	4	11	40	4	None	Yes	Stop	453	439
PHB-AU-066	B, C	4	11	45	4	Raised	Yes	Stop	809	870
PHB-AU-067	B, C	2	11	30	2	TWLTL	Yes	Stop	458	149
PHB-AU-068	B, C	4	9	40	3	TWLTL	Yes	Stop	3741	3287
RRFB-AU-004	B, C	2	10	30	4	Raised	No	Yield	351	257
RRFB-CS-003	B, C	2	12	30	3	TWLTL	No	None	525	188
RRFB-DEN-01	B, C	4	9.5	30	3	Raised	Yes	Yield	799	444
RRFB-GA-002	B, C	4	11	40	4	Raised	Yes	Yield	901	666
RRFB-GA-006	B, C	4	11	40	4	Raised	No	Yield	324	333
RRFB-GA-007	B, C	4	11	45	4	Raised	No	Yield	936	978
RRFB-GA-010	B, C	4	11.5	40	4	Raised	Yes	Yield	268	281
RRFB-GA-013	B, C	4	12	40	4	Raised	No	Yield	843	690
RRFB-MA-002	B, C	2	14	30	3	None	Yes	None	453	124
RRFB-SA-002	B, C	4	12	40	3	Raised	Yes	Yield	703	930
RRFB-SA-005	B	2	13.5	30	4	Raised	Yes	None	835	ND
RRFB-SA-006	B, C	2	14	30	3	Raised	Yes	None	118	120
LED-Em-CB-001	A, B, C	4	12	35	3	TWLTL	Yes	None	404	161
LED-Em-CB-002	A, B	4	12	35	4	TWLTL	Yes	None	609	ND
LED-Em-CS-001	A, C	4	11	30	2	Raised	Yes	Yield	437	178
LED-Em-DF-001	A, B, C	4	12	45	2	TWLTL	Yes	None	594	437
LED-Em-HS-001	A	2	12	50	4	None	No	None	686	ND
LED-Em-KT-001	A	4	12	35	3	Raised	No	Yield	438	ND
LED-Em-NB-001	A, B, C	2	11.5	30	3	None	Yes	None	177	88
LED-Em-NS-001	A, B, C	4	10.5	30	3	None	No	None	849	413
LED-Em-RW-001	A	2	11	50	3	TWLTL	No	None	482	ND
LED-Em-SA-001	A, B	4	12	35	2	Raised	Yes	Yield	1633	ND
LED-Em-SA-002	A	2	12	30	2	None	No	None	354	ND
LED-Em-SP-001	A, B, C	4	12	30	3	Raised	Yes	None	351	280
LED-Em-YT-001	A	2	11	30[6]	4	None	No	None	539	ND

[1] Variable descriptions available in Table 1.
[2] Calendar period for data collection along with light level, where A = day, spring 2019; B = day, winter 2019–2020; and C = night, winter 2019–2020.
[3] LnWd = 9, 9.5, 10, 10.5, 11, 11.5, 12, 13.5, 14 ft = 2.7, 2.9, 3.0, 3.2, 3.4, 3.5, 3.7, 4.1, 4.3 m, respectively.
[4] PSL = 30, 35, 40, 45, 50 mph = 48.3, 56.3, 64.4, 72.4, 80.5 kph, respectively.
[5] D-HV = daytime average hourly volume (veh/hr), N-HV = nighttime average hourly volume (veh/hr), ND = no data collected.
[6] Site in school zone active during data collection; therefore, 20 mph (32.2 kph) used in analysis.

data collected in winter of 2019–2020, or (c) nighttime data collected in the winter of 2019–2020. At one of the sites, the LEDs flashes for 80 seconds upon activation. The other sites where the flash rate is known have a range of 30–60 s for the length of time the LEDs were flashing.

3.3. Data collection protocol

The protocol for data collection was developed and refined based on experiences from several previous research projects (see especially Fitzpatrick & Pratt, 2016; Fitzpatrick et al., 2013). For this study, a goal of 60 staged pedestrian crossing events or four hours of data (the smaller of the two) was collected at each location. A staged pedestrian is a member of the research team who wears a "uniform" of gray t-shirt or sweatshirt, blue jeans, and predominantly dark shoes while completing the street crossings. A baseball cap and sunglasses are permitted. The stage pedestrian is trained to approach the crossing in a similar manner for each location so to minimize the effects of pedestrian behavior on drivers. Training also covers when the staged pedestrian should approach the pedestrian push button so that there is at least one driver who must decide whether to yield or not yield to the waiting pedestrian once the treatment is activated. Placing a foot on the pavement is also part of the training so that the staged pedestrian meets the state law requirement that the pedestrian needs to be on the pavement (rather than just waiting on the curb).

The staged pedestrian activates the pedestrian treatment and then waits until the vehicular traffic approaching has stopped before initiating the crossing. For the next staged pedestrian crossing event, the staged pedestrian is to have at least 1 minute between events so that all queued vehicles clear before beginning another staged crossing. The 1-minute gap also permits the counting of the number of vehicles present at the site without including vehicles being in a queue for a previous crossing pedestrian.

The second member of the research team waits in an area where he or she will not attract the attention of drivers or natural pedestrians while at the same time having a clear view of the crosswalk, pedestrians, and traffic from both directions. This person records the number of drivers that did not and did yield to the staged pedestrian.

A video camera was also installed prior to data collection. The recordings served as a backup for the yielding data collected and was used to obtain the 1-min volume vehicle counts prior to each pedestrian crossing. While the site could be within a school zone, researchers attempted to collect data when the school zone was not active. Researchers collected data when a school zone was active at only one site (YT-001) and the school zone speed limit was used in the analysis rather than the posted speed limit.

3.4. Data collection

For this research effort, researchers began collecting data in November 2019 and completed the data collection in February

Table 3
Summary statistics or number of sites by treatment type.

Variable Name[1]	Level[2]	LED-Em	PHB	RRFB
LnWd	Min	10.5 ft (3.2 m)	9 ft (2.7 m)	9.5 ft (2.9 m)
	Max	12 ft (3.7 m)	11 ft (3.4 m)	14 ft (4.3 m)
	Ave	11.6 ft (3.5 m)	10.3 ft (3.1 m)	11.8 ft (3.6 m)
PSL	Min	30 ft (48.4 m)	30 ft (48.3 m)	30 ft (48.3 m)
	Max	50 ft (80.5 m)	45 ft (72.4 m)	45 ft (72.4 m)
	Ave	35.8 ft (57.6 m)	37 ft (59.5 m)	35.4 ft (57 m)
HourlyVol, day	Min	177 veh/hr	453 veh/hr	118 veh/hr
	Max	1633 veh/hr	3741 veh/hr	936 veh/hr
	Ave	581 veh/hr	1177.5 veh/hr	588 veh/hr
HoulyVol, night	Min	88 veh/hr	149 veh/hr	120 veh/hr
	Max	437 veh/hr	3287 veh/hr	978 veh/hr
	Ave	259.5 veh/hr	951.4 veh/hr	455.5 veh/hr
MedType	None	5	3	1
	Raised	4	2	10
	TWLTL	4	5	1
AdvSign	No	6	0	5
	Yes	7	10	7
Line	None	10	0	4
	Stop	0	10	0
	Yield	3	0	8
Legs	2	4	5	0
	3	6	3	5
	4	3	2	7
Dev	Commercial	4	4	4
	Mix	1	4	1
	Residential	7	2	6
	Hos/Uni	1	0	1

[1] Variable descriptions available in Table 1.
[2] Column includes Min = minimum, Max = maximum, Ave = average, or variable level

2020. Data from a previous effort (collected May 2019) were also included in the statistical analysis. This study included about 224 h of video recordings. The previous TxDOT study provided about 48 h of video (Finley et al., 2020). Table 4 summarizes the number of staged pedestrian crossings along with the total number of drivers reacting to the staged pedestrians by treatment type, light level, and data collection period. Data for 9,301 drivers over 3,871 pedestrian crossings were reduced.

3.5. Video data reduction

Video data reduction primarily focused on obtaining 1-min volume counts. The video was also used to confirm the driver yielding or not yielding data for several sites, as the video permitted replaying of the recording which allowed for better quality control, especially at the PHB sites.

Researchers used the video to count the number of vehicles driving across the crosswalk in both directions for 1-min prior to each staged pedestrian crossing. The 1-min increment provides an appreciation of the amount of traffic present just prior to the specific pedestrian crossing. The theory is that with more vehicles, drivers may be hesitant to stop for the pedestrian because of a concern with being rear-ended. In general, the researcher identified the video frame during which the staged pedestrian pressed the button to activate the treatment and then rewound the video for at least 1 minute. In a few cases a slightly longer time period was used to be able to avoid starting the count with a vehicle on the crosswalk. There were also a few cases when a shorter time period was used because of the start time of the video file.

Researchers converted the 1-min traffic counts into hourly volumes by using the exact number of seconds reflected in the vehicle count. The final columns in Table 2 provide the average hourly vehicle counts by site and light level.

4. Analysis

Data were collected by pedestrian crossing event where the number of vehicles yielding and not yielding was recorded. This format was revised to reflect the decision of each driver so that each driver was assigned a value of 1 if yielding or a value of 0 if not yielding.

The objective of this analysis was to explore the relationship between driver yielding and independent variables and assess

Table 4
Number of staged pedestrian crossings and drivers included in analysis.

Current or previous study	Data collection dates	Treatment type	Daytime number of staged Ped crossings	Nighttime number of staged Ped crossings	Daytime number of drivers	Nighttime number of drivers
Current	November 2019 – February 2020	PHB	570	623	1746	1623
		RRFB	709	546	1420	980
		LED-Em	421	326	1523	579
		Subtotal	1700	1495	4689	3182
Previous	May 2019	LED-Em	676	0	1430	0
Total Used in Analysis	Grand Total	All	2376	1495	6119	3182

their effects on the probability of driver yielding. Because the outcome variable is dichotomous (i.e., did the driver yield or not yield), a logistic regression model was employed.

The log-odds of the probability of driver yielding given the value of independent variables (X), $P(Y = Yield|x)$, can be expressed as follows:

$$g(\boldsymbol{x}) = \ln\left[\frac{P(Y = Yield|\boldsymbol{x})}{1 - P(Y = Yield|\boldsymbol{x})}\right] = \beta_0 + \beta_1 x_1 \cdots + \beta_k x_k \quad (1)$$

where $g(x)$ is the logit (log-odds), **x** denotes a value of the independent variables $X_1, \cdots, X_k$ (such as TreatType, LightLevel, ActiveSL, HourlyVol, Legs, #Thru, Lines, etc.). Note that the logit, $g(x)$, is linear in its parameters. The intercept β_0 represents the baseline level of the logit, and β_k represents the change in the logit that occurs with a unit change in X_k. The conditional probability that the driver yields at site i in j^{th} pedestrian crossing can be expressed as

$$P(Y_{ij} = Yield|x) = \frac{e^{g(x)}}{1 + e^{g(x)}} = \frac{e^{\beta_0 + \beta_1 x_{i,1j} \cdots + \beta_k x_{i,kj}}}{1 + e^{\beta_0 + \beta_1 x_{i,1j} \cdots + \beta_k x_{i,kj}}} \quad (2)$$

To account for possible correlation in the outcome variable obtained for multiple time periods (multiple crossings) from the same site, the Generalized Estimating Equations (GEE) is employed as an estimation method.

Prior to conducting the logistic regression, preliminary analyses were performed using a normal linear model, specifically the analysis of covariance (ANCOVA) model, applied to driver yielding rates averaged by each site and light level. An ANCOVA model was considered since many of the independent variables are site based rather than individual crossing event based and the average driver yielding rates satisfy the underlying assumptions for ANCOVA models. The results from a linear model are also easier to interpret when considering whether the findings are reasonable.

The following section provides a summary of the findings from the two statistical analysis techniques selected for this study:

- Analysis of covariance (ANCOVA) model based on mean yield rates where average is taken over all staged crossings at each site by light level.
- Logistics regression model based on individual driver response to a staged pedestrian crossing.

5. Results

5.1. Average driver yielding rate per site

Each driver responding to a staged pedestrian crossing was coded as being either 1 (for yielding) or 0 (for not yielding). The average driver yielding rate (DYR) was calculated by:

$$DYR = \frac{\sum NumberofDriversYielding}{\sum TotalNumberofDrivers} \quad (3)$$

Table 5 lists the average driver yielding rate by site and by treatment type for daytime and nighttime conditions and Fig. 3 illustrates the same data, plotted across a range of hourly volumes in the data. Table 5 also provides the DYR difference between nighttime and daytime for each site. The distribution of daytime average driver yielding rates for this study is similar to previous studies with the following observations:

Table 5
Average driver yielding rate by site for daytime and nighttime conditions.

Site	Daytime DYR	Daytime drivers	Nighttime DYR	Nighttime drivers	DYR difference (Night-Day)
PHB-AU-001	95%	320	97%	263	2%
PHB-AU-013	100%	153	95%	107	−5%
PHB-AU-014	100%	73	99%	86	−1%
PHB-AU-027	96%	112	97%	145	0%
PHB-AU-035	96%	169	96%	190	0%
PHB-AU-042	98%	102	96%	98	−2%
PHB-AU-045	98%	158	94%	125	−5%
PHB-AU-066	98%	231	99%	221	1%
PHB-AU-067	100%	98	97%	78	−3%
PHB-AU-068	95%	330	95%	310	0%
PHB Average	**97%**	**1746**	**96%**	**1623**	**−1%**
RRFB-AU-004	70%	84	76%	84	6%
RRFB-CS-003	74%	93	83%	69	8%
RRFB-DEN-001	86%	140	91%	155	5%
RRFB-GA-002	81%	162	79%	117	−2%
RRFB-GA-006	79%	97	79%	63	0%
RRFB-GA-007	78%	165	97%	72	20%
RRFB-GA-010	85%	106	88%	66	3%
RRFB-GA-013	90%	145	96%	85	7%
RRFB-MA-002	76%	95	75%	73	0%
RRFB-SA-002	60%	159	72%	154	12%
RRFB-SA-005	68%	121	ND	ND	ND
RRFB-SA-006	70%	53	67%	42	−3%
RRFB Average	**77%**	**1420**	**83%**	**980**	**5%**
LED-Em-CB-001	25%	224	12%	77	−14%
LED-Em-CB-002	29%	400	ND	ND	ND
LED-Em-CS-001	84%	80	71%	78	−13%
LED-Em-DF-001	16%	354	3%	131	−13%
LED-Em-HS-001	18%	160	ND	ND	ND
LED-Em-KT-001	42%	117	ND	ND	ND
LED-Em-NB-001	58%	151	38%	45	−20%
LED-Em-NS-001	58%	295	36%	123	−22%
LED-Em-RW-001	15%	126	ND	ND	ND
LED-Em-SA-001	5%	643	ND	ND	ND
LED-Em-SA-002	31%	80	ND	ND	ND
LED-Em-SP-001	38%	211	20%	125	−18%
LED-Em-YT-001	69%	112	ND	ND	ND
LED-Em Average	**29%**	**2953**	**27%**	**579**	**−17%**

ND = No data available.

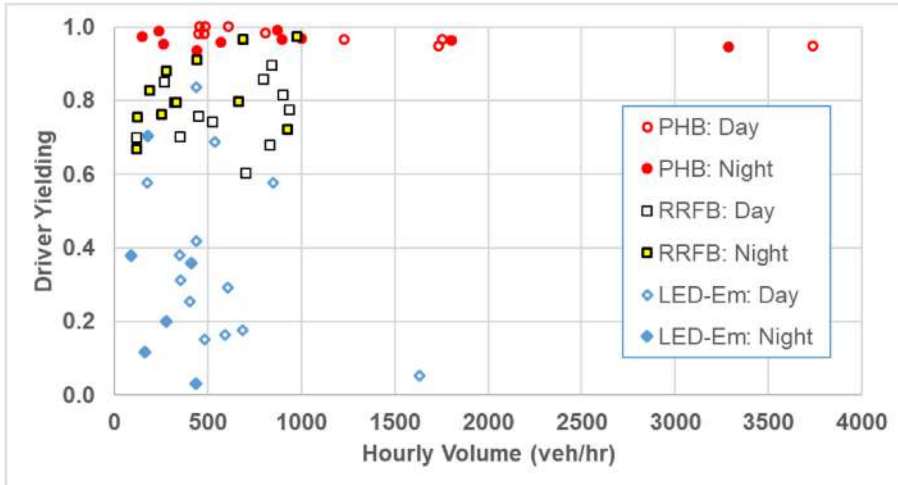

Fig. 3. Driver Yielding by Treatment, Light Level, and Site.

- PHB – average driver yielding rate is high (range of 95–100% with the average being 97%).
- RRFB – a large range of per site average driver yielding rates (60–90%) is present with an average (77%) below the yielding rate for the PHBs.
- LED-Em – an even larger range of per site average driver yielding rates (5–84%) compared to RRFBs and PHBs with overall daytime average (29%) below both the PHBs and RRFBs.

The focus of this research effort was on nighttime conditions as compared to daytime conditions. Table 5 shows that the overall average driver yielding rates for nighttime conditions are generally similar to the rates observed for daytime conditions. For PHBs the rates appear to be very similar (i.e., average of 97% for daytime and 96% for nighttime across all PHB sites and within each site the daytime and nighttime rates are similar).

For LED-Em, the overall average nighttime rate also looks similar to daytime with 29% of the drivers during the day and 27% of the drivers during the night yielding to pedestrians. Within each LED-Em site, however, driver yielding during the day is noticeably higher than driver yielding during the night. When reviewing the difference between nighttime and daytime yielding within each site when nighttime data were available, those LED-Em sites appear to have large differences between daytime and nighttime. As shown in the final column of Table 5, the differences were between 13% and 22% lower nighttime driver yielding for a site. The statistical analysis (see following section) did find a statistically significant difference in daytime and nighttime yielding when site-to-site variability (resulting from different site characteristics) is incorporated into the analysis.

Previous research along with the range of yielding rates observed, especially for the RRFB and the LED-Em, indicate that other factors than just the subject traffic control device is contributing to the variability of the yielding results. The next two sections discuss the findings from the statistical evaluations that examined potential variable effects on yielding, including the key question for the research – is driver yielding different during daytime and nighttime conditions.

5.2. ANCOVA model for assessing the effect of treatment type based on mean yield rates for sites and light level

There were repeated observations for day and night from 35 sites in the dataset. Researchers conducted several preliminary analyses to identify the best approach and variables to include in the statistical models. Initially, researchers considered all variables, and examined the various combinations to identify the model that seemed to be the most appropriate in terms of model goodness of fit criteria and interpretation. Researchers conducted the analysis utilizing a mixed effect ANCOVA model with LightLevel (i.e., day or night) and site characteristic variables (including TreatType, ActiveSLGroup, and LnWdGroup as discrete factors and Mean (HourlyVol) as a covariate) as fixed effects. Researchers also included Site as a random effect to account for the fact that values of the site characteristic variables are repeated in the data. Two-way interaction effects between TreatType and other site characteristic variables were included in the model to see if the effect of treatment type varies with the levels of other site characteristic variables. Table 6 shows the estimated model coefficients, and Table 7 provides the effect tests results (based on F-tests) for the variables included in the model shown in Table 6. Note that LnWdGroup was included as a nested effect (i.e., effect nested within TreatType) because the levels of LnWdGroup were different for each TreatType (i.e., PHB has only narrow LnWdGroup, LED-Em has narrow and typical, and RRFB has all three levels (narrow, typical, and wide)).

It can be observed from Table 7 that the interaction effects TreatType*LightLevel and TreatType*ActiveSLGroup as well as the main effects (TreatType, LightLevel, ActiveSLGroup, and LnWdGroup nested within TreatType) are statistically significant at $\alpha = 0.05$ and TreatType*Mean(HourlyVol) is statistically significant at $\alpha = 0.1$. When there are significant interaction effects, the effect of each factor involved in the interaction needs to be assessed conditionally on the levels of the other factor because the effect might be different for each level of the other factor. The results from Tables 6 and 7 indicate that the effectiveness of the treatment may vary between nighttime and daytime conditions. The results also show that speed limit groups and lane width groups influence on driver yielding may vary by treatment type. Therefore, the effect of LightLevel needed to be assessed for each level of TreatType. Likewise, the effect of ActiveSLGroup or LnWdGroup needed to be assessed for each level of TreatType.

The research team also determined the least squares means (LSM) of the response (driver yielding rate) for each factor-level combination of significant interactions along with the results of a multiple comparison test. When there are multiple factors in the model, it is not fair to make comparisons between raw cell means in data because raw cell means do not compensate for other factors in the model. The LSM are the predicted values of the response for each level of a factor that have been adjusted for the other factors

Table 6
ANCOVA model including treatment type, light level, and other site characteristic variables using per site mean yield rates.

Parameter Estimates	Estimate	Std Error	DFDen	*t* ratio	Prob > |*t*|
Intercept	0.6982278	0.028413	33.48	24.57	<0.0001
TreatType[LED-Em]	−0.430449	0.029525	26.68	−14.58	<0.0001
TreatType[PHB]	0.3071775	0.02723	23.48	11.28	<0.0001
LightLevel[Day]	0.026969	0.007159	35.91	3.77	0.0006
Mean(HourlyVol)	−4.417e−5	3.91e−5	47.15	−1.13	0.2644
ActiveSLGroup[Low]	0.0454034	0.019072	22.32	2.38	0.0262
TreatType[LED-Em]*LightLevel[Day]	0.0756203	0.011038	39.02	6.85	<0.0001
TreatType[PHB]*LightLevel[Day]	−0.019354	0.009628	34.21	−2.01	0.0523
TreatType[LED-Em]*(Mean(HourlyVol)-668.511)	−0.000145	5.828e−5	42.3	−2.49	0.0168
TreatType[PHB]*(Mean(HourlyVol)-668.511)	3.1058e−5	4.314e−5	43.8	0.72	0.4754
TreatType[LED-Em]* ActiveSLGroup[Low]	0.0920804	0.026653	22.66	3.45	0.0022
TreatType[PHB]*ActiveSLGroup[Low]	−0.04332	0.026191	21.75	−1.65	0.1125
TreatType[LED-Em]:LnWdGroup[narrow]	0.1355606	0.029252	22.36	4.63	0.0001
TreatType[RRFB]:LnWdGroup[narrow]	0.0298317	0.039141	21.53	0.76	0.4542
TreatType[RRFB]:LnWdGroup[typical]	0.0245799	0.044553	21.08	0.55	0.5870

Summary of Fit	
RSquare	0.987749
RSquare Adj	0.984512
Root Mean Square Error	0.047239
Mean of Response	0.685299
Observations (or Sum Wgts)	68

Notes: Std Error = Standard Error; DFDen: Degrees of Freedom in denominator; *t* ratio: test statistic used for the t test; Prob > |*t*|: *p*-value for the *t*-test.

Table 7
Fixed Effect Tests for Model in Table 6.

Source	Nparm	DF	DFDen	*F* Ratio	Prob > F
TreatType	2	2	25.09	113.2088	<0.0001
LightLevel	1	1	35.91	14.1898	0.0006
Mean(HourlyVol)	1	1	47.15	1.2759	0.2644
ActiveSLGroup	1	1	22.32	5.6676	0.0262
TreatType*LightLevel	2	2	35.06	26.1621	<0.0001
TreatType*Mean(HourlyVol)	2	2	44.07	3.0958	0.0552
TreatType*ActiveSLGroup	2	2	22.29	5.9805	0.0083
LnWdGroup[TreatType]	3	3	21.69	7.5270	0.0012

Notes: Nparm: Number of parameters; DF: Degrees of Freedom; DFDen: Degrees of Freedom in denominator; *F* Ratio: test statistics used for the F test; Prob > F: *p*-value for the F test.

in the model. A multiple comparison procedure such as Tukey's Honestly Significant Difference (HSD) test can be employed to determine which pairs of factor levels (estimated by the least squares means) are statistically significantly different (see, e.g., Spiegelman, Park, & Rilett, 2021). When multiple hypotheses are tested based on the same dataset (e.g., conducting several pairwise *t*-tests to determine which of the factor levels are statistically different), the multiple comparisons problem arises. That is, even if each individual test is performed at the specified comparison-wise Type I error rate (e.g., $\alpha = 0.05$), an overall experiment-wise error rate (the probability of making at least one incorrect rejection) can significantly exceed the designated significance level α. Tukey's HSD test is a popular procedure that accounts for multiple comparisons on an experiment-wise basis so that the overall experiment-wise type I error rate is limited to α.

Fig. 4 shows the LSM plots for the comparison of daytime and nighttime driver yielding rates by treatment type. The plot shows that driver yielding was slightly higher at night for RRFBs, lower at night for LED-Ems, and similar for PHBs. While differences can be seen in Fig. 4, the LSM Differences Tukey HSD test shown in Table 8 demonstrated that whereas the treatment types were statistically different, driver yielding by light level (day or night) for PHBs and RRFBs were similar but were different for LED-Ems.

Fig. 5 shows the comparison of speed limit groups, and Table 9 provides the corresponding LSM Differences Tukey HSD results. The differences among the three treatments were again obvious with LED-Ems being statistically different from PHBs and RRFBs.

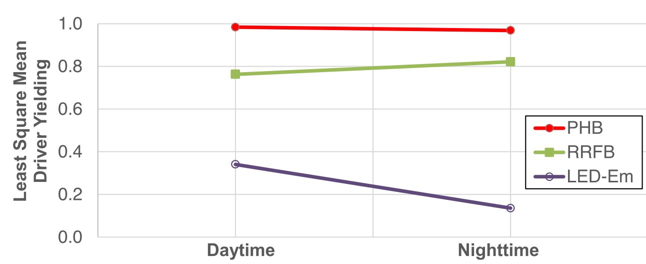

Fig. 4. LSM Driver Yielding for Daytime and Nighttime by Treatment Type.

In addition for LED-Ems, the driver yielding rate for the high-speed group was lower than the low-speed group. There was a minimal difference between speed limit groups for PHBs and RRFBs.

Fig. 6 shows the comparison of lane width groups and treatment type. Table 10 provides the corresponding LSM Differences Tukey HSD results. The differences among the three treatments were again obvious. These data also show an insignificant difference between lane width groups for RRFBs, and a statistically significant difference between narrow and typical lane width groups for LED-Ems.

As explained above, the significant interaction terms indicate that the effect of site characteristic variables as well as light conditions on driver yielding varies by treatment type. These findings

Table 8
LSM differences Tukey HSD by treatment type and light level.

Level	A	B	C	D	Least Sq Mean
PHB, Day	A				0.98349431
PHB, Night	A				0.96826384
RRFB, Night		B			0.82127040
RRFB, Day		B			0.76267557
LED-Em, Day			C		0.34084186
LED-Em, Night				D	0.13566327

Levels not connected by same letter are significantly different at $\alpha = 0.050$.

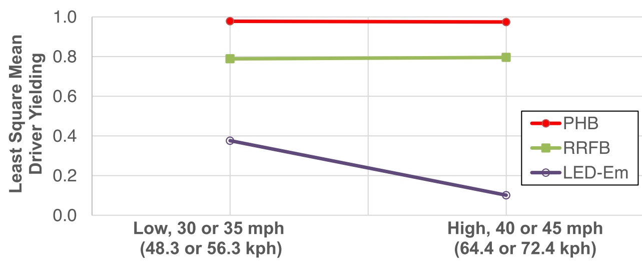

Fig. 5. LSM Driver Yielding for Speed Limit Groups by Treatment Type.

Table 9
LSM differences Tukey HSD by treatment type and speed group.

Level	A	B	C	Least Sq Mean
PHB, Low	A			0.97796261
PHB, High	A			0.97379553
RRFB, Low	A			0.78861591
RRFB, High	A			0.79533007
LED-Em, Low		B		0.37573638
LED-Em, High			C	0.10076875

Levels not connected by same letter are significantly different at $\alpha = 0.050$.

Table 10
LSM differences Tukey HSD by treatment type and lane width.

Level	A	B	C	D	Least Sq Mean
PHB, Narrow	A				0.97587907
RRFB, Narrow	A	B			0.82180473
RRFB, Typical	A	B			0.81655294
RRFB, Wide		B			0.73756129
LED-Em, Narrow			C		0.37381321
LED-Em, Typical				D	0.10269192

Levels not connected by same letter are significantly different at $\alpha = 0.050$.

provided support for conducting additional separate analyses by treatment type.

5.3. PHB

5.3.1. ANCOVA model based on mean yield rates

The best ANCOVA model selected for the PHB is shown in Table 11. The only variables found to be statistically significant was light level and hourly volume. Lower driver yielding was associated with higher volumes with values ranging from 100% to 94%. Light level was also significant with slightly higher driver yielding occurring during the daytime. As a comparison, the least squares mean driver yielding for daytime is 98%, while it is 96% for nighttime conditions. As illustrated in several studies (Fitzpatrick & Pratt, 2016; Fitzpatrick, Cynecki, Pratt, Park, & Beckley, 2019), driver yielding is very high at PHBs. With such high driver yielding at PHBs, finding a difference by a roadway characteristic is challenging and even if a difference was detected statistically, the difference between, say 96% and 98%, is questionable on a practical level. So, while the statistical model found a statistical difference in driver yielding during different light conditions, whether it is of practical difference can be debated.

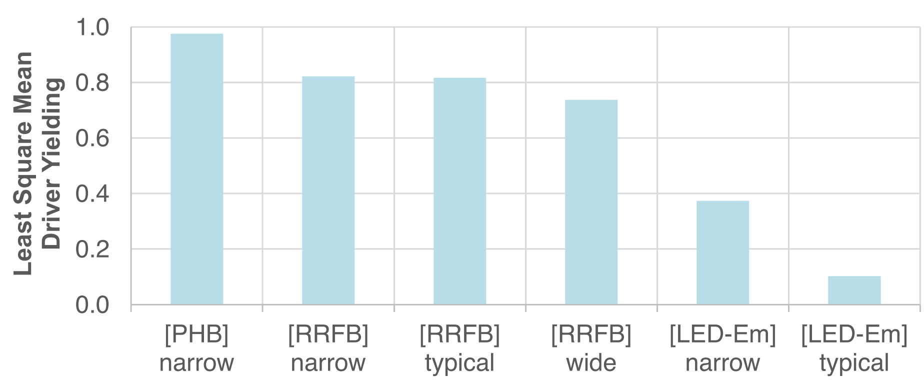

Fig. 6. LSM Driver Yielding for Lane Width Group by Treatment Type.

Table 11
ANCOVA model using per site mean yield rates at PHBs.

Parameter Estimates		Estimate	Std Error	*t* ratio	Prob > |*t*|
Intercept		1.0495921	0.030284	34.66	<0.0001
LightLevel[Day]		0.0081907	0.003749	2.18	0.0432
Log(Mean(HourlyVol))		−0.011905	0.004536	−2.62	0.0177
Summary of Fit					
RSquare	0.363034				
RSquare Adj	0.288097				
Root Mean Square Error	0.016395				
Mean of Response	0.970689				
Observations (or Sum Wgts)	20				

Notes: Std Error = Standard Error; *t* ratio: test statistic used for the t test; Prob > |*t*|: *p*-value for the *t*-test.

Table 12
Logistic Regression Based on Driver Response at PHBs.

Intercept	Level	Estimate	Standard error	95% Confidence limits		Z	Prob > $\|Z\|$
Intercept		4.6580	0.7950	3.0998	6.2162	5.86	<0.0001
LightLevel	Day	0.2379	0.2239	−0.2009	0.6767	1.06	0.2879
LightLevel	Night	0.0000	0.0000	0.0000	0.0000	NA	NA
LnVol		−0.2032	0.1068	−0.4125	0.0062	−1.90	0.0571

Notes: Z: test statistic used for the Z test; Prob > $|Z|$: p-value for the Z test; NA = Not Applicable (the value is not relevant since this level represents base condition for the variable).

5.3.2. Logistic regression based on driver response to crossing pedestrian

Table 12 provide the results of the logistic regression estimated by GEE using Site as a cluster variable for PHB. Only two variables were found significant in the ANCOVA model and were included in the logistic regression. A similar relationship was found for hourly volume (lower driver yielding for higher volumes); however, it was just barely not significant (p-value of 0.0571). The odds ratio (OR) for LightLevel can be estimated by Exp(LightLevel). In this case the effect of LightLevel is not statistically significant, however. OR = 1.2686(=EXP(0.2379)) means that driver yielding for PHB is 1.27 times as likely (although this effect is not statistically significant) to occur during day compared to night.

5.4. RRFB

5.4.1. ANCOVA model based on mean yield rates

The analysis for RRFB was conducted utilizing a mixed effect ANCOVA model with LightLevel and several site characteristic variables as fixed effects and Site as a random effect to account for the fact that values of the site characteristic variables are repeated in the data. Several combinations of variables were considered, including developing a refined variable to capture the apparent variation associated with nearby development. However, most of the site characteristic variables were statistically insignificant. Table 13 provides the model that had the best fit along with reasonable interpretations of the variable estimates.

Light conditions were significant at the 0.05 level (p-value of 0.0286) with a trend of slightly higher driver yielding during nighttime conditions (i.e., least squares mean of 80% for nighttime compared to 75% for daytime). The research team theorized that the brightness levels associated with RRFBs (especially compared to LED-Ems) may be contributing to finding higher driver yielding at night for RRFB and lower driver yielding at night for LED-Ems.

The previous study on the RRFB (Fitzpatrick, Brewer, et al., 2016) also found the following variables significant: presence of median refuge, crossing distance, school within 0.5 mi of crosswalk, presence of yield lines, and direction of vehicle travel (one-way or two-way). All of the sites in this study were two-way streets. All but two of the sites had a raised median, so the lack of variability in that variable limited its use. Presence of yield lines, which was significant in the previous study, was found to be borderline significant (p-value of 0.1086) in this study.

5.4.2. Logistic regression based on driver response to crossing pedestrian

Table 14 provide the results of the logistic regression with including LightLevel and Lines as independent variables for RRFBs, estimated by GEE using Site as a cluster variable. LightLevel was found to be statistically significant at $\alpha = 0.05$ and Lines was significant at $\alpha = 0.1$. The findings indicate that drivers are 1.32 times more likely to yield during the nighttime as compared to daytime (calculated with Exp(LightLevel) or Exp(0.3237)).

Table 13
ANCOVA model using per site mean yield rates at RRFBs.

Variables		Estimate	Std Error	DFDen	t ratio	Prob > $\|t\|$
Intercept		0.7752704	0.024422	10.44	31.74	<0.0001
LightLevel[Day]		−0.025476	0.010032	10.40	−2.54	0.0286
Lines[None]		−0.042848	0.024422	10.44	−1.75	0.1086
Summary of Fit						
RSquare	0.865103					
RSquare Adj	0.851614					
Root Mean Squares Error	0.047154					
Mean of Response	0.791813					
Observations (or Sum Wgts)	23					

Notes: Std Error = Standard Error; DFDen: Degrees of Freedom in denominator; t ratio: test statistic used for the t test; Prob > $|t|$: p-value for the t-test.

Table 14
Logistic regression based on driver response at RRFBs.

Parameter	Level	Estimate	Standard error	95% Confidence limits		Z	Prob > $\|Z\|$
Intercept		0.9043	0.0927	0.7226	1.0860	9.75	<0.0001
LightLevel	Night	0.3237	0.1137	0.1007	0.5466	2.85	0.0044
LightLevel	Day	0.0000	0.0000	0.0000	0.0000	NA	NA
Lines	Yield	0.4121	0.2311	−0.0408	0.8650	1.78	0.0745
Lines	None	0.0000	0.0000	0.0000	0.0000	NA	NA

Notes: Z: test statistic used for the Z test; Prob > $|Z|$: p-value for the Z test; NA = Not Applicable (the value is not relevant since this level represents base condition for the variable).

5.5. LED-Em

5.5.1. ANCOVA model based on mean yield rates

The analysis for LED-Ems was conducted utilizing a mixed effect ANCOVA model with LightLevel and site characteristic variables (including ActiveSLGroup, LnWdGroup, Lines, AdvSign, and #Thru as discrete factors and Mean(HourlyVol) as a covariate) and Site as a random effect to account for the fact that values of the site characteristic variables are repeated in the data. Several variables were found to be statistically significant for the groups of sites with the pedestrian/school crossing warning signs with embedded LEDs (see Table 15). With a range of driver yielding per site of 5% to 84%, having more variables related to a difference in driver yielding for LED-Em as compared to the PHB is not surprising. A discussion of the findings by variable for the LED-Em follows.

- *Light level (LightLevel):* Driver yielding is higher during daylight conditions. The least squares mean driver yielding for daytime was 54% while nighttime has 31%.
- *Hourly volume (HourlyVol):* Similar to the findings for the PHB, higher hourly volumes were associated with lower driver yielding although the range for LED-Em was much greater as compared to the range for PHBs.
- *Active speed limit group (ActiveSLGroup):* When LED-Em was used on roads with 30 or 35 mph (48.3 or 56.3 kph) posted speed limits, driver yielding was found to be higher as compared to roads with 45 or 50 mph (72.4 or 80.5 kph) speed limits with borderline statistical significance (*p*-value of 0.1070). The least squares mean driver yielding for the low-speed group was 48%, while the high-speed group was 37%.
- *Number of through lanes (#Thru):* When a LED-Em was used on a 2-lane road as compared to a 4-lane road, driver yielding was higher with borderline statistical significance (*p*-value of 0.0582). The least squares mean driver yielding for the 2-lane road was 48%, while it was 36% for the 4-lane road group.
- *Lane width groups (LnWdGroup(narrow)):* LED-Em on roads with narrow lane widths (10.5 or 11 ft (3.2 or 3.4 m)) have higher driver yielding as compared to roads with typical lane widths (11.5 or 12 ft (3.5 or 3.7 m)). None of the sites with the LED-Em treatment had a wide lane width (13 ft (4.0 m) or more). The least squares mean driver yielding for narrow lane width was 62% while typical lane widths were associated with 22% driver yielding.
- *Advance lines (Lines):* The value of the yield lines when used with the LED-Em was demonstrated in this evaluation. For this dataset, those with yield lines have a least squares mean driver yielding of 48%, while those sites without a yield line have 36%.

Table 15
ANCOVA model using per site mean yield rates at LED-Ems.

Parameter Estimates	Estimate	Std Error	DFDen	*t* ratio	Prob > |*t*|
Intercept	0.5682309	0.050166	7.188	11.33	<0.0001
LightLevel[Day]	0.1156761	0.018991	13.7	6.09	<0.0001
Mean(HourlyVol)	−0.0003	6.563e−5	10.81	−4.57	0.0008
ActiveSLGroup[Low]	0.0528672	0.026616	4.733	1.99	0.1070
LnWdGroup[narrow]	0.1992876	0.024881	7.473	8.01	<0.0001
Lines[None]	−0.061551	0.025504	6.457	−2.41	0.0494
AdvSign[yes]	0.0474033	0.023678	7.578	2.00	0.0822
#Thru[2]	0.0584831	0.024215	5.24	2.42	0.0582

Summary of Fit	
RSquare	0.942926
RSquare Adj	0.917956
Root Mean Square Error	0.066483
Mean of Response	0.367668
Observations (or Sum Wgts)	24

Notes: Std Error = Standard Error; DFDen: Degrees of Freedom in denominator; *t* ratio: test statistic used for the *t* test; Prob > |*t*|: *p*-value for the *t*-test.

Table 16
Logistic regression based on driver response at LED-Ems.

Intercept	Level	Estimate	Standard error	95% Confidence limits		*Z*	Prob > |*Z*|
Intercept		−2.3342	0.3683	−3.0559	−1.6124	−6.34	<0.0001
LightLevel	Day	1.2102	0.1828	0.8519	1.5685	6.62	<0.0001
LightLevel	Night	0.0000	0.0000	0.0000	0.0000	NA	NA
HourlyVol		−0.0015	0.0003	−0.0021	−0.001	−5.21	<0.0001
ActiveSLGroup	Low	0.7089	0.1292	0.4556	0.9622	5.49	<0.0001
ActiveSLGroup	High	0.0000	0.0000	0.0000	0.0000	NA	NA
LnWdGroup	narrow	1.9476	0.2658	1.4265	2.4686	7.33	<0.0001
LnWdGroup	typical	0.0000	0.0000	0.0000	0.0000	NA	NA
Lines	Yield	0.1592	0.3277	−0.4832	0.8015	0.49	0.6272
Lines	None	0.0000	0.0000	0.0000	0.0000	NA	NA
AdvSign	Yes	0.3006	0.2832	−0.2545	0.8556	1.06	0.2885
AdvSign	No	0.0000	0.0000	0.0000	0.0000	NA	NA
#Thru	2	0.4721	0.2315	0.0184	0.9258	2.04	0.0414
#Thru	4	0.0000	0.0000	0.0000	0.0000	NA	NA

Notes: *Z*: test statistic used for the *Z* test; Prob > |*Z*|: *p*-value for the *Z* test; NA = Not Applicable (the value is not relevant since this level represents base condition for the variable).

Table 17
Contrast estimate results for LED-Ems.

Label	Estimate	Standard error	95% Confidence limit		Chi-square	Prob > ChiSq
LightLevel	1.2102	0.1828	0.8519	1.5685	43.82	<0.0001
OR = Exp(LightLevel)	3.3542	0.6132	2.3441	4.7996	43.82	<0.0001
ActiveSLGroup	0.7089	0.1292	0.4556	0.9622	30.09	<0.0001
OR = Exp(ActiveSLGroup)	2.0318	0.2626	1.5771	2.6175	30.09	<0.0001
LnWdGroup	1.9476	0.2658	1.4265	2.4686	53.67	<0.0001
OR = Exp(LnWdGroup)	7.0116	1.8639	4.1643	11.8058	53.67	<0.0001
#Thru	0.4721	0.2315	0.0184	0.9258	4.16	0.0414
OR = Exp(#Thru)	1.6034	0.3712	1.0185	2.5240	4.16	0.0414

Notes: Chi-Square: test statistic used in the Chi-square test; Prob > ChiSq: p-value of the Chi-square test.

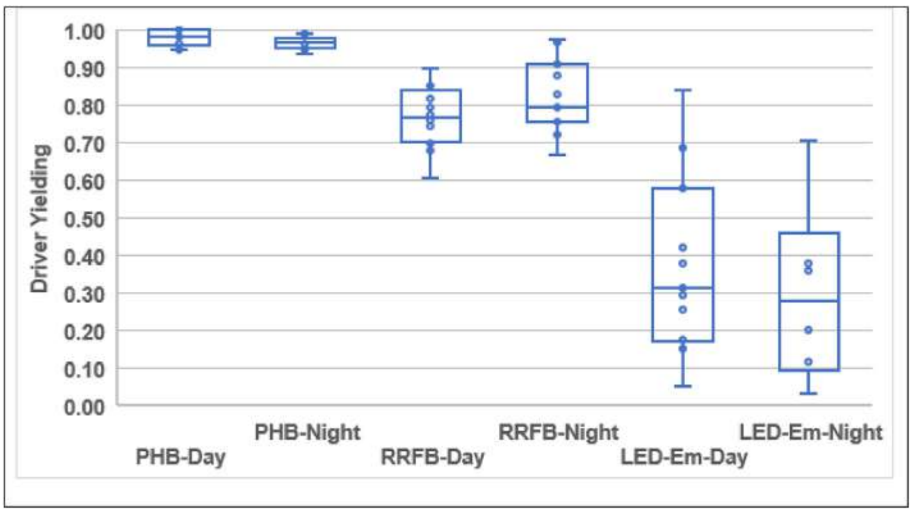

Fig. 7. Per Site Driver Yielding by Treatment Type and Light Level.

- *Advance sign (AdvSign):* The findings from this analysis demonstrated an advantage to having an advance sign for a crossing with an LED-Em. When an advance sign as compared to no sign was present prior to the LED-Em, driver yielding was higher with borderline statistical significance (p-value of 0.0822).

5.5.2. Logistic regression based on driver response to crossing pedestrian

Most of the available variables for the analysis were site characteristics that has the same value for all staged crossings, such as the presence of a yield line or the lane width group. The one variable that varied based upon a particular staged pedestrian crossing was the hourly volume estimated from a count of vehicles that drove over the crosswalk for the 1-min before the crossing. The previous ANCOVA analysis used the average hourly volume at each site (day and night). Logistic regression considers the unique hourly volume associated with the particular staged pedestrian crossing and the results of logistic regression estimated by GEE using Site as a cluster variable are shown in Table 16. The hourly volume was statistically significant again supporting the theory that drivers are less likely to stop when volumes are higher. For the range of hourly volumes included in this study, none of the crossings occurred at a volume where congestion would have been a concern.

Table 17 provides the contrast estimate results which includes the OR estimates for those variables that were found statistically significant in the logistics regression. While the ANCOVA model found Lines and AdvSign significant, they were not significant within the logistic regression model. The OR for LightLevel is estimated by Exp(LightLevel)(=Exp(1.2102)). An OR = 3.3542 means that driver yielding at LED-Ems was 3.35 times as likely to occur during the day compared to night. In other words, for LED-Ems a driver would yield to pedestrians during the daytime 3.35 times more likely compared to the nighttime.

6. Discussion

For this research analysis, researchers considered 9,301 drivers for 3,871 staged pedestrian crossings. All evaluations clearly show that overall, the driver yielding rate was different for the three pedestrian treatments studied with the PHB having the highest yielding and the LED-Ems having the lowest yielding as illustrated in Fig. 7. While overall there is a statistically significant difference between the treatment types, there were sites where a treatment had a higher (or lower) yielding rate than the average for the other treatments. For example, the LED-Em located on a college campus had a daytime driver yielding rate of 84%, which is higher than the average RRFB driver yielding rate of 77% and is near the maximum per site driver yielding rate of 90% observed for any RRFB site. Fig. 7 summarizes the per site findings by treatment type and light level.

The initial statistical evaluation that included interaction terms between treatment type and other site characteristic variables found significant interaction effects as well as a significant difference between treatment types. That evaluation also found that driver yielding compliance for a treatment with respect to daytime and nighttime conditions varies for the different treatments, which supported conducting evaluations separately for each treatment type.

For each treatment, two statistical evaluations were conducted: ANCOVA models that considered per site mean yield rates and logistic regression that considered the individual driver response to crossing pedestrian. Because of the nature of ANCOVA modeling, interpretation of the results is easier; however, the logistic regression modeling provides the opportunity to use data for individual drivers rather than a site average. Being able to use the data for each driver provides the opportunity to consider individual responses rather than collapsing the variability into a site average.

The statistical evaluations for the day and night effectiveness for the PHB found mixed results. The ANCOVA model found a statistically significant difference with daytime driver yielding to be slightly higher, while the logistics regression did not find a statistically significant difference. Even though the ANCOVA model found the PHB to be more effective during the day, the difference was very small (98% during day and 96% during night) and may not be of practical significance. The analyses conducted for each treatment type also provided the opportunity to identify if there are variables that are more influential for one treatment type than another. The PHB, with very high driver yielding, did not have any site characteristics that were found to also influence driver yielding.

The characteristics of the sites with RRFBs included in this analysis provided only limited additional understanding of relationships. A previous study on the RRFB found higher driver yielding at 2-leg (midblock) sites, when a median refuge is present, when a school was within 0.5 miles of the crosswalk, and when yield lines are present. This study found that the light conditions can influence driver yielding with higher yielding being present at night. The presence of yield lines as compared to no lines was also found to affect driver yielding, although the difference was only marginally significant.

This effort provided many insights into how crossing characteristics influence driver yielding at sites with the LED-Em. Using the results from the logistic regression evaluation, higher driver yielding was observed at LED-Em sites in the lower speed limit group (30 or 35 mph (48.3 or 56.3 kph)), with 2 lanes (rather than 4 lanes), with narrow lanes of 10.5 or 11 ft (3.2 or 3.4 m) widths (rather than 11.5 or 12 ft (3.5 or 3.7 m) widths), and lower hourly volumes. The results from the ANCOVA model show a statistically significant difference for yield lines (higher yielding when present) as well as suggesting higher driver yielding for sites with lower average hourly volumes, with narrow lanes, with lower speed limit group (marginally significant), with 2 lanes (marginally significant), and with advance sign (marginally significant).

7. Conclusions

The focus of this research was to identify if the following pedestrian treatments were more or less effective at night: PHB, RRFB, and LED-Em. For the PHB, essentially no difference was found between daytime and nighttime driver yielding. The research found RRFBs to be more effective at night (statistically significant in both ANCOVA and logistical regression evaluations), and the LED-Em to be more effective during the day (statistically significant in both ANCOVA and logistical regression evaluations).

The findings from this study should encourage greater consideration for the PHB to accommodate pedestrian crossings for all conditions. The findings also indicate that the LED-Ems should only be considered for locations associated with lower-speed operations, lower hourly volumes, or narrow lanes. While some of the relationships between roadway geometry and driver yielding at RRFB is known, this research has demonstrated that the reasons for the wide range of driver yielding for RRFBs is still not completely understood and additional research could help to fill that gap. A limitation of this study, along with most if not all research of this nature, is the lack of data for street lighting. The relationship between land use/nearby development and driver yielding is another area where future research is needed. Datasets larger than what was available for this study would probably be needed.

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Nighttime pedestrian fatalities: A comprehensive examination of infrastructure, user, vehicle, and situational factors

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ABSTRACT

Introduction: Pedestrian fatalities in the United States increased 45.5% between 2009 and 2017. More than 85% of those additional pedestrian fatalities occurred at night. *Method:* We examine Fatality Analysis Reporting System (FARS) data for fatal pedestrian crashes that occurred in the dark between 2002 and 2017. Within-variable and before/after examinations of crashes in terms of infrastructure, user, vehicle, and situational characteristics are performed with one-way analysis of variance (ANOVA) and two-sample *t*-tests. We model changes in crash characteristic proportions between 2002–2009 and 2010–2017 using linear regressions and test for autocorrelation with Breusch-Godfrey tests. *Results:* The increase in fatal nighttime pedestrian crashes is most strongly correlated with infrastructure factors: non-intersection unmarked locations (saw 80.8% of additional fatalities); 40–45 mph roads (54.6%); five-lane roads (40.7%); urban (99.7%); and arterials (81.1%). In addition, SUVs were involved in 39.7% of additional fatalities, overrepresenting their share of the fleet. Increased pedestrian alcohol and drug involvement warrant further investigation. The age of pedestrians killed increased more (18.1%) than the national average (3.2%). *Conclusions:* By identifying factors related to the increase in nighttime pedestrian fatalities, this work constitutes a vital first step in making our streets safer for pedestrians. *Practical Applications:* More research is needed to understand the efficacy of different solutions, but this paper provides guidance for such future research. Engineering solutions such as road diets or traffic calming may be used to improve identified infrastructure issues by reducing vehicle speeds and road widths. Rethinking vehicle design, especially high front profiles, may improve vehicle issues. However, the problems giving rise to these pedestrian fatalities are likely a result of not only engineering issues but also interrelated social and political factors. Solutions may be correspondingly comprehensive, employing non-linear, systems-based approaches such as Safe Systems.

1. Introduction

5,977 pedestrians were killed by motor vehicles in the United States in 2017 – a 45.5% increase in pedestrian fatalities over the previous eight years (NHTSA, 2018) (Fig. 1). Other than the 6,080 pedestrians killed in 2016, this represents the highest number of pedestrians killed since 1990. While the number of pedestrian fatalities was nearly cut in half in the 30 years between 1979 and 2009, more than half of that progress was erased in just eight years.

Much of this sharp increase in pedestrian fatalities has occurred at night (Hu & Cicchino, 2018; Retting, 2019). Between 2009 and 2017, pedestrian fatalities increased by 1,868. 1,594 of these fatalities occurred in the dark, representing more than 85% of the total increase (Fig. 2). Only 21.2% of pedestrian fatalities in 2017 occurred in daylight.

This study identifies factors related to the recent nighttime pedestrian fatality trend by examining Fatality Analysis Reporting System (FARS) data between 2002 and 2017 to see whether changes in infrastructure, user, vehicle, or situational characteristics are related to increases in fatal nighttime pedestrian crashes. Doing so will help to ensure safety for this vulnerable group of road users and inform possible solutions.

Hu and Cicchino (2018) recently completed pioneering work on the topic that used Poisson and linear regressions to investigate roadway, environmental, personal, and vehicle factors underlying the recent pedestrian safety crisis. They found that between 2009 and 2016, the largest increases in pedestrian deaths occurred in urban areas, on arterials, at non-intersections, and in dark conditions. Hu and Cicchino (2018) also found that the rise in SUV (sport

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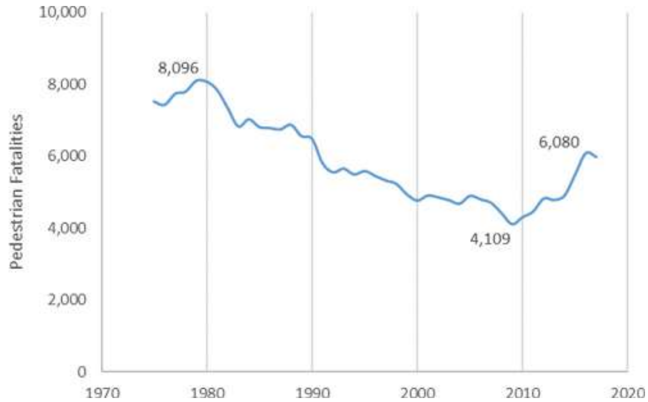

Fig. 1. Pedestrian fatalities in the U.S. *(Data source:* NHTSA, 2018*).*

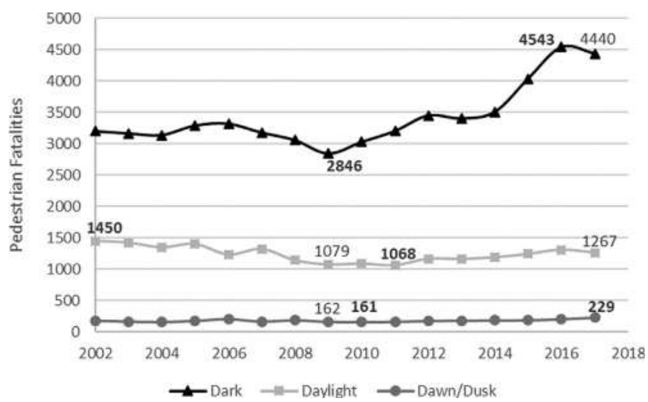

Fig. 2. Pedestrian fatality trend by light condition (minimum and maximum values in bold) *(Data source:* NHTSA, 2018*).*

utility vehicle) involvement was larger than the increases for cars, vans, pickups, or medium/heavy trucks. While Hu and Cicchino (2018) provide a strong foundation, our current work adds several novel perspectives. First, our paper examines the share of the total night time pedestrian fatality increase (both frequency and proportion) for each category within each variable. Second, we account for both the before and after periods to understand whether post-2009 changes represent new trends. Third, we include additional variables, several of which are significant to the final findings.

Retting (2019) also examined the recent increase in U.S. pedestrian fatalities, similarly finding that SUV involvement has been increasing at a faster rate (50%) compared to passenger cars (30%). Their work was some of the first to identify the nighttime trend and also hypothesized that driver and pedestrian distraction are at least partially responsible for the recent increase in nighttime pedestrian fatalities (Retting, 2019).

Research has found that pedestrians are at higher risk of a collision in the dark, all else being held equal (Uttley & Fotios, 2017). Severity of nighttime collisions is worse than that of daytime collisions, with nighttime pedestrian collisions at intersections having an 83% higher chance of being fatal without street lighting and a 54% higher chance of being fatal even with street lighting (Siddiqui, Chu, & Guttenplan, 2006). Specifically, pedestrians have been found to be at highest risk of death between 3 a.m. and 6 a.m. (Chang, 2008).

The reason for this increased nighttime risk is not clear. Sullivan and Flannagan (2001) identified vehicle speed, limited-access roadways, and alcohol use by pedestrians as contributors to high pedestrian risk at night. However, the researchers utilized data from 1987 to 1997, meaning that it does not explain what has caused the substantial increase in nighttime pedestrian fatalities over the last eight years.

Much research has been completed on vehicular headlighting (Shinar, 1984; Sullivan & Flannagan, 2007; Sullivan & Flannagan, 2011; Wood, Tyrrell, & Carberry, 2005), reflective clothing (Moberly & Langham, 2002; Shinar, 1984; Venable & Hale, 1996; Wood, Tyrrell, & Carberry, 2005), and nighttime pedestrian detection systems for vehicles (Jeong, Kwak, Son, Ko, & Nam, 2014; Luo, Remillard, & Hoetzer, 2010). Results suggest that these countermeasures may improve nighttime pedestrian safety outcomes. However, the research was specific to these countermeasures and did not explore whether these issues were responsible for the crashes in the first place. And again, many of these studies were performed prior to the recent increase in pedestrian fatalities that this paper seeks to understand.

In general, pedestrian crash prevalence and severity has been found to be related to infrastructure, user, vehicle, and situational characteristics (Martin, 2016). Although not specific to nighttime pedestrian safety, we use existing literature to identify variables within these groups that warrant investigation. In an analysis of all U.S. pedestrian fatalities between 1997 and 2006, Chang (2008) found that pedestrians have higher probabilities of being killed when a male or older pedestrian is involved, collisions occur in urban areas, and when alcohol is involved. However, this report explored pedestrian fatalities before the current upward trend commenced (Chang, 2008). Pedestrian injury severity in rural Connecticut crashes was significantly related to pedestrian age, vehicle type, roadway width, and alcohol involvement (Zajac & Ivan, 2003). Pedestrian injury severity at intersections in Illinois was significantly related to pedestrian age, vehicle type, point of first contact, and weather condition (Ma, Lu, Chien, & Hu, 2017). Pedestrian injury severity in South Korea was significantly related to driver and pedestrian gender and age, vehicle type, roadway width, driver intoxication, weather condition, and vehicle speed (Tay, Choi, Kattan, & Khan, 2011). While these studies are not specifically focused on nighttime factors, we use this literature as a guide to select variables that may be related to the recent increase in nighttime pedestrian fatalities, thereby helping us to fill this significant knowledge gap.

2. Methods

To explore possible factors associated with the recent increase in nighttime pedestrian fatalities, we examined motor-vehicle crashes that incurred a pedestrian fatality at night between 2002 and 2017. This timeframe allows us to have eight years (2002–2009) where pedestrian fatalities were decreasing and eight years (2010–2017) where pedestrian fatalities were increasing. By solely looking at nighttime fatalities, we control for the lighting factor and therefore can determine which variables are related to this nighttime trend.

We utilized fatality data from FARS, a national database maintained by the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA). We would have preferred to examine data pertaining to all pedestrian injuries because other factors (e.g., improved emergency medical care) may have concurrently impacted fatality rates over the study period (Cruz & Ferenchak, 2020). Unfortunately, longitudinally examining all pedestrian injuries on the national level and specific to our variables is not currently feasible due to pedestrian injuries being underreported and inconsistently reported (Pucher & Dijkstra, 2003).

For a fatality to be included in the FARS database, a crash must involve a motorist on a roadway that is open to the public and must result in a fatality within 30 days of the collision. Bicyclist-on-pedestrian crashes and other incidents that resulted in a pedestrian fatality but did not involve a motor vehicle are not included in the FARS database. We queried Person worksheets for non-occupant pedestrians whose injury severities were classified as fatal to identify the crashes used in this study.

Nighttime was defined by the Light Condition variable (LGT_COND) from the Accident worksheets. Specifically, any crashes that were listed as "Dark," "Dark – Not Lighted," "Dark but Lighted," "Dark – Lighted," or "Dark – Unknown Lighting" were considered as nighttime crashes. This analysis does not include crashes that occurred in "Daylight," "Dawn," "Dusk," "Other," or "Unknown."

Variables are broken into four groups: infrastructure, users, vehicles, and situation (Table 1). Six of the variables (functional classification, number of lanes, speed limit, alignment, driver distraction, and urbanized area) changed data elements or data files in the FARS database during the study period. However, consistent classifications across the data elements and data files allowed for analysis over the desired timeframe. All variables are categorical except for pedestrian age.

We first employed one-way ANOVA or two-sample *t*-tests (depending on the number of categories in each variable) to compare the frequency of fatal nighttime pedestrian crashes between categories within each variable. We performed this test separately for 2002 to 2009 and for 2010 to 2017. Using the functional classification variable as an example, we answer: is there a statistically significant difference in the frequency of fatal nighttime pedestrian crashes between the different functional classification categories?

We then illustrated trends for each variable between 2002 and 2017 using scatterplots and use two-sample *t*-tests to compare fatal crash frequencies in the before versus after time periods (2002–2009 vs. 2010–2017) for each category of each variable to determine whether there has been a statistically significant increase in fatal nighttime pedestrian crashes. Again, using the functional classification variable as an example, we answer: has there been a statistically significant increase in the frequency of fatal nighttime pedestrian crashes on arterials? Has there been a statistically significant increase in the frequency of fatal nighttime pedestrian crashes on collectors? And so on for each category of each variable.

Linear regressions then allowed us to explore the changes in proportions of the categories in each of the variables between 2002–2009 and 2010–2017. This allowed us to answer, for instance, whether the likelihood that a pedestrian fatality occurred on an arterial increased or decreased throughout the study period. We were able to identify whether trends within the time series were statistically significant. We tested for temporal autocorrelation in these regression models using Breusch-Godfrey Lagrange multiplier tests, a general test of serial correlation used for identifying temporal autocorrelation of any order and a common approach for time series traffic safety data (Abdulhafedh, 2017; Bernal et al., 2017; Lavrenz et al., 2018).

Table 1
Variables and source from FARS.

	Field	Worksheet
Infrastructure		
Functional classification	ROAD_FNC	Accident
	FUNC_SYS	Accident
Relation to intersection	LOCATION	Person
Number of lanes	NO_LANES	Accident
	VNUM_LAN	Vehicle
Speed limit	SP_LIMIT	Accident
	VSPD_LIM	Vehicle
Alignment	ALIGNMNT	Accident
	VALIGN	Vehicle
Lighting condition	LGT_COND	Accident
Users		
Drinking by driver	DR_DRINK	Vehicle
Drinking by pedestrian	DRINKING	Person
Drug use by pedestrian	DRUG	Person
Gender of pedestrian	SEX	Person
Age of pedestrian	AGE	Person
Driver's license status of driver	L_STATUS	Vehicle
Hit and run	HIT_RUN	Vehicle
Driver distraction	DR_CF	Vehicle
	MDRDSTRD	Distract
Vehicles		
Body type of striking vehicle	BODY_TYP	Vehicle
Age of vehicle	MOD_YEAR	Vehicle
Vehicle speed	TRAV_SP	Vehicle
Situation		
Time of day	HOUR	Accident
	MINUTE	Accident
Day of week	DAY_WEEK	Accident
Month	MONTH	Accident
Weather	WEATHER	Accident
Urbanized area	ROAD_FNC	Accident
	RUR_URB	Accident

3. Results

We first wanted to understand whether pedestrians involved in motor-vehicle collisions were more likely to be killed later in the study period. This would help illuminate whether the increase in pedestrian fatalities has been a result of increasing severity or simply increasing exposure. We used data from NHTSA's National Automotive Sampling System (NASS) General Estimates System (GES) to derive the proportion of injured pedestrians that were killed for each study year (regardless of lighting condition, for which data was not available). NASS GES was replaced by the Crash Report Sampling System (CRSS) in 2016. The 2016 and later year estimates from CRSS were not comparable to earlier year estimates from NASS GES. Our proportion analysis therefore covered the years 2002 until 2015. Findings suggest that pedestrians in 2015 were more likely to be killed (7.85% of injured pedestrians were killed) than those in 2010 (6.14%) (Fig. 3). However, these numbers are on average consistent with those in the before period. Pedestrians involved in motor-vehicle collisions between 2002 and 2009 were actually more likely to be killed (7.00%) than those in 2010–2015 (6.93%) (one-tail *t*-test *p*-value = 0.417). While these exploratory findings indicate that severity did increase from 2010 to 2015, that severity was not significantly different from pre-2010 levels, suggesting that the 2010–2017 increase in pedestrian fatalities is likely a result of both increasing severity and frequencies. More

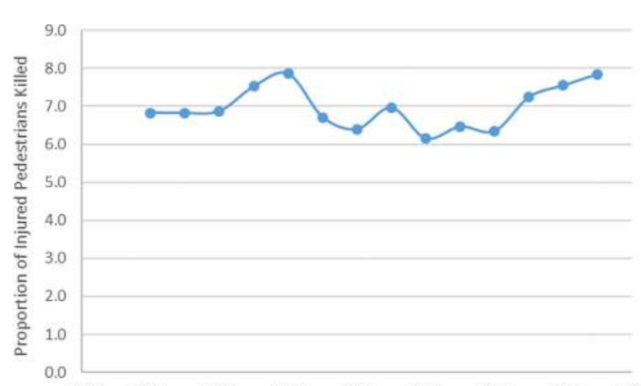

Fig. 3. Proportion of injured pedestrians that were killed.

detailed work – likely at a subnational level – is needed to explore the entire injury severity spectrum to further answer this severity versus exposure question.

3.1. Infrastructure

Adopting a 0.05 significance level, there was statistically significant within-variable variation in each time period for all the infrastructure variables except for lighting condition (see the two ANOVA columns in Table 2). This means that – except for lighting condition – there is a statistically significant difference between categories' frequencies of fatal pedestrian crashes. There was not a statistically significant difference between the number of fatal nighttime pedestrian crashes with lighting present versus without lighting present during the before period or during the after period.

The average annual count of fatal nighttime pedestrian crashes increased by 440.8 for arterials from the before to after period, representing 81.1% of the known increase (Fig. 4a). Over this time, average annual fatal crashes on interstates/freeways increased by 64.4, collectors increased by 9.8, and local roads increased by 28.4, which were not statistically significant changes (see the t-test column in Table 2). There was a strong increase in the proportion of pedestrian fatalities that occurred on arterials from 2010 to 2017 (Table 3). The coefficient value of 1.285 for arterials from 2010 to 2017 in Table 3 means that the proportion of pedestrian fatalities that occurred on arterials increased 1.285% per year over the period (Table 3).

These fatal crashes primarily occurred at non-intersection locations away from a crosswalk, where there were an additional 576.8 average annual crashes in the after period, representing 80.8% of the known change (Fig. 4b). Non-intersection, non-crosswalk locations also saw a strong and statistically significant increase in the proportion of fatalities from 2010 to 2019 (coef. = 0.218; p-value = 0.025) (Table 3).

Five-lane roads saw a 270.1% increase in frequency (statistically significant) from before to after, representing the largest categorical change at 40.7% of the total known change (Fig. 4**c**). Five-lane roads also had the strongest increase in the proportion of fatalities from 2010 to 2017 (coef. = 2.074; p-value = 0.001) (Table 3). This is interesting as relatively few of the fatalities occurred on five-lane roads in the before period. This is interesting as relatively few of the fatalities occurred on five-lane roads in the before period.

Roads with speed limits of 40 mph or 45 mph saw the largest and only statistically significant growth in frequency from before to after, representing 54.6% of the total increase (Fig. 4d). The proportion of these 40 mph or 45 mph roads experienced the largest increases for both 2002–2009 (coef. = 0.524; p-value = 0.036) and 2010–2017 (coef. = 0.237; p-value = 0.020) (Table 3). Interestingly, the proportions for 30/35 mph and 50/55 mph roads decreased for both time periods.

All of the known increase occurred on straight alignments, as average annual crashes on curves actually decreased (Fig. 4e). The percentage increases in crashes with lighting present and without lighting present were similar (19.4% and 13.0%, respectively) and the proportion differences were weak and not statistically significant, indicating that the presence of lighting was not as strong a factor as other infrastructure variables (Fig. 4f and

Table 2
Statistical analysis of infrastructure variables.

Variable	Mean				*t*-test (02–09 vs. 10–17)		ANOVA (2002–09)		ANOVA (2010–17)	
	2002–09	2010–17	% increase	% of total increase	*t*	*p*	*F*	*p*	*F*	*p*
Functional Classification							1240.1	**0.000**	101.3	**0.000**
Interstate/Freeway	535.5	599.9	12.0	11.9	1.856	0.096				
Arterial	1688.6	2129.4	26.1	81.1	2.797	**0.027**				
Collector	336.1	345.9	2.9	1.8	0.338	0.744				
Local	513.1	541.5	5.5	5.2	0.825	0.429				
Location							1142.2	**0.000**	239.0	**0.000**
Intersection (Crosswalk)	194.0	272.6	40.5	11.0	4.068	**0.004**				
Intersection (No Crosswalk)	248.4	305.5	23.0	8.0	4.035	**0.001**				
Non-Intersection (Crosswalk)	19.4	20.6	6.2	0.2	0.370	0.717				
Non-Intersection (No Crosswalk)	1998.5	2575.3	28.9	80.8	3.556	**0.006**				
Number of Lanes							937.9	**0.000**	162.3	**0.000**
One	35.3	50.1	41.9	2.6	3.018	**0.009**				
Two	1755.4	1781.9	1.5	4.6	0.388	0.703				
Three	411.8	564.9	37.2	26.5	2.893	**0.023**				
Four	633.3	728.9	15.1	16.5	2.487	**0.038**				
Five	87.1	322.4	270.1	40.7	2.679	**0.032**				
Six or More	113.0	165.6	46.5	9.1	1.960	0.091				
Road Speed Limit (mph)							304.8	**0.000**	68.0	**0.000**
25 or less	185.1	215.0	16.2	5.6	1.458	0.179				
30 or 35	775.3	881.1	13.6	19.9	2.089	0.066				
40 or 45	890.4	1180.3	32.6	54.6	3.789	**0.005**				
50 or 55	651.0	697.9	7.2	8.8	1.442	0.175				
60 or more	461.1	519.6	12.7	11.0	1.734	0.111				
Alignment							53.2[a]	**0.000**	19.01[a]	**0.000**
Straight	2880.3	3358.4	16.6	100.6	2.758	**0.025**				
Curve	202.1	199.1	−1.5	−0.6	0.301	0.770				
Lighting Condition							1.2[a]	0.270	1.2[a]	0.265
Lighting Present	1573.8	1879.4	19.4	60.8	2.801	**0.026**				
No Lighting Present	1521.3	1718.6	13.0	39.2	2.067	0.066				

[a] *t*-test performed as only two categories existed.

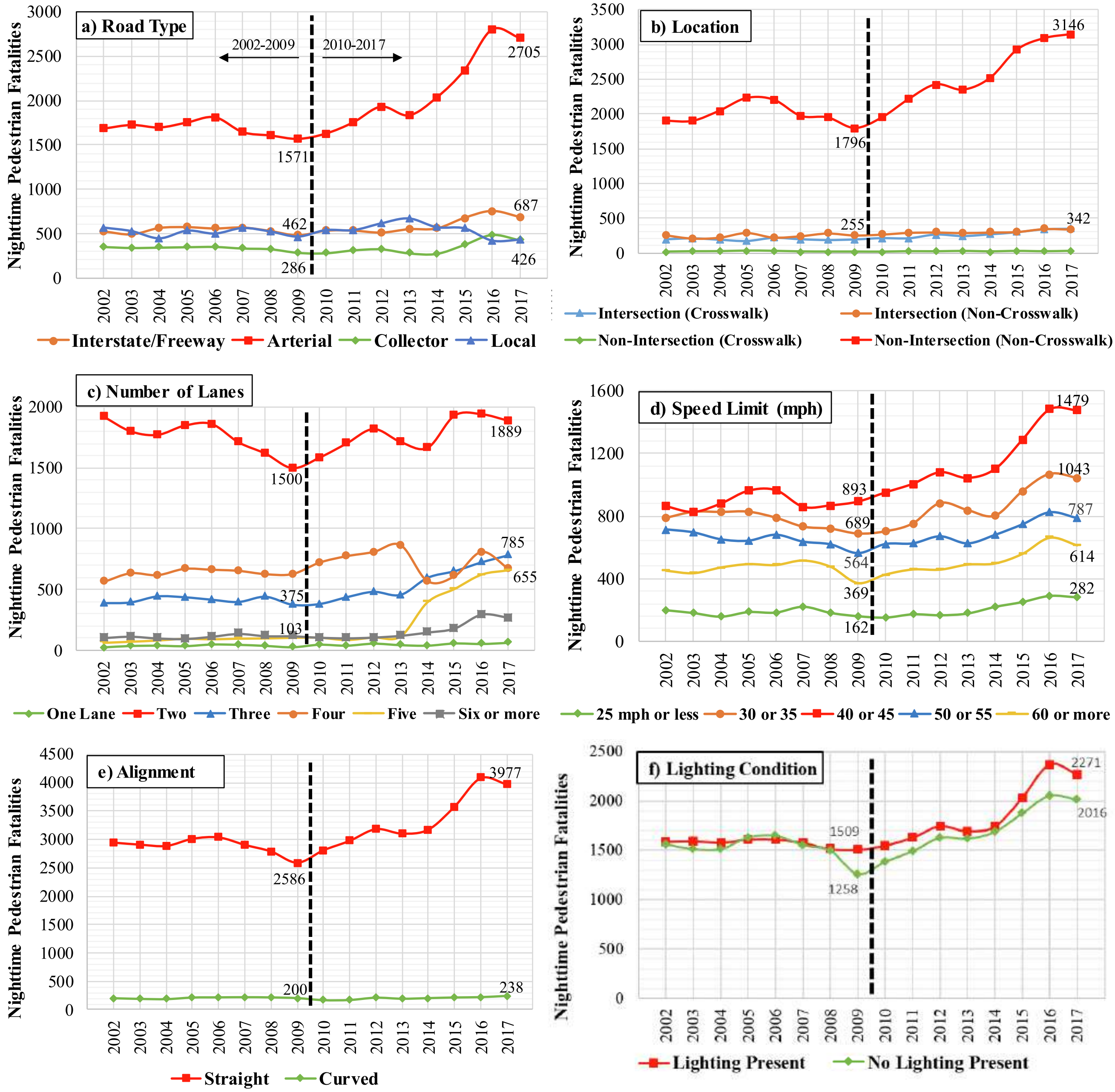

Fig. 4. Fatal nighttime pedestrian crash trend by infrastructure.

Table 3). The sharp increase in fatal nighttime pedestrian crashes in the after period is clearly focused on specific roadway types: straight, non-intersection, and unmarked locations of arterials, primarily signed at 40 mph or 45 mph and consisting of five lanes.

3.2. Users

Examining each time period, there was statistically significant within-variable variation for all user variables except for pedestrian age (which was not applicable as a discrete variable) and distraction for the before period (which could not be analyzed because of a lack of data) (Table 4).

The most significant changes in user variables were in pedestrians under the influence of alcohol and drugs and pedestrian age. Increases the frequencies of both pedestrian alcohol and drug involvement from before to after were statistically significant (Fig. 5b). However, the proportion of pedestrian fatalities with a pedestrian under the influence of alcohol actually had a strong decrease from 2010 to 2017 (coef. = –0.917; p-value = <0.001) (Table 3). The proportion of pedestrian fatalities with a pedestrian under the influence of drugs increased during the after period too, but the increase in pedestrian drug involvement during the before period was actually stronger (Table 3). However, little research has been conducted on the dose-risk response relationship between drug use and driving or walking, leading to differences in measurement validity between drunk (valid) and drugged (unknown validity) road user testing (Pasnin & Gjerde, 2021). These results suggest that while changes in pedestrian alcohol and drug involvement are of interest, more research is needed to clarify the importance of their role in the overall trends.

The median age of pedestrians killed rose from 44.3 years to 52.3 years from before to after (an 18.1% increase, statistically sig-

Table 3
Linear regression results for changes in proportions (BG Test = Breusch-Godfrey *p*-values).

	2002–2009				2010–2017			
	Coef.	S.E.	*p*-value	BG Test	Coef.	S.E.	*p*-value	BG Test
Road Type								
Interstate/Freeway	0.127	0.129	0.363	0.536	−0.074	0.133	0.599	0.874
Arterial	−0.022	0.211	0.922	0.407	1.285	0.221	**<0.001**	0.722
Collector	−0.111	**0.033**	0.016	**0.029**	0.103	0.152	0.525	0.295
Local	0.006	0.208	0.977	0.867	−1.314	0.378	**0.013**	0.259
Location								
Intersection (Crosswalk)	−0.018	0.135	0.896	0.976	0.091	0.061	0.187	0.051
Intersection (Non-Crosswalk)	0.207	0.186	0.308	0.623	−0.319	0.052	**<0.001**	0.413
Non-Intersection (Crosswalk)	−0.020	0.042	0.656	0.288	0.010	0.024	0.704	0.116
Non-Intersection (Non-Crosswalk)	−0.169	0.168	0.353	0.287	0.218	0.074	**0.025**	0.536
Number of Lanes								
One Lane	0.030	0.047	0.544	0.717	−0.016	0.034	0.644	0.074
Two	−0.984	0.161	**<0.001**	0.837	−1.682	0.234	**<0.001**	0.716
Three	0.146	0.124	0.282	0.500	0.704	0.148	**0.003**	0.250
Four	0.447	0.106	**0.006**	0.187	−1.544	0.421	**0.010**	0.739
Five	0.220	0.021	**<0.001**	0.869	2.074	0.358	**0.001**	0.822
Six or More	0.141	0.063	0.068	0.750	0.464	0.101	**0.004**	0.836
Speed Limit								
25 mph or less	0.042	0.103	0.694	0.891	0.234	0.058	**0.007**	0.977
30 or 35	−0.320	0.142	0.065	0.691	−0.096	0.156	0.560	0.843
40 or 45	0.524	0.194	**0.036**	0.885	0.237	0.076	**0.020**	0.130
50 or 55	−0.328	0.122	**0.036**	0.500	−0.382	0.065	**0.001**	0.334
60 or more	0.081	0.184	0.676	0.967	0.008	0.076	0.918	0.070
Alignment								
Straight	−0.172	0.034	**0.002**	0.883	0.023	0.055	0.693	0.811
Curved	0.172	0.034	**0.002**	0.883	−0.023	0.055	0.693	0.811
Lighting Condition								
Lighting Present	0.249	0.245	0.349	0.601	0.091	0.151	0.569	0.208
No Lighting Present	−0.249	0.245	0.349	0.601	−0.091	0.151	0.569	0.208
Driver Drinking								
Driver No Drinking	0.282	0.096	**0.026**	0.241	0.454	0.063	**<0.001**	0.173
Driver Drinking	−0.282	0.096	**0.026**	0.241	−0.454	0.063	**<0.001**	0.173
Ped Drinking/Drug								
Drinking (by ped)	0.791	0.272	**0.027**	0.792	−0.917	0.098	**<0.001**	0.542
Drugs (by ped)	0.553	0.093	**<0.001**	0.408	0.511	0.131	**0.008**	0.280
Pedestrian Gender								
Male	0.035	0.141	0.811	0.996	0.065	0.111	0.578	0.965
Female	−0.035	0.141	0.811	0.996	−0.065	0.111	0.578	0.965
Driving License								
Properly Licensed	−0.008	0.066	0.914	0.058	−0.283	0.065	**0.005**	0.543
Not Licensed/Suspended/Revoked	0.008	0.066	0.914	0.058	0.283	0.065	**0.005**	0.543
Crash Type								
No Hit and Run	0.064	0.247	0.805	0.755	−0.209	0.093	0.066	**0.021**
Hit and Run	−0.064	0.247	0.805	0.755	0.209	0.093	0.066	**0.021**
Distraction								
Inside	−0.103	0.104	0.357	0.941	−0.027	0.026	0.351	0.381
Outside	na	na	na	na	−0.056	0.034	0.159	0.253
Inattention	na	na	na	na	0.021	0.070	0.770	0.873
Other	na	na	na	na	0.050	0.065	0.470	0.579
Cell Phone	na	na	na	na	0.006	0.030	0.852	0.169
Not Distracted	na	na	na	na	−0.046	0.072	0.544	**0.025**

(*continued on next page*)

Table 3 (*continued*)

	2002–2009				2010–2017			
	Coef.	S.E.	*p*-value	BG Test	Coef.	S.E.	*p*-value	BG Test
Vehicle Type								
Sedan/Coupe	−0.419	0.130	**0.018**	0.669	−0.070	0.167	0.690	0.434
Van/Minivan	−0.263	0.091	**0.028**	0.202	−0.332	0.072	**0.004**	**0.019**
SUV	0.669	0.101	**<0.001**	0.069	0.361	0.100	**0.011**	0.154
Pickup/Light Truck	−0.136	0.129	0.336	0.341	0.034	0.072	0.658	0.926
Bus	−0.007	0.019	0.710	0.847	−0.043	0.020	0.082	0.615
Heavy Truck	0.054	0.040	0.232	0.281	−0.029	0.075	0.712	**0.031**
Vehicle Speed								
25 or less	−0.185	0.122	0.179	0.391	0.021	0.080	0.801	0.939
26–35	−0.031	0.189	0.875	0.116	0.445	0.186	0.054	0.330
36–45	0.002	0.282	0.994	0.423	0.520	0.112	**0.004**	0.968
46–55	−0.284	0.292	0.367	0.919	0.046	0.144	0.762	0.660
56 or more	0.499	0.342	0.195	0.084	−1.032	0.323	**0.019**	0.423
Weather Condition								
Clear/Cloudy	−0.026	0.110	0.817	0.813	−0.013	0.079	0.878	0.227
Rain	0.026	0.110	0.817	0.813	0.013	0.079	0.878	0.227
Area								
Urban	0.136	0.164	0.439	0.446	1.157	0.202	**0.001**	0.386
Rural	−0.136	0.164	0.439	0.446	−1.157	0.202	**0.001**	0.386

Table 4
Statistical Analysis of User Variables.

Variable	Mean				*t*-test (02–09 vs. 10–17)		*t*-test (2002–09)		*t*-test (2010–17)	
	2002–09	2010–17	% increase	% of total increase	*T*	*p*	*t*	*p*	*t*	*p*
Driver Drinking							54.1	**0.000**	15.4	**0.000**
Driver Not Drinking	2739.8	3317.8	21.1	103.8	2.924	**0.019**				
Driver Drinking	355.4	334.1	−6.0	−3.8	1.402	0.186				
Pedestrian Drinking/Drug							19.8	**0.000**	13.7	**0.000**
Drinking	754.1	875.6	16.1	22.1	3.428	**0.004**				
Drugs	141.0	295.3	109.4	28.0	3.988	**0.003**				
Pedestrian Gender							31.4	**0.000**	10.6	**0.000**
Male	2286.1	2666.3	16.6	69.6	2.501	**0.037**				
Female	862.8	1029.0	19.3	30.4	3.054	**0.016**				
Driving License							64.6	**0.000**	18.5	**0.000**
Not Licensed/Suspended	231.6	292.4	26.3	12.0	2.526	**0.035**				
Properly Licensed	2412.8	2859.9	18.5	88.0	3.179	**0.013**				
Crash Type							42.9	**0.000**	13.3	**0.000**
Hit and Run	715.1	787.6	10.1	13.1	1.309	0.219				
Not Hit and Run	2379.9	2859.0	20.1	86.9	3.173	**0.013**				
Distraction							n/a	n/a	822.1[a]	**0.000**
Inside	52.6	56.4	7.2	1.3	0.520	0.614				
Outside	n/a	39.4	n/a	n/a	n/a	n/a				
Inattention	n/a	113.0	n/a	n/a	n/a	n/a				
Other	n/a	36.6	n/a	n/a	n/a	n/a				
Cell Phone	n/a	26.8	n/a	n/a	n/a	n/a				
Not Distracted	n/a	2847.9	n/a	n/a	n/a	n/a				
Pedestrian Age							n/a	n/a	n/a	n/a
Age	44.3	52.3	18.1	n/a	5.628	**0.000**				

[a] One-way ANOVA performed as more than two categories existed.

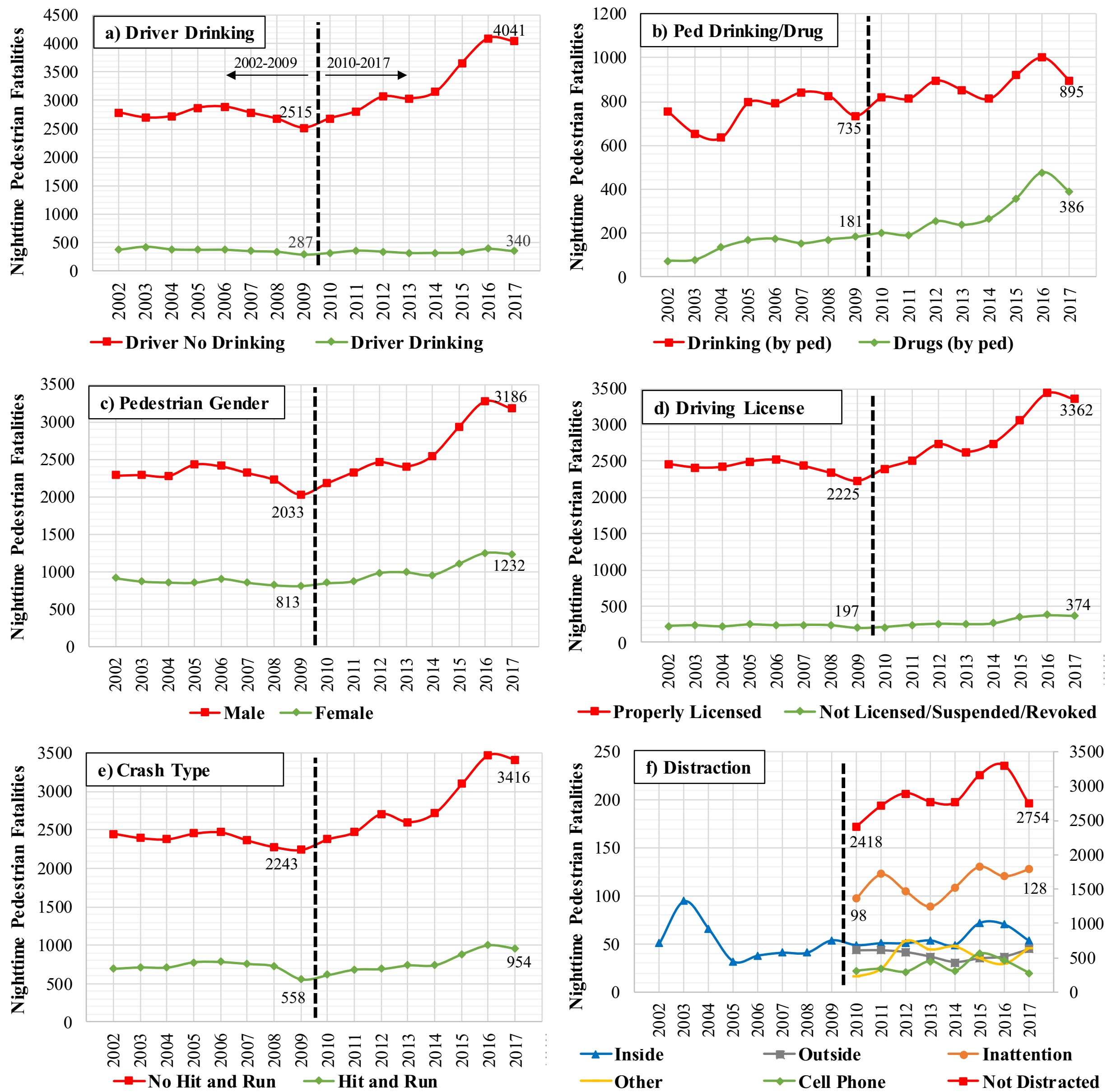

Fig. 5. Fatal nighttime pedestrian crash trend by users. Note: The secondary y-axis on the right of the distraction (f) graph is for the "Not Distracted" category while the primary y-axis is for all other categories.

Table 5
Statistical analysis of vehicle variables.

Variable	Mean				*t*-test (02–09 vs. 10–17)		ANOVA (2002–09)		ANOVA (2010–17)	
	2002–09	2010–17	% increase	% of total increase	*t*	*P*	*F*	*p*	*F*	*p*
Vehicle Type							1021.4	**0.000**	182.6	**0.000**
Sedan/Coupe	1339.8	1562.4	16.6	44.1	2.550	**0.031**				
Van/Minivan	239.1	210.9	−11.8	−5.6	2.029	0.065				
SUV	415.9	616.4	48.2	39.7	4.041	**0.003**				
Pickup/Light Truck	533.1	602.4	13.0	13.7	1.996	0.077				
Bus	24.5	26.5	8.2	0.4	1.116	0.285				
Heavy Truck	133.9	172.8	29.1	7.7	3.883	**0.004**				
Vehicle Speed (mph)							187.6	**0.000**	125.6	**0.000**
25 or less	84.3	94.6	12.2	7.6	2.207	**0.046**				
26–35	250.1	292.3	16.9	31.3	2.973	**0.011**				
36–45	408.6	475.9	16.5	49.9	3.228	**0.007**				
46–55	270.3	264.6	−2.1	−4.2	0.507	0.620				
56 or more	232.6	253.5	9.0	15.5	1.188	0.256				

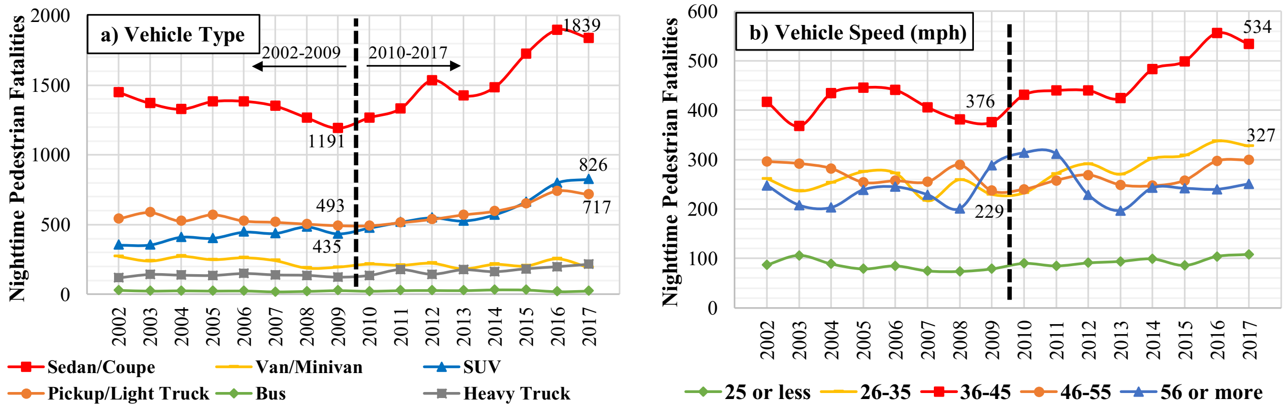

Fig. 6. Fatal nighttime pedestrian crash trend by vehicles.

nificant) while the median age in the United States rose from 36.4 years to 37.6 years (3.2%) (Table 4).

While there were other statistically significant increases, none seem to be primary drivers of the nighttime pedestrian fatality trend. The increases in frequency of male pedestrians killed and female pedestrians killed were both statistically significant, but the increases were nearly equal (16.6% and 19.3%, respectively), and the differences in proportion change were weak (Fig. 5c and Table 3). The frequency of drivers with revoked licenses increased (statistically significant) more than the frequency of those properly licensed, but still only represented 12.0% of the total known increase (Fig. 5d).

The frequency of crashes involving a driver that had been drinking decreased from before to after and was not statistically significant (Table 4). The proportion of driver drinking crashes in the after period actually decreased (coef. = −0.454; *p*-value = <0.001) (Table 3). The frequency of hit-and-runs increased less than the frequency of non-hit-and-runs and was not statistically significant (Fig. 5**e**). The proportion of hit-and-runs increased from 2010 to 2017 but the change was not statistically significant (coef. = 0.209; *p*-value = 0.066) (Table 3).

FARS began providing much of their distraction data in 2010. Therefore, we perform much of the distraction analysis from 2010 to 2017. Annual crashes where the driver was distracted

Table 6
Statistical analysis of situation variables.

Variable	Mean				*t*-test (02–09 vs. 10–17)		ANOVA (2002–09)		ANOVA (2010–17)	
	2002–09	2010–17	% increase	% of total increase	*t*	*p*	*t*	*p*	*t*	*p*
Weather Condition							51.1[a]	**0.000**	18.3[a]	**0.000**
Clear/Cloudy	2705.3	3145.3	16.3	91.0	2.763	**0.025**				
Rain	294.7	338.1	14.7	9.0	2.402	**0.040**				
Area							31.8[a]	**0.000**	10.4[a]	**0.000**
Urban	2226.8	2763.1	24.1	99.7	2.886	**0.020**				
Rural	861.6	863.1	0.2	0.3	0.062	0.951				
Month							63.8	**0.000**	17.4	**0.000**
January	308.8	337.8	9.4	5.3	1.193	0.267				
February	249.9	292.5	17.0	7.7	2.468	**0.036**				
March	240.1	278.6	16.0	7.0	2.269	**0.047**				
April	200.6	236.4	17.8	6.5	2.523	**0.036**				
May	190.5	228.0	19.7	6.8	2.454	**0.034**				
June	193.9	215.8	11.3	4.0	1.506	0.166				
July	207.8	246.1	18.4	6.9	2.838	**0.014**				
August	235.9	266.3	12.9	5.5	1.546	0.161				
September	253.8	301.8	18.9	8.7	2.361	**0.036**				
October	317.5	397.4	25.2	14.5	2.938	**0.015**				
November	348.0	412.3	18.5	11.7	2.517	**0.036**				
December	353.9	438.8	24.0	15.4	4.077	**0.003**				
Day of Week							86.7	**0.000**	10.2	**0.000**
Sunday	508.4	565.6	11.3	10.4	1.595	0.137				
Monday	345.9	448.5	29.7	18.6	3.437	**0.009**				
Tuesday	350.5	436.3	24.5	15.6	3.030	**0.016**				
Wednesday	388.6	445.5	14.6	10.3	1.993	**0.081**				
Thursday	377.8	480.1	27.1	18.6	3.026	**0.016**				
Friday	512.0	597.4	16.7	15.5	2.809	**0.023**				
Saturday	617.0	678.1	9.9	11.1	1.956	**0.079**				

[a] *t*-test performed as only two categories existed.

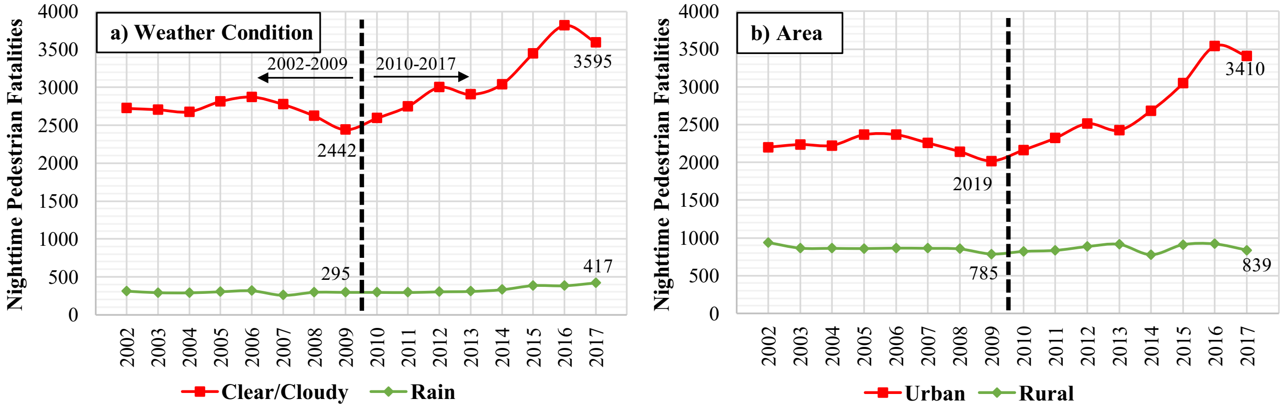

Fig. 7. Fatal nighttime pedestrian crash trend by situation.

inside the vehicle increased by only 5 between 2010 and 2017, distraction outside the vehicle increased by 1, and inattention increased by 30, compared to an increase of 1,384 for all nighttime pedestrian fatalities over the same time period (Fig. 5f). Distraction inside the vehicle was the only category for which we had data for the entire before period, and the change in frequency of these crashes from before to after was not strong or statistically significant (Table 4). There were no strong or statistically significant changes in distraction proportion (Table 3). However, it is important to note that there are limitations with the distraction data, as detailed in the Conclusions.

3.3. Vehicles

There was statistically significant within-variable variation for all the vehicle variables (Table 5). There were three vehicle type categories that experienced statistically significant frequency increases from before to after: sedan/coupe, sport utility vehicle (SUV), and heavy truck (Table 5). Much of the overall frequency increase in the after period was a result of increases in sedan/coupe and SUV. Sedan/coupes represented 44.1% of the known increase. However, because sedan/coupe was relatively common to begin with, the category only increased 16.6%. On the other hand, SUVs represented 39.7% of the known increase and the category saw a 48.2% increase. While heavy trucks had a statistically significant increase, they were only 7.7% of the total known change (Fig. 6**a**). In terms of proportions, SUVs had the only statistically significant increase from 2010 to 2017 (coef. = 0.361; p-value = 0.011) (Table 3). While it appears that SUVs played a key role in the overall increase in pedestrian fatalities since 2009, it is interesting to note that the SUV proportion actually had a much stronger increase in 2002–2009 (coef. = 0.669; p-value = <0.001), calling into question the degree to which this variable was responsible for the post-2009 increase.

Echoing posted speed limit findings, much of the increase in fatalities happened with vehicle speeds between 36 mph and 45 mph (49.9% of the total known increase) and 26 mph and 35 mph (31.3% of the total known increase) (Fig. 6b). While these findings support the posted speed limit findings, reported vehicle speeds had a small sample size (for example, only 1,519 crashes out of 4,380 total crashes had data reported in 2017).

3.4. Situation

There was statistically significant within-variable variation for all the situational variables (Table 6). Urban context had the strongest relationship with the fatal nighttime pedestrian crash trend. Urban crashes increased 24.1% from before to after (representing 99.7% of the total known increase) while rural only increased 0.2% (Fig. 7b). The proportion of pedestrian fatalities that occurred in urban areas also had a strong and statistically significant increase (coef. = 1.157; p-value = 0.001) (Table 3).

There were also interesting patterns for month and day of the week. October, November, and December had the highest average crashes in the before period, experienced the largest percentage increases, and were responsible for the largest proportion of the total change (Table 6). Inversely, Monday, Tuesday, and Thursdays had the lowest counts in the before period but saw the largest percentage increases and were responsible for a large proportion of the total change.

The frequency of crashes occurring in rain increased less than clear/cloudy weather and was only responsible for 9.0% of the total known change (Fig. 7a). There were no strong or statistically significant difference for weather proportion (coef. = 0.013; p-value = 0.878) (Table 3).

4. Conclusions

The increase in fatal nighttime pedestrian crashes is most strongly correlated with infrastructure factors. Specifically, non-intersection unmarked locations of 40–45 mph, five-lane urban arterials are host to much of the increase in pedestrian fatalities. Not only have nighttime pedestrian fatalities concentrated on these roadways, but these roadways only began to experience higher proportions at the same time that overall pedestrian fatalities began increasing in 2010. This suggests that infrastructure has played a key role in the recent increase in pedestrian fatalities.

In addition, an increasing prevalence of SUV involvement was identified. While SUV involvement warrants further investigation, it is important to note that the proportion of nighttime pedestrian fatalities involving SUVs had a stronger increase in 2002–2009, when overall pedestrian fatalities were still decreasing.

The age of pedestrians killed has increased significantly more than the national average. Increases in pedestrian alcohol and drug use justify further exploration. However, while pedestrian alcohol use has increased significantly, the proportion of pedestrian fatalities with an alcohol-intoxicated pedestrian actually decreased. Drug results should be interpreted cautiously because of unknown measurement validity (Pasnin & Gjerde, 2021).

Future research might investigate to what degree these findings are related as causal hints probably lie in the interactions among variables. For instance, recent research exploring Albuquerque, NM found that pedestrian fatalities and serious injuries are concentrated near alcohol establishments, which are often located along arterial roads (Long & Ferenchak, 2021). In this way, the infrastructure and alcohol findings from this paper may be dependent upon land use changes and attendant shifts in social behavior over the 16 year-period of the study. In addition, as the U.S. population ages, older pedestrians may be more likely to visit these alcohol establishments, leading to increased exposure for older and more vulnerable populations, a further association among variables. Pedestrian safety outcomes in Albuquerque were also found to be especially poor in minority neighborhoods (Long & Ferenchak, 2021), suggesting the need for further analyses exploring how socio-demographic and socio-economic factors interact with these trends (Ferenchak & Marshall, 2019; Marshall & Ferenchak, 2017).

While past studies have hypothesized that increased driver distraction may be related to increased pedestrian fatalities (Retting, 2019), our analysis suggests that this is not the case. However, further investigation is warranted as distraction may be prone to reporting issues and the reported sample size was relatively low. Also, pedestrian distraction is not tracked by FARS and may be worth examining with future research.

Another variable that had a surprising lack of relationship was lighting condition. Crashes with and without lighting saw similar increases, suggesting that a lack of lighting is not a primary issue. However, we expect lighting would be installed in areas with high pedestrian activity, meaning that further analyses accounting for exposure are needed.

Another limitation of the current work is our lack of accounting for temporal autocorrelation. Future work might explore alternative statistical methods – such as autoregressive integrated moving average (ARIMA) models or generalized linear mixed models (GLMM) – that account for such autocorrelation. However, we used Breusch-Godfrey tests to identify autocorrelation issues and only found five categories with statistically significant autocorrelation issues out of 103 possibilities. None of the identified autocorrelation issues impacted key categories (the identified autocorrelation issues were for collectors 2002–2009; hit and run 2010–2017; not distracted 2010–2017; van/minivan 2010–2017; and heavy truck 2010–2017). We imagine that the lack of autocorrelation issues is at least in part a result of the removal of seasonality from the data.

Exposure is an important factor to account for in future research. The increase in nighttime pedestrian fatalities may be driven by more people walking or driving at night (although a 45.5% increase in pedestrian fatalities is unlikely to be a result of increased exposure alone). The 2017 National Household Travel Survey (NHTS) estimates that pedestrian trips per household decreased 9.1% and private vehicle trips decreased 10.4% from 2009 to 2017, suggesting that the issue is not simply a result of more pedestrians or vehicles on the road and that there are most likely other contributing factors at play (McGuckin & Fucci, 2018). However, these exposure estimates were not specific to nighttime activity. Similarly, while the U.S. population increased 5.1% from 2010 to 2017, the per capita pedestrian fatality rate increased at a significantly higher rate of 32.4% (from 1.39 to 1.84 pedestrian fatalities per 100,000 population). This again suggests that the increase in pedestrian fatalities is being driven by more than just increases in exposure, although population estimates do not necessarily correlate with nighttime pedestrian activity. These exploratory exposure analyses – along with the analysis of the proportion of injured pedestrians that are killed from the beginning of the Results section – all indicate that increasing pedestrian fatalities are not simply a result of more pedestrians or vehicles on the streets, but instead have resulted from some contributing factors and changes to severity. These factors may be related to infrastructure or vehicle design (as our study suggests), or they may consist of complex interactions between such factors and underlying political or social changes (for which more research is needed). We did not use vehicle miles travelled (VMT) as an exposure metric because pedestrian conflicts and collisions are more dependent upon pedestrian volumes than vehicle volumes (Ferenchak & Marshall, 2018).

The relationships identified in this research may also be a result of changes in exposure for specific variables. For instance, the increase in pedestrian fatalities observed on arterials may be a result of more pedestrians walking on arterials. However, obtaining pedestrian exposure data specific to nighttime activity on a national level to match our analysis variables is not currently feasible. Even if we were able to obtain such data, a lack of historical data would preclude a proper longitudinal study of the trend. Future work might focus on specific sections of cities that already collect comprehensive pedestrian exposure data to better understand these nighttime trends.

To provide a preliminary exposure analysis of contributing factors, we obtained data detailing changes in prevalence of arterials and SUVs in the United States. According to Bureau of Transportation Statistics data, mileage of urban arterials saw a 9.3% increase from the before to after periods (2002–2009 vs. 2010–2017), while overall urban road mileage saw a 15.8% increase (U.S. Department of Transportation, 2018). The fact that 80.1% of the known increase in fatal nighttime pedestrian crashes occurred on arterials, while the proportion of urban arterials relative to all urban roads decreased, suggests that fatalities on arterials are highly overrepresented relative to their exposure and present a safety issue worthy of further investigation. According to NHTS data, SUVs increased from 18% of household vehicles in 2008 to 24% in 2017 (Federal Highway Administration, 2018). Crashes involving SUVs saw a 48.2% increase and represented 39.7% of the total known increase, suggesting that while some of the crash increase is explained by increased SUV exposure, this is another safety issue that warrants further investigation.

In addition to exploring exposure for the identified variables, future work might examine all pedestrian injuries to see if this safety trend is present across the injury severity spectrum. Future research may also investigate specific cities that have experienced increases in nighttime pedestrian fatalities so that crash reports can be inspected, as they may be better able to illuminate causes than broad national trends. Furthermore, geocoding nighttime pedestrian fatalities into GIS would allow future researchers to examine factors that are not reported by FARS, such as surrounding land use and clustering. Finally, once pertinent variables have been identified, future research should work toward identifying countermeasures to best fix the identified problems.

4.1. Practical applications

Although our paper helped to better define a problem, we did not explore the effectiveness of any solutions. However, we now propose practical applications, noting that they are currently speculative and more work is needed. Engineering solutions may be used to combat the infrastructure issues. Specifically, design solutions such as road diets or traffic calming may help lower vehicle speeds and road widths and provide more protection to pedestrians, thereby reducing frequency and severity of crashes and the number of pedestrian fatalities. Such design solutions are currently promoted by traffic safety philosophies Vision Zero and Safe Systems and deserve more investigation.

However, we must also keep in mind that Safe Systems promotes a non-linear, systems-based approach to traffic safety, meaning that solving the pedestrian safety crisis is likely not as simple as solely improving road design (Collaborative Sciences Center for Road Safety, 2021). Just like the previous discussion about the interaction between variables, the problems giving rise to these pedestrian fatalities are likely a result of not only engineering issues but also interrelated social and political factors. Solutions should be correspondingly comprehensive. For example, the suburbanization of poverty has been identified as a possible driver of recent pedestrian safety trends (Benediktsson, 2017; Schmitt, 2020; Sheller, 2015). As disinvestment occurs in aging suburban areas and capital is transferred to gentrifying urban centers, the cost of postwar suburban housing has declined. This has caused a migration of poverty, with more than half of the people living below the poverty line in the United States now residing in suburban areas (Benediktsson, 2017). Poor suburban residents must increasingly navigate auto-centric roads on foot, with key destinations often located along fast and busy arterials. In this way, solutions may require coordinated changes to existing practice across players within diverse societal sectors including housing availability, land use, homelessness, alcohol/drug treatment, and road design.

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6. Disclosure Statement

There are no conflicts of interest to disclose.

7. Data availability

The data used in this publication is publicly-available from the National Highway Traffic Safety Administration's Fatality Analysis Reporting System.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Perceived stress, mental health, organizational factors, and self-reported risky driving behaviors among truck drivers circulating in France

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ABSTRACT

Introduction: The growth of the European market for road-freight transport has recently led to important changes. The growing number of foreign pavilion drivers transiting in France, which plays a bridging role among European countries, has influenced the lives of truck drivers by increasing competition, pressure on day-to-day activities, and constraints related to delivery deadlines. Adding this new pressure to those inherent in the road-freight transport sector has raised concerns, especially ones linked to levels of perceived stress by truck drivers. *Method:* With safety concerns in mind, we devised a questionnaire aimed at understanding how French truck drivers and non-French truck drivers, passing through four highway rest areas in France perceive stress, organizational factors, mental health, and risky driving behaviors. A sample of 515 truck drivers took part in the survey (260 French nationals), 97.9% of whom were male. *Results:* The results of a structural equation model indicated that perceived stress can increase self-reported risky driving behaviors among truck drivers. Furthermore, organizational factors and mental health were closely linked to perceived stress. Finally, some differences were found between French and non-French truck drivers with respect to mind-wandering and mental health, and to perceive driving difficulties to overcome and driving skills. *Practical Applications:* Several recommendations based on the findings are provided to policymakers and organizations.

1. Introduction

In 2014, truck drivers represented almost three million employees working in more than 549,000 companies throughout the European Union and were involved in 15% of all crashes (European Commission, 2017; European Road Safety Observatory, 2019). At that time, the road freight transport sector was generating approximately 330 billion euros in revenue, with the largest companies situated in countries including Germany, France, and the Netherlands (European Commission, 2017). According to a review of social issues related to road-freight transport (Brasseur, Paquel, Colussi, Rageau, Lambrey, Sarron, & Prat, 2018), the estimated activity of European Union road-freight transport in 2015 was approximately 1,768 billion tons/kilometer, which represents an increase of 2.4% over 2014. However, this increase was not equally distributed among all of the European Union members. The activity of companies from the EU-13[1] members rose by 5.2%, whereas that of EU-15[2] members grew by only 1.2%. Furthermore, the total number of road-freight companies decreased in EU-15 but increased in EU-13, especially in Romania (10.3%) and Poland (2.5%) (Brasseur et al., 2018). This new reality is leading to a greater number of foreign pavilion (foreign flag) drivers transiting through various European countries.

In this context, France plays a bridging role, allowing truck drivers to link Eastern Europe to Southern and Western Europe (Limbourg & Jourquin, 2009), which implies that France is one of the most widely traveled countries in Europe by truck drivers. Recently, Brasseur et al. (2018) pointed out that approximately 34.5% of all truck drivers circulating in France in 2015 were registered under a foreign company.

Taking into account truck drivers' high exposure to traffic, the risk of crashes represents a significant concern. In the early 2000s, a period of constant decline in mortality from crashes

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[1] EU-13 refers to the 13 member states that adhered to the European Union in 2004, 2007, and 2013. The 13 members are Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia.

[2] EU-15 refers to the 15 member states of the European Union as of December 31, 2003, before the new member states joined the EU. The 15 members are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, The Netherlands, Portugal, Spain, Sweden, and The United Kingdom.

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involving heavy trucks was due both to new policies on legal daily work hours and better technical conditions of trucks, improved infrastructures, and better road signaling (Medina-Flintsch et al., 2017). However, between 2015 and 2016 an increase of 4.2% in mortality from crashes involving heavy trucks prompted a renewed awareness of this issue. The situation is worrisome if we also consider the severity of these crashes. In France, for 2016, Brasseur et al. (2018) found that 176 persons were killed for every 1,000 crashes involving heavy trucks, almost three times as many as for road crashes in general, where the count was 60 deaths for every 1,000 crashes. Furthermore, more fatal crashes involving heavy trucks occur on divided highways (31%) as compared to fatal road crashes in general (10%) (Brasseur et al., 2018), and as a consequence, 18% of persons killed and 27% of persons injured in crashes involving heavy trucks in 2016 occurred on divided highways (Observatoire National Interministériel de la Sécurité Routière, 2017).

Speeding has constantly been found to be the most common offense among vehicle drivers in general (Elvik, Vadeby, Hels, & van Schagen, 2019) and has consistently been linked to the number of crashes and their severity (Imprialou, Quddus, Pitfield, & Lord, 2016). Truck drivers also report speeding more often than any other driving offense (Newnam, Lewis, & Warmerdam, 2014; Tseng, Yeh, Tseng, Liu, & Lee, 2016).

To create actions aimed at reducing crashes and risky behaviors among truck drivers, one approach is to gain a better understanding of their behavior. The particular reality faced by professional truck drivers such as long working hours, constraints due to delivery deadlines, tiredness due to loading/unloading, work routines, concentration loss (e.g., Sabbagh-Ehrlich, Friedman, & Richter, 2005), as well as changes brought about by the free circulation of goods across the EU (resulting in pressure from business competition) increase the complexity of their working environment (e.g., increase in the number of truck drivers leading to more pressure to find a parking place to rest in highway rest areas). This is leading to serious consequences in terms of stress and mental health. It is therefore important to analyze the behavior, organizational factors, perceived stress, and mental health not only of truck drivers from foreign countries but also the behavior of truck drivers from France. To our knowledge, there are too few studies that look into these factors in the current European setting.

The present paper aims to fill in that gap by analyzing how the perceived stress of truck drivers (French and non-French) is connected to organizational support and job characteristics, mental health, perceived risk, and risky driving behavior. The paper is divided into four main sections. The first section focuses on truck drivers' perceived stress. It is divided into two subsections, one dealing with factors contributing to truck drivers' perceived stress, the other focusing on the impact of perceived stress on truck drivers. The second section focuses on the method used in the present study. The third section provides the results. The fourth and last section discusses the findings, implications, and future research.

1.1. Truck drivers' perceived stress

Perceived stress is the "degree to which individuals find their life unpredictable, uncontrollable, and overloading" (Lesage, Berjot, & Deschamps, 2012, p. 178).

1.1.1. Factors contributing to drivers' perceived stress

Here, we are considering two factors: organizational (such as organizational support, supervisor pressure, job satisfaction) and individual factors (such as mental health, physical health, and perceived driving skills).

1.1.1.1. Organizational factors. Organizational support has been shown to have an impact on stress and on driving performance by way of working conditions, management style, and training, and also through job satisfaction. On one hand, management and working conditions are considered crucial to ensuring productivity and safety. For example, management style and more specifically, supervisor pressure (Johnson, Bristow, McClure, & Schneider, 2009), was connected to transgressive work behaviors, stress, and a greater intention to leave the organization (Spector & Fox, 2010). Hege, Lemke, Apostolopoulos, and Sönmez (2019) corroborated these findings by linking supervisor support and work hours per day to truck drivers' stress levels. Working conditions, especially, were shown to contribute to employees' stress levels. Truck drivers have often indicated poor working conditions such as long work hours, repetitive tasks, and frequent constraints due to delivery deadlines (often in contradiction with safety regulations). These conditions are imposed by trucking companies who are forced to deliver to customers whose goods are out of stock or lack a place to store them, thus requiring truck drivers to work on a just-in-time basis, with long periods of separation from their family, and overly strict regulations (such as speed limits, highly regulated work hours, and breaks). These things can even cause them to lose their drivers' license, one the main drawbacks of this occupation. Such working conditions have been shown to raise everyday levels of stress (Hege et al., 2019; Johnson et al., 2009; Semeijn, de Waard, Lambrechts, & Semeijn, 2019).

On the other hand, training and adequate safety awareness programs implemented by the organization have been shown to lower employee stress by increasing the level of perceived preparedness in case of an emergency (Atombo, Wu, Tettehfio, Nyamuame, & Agbo, 2017) and contributing to the creation and maintenance of a safety-oriented work environment (Murphy, Huang, Lee, Robertson, & Jeffries, 2019). Not all truck drivers' jobs are stressful or difficult. Some aspects are seen as positive, especially those linked to the salary level, which is one of the most important factors of satisfaction (Prockl, Teller, Kotzab, & Angell, 2017) along with the amount of freedom the job involves. These factors contribute to the attractiveness of the occupation insofar as most truck drivers appreciate the independent nature of their work and are quite satisfied with their wages. All of these factors contribute to job satisfaction, and previous studies have shown that low job satisfaction is linked to high levels of stress and poor health (Hoboubi, Choobineh, Ghanavati, Keshavarzi, & Hosseini, 2017; Peltzer, Shisana, Zuma, Van Wyk, & Zungu-Dirwayi, 2009).

1.1.1.2. Individual factors. As far as individual factors are concerned, mental health (e.g. well-being, burnout, mind-wandering), physical health, and job skills have all been linked to stress. First, stress has been connected to poor mental health (Alavi et al., 2017). Wellbeing, for example, has frequently been correlated to low levels of stress. Low levels of well-being have been linked to a greater intention to leave the organization and to poor work performance (Bliese, Edwards, & Sonnentag, 2017). In the same vein, burnout is strongly correlated to high-stress levels and low levels of wellbeing and has been shown to have critical effects on the organization as a whole. Burnout is known to be linked to lower performance and a higher frequency of transgressive behaviors (Bliese et al., 2017; Lazaro, Shinn, & Robinson, 1984; Selamu, Thornicroft, Fekadu, & Hanlon, 2017). Evidence of the link between stress and mind-wandering has been provided by several studies showing that stressed participants were more likely to manifest mind-wandering behaviors (Vinski & Watter, 2013). Mind-wandering is especially dangerous for drivers because it has been associated with crashes (Walker & Trick, 2018). Another important factor frequently linked to drivers' proneness to crashes is driver fatigue. Sleep quality is crucial for drivers because it affects their ability to stay alert and make good decisions while driving (Filtness et al., 2020). Insomnia is known to correlate with higher levels of stress and depression (Hall et al., 2000). Among truck drivers, difficulty sleeping and getting proper rest in their cabins at highway rest areas are common complaints.

Secondly, physical health is known to be linked to stress. The physical fitness of persons who drive for a living is one of the largest concerns in the industry (Filtness et al., 2020) since it has been found to be correlated to higher stress levels and caffeine consumption. Furthermore, some of the complaints of truck drivers involve food quality and lifestyle (Johnson et al., 2009).

Finally, some studies have pointed out that stress can also be correlated with driving skills. Research has also shown that drivers with low levels of perceived driving skills feel more stressed in complex traffic situations (Ringhand & Vollrath, 2019) and that drivers with little confidence in their driving abilities report higher levels of driving-related stress (Siren & Meng, 2013).

1.1.2. Consequences of perceived stress on truck drivers' driving performance and risky behaviors

The main consequences of stress have frequently been linked to poor driving performance and accident proneness (Christian, Bradley, Wallace, & Burke, 2009; Gao, González, & Yiu, 2020; Sutherland & Cooper, 1991). Other studies have shown that driver behavior and driver performance can be influenced by stress (Day, Brasher, & Bridger, 2012; Taylor & Dorn, 2006). Stress can affect drivers' performance in two ways: it can interfere with their ability to focus on the task at hand by triggering feelings of anxiety (Hoseinabadi et al., 2015; Matthews et al., 1998), and high-stress levels can impair drivers' judgments, thereby contributing to poor decision-making while driving and also increasing crash risk (Day et al., 2012). Riskier driving behaviors (Öz, Özkan, & Lajunen, 2010; Useche, Ortiz, & Cendales, 2017), as well as higher perceived risk (Rundmo, 1995), were also linked to higher levels of stress.

The following section describes the main concerns noted in the literature concerning risky driving behaviors. Compared to car drivers, truck drivers have been shown to drive more often with their seat belt unfastened (Cook, Hoggins, & Olson, 2008). In France in 2016, among 44 truck drivers killed in road crashes for whom information was available, 11 had not fastened their seatbelt (Observatoire National Interministériel de la Sécurité Routière, 2017). Another risky driving behavior is phone use while driving. Studies have found that truck drivers link hand-held phone use to causing and experiencing potentially dangerous situations (Troglauer, Hels, & Christens, 2006). Finally, transgressions regarding working hours (such as driving over the daily time limit per day or counting loading and unloading times as break times[3]) can significantly contribute to increased risk of fatigue (Friswell & Williamson, 2019).

There is still a need for a more systematic and comprehensive understanding of how organizational and individual factors can influence truck drivers' perceived stress, and how perceived stress can affect perceived risk and risk-taking behaviors. The initial version of the model proposed in this study is the one tested by Hege et al. (2019), who argued that working conditions and organizational support can have an impact on stress. To develop this starting point, we relied on the international and European (European Commission, 2017; European Road Safety Observatory, 2019) literature, as well as French analyses (Brasseur et al., 2018; Interministériel, 2017), to create a somewhat more comprehensive picture of the perceived stress of truck drivers circulating in France and its impact on perceived risk and risk-taking behaviors.

The aim of this study, carried out with a face-to-face survey administrated to truck drivers circulating in France, was twofold. Our first aim was to look into both the stress level of truck drivers (whose job conditions can be difficult, repetitive, and subject to many constraints) and its connection to organizational and individual factors. The second aim was to analyze how individual and organizational factors affect perceived stress and what its consequences are on perceived crash risk and risky behaviors, including whether these relationships depend on whether the driver is French or non-French. We hypothesized that non-French drivers' lack of familiarity with the environment, the different types of training received in their country of origin, and language and cultural differences might lead to a different pattern of relationships between perceived stress and organizational, individual, self-reported risky behaviors, and perceived crash risk than those found for French drivers.

2. Method

The survey addressing the truck drivers' characteristics and behaviors was conducted using a questionnaire displayed on an iPad in various highway rest areas of France (Center, Southeast, Southwest, and Ile-de-France). The rest areas were chosen based on two criteria: their use by truck drivers of different nationalities and the easiness of obtaining permission for data collection.

The research program was conducted in compliance with the ethical standards of the French Society of Psychology and was systematically monitored for compliance with the ethical guidelines of the Ethical Committee of the French institute of science and technology for transport, development, and networks.

2.1. Participants

The participants were all truck drivers who were transiting French highways. Overall, the sample had 515 respondents (11 women) with an average of 20.5 years of work experience (SD = 11.42, range: 0–48) who took part in the survey. The mean age in the sample was 45.83 (SD = 10.18, range 21–70). The drivers covered an average of 588 km per day (σ = 162.34, range: 100–900) in their truck. Most of the participants indicated that they are employed (91.1%), while fewer said they were owners or self-employed (8.9%). Many truck drivers (94.8%) acknowledged existing pressure to respect strict schedules and timetables, as well as direct supervisor pressure under threat of financial penalties if the organization loses the client.

2.2. Measures

2.2.1. Questionnaire

The content of the questionnaire was based on a literature review and two series of preliminary, semi-structured interviews. The interviews aimed to: obtain up-to-date knowledge of truck drivers' experiences while on the road and during rest periods; their opinions and impressions about their occupation; and their driving behaviors, difficulties, and work conditions in general. The information collected made it possible for us to devise appropriate ad hoc measures.

The questionnaire, developed in French, was translated into Bulgarian, English, Italian, Polish, Portuguese, Romanian, and Spanish by native speakers specialized in transport and transportation. Most of the questions required answers on five-point Likert scales of frequency ranging from 1 (never) to 5 (very often), and intensity of agreement ranging from 1 (not at all) to 5 (absolutely). Some

[3] Setting loading and unloading as break time means that while truck drivers who are working loading and unloading their truck they should not register that time as a break. However, this illegal practice is a common practice since it allows the drivers to increase their work time period.

questions required a simple yes or no answer. The reliability of the scales was assessed using Chronbach Alpha test.

The questionnaire contained six sections assessing four organizational factors and six categories of individual factors.

2.2.2. Organizational factors

Supervisor pressure. Participants were asked whether they felt their supervisor was pressuring them to meet delivery deadlines. There was only one item assessing supervisor pressure and the answers ranged from 1 (not at all) to 5 (almost all the time).

Discontent. The discontent scale was aimed at assessing several known problems linked to truck driving. An average of the responses was computed from items assessing various issues such as safety and deadlines, healthy lifestyle, food quality, and constraints for truck drivers (e.g., *I feel there is a contradiction between safety and deadlines).* The answers to each item ranged from 1 (not at all) to 5 (all the time) (α = 0.65).

Training. Training assessed the investment in training made by the organization. Participants were asked to indicate whether the organization they belonged to offered training activities related to road safety in general and specific risks such as sleepiness, inattention, or distractibility. The higher the final score, the more such training activities the company offered. The scores ranged from 0 (none of the programs listed) to 4 (all of the training programs listed).

Job satisfaction. This factor assessed participants' job satisfaction on five items. Participants were asked to rate, on a scale from 1 (not at all) to 5 (completely): whether their work-life corresponded to their ideal, whether their work conditions are excellent, if they are satisfied with their professional life, whether they have achieved the most important things in their professional life, and whether they would change something if they could start again (e.g., *My professional life is completely in line with my ideals).* The scale was adapted to the French population by Fouquereau and Rioux (2002) (α = 0.85).

2.2.3. Individual factors

a. Mental health was assessed on three factors:

Wellbeing. This factor was measured with the World Health Organization's (WHO) five-item wellbeing scale (World Health Organization. (1998) (1998), 1998). Participants were asked to rate items such as *I feel calm and happy* on a scale from 1 (never) to 6 (all the time) (α = 0.90). The individual score could vary between 0 and 100.

Burnout. This was measured using a French version (Doppia, Estryn-Béhar, Fry, Guetarni, & Lieutaud, 2011) of the six-item personal burnout subscale of the Copenhagen Burnout Inventory (Kristensen, Borritz, Villadsen, & Christensen, 2005). Participants were asked to rate items such as *I feel empty* on a scale from 1 (never) to 5 (all the time) (α = 0.90). The participants' scores could vary between 0 and 100.

Mind-wandering. This was measured using a French translation of Mrazek, Phillips, Franklin, Broadway, and Schooler (2013) five-item scale. The scale assesses concentration issues and difficulties such as *I have trouble maintaining my focus during simple or repetitive tasks* on a scale from 1 (almost never) to 6 (almost always) (α = 0.85). An individual's score could vary between one and five.

Insomnia severity. Insomnia was measured using the seven-item Insomnia Severity Index (Bastien, Vallières, & Morin, 2001; Gagnon, 2012). Participants were asked about whether they had trouble falling and staying asleep, had difficulties waking up, how happy they were with the sleep they were currently getting, and whether they felt worried about sleeping issues, on a scale ranging from 1 (not at all) to 5 (completely) (e.g., *Please estimate the current gravity (last month) of your sleep difficulties: Trouble falling asleep*) (α = 0.74).

b. Physical health was assessed via a composite index derived from several questions. We took into account whether participants said they smoked, has gained weight in the last three years, felt their diet was unbalanced, did not exercise, had blood pressure issues, drank alcohol, and whether they perceived their overall health as poor or acceptable (versus good and excellent). The higher the score, the less physically healthy the participant was. An individual's score could vary between 0 (none of the above issues) and 6 (at least six of the above issues).

c. Driving skills were measured via two factors:

Perceived driving skills. This index assessed general and specific driving situations such as keeping a safe inter-vehicle distance, managing downhills or dangers on the road, and maneuvering into parking spaces (e.g., *I feel competent at foreseeing dangers on the road*). The seven items were measured on a scale ranging from 1 (not at all) to 5 (completely) and were averaged to obtain a perceived driving skills index (α = 0.92).

Perceived driving difficulties. This index measured the perceived driving difficulty to overcome of various general and specific driving situations. The six items assessed maneuvers such as managing blind spots, breaking while driving downhill, and managing driving in rain or snow, on a scale ranging from 1 (very hard to manage) to 5 (very easy to manage) (e.g., *When driving my truck blind spots are ..*) (α = 0.82).

d. Perceived stress was measured using the 10-item Perceived Stress Scale (Cohen, Kamarck, & Mermelstein, 1983; for the French version, see Lesage et al., 2012). The Perceived Stress Scale (PSS) measures "the degree to which respondents find their life unpredictable, uncontrollable, and overloading" (p. 178, Lesage et al., 2012). Participants used a scale ranging from 1(never) to 5 (very often) the give their answers for items such as *How often were you disturbed by an unexpected event?* (α = 0.80).

e. Perceived crash risk was measured by averaging eight items related to the perceived risk of having a crash with various road users such as another truck, a car, a motorcycle, a highway patrol car, a caravan, a bus, while loading/unloading, when another truck is changing lane, when I am changing lane (e.g., *The risk of having a crash with another truck is..*). Participants were asked to indicate their answers on a scale ranging from 1 (very low) to 5 (very high) (α = 0.86).

f. Self-reported risky behaviors were assessed by averaging participants answers to eight self-reported risky-behavior items such as going over the speed limit, driving under the influence of alcohol or drugs, driving more hours than the legal daily time limit, or reporting loading time to breaks and vice versa (α = 0.70). Participants had to indicate their answer using a Likert scale from 1 (never) to 5 (almost all the time) (e.g., *I drive over the speed limit).*

g. Demographic characteristics such as gender, marital status, nationality, daily kilometers driven on the highway, age, truck driving experience, demerit points (anywhere in the EU and only when driving a truck), and involvement in road crashes (within the last three years) were also collected. They are summarized in Table 1.

2.3. Procedure

Professional interviewers administered the questionnaire at four highway rest areas in France where truck drivers of different nationalities frequently stop. About three or four interviewers were stationed at each area from about 5 p.m. to about 9 p.m. on nine workdays in mid-March 2018. Truck drivers were contacted in the parking zones and/or in the vending facilities of the rest areas. Participants were asked to choose the language in which they wished to answer the questionnaire (from the list of eight languages available). They were informed that the study was about the perceived risks inherent in truck driving, and told that the

Table 1
Descriptive statistics for sociodemographic variables.

Sex	Men	97.9%
Marital status	Single	19.8%
	Couple	64.1%
	Separated	16.1%
Kilometers on highway	50 km	3.7%
	150 km	6.6%
	250 km	6.6%
	350 km	15.1%
	450 km	68.0%
French or non-French	*Number*	*Percent*
	French	50.5%
	N = 260	
	Non-French	*45.5%*
	N = 255	
Nationality	Romanian	7.8%
	Portuguese	7.4%
	Spanish	6.4%
	Polish	6.2%
	Italian	5.6%
	Bulgarian	4.9%
	Belgian	4.7%
	Other	7.2%
	M	*SD*
Age	45.83	10.18
Experience	20.47	11.41
Demerit points	1.05	1.98
Car crashes	0.28	0.74

study was anonymous and confidential, and abided by current legal regulations. They were also told that at least 30 minutes were needed to answer all of the questions. Then the truck driver could decide whether or not he/she wanted to participate. The average responding time was around 35 min. A scarf and coffee were offered as gifts to thank the participants.

3. Results

In line with our first aim, which was to examine the perceived stress level of truck drivers and its connections to organizational and individual factors, we conducted a descriptive analysis by looking at means, standard deviations, and correlations to better understand the sample and to be able to identify relevant relations between stress, self-reported risky driving behaviors, individual factors such as mental and physical health, and organizational factors.

In line with our second aim, which was to explain how perceived stress is experienced by truck drivers and to test whether it differs according to the drivers' familiarity with the environment (French or non-French drivers), we used path analysis (measurement and structural modeling) to test a model implying different relations between perceived stress, self-reported risky driving behaviors, organizational factors, and individual factors. All analyses were conducted in SPSS or AMOS.

3.1. Descriptive statistics for stress and organizational and individual factors

3.1.1. Organizational, individual factors, and mental health

Training programs are offered in many organizations to increase safety. In our sample, 36.1% of the participants indicated that their organization was taking training seriously and provided sessions for all of the four issues in the questionnaire (see section 2.2.1, Measures) whereas 34% said their organization was offering training for at least one or more of these issues, but not for all four. The rest of the participants (29.9%) stated that their organization provided none of the above training programs. Training also correlated with low stress, low supervisor pressure, and high wellbeing and perceived driving skills, indicating that the truck drivers felt more prepared and safer when the organization provided training. Supervisor pressure scored quite low in the sample but had a high standard deviation, indicating a large dispersion in the answers of our truck drivers. Higher scores for supervisor pressure correlated with low job satisfaction, low wellbeing, and high burnout and insomnia scores, indicating that the impact of supervisor behavior significantly impacted the overall work and home lives of the truck drivers. Participants seemed to be rather discontent concerning the working conditions at their current jobs but were satisfied with their job, presenting higher means for job satisfaction than the general population. Discontent correlated with low levels of job satisfaction and wellbeing, and with high levels of supervisor pressure, burnout, and mind-wandering. Job satisfaction, however, was linked to high levels of wellbeing and low levels of insomnia severity and burnout. Concerning mental health, the participants reported quite a high level of wellbeing and low levels of burnout and mind-wandering. On driving skills, the participants felt confident in their driving abilities, displaying high means for perceived driving skills and low means for perceived difficulties to overcome. This suggests that they felt they can manage the various driving situations that might arise during their activity.

3.1.2. Perceived stress level of truck drivers

We used descriptive statistics to achieve the first aim of examining the perceived stress level of truck drivers. As seen in Table 2, perceived stress was present among the participants in the sample, as reflected by both the range (42) and standard deviation of the ratings on this scale. Furthermore, more than half of the sample (53.2%) scored higher than the midpoint of the scale (22), suggesting that perceived stress is common among truck drivers. No significant difference in perceived stress between French and non-French participants was observed in terms of ($t = 0.067_{(513)}$; $p = 0.50$). As seen in Table 3, perceived stress correlated highly with mental health variables such as wellbeing, burnout, and insomnia, suggesting that high levels of wellbeing and low levels of burnout and insomnia are linked to low levels of stress. A somewhat more moderate correlation was identified between stress and organizational factors such as discontent and supervisor pressure as well as with individual factors such as perceived driving skills. More specifically, the lower truck drivers perceived their driving skills, the higher their perceived stress. Also, the higher their discontent with the job, the higher the perceived stress. Finally, perceived stress correlated positively with both self-reported risky behaviors and perceived crash risk, suggesting that high perceived crash risk is linked to high perceived stress.

3.1.3. Perceived crash risk and Self-reported risky behaviors

Perceived crash risk scores were near the high end of the scale, indicating that truck drivers perceived crash risk as quite elevated. Furthermore, perceived car crash-risk correlated positively with stress, insomnia severity, mind-wandering, and burnout. The risky-behaviors mean was very low in the sample, indicating that the truck drivers said that they did not engage in risky behaviors, and it correlated positively with stress, discontent, insomnia severity, and burnout. Therefore, drivers who reported being less able to sleep and get well-rested (i.e., ones reporting high insomnia severity), were not happy with their job conditions (high scores on the discontent scale); they thus reported high levels of stress and were more likely to have high scores on risky behaviors and perceived car-crash risk.

Fig. 1 summarizes the main correlations between the variables.

Table 2
Descriptive statistics for organizational and individual factors, perceived crash risk and risky driving behaviors.

	Minimum	Maximum	Mean	Std. Deviation
Organizational Factors				
Discontent	1.00	5.00	3.13	0.90
Supervisor Pressure	1.00	5.00	2.44	1.38
Job Satisfaction	1.00	5.00	3.53	0.93
Individual Factors				
Driving Skills				
Perceived driving competences	1.00	5.00	4.37	0.79
Perceived difficulties to overcome	1.00	5.00	3.49	0.80
Mental Health				
Wellbeing	0.00	100.00	70.41	19.78
Burnout	0.00	100.00	26.13	21.75
Mind-wandering	1.00	5.00	2.33	0.94
Insomnia severity	1.00	26.00	8.24	5.30
Perceived stress	10.00	43.00	23.08	6.91
Perceived crash risk	1.00	5.00	2.79	0.90
Self-reported risky behaviors	1.00	4.00	1.62	0.51

Table 3
Covariance added to the overall model.

Pearson correlation			Modification Indices (M.I.)	*r*
Driving skills	< –>	Organizational support	17.95	0.57***
Mental health	< –>	Organizational support	33.10	0.78***
Mental health	< –>	Driving skills	18.17	0.49***

*** $p < 0.000$.

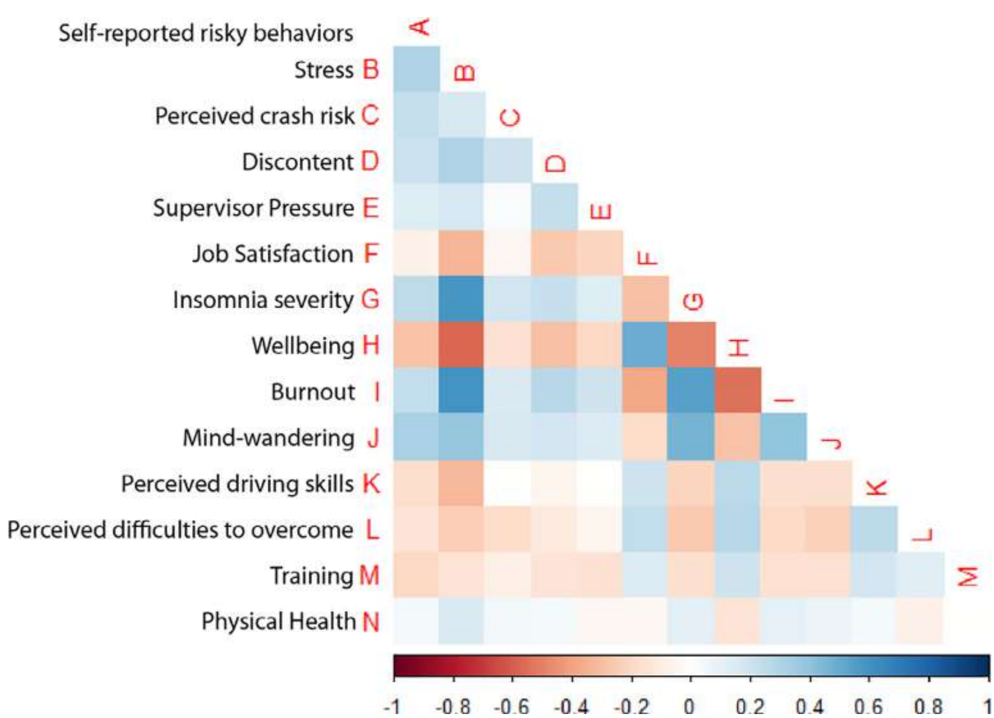

Fig. 1. Pearson correlations between perceived stress, perceived crash risk, risky behaviors, organizational factors, and individual factors.

3.2. Testing for the relations between perceived stress and organizational and individual factors

The structural equation modeling (SEM) technique is generally used to analyze structural relationships. SEM represents a combination of factor analysis and multiple regression analysis allowing to identify and to emphasize paths between latent variables, which serve the purposes of the current paper (Byrne, 2004; Streiner, 2006). The first purpose was to develop and test a model indicating the relationships between stress and various organizational and individual factors. The second purpose was to use the Fig. 1 model to compare two samples: French and non-French truck drivers. This comparison was meant to identify whether the baseline model varied with familiarity with the environment (French drivers know the highways, understand the written and spoken warnings better, can reserve parking spaces and navigate rest areas more easily than non-French drivers, and are closer to their families). The use of structural equation modelling was considered suited to the aims of the paper since relations between the constructs can be considered simultaneously and tested holistically (Byrne, 2004; Hair, Black, Babin, Anderson, & Tatham, 2010). The two analyses were carried out in AMOS (Arbuckle, 2006) using maximum likelihood estimation The model comprised three latent variables: (a) organizational support for which discontent, supervisor pressure, training, and job satisfaction were considered as observed variables; (b) driving skills for which perceived driving competences and perceived driving difficulties to overcome were considered; and (c) mental health for which we considered well-being, burnout, mind-wandering, and insomnia severity. Finally, perceived stress, self-reported risky behaviors, perceived car-crash risk, and health were treated as observed variables. The model tested can be seen in Fig. 2. However, based on the goodness of fit indicators, this model was considered to have a somewhat poor fit ($\chi^2 = 332.58_{(73)}$, $p < 0.00$, TLI = 0.78, CFI = 0.83, RMSEA = .083 C.I. [0.074–0.092]). Acceptable goodness of fit indicators are considered to be over 0.90 for TLI and CFI and around 0.05 for RMSEA (Byrne, 2010). To improve the models' fit, and in line with the somewhat exploratory nature of the analysis, we decided to add several covariances (see Table 3) as well as a direct path between the observed mind-wandering and risky-behaviors variables (marked in Fig. 2 with a dotted line). The decision was based on modification indices values, as suggested by Byrne (2010). Following these model re-specifications, the fit indexes improved and were considered to be acceptable ($\chi^2 = 201.50_{(68)}$, $p < 0.00$, TLI = 0.89, CFI = 0.91, RMSEA = .062 C.I. [0.52–0.72]).

As seen in Fig. 2, stress was directly linked to mental health and to risky behaviors, suggesting that highly stressed truck drivers are less likely to report good mental health and could therefore be more prone to engaging in risky behaviors. Organizational support affected stress and driving skills. Both variables had negative loadings, suggesting that the higher the organizational support and driving skills the lower the truck drivers' stress. The relations between organizational support and driving skills were further strengthened by the covariance added to the model, suggesting that strong organizational support is linked to good driving skills. Furthermore, organizational support was strongly linked to mental health as well, implying that drivers who perceive high organizational support are more likely to indicate good mental health. A very interesting result was the direct link that emerged following model re-specifications based on modification indices (M.I. = 20.34). It indicated that mind-wandering influences risky behaviors, suggesting that drivers who are not able to concentrate are more likely to engage in risky behaviors.

The analysis used the model identified above and compared the structure of the two samples: French and non-French. In testing for between group equivalencies, a set of parameters are put to the test in a logical order and in an increasingly restrictive fashion. After analyzing the baseline model (the freely estimated model), the test usually starts with the analysis of the measurement model. When analyzing the measurement model, the pattern of factor loadings for each measure is tested for equivalence across the two groups: French and non-French. Following this stage a new set of parameters is constrained and the new models are tested. The constraints follow an increasing restrictive direction from constraining measurement (factor loadings), to structural weights (regression paths), to structural covariances (covariances), to structural residuals (residuals of latent factors). The unconstrained model has no constraints added and functions as a baseline model (Byrne, 2004). Based on nationality verification, we eliminated a French-Belgian national due to his dual citizenship that went against our split variable (we could not decide where to place the participant). The final sample thus had 514 participants, 260 of French nationality, and 254 of various other nationalities (see Table 1 for full details on nationality). The same model was used for the two groups. The model proved to have a good fit ($\chi^2 = 303.64_{(138)}$, $p < 0.00$, AGFI = 0.89, CFI = 0.89, RMSEA = .048 C. I. 0.41–0.56). The italicized numbers in Fig. 3 are those of the non-French nationals.

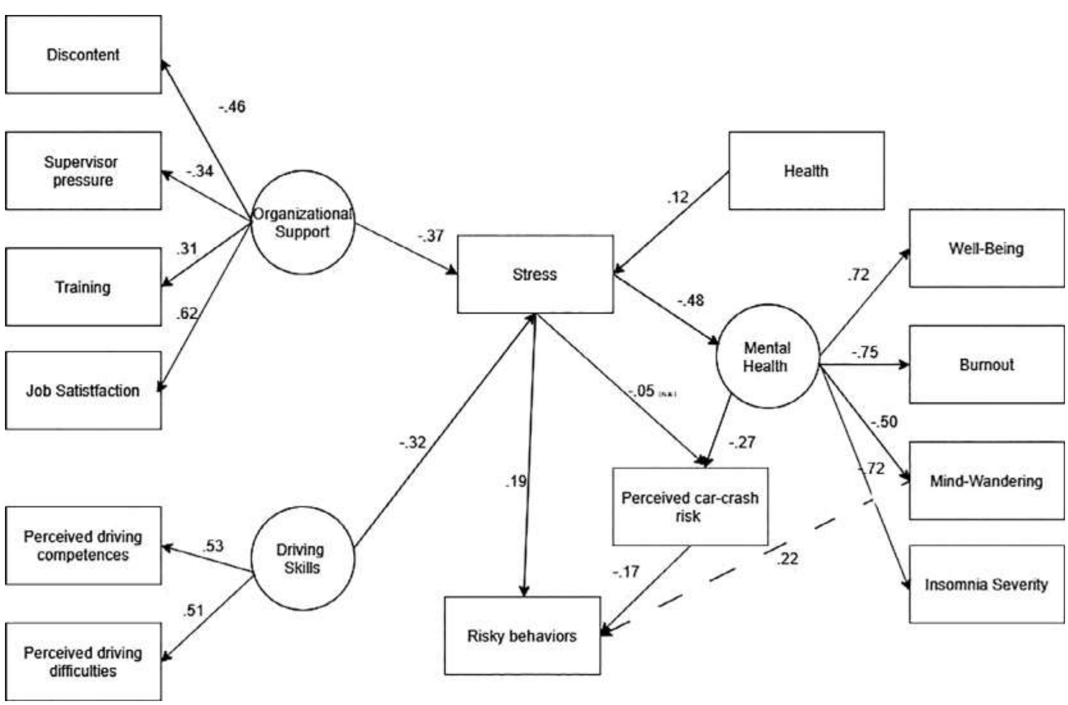

Fig. 2. Structural equation modelling on overall sample. *Lines between latent variables and observed variables depict factor loading values, while lines between observed variables depict path weights.*

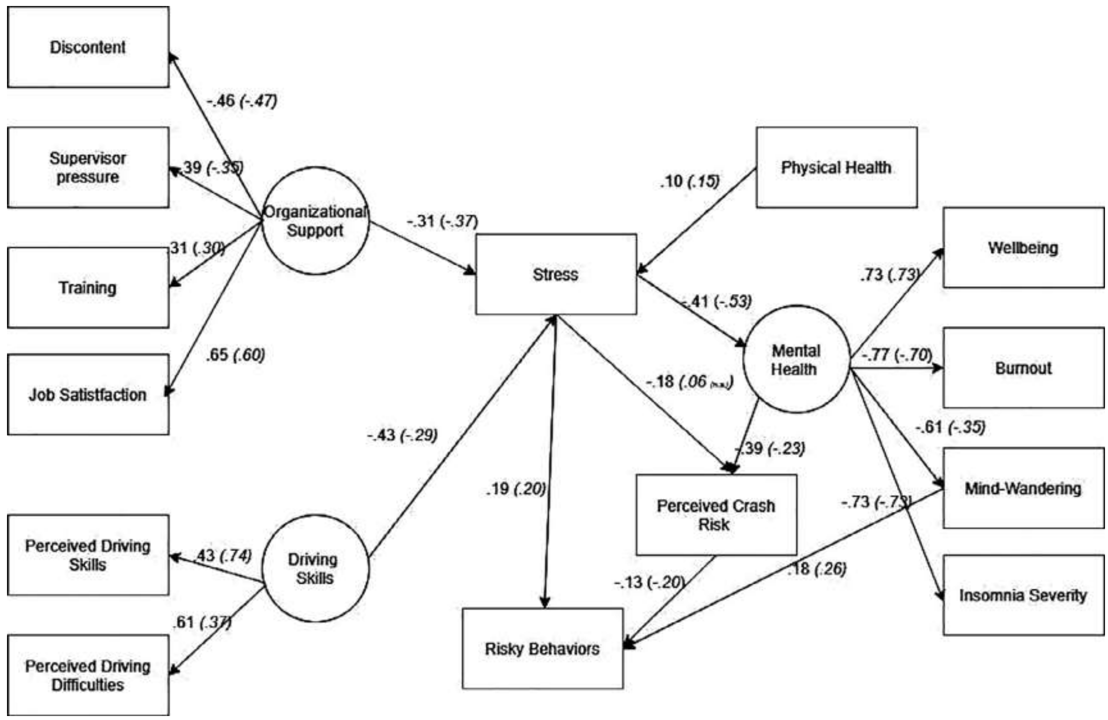

Fig. 3. Structural equation modelling for comparing French and non-French samples. *Lines between latent variables and observed variables depict factor loading values, while lines between observed variables depict path weights. Values italicised and between parenthesis represent the values for the non-French national model.*

First, we checked for the invariance of the measurement and structural model. The results can be seen in Table 4. Based on these results, if the unconstrained model is correct, then the significant chi-square difference is evidence of a lack of invariance between the two models. The other results suggested the invariance of the models across the two groups.

Taking into account that the chi-square difference between the unconstrained model and measurement model was marginally significant ($p = 0.051$, see Table 4), and in line with the exploratory nature of our analyses, we chose to compare the paths of these two models (one by one) to identify where those differences appeared. Following verification, two significant differences emerged. There was a significant difference for perceived driving difficulties to overcome and driving skills ($t_{(512)} = 2.52$, $p = 0.01$) and for mind-wandering and mental health ($t_{(512)} = 2.65$, $p = 0.008$) between the two samples (French and non-French). For the French participants, perceived driving difficulties to overcome contributed more to defining driving skills than for the non-French participants. Similarly, for the French participants, mind-wandering contributed significantly more to mental health than for the non-French participants (Table 5).

Table 4
Invariance model testing for differences between French and non-French truck drivers.

Invariance test	Chi-square difference	p
Unconstrained vs Measurement weights	18.23 $_{(10)}$	0.051
Measurement weights vs. Structural weights	6.12 $_{(6)}$	0.408
Structural weights vs. Structural covariances	5.75$_{(5)}$	0.330
Structural covariances vs. Structural residuals	4.81$_{(3)}$	0.186

Table 5
Covariance added to the comparison model.

Pearson correlation			French r	non-French r
Driving skills	< –>	Organizational support	0.59***	0.44***
Mental health	< –>	Organizational support	0.80***	0.82***
Mental health	< –>	Driving skills	0.68***	0.31***

*** $p < 0.000$.

4. Discussion

Road freight transport by truck drivers is indispensable for the proper functioning of our countries, as we were able to see during the Covid-19 lockdown (International Transport Forum, 2020). Therefore taking an interest in the well-being of truck drivers is of utmost importance. Truck drivers represent a very particular population among professional drivers. Their behavior, as well as any factors that influence stress levels, mental health, or physical health, need to be assessed by taking into account their very peculiar work context.

The current paper had two aims: (a) assess the perceived stress levels of truck drivers and how they perceive their work, and look at some relevant individual (mental and physical health) and organizational (support, management, working conditions) factors; (b) analyze the impact of individual and organizational factors on perceived stress and its consequences on perceived crash risk and risky behaviors, and determine whether these relationships are different for French and non-French truck drivers.

The results, as Fig. 2 revealed, that among our sample of truck drivers circulating in France, organizational factors were linked to increased stress, in line with the findings of Hege et al. (2019). Lack of job control, strong time pressure caused by just-in-time freight delivery systems, and long work hours were frequently linked to greater stress among truck drivers (Apostolopoulos, Peachey, & Sonmez, 2011). Furthermore, the results showed that low job satisfaction coupled with discontent related to working conditions, such as unhealthy lifestyle and low-quality food, can increase driver's stress levels (Sabbagh-Ehrlich et al., 2005). Even though not extremely strong (in our findings as well those of Hege et al., 2019), particular attention must be paid to the relation between perceived stress levels and health consequences, since their long-term effects can be extremely serious. The fact that stress can lead to overeating and lack of energy for exercising can impact the long-term health of truck drivers and thereby lead to severe health problems (Apostolopoulos et al., 2011; Sabbagh-Ehrlich et al., 2005).

Stress was directly linked to risky driving behaviors. The fact that stress can affect behavioral outcomes is well known in organizational psychology, where stress is considered an antecedent of poor employee performance (Jamal, 1984; Nisar & Rasheed, 2020). Our results corroborate the findings showing that psychological stress is linked to risky driving behaviors (Oliveras et al., 2002; Useche, Cendales, & Gómez, 2017). Drivers exposed to stress might experience decreased cognitive abilities, which can lead to poorer decision-making (Michailidis & Banks, 2016). Furthermore, other studies have shown that individuals exposed to stress will rely more heavily on low-level, automatic processes (Porcelli & Delgado, 2009), an aspect that can lead to negative outcomes in highly complex situations.

Aside from these findings, an interesting relation between the role of perceived driving skills and stress emerged here. Self-confidence is well known among drivers (e.g., Delhomme, 1991; Sundström, 2008) and it could be able to reduce a driver's perceived stress (Wohleber & Matthews, 2016). The effect of self-confidence on perceived stress seems to be similar to the one played by organizational factors. However, although these findings seem to point to the importance of confidence in one's skills, overconfidence while driving has been frequently linked to crashes. Measures aimed at increasing drivers' skills should thus be taken cautiously.

In line with individual factors, perceived stress was correlated here with low levels of well-being (Rony & Ahmed, 2019), high levels of burnout (Useche, Cendales, Alonso, & Serge, 2017), and high levels of mind-wandering (Vinski & Watter, 2013). This particular set of relations is of great interest, since mind-wandering, in particular, has been linked to crashes (Gil-Jardiné et al., 2017; Yanko & Spalek, 2014), while burnout and well-being have frequently been linked to a greater intention to leave one's job (Lee, Kim, Gong, Zheng, & Liu, 2020; Moneta, 2011). Particular attention should be given to the relationship between stress and sleep. A positive correlation was found here between the level of self-reported stress and the insomnia index, indicating that poor sleep was connected to high levels of stress. Pylkkönen, Sallinen, Forsman, Holmström, Hyvärinen, Mutanen, and Sirola (2013) also found that sleep quality was linked to long-haul drivers' stress. Furthermore, low sleep quality has recently been linked to risky driving and crash involvement (Shams, Mehdizadeh, & Khani Sanij, 2020).

Finally, as seen in Fig. 3, we noted that the link between stress and all of the other factors analyzed were very close regardless of whether the drivers were familiar (French truck drivers) or not (non-French drivers) with the traffic environment, had different training depending on their country of origin, or had different cultural backgrounds and native languages. However, it should be noted that some differences were identified between French and non-French truck drivers with respect to mind-wandering and mental health and to perceive driving difficulties to overcome and driving skills. It is possible that French drivers who are very familiar with the traffic environment are less alert and thus allow themselves to daydream more frequently compared to non-French drivers, whom, being in a less familiar environment stay more alert. With respect to the perceived driving difficulties to overcome, it is possible that differences in initial truck driver training is responsible for the difference identified. Awareness campaign linked to mind-wandering should help all road traffic users (not only truck drivers) to increase understanding of the phenomena and increase vigilance. Similarly, training could be offered to truck drivers who feel they need to improve certain skills (such as managing dead angles). Another useful approach could be to increase awareness among all road traffic users on specific truck drivers' difficulties as well as providing various driving assistance systems.

Based on the findings, several other recommendations can be advanced. Firstly, particular attention must be paid to the long-term consequences on truck drivers' mental and physical health. In terms of physical health, making healthy food and beverages more available and easy to see in rest areas, at affordable prices, could be a start. Besides, clear information about healthy nutrition should be available through training sessions provided by the organizations and also in the rest areas themselves. Another possibility worth investing in would be to give drivers access to sports facilities both at the organization's headquarters and at rest areas, insofar as a proper diet and physical exercise are considered vital to the well-being of an individual, especially in the long term (McNaughton, Crawford, Ball, & Salmon, 2012). Another useful approach would be to reduce work constraints and difficulties that are specific to truck drivers since our results seem to suggest these factors have a direct impact on stress levels. One potential course of action could be to reduce delivery time pressure so that truck drivers could have more control over their time and increase their job autonomy, satisfaction, and identification with their job. Another course of action could be to introduce surveillance (video or patrol led) in parking lots and rest areas to make drivers feel safer and able to rest better. Employers could and should be encouraged to take steps towards monitoring and reducing employee stress. In an industry where it is well known that truck drivers are increasingly difficult to find (IRU, 2019), managers should strive to monitor and reduce the stress levels of their employees. Since organizational factors seem to have a strong impact on truck drivers' perceived stress, employers could consider creating an on-site diagnosis procedure and then addressing the most stringent needs identified therein, in view of reducing the stress levels of their employees. Furthermore, employers could consider implementing wellness programs tailored to the organization's needs.

Some limitations of this paper should be considered. The first is linked to the use of self-reported measures, which may be sensitive to social desirability. Another limitation is linked to the translation of the survey questionnaire, even though many precautions were taken (e.g., only native speakers with expertise in transport psychology were used as translators), and there were no complaints from the participants about the comprehensibility of the questionnaire.

Future research should focus on assessing the effects of actions and interventions based on the recommendations made here on the perceived stress levels of truck drivers.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Ride-hailing with kids: Who's got their back?

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ABSTRACT

Introduction: As transportation network companies (TNC) are on the rise, assessing the safety of children traveling in these vehicles is imperative. For this reason, this study developed and adopted a scoring system to assess states' safety standards for children traveling in TNC vehicles. *Methods:* The scoring was based on two parameters pertaining to child car seat laws for TNCs: clarity and stringency. For each parameter, three criteria that could impact child safety in TNC vehicles were formulated. If a state met a certain criterion it got 1 point and 0 otherwise. The authors gathered all the necessary information by reviewing state statutes in Nexus Uni, a legal research database. These reviews took place between December 2019 and October 2020, and this study evaluated state laws in effect on October 28, 2020. *Results:* During this assessment, the authors observed a lack of clarity in state child car seat laws, which could compromise safety of children traveling in TNC vehicles. For clarity of laws, Georgia and Indiana received the highest scores (3 out of 3 points), while 16 states scored only 1 point, which was the lowest score in this category. In terms of stringency of laws, Pennsylvania received the highest score (3 out of 3 points), while Indiana scored the least (0 points). *Conclusions:* Besides one state (Oregon), all other states defined TNCs in their state laws. All states except for Indiana and Washington required child car seats in TNC vehicles. The responsibility for child car seat use was clearly defined in 35 states. The fine for child car seat violation was $50 or more in 28 states. *Practical Application:* This study will help TNCs, policymakers, and stakeholders identify states that need to improve their standards for child safety in TNC vehicles, and comprehensively address the issue.

1. Introduction

In the last decade, a new travel option has evolved: transportation network companies (TNC), better known as ride-sharing or ride-hailing companies. TNCs provide pre-arranged transportation services using an online-enabled application or platform (California Public Utilities Commission, n.d.). In the United States, Uber and Lyft are the frontrunners of TNCs (Statista.com, 2020). In 2017, TNC vehicles transported over 2.6 billion passengers, a 37% increase from 2016 (Schaller Consulting, 2018). TNC services are predominantly used by younger people and concentrated in urban areas (Jiang, 2019). A survey conducted in the first quarter of 2017 found that 65% of all ride-share service users are between the ages of 16 and 34 (Mazareanu, 2018). With the average age at which women first become mothers in the United States being 26.4 (Livingston, 2018), the majority of U.S. ride-sharing service users fall within the age group that is most likely to have young children. A rapidly growing trend in the use of TNC services makes it only logical to assume that their use by families with children is on the rise as well, and will likely continue to grow in the future. The lack of clarity in the states' regulations of child car seat use by TNCs may negatively affect the safety of children traveling in TNC vehicles (Owens et al., 2019).

The objective of this study was to assess the states' safety standards for children traveling in TNC vehicles. The assessment was performed using a scoring system that was based on a host of factors that directly and indirectly influence child safety in TNC vehicles. The scoring system presented in this paper will be valuable to policymakers, TNCs, transportation professionals, and social activists, among others, to identify states with lower safety standards for children traveling in TNC vehicles and tackle the issue of child safety comprehensively.

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2. Background

In the United States, motor-vehicle crashes are the leading cause of death among children. According to reports released by the National Highway Traffic Safety Administration (NHTSA), 880 children aged 12 years and younger died, and nearly 190,000 children aged 0–14 years old were injured in motor-vehicle crashes in 2018 in the United States (NHTSA, 2020).

The use of child car seats and booster seats in passenger cars reduces the risk of fatal injury by 71% for infants (younger than 1 year old) and 54% for toddlers (1–4 years old; Greenwell, 2015). Therefore, parents and caregivers can make a lifesaving difference if appropriate restraint measures are used to secure children in car seats. There are primarily three types of child car seats: rear-facing, front-facing, and booster seats. NHTSA recommends different types of car seats depending on a child's age, height, and weight. Currently, all 50 states and Washington DC have laws requiring children to be transported in appropriate child car seats. These state laws vary by age and type of child car seat (IIHS, 2020).

Since for-hire vehicles like taxis have operated in the United States for a long time, several states have specifically formulated laws to deal with the use of child car seats in taxis. To that end, most states (except for California and Mississippi) exempt taxis by law from the use of car seats for children. However, as TNC vehicles are a relatively recent emergence on U.S. roads, the laws governing the use of car restraint systems in TNC vehicles barely exist. Furthermore, current information on regulations surrounding child restraint systems exists mainly in publicly available legal documents, which are vague and may have different interpretations. This results in confusion for TNC vehicle drivers, riders, and law enforcement officers.

While taxi drivers are not obligated to provide child car seats for their riders, both Uber and Lyft have introduced a "child car seat" feature that offers passengers the opportunity to ride in vehicles equipped with a child car seat. This feature is offered for an additional fee of $10 to prospective riders (Uber, n.d.; Lyft, n.d.). Importantly, both Uber and Lyft only offer the option of one forward-facing car seat (no rear-facing or booster seats) for a child who is at least 2 years old, weighs between 22–48 pounds, and is 31–52 inches in height.

Past research has shown that there may be multiple sources of ambiguity when it comes to fully understanding child car seat laws for TNCs, including a lack of clarity as to which types of vehicle classes are exempt from child car seat laws and uncertainty about who is legally responsible for the use and installation of appropriate child restraint systems in vehicles (VTTI, 2020). Among other regulatory issues, the lack of legal clarity regarding child car seat laws may create challenges for enforcement of such laws.

There are additional challenges associated with the use of child car seats in TNC vehicles, such as increased fare for the use of the child car seat feature for riders, access to only one forward-facing child car seat per ride, and limited number of U.S. cities where the feature is currently being offered by TNCs. Given these limitations, safety of children traveling in TNC vehicles might be compromised. Children, while constituting a small share of all TNC riders, may be among the most vulnerable groups of riders whose safety must be protected (Womack, 2020). A rapid rise in the use of ride-share services also means that the matter of child safety in TNC vehicles may become a pressing issue in the years to come and thus needs to be addressed through further research and policy work (Statista.com, n.d.). Hence, this study may also provide safety advocates with information related to child safety standards for TNCs across the United States.

3. Methods & materials

This research was primarily based on information publicly available in state statutes. It involved entering various keywords, search connectors, and commands in Nexus Uni, a legal research database. Each state's laws were thoroughly studied one at a time and extensively reviewed to determine key questions about whether child restraints were required in TNC vehicles, who was responsible for ensuring that child restraint laws were followed, and what the penalties were for non-compliance. These reviews took place between December 2019 and October 2020 and this study evaluated state laws in effect on October 28, 2020.

Child safety standards in TNC vehicles were assessed at the state level using two parameters: clarity and stringency of the state child car seat laws. To perform the assessment, the authors developed a scoring system that included six scoring categories with an equal weight of 1 point per category and therefore a maximum score of 6 points for each state. A higher score implied higher standards for child safety (a higher level of legal clarity and stringent laws). Using a rating system to compare legislative landscapes across different jurisdictions is a common practice in legal and policy research and has been widely used across different research areas including healthcare, parity policy and implementation, prison policy, gun laws, and others (Franki, 2013; Renaud, 2019; Giffords Law Center, 2019).

Using the scoring system described above, authors ranked the 50 states and Washington DC across two major parameters: clarity and stringency of laws from a safety standpoint.

- ***To assess a state's law on its clarity in addressing child car seats in TNC vehicles, the following questions have been formulated:***
  (a) Do state child car seat laws specifically address TNCs? (Yes = 1, No = 0)
  The formulation of laws specifically targeting TNCs and child car seats are ideal as they address issues specifically related to these vehicles. However, states typically only address the specific vehicle classes that they want to exclude from the child car seat requirement. It is possible though that a state intends to require child car seat usage in TNC vehicles but will not directly mention TNCs in its statute. Consequently, it is difficult to determine whether a state has excluded TNCs either because child car seat usage is not exempt in TNC vehicles or TNCs did not exist at the time the statute and exemptions were created. This leaves little clarity in the intent behind the law unless a state directly communicates it through official media outlets, like it was in the case of Georgia.
  (b) Are TNCs specifically defined in the state laws? (Yes = 1, No = 0)If a state does not explicitly address child car seat laws for TNCs, the next best option is to define TNCs in general rather than to completely ignore the presence of these types of vehicles. It is important to determine whether TNCs are defined elsewhere because the definition of a TNC could help understand whether they fit into one of the other vehicle classes where child car seat usage is exempted. Examples of other vehicle classes that may be excluded by law are for-hire vehicles, commercial vehicles, or limousines. When TNCs are not defined by statute, the next option is to look up the definition of excluded vehicle class
  (e.g., taxis) to determine if TNCs fall within their legal definition. However, if TNCs are specifically defined, this extra step of reviewing definitions of other vehicle classes is not

required, and one would only have to review the definition of TNCs. If a state gets 1 point for criteria *a* it will automatically get 1 point for *b*.

(c) Do the state laws clearly state who is responsible for child car seat use? (Yes = 1, No = 0)If the law does not clearly define who
(parent/guardian, driver, etc.) is responsible for ensuring proper installation and use of car restraint systems, the discrepancy could cause significant confusion about enforcement of the law.

- ***To assess a state's law on its rigor in ensuring the safety of children traveling in TNC vehicles, the following questions have been formulated:***

(d) Do the state laws require the use of a child car seat in TNC vehicles? (Yes = 1, No = 0)
Irrespective of whether TNCs are explicitly mentioned in state laws, the authors analyzed existing statutes to determine if child car seats are required in TNC vehicles.

(e) Do TNCs (Uber, Lyft, etc.) offer child car seat programs anywhere in the state? (Yes = 1, No = 0)
Uber and Lyft are highly dominant in urban areas. As this study was conducted at the state level, the authors gave 1 point to a state where at least one of the cities within the state had child car seat programs offered by either Uber or Lyft. The ideal case, of course, would involve having child car seat programs available in all cities where ride-sharing companies operate.

(f) How stringent are the monetary penalties for the first offense in each state? (<$50 = 0, >=$50 = 1)This scoring criterion assumes that higher monetary penalties for violations of child car seat laws may help improve the rate of compliance with the law. This assumption is consistent with past research that a state's traffic and public safety can be improved by increasing minimum fines for violating seat belt laws
(Houston & Richardson, 2006; Nichols et al., 2010). A cutoff of $50 is chosen because it represents the median dollar amount penalty for the first offense across all states.

Nexis Uni was used extensively in this study to find answers to questions *a* through *d* and *f*. To answer question *e*, Lyft and Uber websites were combed to identify which cities offered the child car seat feature. Additionally, the authors installed Uber and Lyft mobile applications on their personal mobile devices and searched for the presence of child car seat programs in the 30 most populated U.S. cities (Table 1A).

For questions a) through f), states were given 1 point if the answer was "yes" and 0 points if the answer was "no." For each state, the total score was calculated by summing individual scores received under these six criteria. A total score of six represents the clearest laws and most stringent safety standards for children traveling in TNC vehicles.

4. Results

Our findings suggest that all states could improve in some aspect when it comes to the clarity and stringency of child car seat laws for TNCs. In addition to states' individual scores for each of these criteria, mean and sum values were estimated and presented at the end of Table 1.

4.1. Do state child car seat laws specifically address TNCs?

Only one state specifically mentioned TNCs in its child car seat statutes: Indiana. Additionally, in Georgia, even though the law did not specifically mention TNCs, the state's Governor's Office of Highway Safety expressly stated that child car seat usage was required in TNC vehicles. Thus, the authors gave 1 point to Georgia under this metric as the enforcement community acknowledged and explicitly addressed the issue of TNCs and child car seats. A sum value close to 0 indicates that almost all the states could improve with this criterion.

4.2. Are TNCs specifically defined in the state laws?

In order to analyze states that did not directly address TNCs in their child car seat statutes, the authors verified whether TNCs were defined in other relevant statutes. For example, TNCs might not be explicitly defined in a state's child car seat statute but could be defined elsewhere as being excluded from the definition of for-hire vehicles like taxis. This analysis found that Oregon was the only state that neither specifically addressed TNCs in its state child car seat laws nor defined TNCs in its state laws. Among the remaining states that did not specifically address TNCs in their child car seats, TNCs were defined in state laws and distinguished from for-hire vehicles or taxis.

4.3. Do state laws clearly identify who is responsible for the use of child car seats?

Since most of the states did not have an explicit law formulated for TNCs and child car seats, standard child car seat laws served as a reference for the authors to identify who was responsible for the use of child car seats in TNC vehicles. State laws included a wide variety of terminology (such as driver, vehicle operator, and parent/guardian) to specify who was responsible for securing a child properly in the car seat. The absence of a specific law addressing child car seat use in TNC vehicles created significant confusion about who should be held liable in case of child car seat violations in TNC vehicles. Some state laws, for instance, used terms like "person transporting the child," which may be construed as either the parent transporting the child or vehicle operator transporting the child and thus, may ultimately lead to issues in enforcing these laws. The sum of the scores for this criterion was 36; ~30% of the states could improve on this criterion. Fig. 1 shows the breakdown of the information at the state level.

4.4. Do state laws require the use of a child car seat in TNC vehicles?

After analyzing state child car seat laws, the authors found that all states except for Indiana and Washington required child car seats to be used in TNC vehicles. In the case of Indiana, there were no laws that require the use of child restraint systems in TNC vehicles. In the case of Washington, once publicly available documents were thoroughly reviewed, it was unclear whether the state had any laws in place that would require the use of child car seats in TNC vehicles. Hence, both Indiana and Washington scored a 0 on this metric.

4.5. Do TNCs (Uber, Lyft, etc.) offer car seat programs anywhere in the state?

Only two states (New York and Pennsylvania) and Washington DC received one point for having the child car seat options available in ride-sharing companies in the states' largest cities. Particularly, Uber offered the child car seat program in New York City, Philadelphia, and Washington DC, while Lyft offered the child car seat program only in New York City.

Table 1
Scoring Clarity and Stringency of Child Car Seat Laws for TNCs By State

State	Do state child car seat laws specifically address TNCs? (Yes = 1, No = 0)	Are TNCs specifically defined in the state laws? (Yes = 1, No = 0)	Do the state laws clearly state who is responsible for child car seat use? (Yes = 1, No = 0)	*Sub-Score (Clarity of Law)*	Do the state laws require the use of a child car seat in TNC vehicles? (Yes = 1, No = 0)	Do TNCs (Uber, Lyft, etc.) offer car seat programs anywhere in the state? (Yes = 1, No = 0)	How stringent are the monetary penalties for the first offense for each state? (< $50 = 0, >=$50 = 1)	*Sub-Score (Stringency of Law)*	Total Score (Out of 6)
Alabama	0	1	0	1	1	0	0	1	**2**
Alaska	0	1	1	2	1	0	0	1	**3**
Arizona	0	1	1	2	1	0	1	2	**4**
Arkansas	0	1	1	2	1	0	0	1	**3**
California	0	1	1	2	1	0	1	2	**4**
Colorado	0	1	1	2	1	0	1	2	**4**
Connecticut	0	1	0	1	1	0	1	2	**3**
Washington, D.C.	0	1	1	2	1	1	0	2	**4**
Delaware	0	1	0	1	1	0	0	1	**2**
Florida	0	1	1	2	1	0	1	2	**4**
Georgia	1	1	1	3	1	0	1	2	**5**
Hawaii	0	1	1	2	1	0	1	2	**4**
Idaho	0	1	1	2	1	0	1	2	**4**
Illinois	0	1	1	2	1	0	1	2	**4**
Indiana	1	1	1	3	0	0	0	0	**3**
Iowa	0	1	0	1	1	0	1	2	**3**
Kansas	0	1	1	2	1	0	1	2	**4**
Kentucky	0	1	1	2	1	0	1	2	**4**
Louisiana	0	1	1	2	1	0	1	2	**4**
Maine	0	1	1	2	1	0	1	2	**4**
Maryland	0	1	0	1	1	0	1	2	**3**
Massachusetts	0	1	0	1	1	0	0	1	**2**
Michigan	0	1	1	2	1	0	0	1	**3**
Minnesota	0	1	1	2	1	0	1	2	**4**
Mississippi	0	1	0	1	1	0	0	1	**2**
Missouri	0	1	1	2	1	0	1	2	**4**
Montana	0	1	0	1	1	0	0	1	**2**
Nebraska	0	1	1	2	1	0	0	1	**3**
Nevada	0	1	0	1	1	0	1	2	**3**
New Hampshire	0	1	1	2	1	0	1	2	**4**
New Jersey	0	1	1	2	1	0	1	2	**4**
New Mexico	0	1	0	1	1	0	0	1	**2**
New York	0	1	1	2	1	1	0	2	**4**
North Carolina	0	1	1	2	1	0	0	1	**3**
North Dakota	0	1	0	1	1	0	0	1	**2**
Ohio	0	1	1	2	1	0	0	1	**3**
Oklahoma	0	1	1	2	1	0	1	2	**4**
Oregon	0	0	1	1	1	0	1	2	**3**
Pennsylvania	0	1	1	2	1	1	1	3	**5**
Rhode Island	0	1	0	1	1	0	1	2	**3**
South Carolina	0	1	1	2	1	0	0	1	**3**
South Dakota	0	1	1	2	1	0	0	1	**3**
Tennessee	0	1	0	1	1	0	1	2	**3**
Texas	0	1	1	2	1	0	0	1	**3**
Utah	0	1	1	2	1	0	0	1	**3**
Vermont	0	1	1	2	1	0	0	1	**3**
Virginia	0	1	1	2	1	0	1	2	**4**
Washington	0	1	0	1	0	0	1	1	**2**
West Virginia	0	1	1	2	1	0	0	1	**3**
Wisconsin	0	1	0	1	1	0	0	1	**2**
Wyoming	0	1	1	2	1	0	1	2	**4**
Sum	***2***	***50***	***36***		***49***	***3***	***28***		
Mean	***0.04***	***0.98***	***0.71***	***1.73***	***0.96***	***0.06***	***0.55***	***1.57***	***3.29***

4.6. How stringent are the monetary penalties for the first offense for each state?

Penalties for not using an appropriate child restraint system depend on the state, number of driver offenses, and child's age. States were found to impose monetary penalties of $25 to over $250 (Fig. 2).

Across all states, the median penalty value for violating the child car seat law was $50 for the first offense. A state got 1 point if its fine was greater than or equal to $50 and 0 points otherwise. In cases where there was a range in penalties, if the lowest value in the range was greater than or equal to $50, then a state got 1 point, and 0 points otherwise. In addition to monetary penalties, a handful of states also imposed non-monetary penalties on violators of child car seat laws. Such non-monetary penalties included extra court costs, points taken off driver's license, and community service hours. Nevada was the only state that offered violators the option of either paying monetary penalty amounts or performing

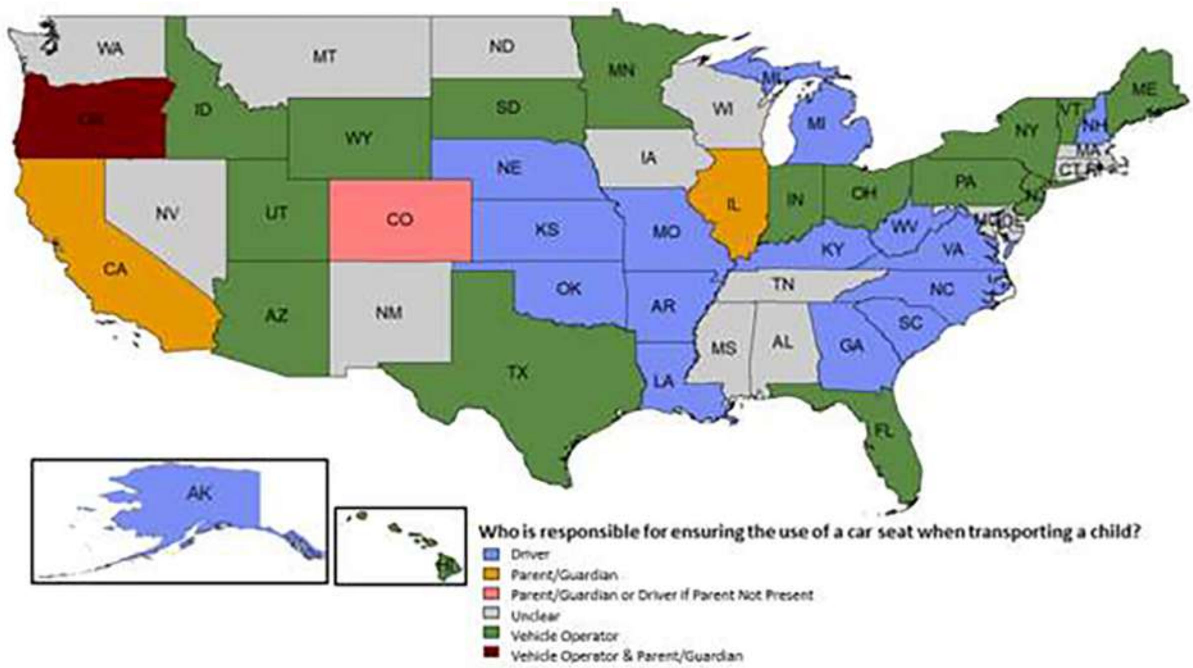

Fig. 1. Responsible party for child car seat use in vehicles by state.

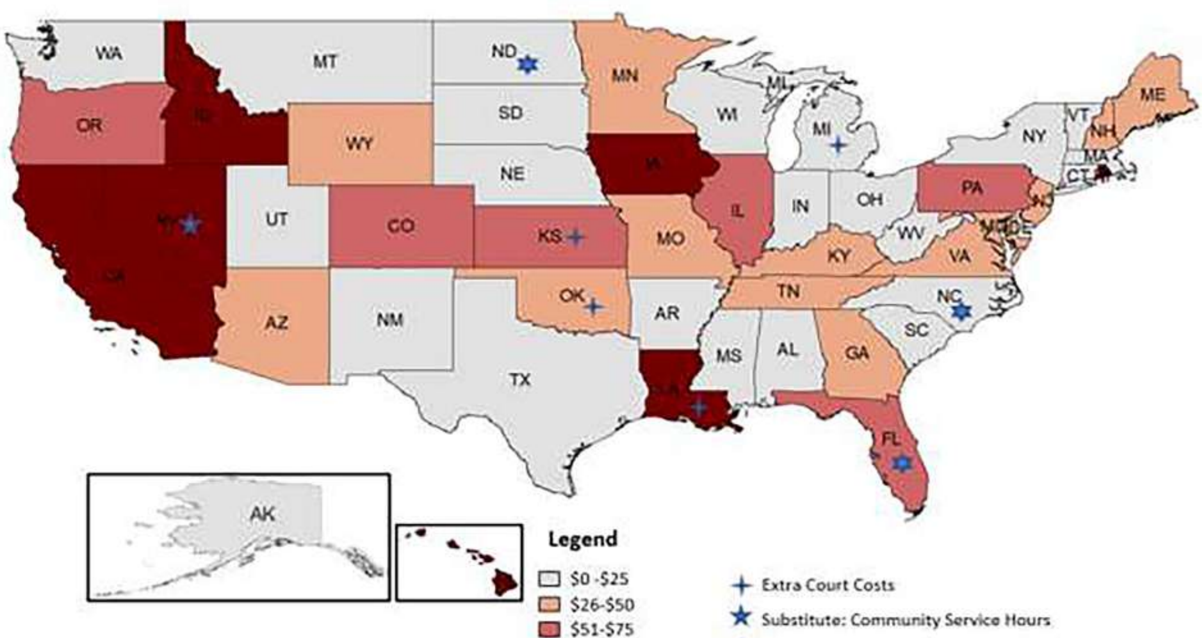

Fig. 2. Penalties for first offense of not using an appropriate child restraint system in TNC vehicles.

a specified number of community service hours. The analysis showed that 22 states and Washington DC had penalties for the first violation of the child car seat law that were less than $50, while 28 states had a penalty for the first violation of at least $50.

This study's findings indicate that for the clarity of law parameter, Georgia and Indiana received the highest scores (each state scored 3 out of 3 points). Sixteen states scored 1 point each, which was the lowest score in this category. The remaining states scored 2 points each. For the stringency of law parameter, Pennsylvania was the only state that secured 3 points, while Indiana scored the lowest with 0 points. The mean value for the clarity of law parameter is higher than the mean value of the stringency of law parameter. This study shows that all states could improve on at least some of the adopted criteria and use it for evaluation of their state laws' clarity and stringency. A majority of states lost points in categories *a* (Do state child car seat laws specifically address TNCs?) and *e* (Do TNCs (Uber, Lyft, etc.) offer car seat programs anywhere in the state?).

The total score provided in the last column of Table 1 indicates the overall safety measure of children riding in TNC vehicles for each state. Based on the total score, Georgia and Pennsylvania scored the highest when both clarity and stringency of state child car seat laws were taken into account (each state scored 5 out of 6 points). At the same time, nine states (Alabama, Delaware, Massachusetts, Mississippi, Montana, New Mexico, North Dakota, Washington, and Wisconsin) scored the lowest (each state scored 2 out of 6 points). Additionally, 19 states and Washington DC each scored 4 out of 6 points, while each of the remaining 20 states scored 3 out of 6 points.

All but one state's laws (Oregon) defined TNCs. All states, except for Washington and Indiana, required child car seats in TNC vehicles (Table 1). At the same time, only two states' child car seat laws (Georgia and Indiana) specifically addressed TNCs, and only two states (New York and Pennsylvania) and Washington DC had TNC child car seat programs available to riders (Table 1). Laws in 35 states clearly defined responsibility for proper child car seat use, and the monetary penalties for child car seat violations was at least $50 in 28 states (Table 1).

5. Discussion

Due to the rapid growth of TNCs in the United States, there is an increased interest from researchers, policymakers, and other stakeholders towards the subject of effective regulation and oversight of ride-sharing companies. At the same time, the use of child car seats in TNC vehicles is one aspect of this rapid increase that has not been widely studied or addressed by lawmakers and researchers alike.

The current ambiguity surrounding state-level child car seat laws for TNCs is mainly due to a lack of laws specifically addressing the use of child car seats in TNC vehicles. Applying private vehicle laws to TNCs is creating confusion among TNC riders and drivers about specific child car seat requirements in their local regions, as well as pressing the question of who is responsible for safely transporting children in ride-sharing vehicles (Owens et al., 2019). This study emphasizes this issue and provides a holistic view of child safety in TNC vehicles. The results of this study should urge leaders in the child safety arena to improve safety of children traveling in TNC vehicles. Additionally, the aforementioned scoring system makes it compare states in terms of clarity, stringency, and overall safety standards of their child car seat regulations.

The scoring system in this study serves as a first step towards developing a standardized method for assessing safety of children traveling in TNC vehicles. Additional factors for future consideration under a more mature framework may include penalties for the second or third offenses of not using appropriate child restraint systems in TNC vehicles and enforcement of child car seat laws by police.

The law enforcement community may face a dilemma when enforcing state child car seat laws as a result of their lack of clarity. In the future, the authors plan to conduct a survey of the law enforcement community to better gauge how the latter enforce child car seat laws in TNC vehicles when the laws do not clearly state who is responsible for child safety in TNC vehicles.

In many states, state and municipal-level TNC ordinances coexist (Moran, 2016). TNC policies at the local level may carry additional rules and requirements that are not typically found in TNC policies developed at the state-level (Moran, 2016). Such local regulations tend to be more restrictive in nature and usually address permit registrations, drivers' background check regulations, automobile insurances, and vehicle safety requirements and inspections among others. As a part of this study, the authors also checked for municipal-level child car seat regulations in the 30 largest U.S. cities by population. This study found that, among these cities, each implemented their respective state's regulations when it came to child car seat laws. If states fail to address the issue of lack of clarity in their child car seat laws described earlier, cities could improve safety of children by forming more stringent and clearer TNC ordinances. The Appendix provides a list of the 30 largest U.S. cities by population (World Population Review, n.d.) for which local ordinances related to child car seat laws in TNC vehicles were examined in this study.

The authors acknowledge certain limitations in this study. In particular, this study did not consider variation of legislation over time. Further, the search for state laws regarding child restraint use in TNC vehicles was limited to reviewing state statutes and did not include any thorough evaluation of relevant case laws. Additionally, since a majority of state child car seat laws contained no mention of TNCs, the authors interpreted the statutes and drew their own conclusions in determining whether child restraints were required in TNC vehicles. Importantly, the authors only interpreted how state statutes were written and had no additional information about whether law enforcement agencies enforce child restraint laws in TNC vehicles in their respective states.

Finally, while clarity" and "stringency" are concepts that can be distinguished analytically, they may also overlap. The analytical strategy followed by the authors could indeed vary, which may or may not result in changing the overall scores of each state.

6. Conclusion

In this paper, the authors developed a rudimentary scoring system for states to assess stringency and clarity of laws targeting child safety in TNC vehicles. Georgia and Pennsylvania had the highest scores and, thus, held the highest safety standards for children traveling in TNC vehicles while nine states (Alabama, Delaware, Massachusetts, Mississippi, Montana, New Mexico, North Dakota, Washington, and Wisconsin) received the lowest scores (each of these states scored 2 points). The results of this study suggest that all states could improve when it comes to clarity and stringency of child car seat laws targeting TNCs. A majority of states do not specifically mention TNCs in their state child car seat laws. This study also revealed that even though TNCs operate in most U.S. cities, only a handful of them offer the child car seat feature.

In addition to the technical contribution, the authors provided the data curated during this study through Mendeley Data (https://data.mendeley.com/datasets/mz3z94ppbn/draft?a=59fd4760-0fc7-4b7e-b4ff-efa10225e6a8), which researchers or traffic safety officials could use for their own research or to improve safety of children traveling in TNC vehicles.

This study is a starting point towards identifying issues in laws regulating child car seat usage in TNC vehicles as well as recognizing gaps in research on child car seat laws. Although the authors identified limited studies documenting perspectives of TNC drivers and riders regarding child car seat laws for TNCs, further research is needed to better understand law enforcement officers' perceptions of the topic. Additionally, the authors observed a gap in research addressing the question of effectiveness of existing child car seat laws for TNCs and sufficiency of existing penalties for violations of child car seat laws by TNC riders or drivers.

As TNCs continue to expand their presence in the transportation services market across the nation, there is a growing need among researchers, policymakers, and other stakeholders to better understand the application of state child car seat laws in TNC vehicles. The scoring system presented in this paper can help key stakeholders assess their state's score relative to the other states, consider implications of existing child car seat laws for both TNC riders and drivers, and identify areas of improvement. This scoring system can help legislators and policymakers gauge different accommodations needed for their constituents with children and may possibly help increase the demand for ride-sharing services by families with young children.

7. Declarations of interest

None.

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Appendix List of 30 largest U.S. cities by population

Rank	Name	State	2020 Population
1	New York City	New York	8,323,340
2	Los Angeles	California	4,015,940
3	Chicago	Illinois	2,694,240
4	Houston	Texas	2,340,890
5	Phoenix	Arizona	1,703,080
6	Philadelphia	Pennsylvania	1,591,800
7	San Antonio	Texas	1,578,030
8	San Diego	California	1,447,100
9	Dallas	Texas	1,382,270
10	San Jose	California	1,033,670
11	Austin	Texas	988,218
12	Fort Worth	Texas	932,116
13	Jacksonville	Florida	926,371
14	Columbus	Ohio	922,223
15	Charlotte	North Carolina	905,318
16	San Francisco	California	896,047
17	Indianapolis	Indiana	875,929
18	Seattle	Washington	783,137
19	Denver	Colorado	734,134
20	Washington	District of Columbia	720,687
21	Boston	Massachusetts	710,195
22	El Paso	Texas	685,575
23	Nashville	Tennessee	673,167
24	Detroit	Michigan	667,272
25	Portland	Oregon	664,103
26	Las Vegas	Nevada	662,000
27	Oklahoma City	Oklahoma	655,407
28	Memphis	Tennessee	647,374
29	Louisville	Kentucky	624,890
30	Baltimore	Maryland	590,479

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Safety and associated parameters influencing performance of rail road grade crossings: A critical review of state of the art

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ABSTRACT

Introduction: Railroad grade crossings (RRGCs) have emerged as critical transportation infrastructures from the point of safety and operational aspects because two modes of transportation intermingle at the intersecting zone; the understanding of safety and traffic operation at RRGC is of prime concern while planning and designing this transportation facility. *Method:* In this context, this work tries to comprehend RRGC performance-related parameters from published literature and figure out critical gaps. An international synthesis on the identified potential parameters influencing the RRGC performance (i.e., safety, driver behavior, and operational impact) was carried out by critically reviewing the articles published worldwide. Furthermore, key findings, used variables, analysis methods, research gaps, and recommendations were studied. *Results:* The review revealed that many researchers had explored the driver behavior and safety aspect based on past crash data and violations prevailing at RRGC. However, little research has been done to evaluate the effect of highways' operational characteristics on the performance of RRGC. Moreover, limited investigation has been carried out to understand the dilemma of drivers and the proactive safety evaluation of pedestrians and non-motorized vehicles at RRGC. A total of seven critical research gaps concerning parameters are recognized, facilitating a clear agenda for further research pertaining to RRGC performance.

1. Introduction

Rail and highway networks play vital roles in enhancing socio-economic growth and uniting the nation by devoting significantly to the mass transportation system in order to serve multiple purposes (Li & Cheng, 2011; Feng et al., 2019). The efficient transportation of people and goods across various nations requires a properly designed and well-planned transport network. Due to the geometrics requirement of transportation networks, many sites in the networks cross each other, forming intersection zones. At grade intersections there can be bottlenecks where performance is considered critical compared to the overall performance of a road network system (Yan et al., 2018). Likewise, for various reasons in many places, two distinct modes of transport network intersect each other at the same or different grade. Railroad grade crossings (RRGCs) are one of them, where two distinct transportation infrastructures share a common space placed under diverse liabilities and performances in their normal operation period, which makes it unique in the world of transport (Indian Railways Year Book, 2017–2018). At RRGCs, railway and road are crossing each other on the same level, and the priority of movement is always given to the train due to the technical constraints (long breaking distance) associated with railway vehicles. RRGCs become a risky and complex location as users of diverse nature interact distinctly to traverse the intersecting zone. Most of the RRGCs across the world are designed and operate in one of the two ways; (a) equipped with passive warning system indicating the presence of the crossing but do not inform about the approaching train; and (b) equipped with active warning systems including flashing lights and/or audible bells and provides a warning about the approaching train (Wigglesworth & Uber, 1991).

To satisfy the escalating rail and road traffic, the expansion of rail and road networks has been done, which has increased the number of RRGCs. But, due to progressive safety and traffic congestion issues, planning for RRGCs removal or consolidation is happening across the globe.

In the United States, there is one RRGC at every 0.6 km of railway line, constituting around 250,000 RRGCs across the nation. Approximately 30% of the crossings have been upgraded with dual gates and 0.6% with four quad-gates (Federal Highway Administration, 2007). Whereas, in India, there are 25,299 RRGCs or one for 2.6 km of railway track, out of which 19,507 are manned RRGCs and 5,792 are unmanned RRGCs (Indian Railway Year Book,

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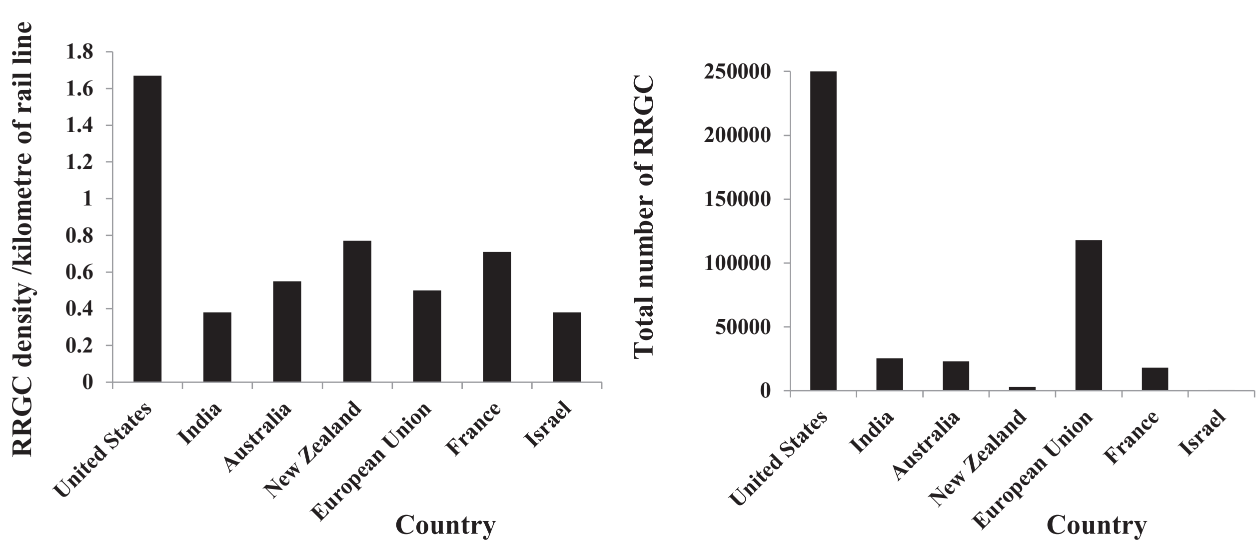
Nomenclature

AC	Active Crossing	NMV	Non-Motorized Violation
BPM	Binary Probit Model	OS	Official Source
CC	Crossing Control	OT	Others
CD	Crash Data	PC	Passive Crossing
CDB	Crash Database	RM	Regression Model
CF	Crossing Features	RRGC	Rail Road Grade Crossing
DSA	Descriptive Statistical Analysis	SR	Sensors
DZ	Dilemma Zone	TC	Traffic Characteristics
EM	Empirical Model	UC	User Characteristics
EN	Environmental	UP	User Perception
HF	Highway Features	VC	Vehicular Characteristics
MO	Manual Observation	VG	Videography
MS	Microsimulation		
MV	Motorized Violation		

2017–2018). Likewise, there are more than 23,000 RRGCs in Australia, with one crossing at every 1.8 km of railway track, and New Zealand with 3,000 RRGCs at every 1.3 km of railway track (Rail Industry Safety and Standards Board, 2009). Similarly, there are around 11,8000 RRGCs in the European Union covering 28 countries having one RRGC per 2 km stretch of the railway line. About 30% of railway accidents are reported with an annual average of 300 fatalities (European Railway Agency, 2014). France railway network is expanded over 30,000 km, which constitute around 18,000 RRGCs, out of which 13,000 RRGCs are held with high volume railway and roadway traffic (SNCF Reseau, 2011). Also, there are around 206 RRGCs in Israel and one crossing at every 2.6 km of the railway line, aggregating a total of 500 RRGCs across the nation (Gitelman & Hakkert, 1996). Country-wise RRGCs density per kilometer of the rail line and the total number of RRGCs has been portrayed in Fig. 1 for reference.

Owning to the complexity of traffic operation at RRGC, in the past few decades, many researchers have explored the driver behavior and safety aspect based on previous crash data and violations prevailing at RRGC. However, little research has been done to evaluate the effect on highways' operational characteristics linked to RRGC. Moreover, little investigation has been done to figure out the other aspects of safety, like the dilemma of drivers and pedestrians at RRGC.

To the best of the authors' knowledge, there are few published review papers on RRGCs. Lobb (2006) highlighted the review on pedestrian trespassing at RRGC. The author mainly focused on factors responsible for train pedestrian collisions, various intervention programs to minimize such collisions (e.g., educational awareness, environmental changes, punishment for safe and unsafe crossing behavior), and physiological research. Further, Yeh and Multer (2008) reviewed the driver behavior at RRGCs from 1990 to 2006. The authors focused on various factors that influence the driver behavior such as traffic control devices, crossing characteristics, driving skill and style, organizational behavior, and environmental context. Edquist et al. (2009) reviewed countermeasures like education, enforcement, speed reduction, sight distance, signs, warning credibility, queue prevention, obstacle detection, and pedestrian safety. Freeman et al. (2013) highlighted various crossing attributes of pedestrians such as contextual factors and human factors (including error and deliberate violation at RRGCs). While previously published review papers mainly highlight the driver behavior and safety aspects prevailing at RRGC, operational impact at RRGCs is not encompassed. However, De



(a) Country wise analysis of RRGC density (b) Country wise analysis of total RRGCs

Fig. 1. Country wise RRGC density per kilometer of the rail line and the total number of RRGCs. Source: (Federal Highway Administration, 2007; Railway Year Book, 2017–2018; Rail Industry Safety and Standards Board, 2009; European Railway Agency, 2014; SNCF Reseau, 2011; Gitelman & Hakkert, 1996).

Gruyter and Currie (2016) reported various RRGC impacts including transport, social, economic, and environmental impact. The authors under transport impacts have covered various aspects, including safety based on accidents, but other attributes such as safety based on the violation, dilemma zone, and driver behavior are untouched. Therefore, the present study provides a comprehensive look at the potential parameters affecting RRGC performance (e.g., driver behavior, safety based on crash data, violation and dilemma zone, and operational impacts) and delivers useful yields in the form of considered variables, analysis method, and research gaps pertaining to identified parameters. Thus, this article will focus on the following known RRGCs issues: collisions and their consequences; road user behavior; and their effects on traffic flow.

Section 2 of this paper depicts the review methodology, starting from selecting research topics to identifying research gaps and recommendations of future work. The overall methodology is split into three steps and portrayed in the form of a flow chart. Section 3 covers the identification of potential parameters influencing RRGC performance based on the comprehension of a detailed literature survey. Findings of each parameter are discussed in subsections separately, and variable types and analysis methods used in various studies are portrayed in Table 1, 2, and 3. Section 4 includes critical observations, identified research gaps, and future research

Table 1
Summary of variables used and analysis methods associated with driver behavior studies.

Authors	Country	RRGC Type		Data Collection Method					Variable Types								Analysis Method				
		AC	PC	CDB	VG	MO	SR	UP	VC	UC	HF	CF	CC	TC	EN	OT	DSA	MS	EM	RM	BPM
Berg and Oppenlander, 1969	United States	✓	✓	✓							✓	✓	✓	✓	✓	✓	✓				
Mounce, 1981	United States		✓		✓						✓		✓	✓	✓	✓	✓				
Aberg, 1987	Sweden	✓			✓					✓				✓	✓		✓				
Richards and Heathington, 1988	United States	✓	✓					✓		✓	✓						✓				
Meeker and Barr, 1989	United States	✓				✓				✓					✓	✓	✓				
Tenkink and Horst, 1989	Netherlands	✓			✓					✓			✓	✓		✓	✓				
Fambro et al., 1994	United States		✓					✓			✓	✓		✓			✓				
Ward & Wilde, 1995	United Kingdom	✓					✓				✓	✓		✓	✓	✓	✓				
Meeker et al., 1996	United States	✓			✓								✓	✓			✓				
Raslear, 1996	United States	✓	✓		✓						✓	✓		✓		✓	✓				
Ward & Wilde, 1996	United Kingdom		✓				✓				✓	✓		✓	✓	✓	✓				
Coleman and Moon, 1997	United States	✓			✓						✓	✓		✓	✓	✓		✓			
Picha et al., 1997	United States		✓					✓		✓			✓				✓				
Osemenam, 1998	United States	✓	✓		✓	✓						✓	✓	✓			✓				
Moon and Coleman, 1999	United States	✓			✓				✓					✓			✓		✓		
Carroll et al., 2001	United States		✓				✓		✓		✓		✓	✓		✓	✓				
Smailes et al., 2002	United States		✓		✓	✓					✓	✓	✓	✓			✓				
Radalj & Kidd, 2005	Australia		✓		✓	✓					✓	✓		✓			✓				
Oh et al., 2006	Korea	✓		✓					✓		✓	✓	✓	✓	✓	✓				✓	
Peltola, 2006	Finland		✓		✓	✓			✓		✓	✓		✓			✓				
Park, 2007	United States	✓	✓	✓	✓	✓					✓	✓	✓	✓	✓	✓	✓			✓	
Russell et al., 2007	United States	✓	✓	✓							✓	✓	✓	✓			✓				
Davey et al., 2008	Australia	✓	✓					✓	✓	✓	✓						✓				
Lenne et al., 2011	Australia	✓	✓	✓						✓			✓	✓			✓				
Tey et al., 2011	Australia	✓	✓		✓						✓	✓	✓	✓						✓	
Kasalica et al., 2012	Serbia		✓		✓					✓	✓			✓			✓				
Kumar, 2012	India		✓		✓					✓				✓			✓				
Salmon et al., 2012	Australia	✓	✓			✓		✓		✓		✓				✓	✓				
Tey et al., 2012	Australia	✓	✓		✓					✓	✓		✓	✓		✓		✓			
Basacikl et al., 2013	United Kingdom	✓	✓					✓		✓	✓		✓				✓				
Lenne et al., 2013	Australia	✓	✓		✓	✓	✓			✓	✓	✓	✓				✓				
Turner et al., 2013	United Kingdom		✓			✓	✓	✓		✓	✓	✓	✓				✓				
Mulvihill et al., 2014	Australia	✓				✓		✓		✓	✓		✓	✓			✓				
Kim et al., 2015	Australia	✓	✓			✓				✓			✓	✓		✓		✓			
Larue et al., 2015	Australia	✓	✓			✓							✓				✓				
Tung and Khattak, 2015	United States	✓			✓						✓	✓	✓	✓							✓
Young et al., 2015	Australia	✓				✓		✓		✓	✓		✓	✓		✓	✓				
Metaxatos and Sriraj, 2016	United States	✓	✓					✓	✓			✓	✓	✓	✓		✓				
Mulvihill et al., 2016	Australia	✓				✓		✓		✓	✓		✓	✓			✓				
Beanland et al., 2017	Australia		✓			✓				✓			✓	✓		✓	✓				
Cale et al., 2017	Israel	✓	✓			✓			✓	✓	✓						✓				
Larue and Wullems, 2017	Australia		✓				✓					✓		✓			✓				
Larue et al., 2017	Australia		✓		✓	✓		✓		✓			✓	✓			✓				
Larue et al., 2018a	Australia	✓			✓						✓		✓	✓		✓	✓				
Larue et al., 2018b	Australia	✓				✓			✓		✓	✓	✓	✓			✓			✓	
Young et al., 2018	Australia	✓	✓			✓	✓			✓						✓	✓				
Larue et al., 2019a	Australia	✓						✓					✓	✓		✓	✓				
Larue et al., 2019b	Australia		✓			✓				✓	✓		✓	✓		✓	✓				
Larue et al., 2019c	Australia	✓						✓			✓	✓	✓				✓				
Russo et al., 2020	United States	✓	✓		✓					✓	✓	✓	✓	✓	✓		✓				

Table 2
Summary of variables used and analysis methods associated with safety studies.

Authors	Country	RRGC Type		Study Type				Data Collection Mode					Variables Types								Analysis Method
		AC	PC	CD	MV	NMV	DZ	CDB	VG	MO	SR	UP	VC	UC	HF	CF	CC	TC	EN	OT	
Gitelman and Hakkert, 1996	Israel	✓	✓	✓				✓									✓	✓	✓		Descriptive statistical analysis
Coleman and Moon, 1997	United States	✓					✓		✓						✓	✓		✓			Simulation technique (CROSSIM)
Carlson and Fitzpatrick, 1999	United States	✓			✓				✓						✓	✓	✓	✓			Logistic regression models
Lobb et al., 2000	New Zealand		✓			✓				✓				✓							Descriptive statistical analysis
Austin and Carson, 2002	United States	✓	✓	✓				✓							✓	✓	✓	✓		✓	Negative binomial regression
Lobb et al., 2002	New Zealand		✓			✓				✓				✓						✓	Descriptive statistical analysis
Moon and Coleman, 2002	United States	✓					✓		✓						✓	✓		✓			Empirical models
Ko et al., 2007	United States	✓			✓				✓								✓	✓		✓	Descriptive statistical analysis
Khattak and McKnight, 2008	United States	✓			✓				✓								✓	✓	✓		Descriptive statistical analysis & Negative binomial model
Hu et al., 2009	Taiwan		✓	✓				✓							✓	✓	✓	✓			Generalized logit model
Millegan et al., 2009	United States		✓	✓				✓								✓	✓	✓		✓	Descriptive statistical analysis & Negative binomial regression
Yan et al., 2009	United States		✓	✓				✓							✓			✓		✓	Hierarchical tree-based regression model
Yan et al., 2010	United States		✓	✓				✓					✓		✓		✓	✓	✓	✓	Logistic regression model
Evans, 2011	United Kingdom	✓	✓	✓				✓										✓		✓	Descriptive analysis & Poisson log linear model
Khattak and Luo, 2011	United States	✓			✓	✓			✓					✓			✓		✓		Poisson model
Meiers et al., 2012	Australia	✓	✓	✓				✓					✓	✓	✓				✓		Descriptive statistical analysis
Hao and Daniel, 2014	United States	✓	✓	✓				✓					✓	✓	✓			✓	✓	✓	Ordered probit model
Khattak, 2014	United States	✓			✓				✓								✓	✓		✓	Descriptive statistical analysis & Poisson regression model
Freeman and Rakotonirainy, 2015	Australia		✓			✓						✓		✓							Descriptive statistical analysis
Haleem and Gan, 2015	United States	✓	✓	✓				✓					✓	✓	✓		✓	✓	✓	✓	Descriptive Statistical analysis & Mixed logit model
Laapotti, 2015	Finland	✓	✓	✓				✓					✓	✓	✓			✓	✓	✓	Descriptive statistical analysis
Liu et al., 2015	United States	✓	✓	✓				✓						✓			✓		✓		Descriptive, Path analysis & Ordered logit model
Read et al., 2015	Australia		✓			✓						✓		✓			✓		✓		Descriptive statistical analysis
Stefanova et al., 2015	Australia	✓	✓			✓						✓		✓			✓	✓		✓	Descriptive statistical analysis
Zhao and Khattak, 2014	United States	✓	✓	✓				✓					✓	✓				✓	✓	✓	Multinomial logit model, Ordered probitmodel&Random parameter logit model
Haleem, 2016	United States	✓	✓	✓				✓					✓	✓	✓			✓	✓	✓	Mixed logit model & Binary logit model
Hao et al., 2016	United States	✓	✓	✓				✓					✓	✓	✓		✓	✓	✓	✓	Ordered probit model
Lu and Tolliver, 2016	United States	✓	✓	✓				✓							✓	✓	✓	✓			Poisson regression models
Barić et al., 2017	Croatia	✓				✓			✓					✓	✓	✓	✓				Descriptive statistical analysis
Hao et al., 2017	United States	✓	✓	✓				✓					✓	✓				✓	✓	✓	Mixed logit model
Liang et al., 2017a	France	✓			✓						✓						✓	✓		✓	Descriptive statistical analysis
Liang et al., 2017a	France	✓			✓						✓						✓	✓			Descriptive statistical analysis
Liu and Khattak, 2017	United States	✓			✓			✓					✓	✓	✓	✓			✓	✓	Descriptive statistical analysis & Binary logistic model
Zhang et al., 2017	United States		✓		✓				✓								✓		✓		Artificial intelligence-based computer vision algorithm
Larue et al., 2018	Australia	✓	✓		✓					✓				✓			✓			✓	Generalized linear mixed models
Liu and Khattak, 2018	United States	✓			✓			✓						✓	✓	✓	✓	✓	✓	✓	Descriptive statistical analysis & Binary logit model
Zhang et al., 2018	United States	✓	✓	✓				✓					✓	✓					✓	✓	Descriptive analysis & Ordered logistic regression model
Tjahjono et al., 2019	Indonesia	✓	✓	✓				✓					✓	✓				✓	✓		Ordered probit model
Keramati et al., 2020	United States	✓	✓	✓				✓							✓	✓	✓	✓			Descriptive statistical analysis
Larue and Naweed, 2020	Australia	✓					✓		✓								✓	✓	✓		Descriptive statistical analysis

Table 3
Summary of variables types used and analysis methods associated with operational studies.

Authors	Country	RRGC Type		Data Collection Mode				Variables used						Analysis Method		
		AC	PC	VG	MO	UP	OS	VC	HF	CF	CC	TC	OT	DSA	MS	EM
Powell, 1982	United States	✓			✓				✓	✓	✓	✓			✓	
Hakkert and Gitelman, 1997	Israel	✓			✓			✓			✓	✓				✓
Chandler and Hoel, 2004	United States	✓			✓						✓	✓			✓	
Rilett and Appiah, 2008	United States	✓					✓		✓		✓	✓	✓		✓	
Okitsu et al., 2010	United States	✓		✓							✓	✓				✓
Protopapas et al., 2010	United States	✓					✓		✓	✓	✓	✓				✓
Mitrovic, 2011	United States	✓			✓						✓	✓	✓		✓	
Tey et al., 2012	Malaysia	✓		✓					✓	✓	✓	✓			✓	
VicRoads, 2010	Australia	✓					✓				✓	✓	✓	✓		
Hasnat et al., 2016	Bangladesh	✓		✓							✓	✓				✓
Nguyen-Phuoc et al., 2017	Australia	✓	✓		✓	✓			✓				✓		✓	
Trivedi and Gor, 2017	India	✓		✓							✓	✓	✓			✓
Beanland et al., 2018	Australia	✓	✓		✓				✓		✓	✓		✓		
Larue et al., 2020	Australia	✓			✓						✓	✓			✓	

direction along with their significance, and ultimately, the conclusions drawn from the study are presented in Section 5.

2. Review methodology

The overall methodology of the study is mainly comprised of three steps, as shown in Fig. 2. RRGC was chosen as a research topic, then various relevant articles were obtained using different keywords (such as level crossings, at grade railroad crossings, railway crossings, railroad crossings, and railroad grade crossings). Multiple scientific databases were used for collecting relevant articles, such as Google Scholar, Science Direct, Scopus, ProQuest, and research reports. In addition, the snowball criterion was used to obtain additional articles through citations from multiple publications. Thereafter, each article was analyzed in detail and potential parameters in context to RRGC impact on road users were identified. The identified parameters are safety, driver behavior, and operational impact. Safety was further analyzed in context to past crash data, violations by motorists, pedestrians and bicyclists, and dilemma zone. Likewise, driver behavior at passive and active RRGCs was analyzed separately. Ultimately, on comprehension of complete analysis, various research gaps were identified and future works were recommended.

3. Parameters influencing RRGC performance

Based on the comprehension of a detailed literature survey, it was recognized that the performance of RRGC greatly depends on driver behavior, safety, and operational characteristics. Each influencing parameter and findings from various studies across the world are discussed in the following subsections separately. Also, the studies in association with the mentioned parameters are presented in Tables 1, 2, and 3. Each table presents the details of the country where the study was carried out, the type of RRGC, the data collection method utilized, variables used, and the analysis method for each study. Various nomenclature used in this study are compiled in the form of a table, and the table is presented as nomenclature.

3.1. Driver behavior (motorized and non-motorized)

In this study, driver behavior was carried out in the context of motorized and non-motorized road users. Motorized road users include two-wheeler riders, car and heavy vehicle drivers, and non-motorized road users (including pedestrians and bicyclists). Despite the widespread installation of active protection devices such as warning bells, flashing lights, and barrier gates at RRGCs, traffic collisions appear to be a serious issue (Meeker et al., 1996). The prime cause of collision at RRGCs is risky driving behavior, as many drivers do not comply with the traffic rules due to human, vehicular, and environmental factors (Tey et al., 2012; Larue et al., 2019). Therefore, driver behavior contributes significantly to the safety of RRGCs. Risky movement of road users during multiple stages of gate operation can lead to single vehicle collision as well as with the approaching train and road users (Khattak, 2014). Driver behavior at RRGC is segregated into two categories based on the type of RRGC (i.e., active and passive). The detailed synthesis of literature pertaining to driver behavior is presented in the following two sub-sections. Studies related to driver behavior are presented in Table 1 in chronological order. Under variable types, Vehicular Characteristics (VC) covers vehicle length and type. User Characteristics (UC) encompasses age, gender, head movement, eye movement, driver experience, reaction time, and user perception. Highway Features (HF) encircles road geometry and the presence of rumble strips. Crossing features (CF) includes crossing geometry and roughness. Crossing Control (CC) covers types of warnings and protection devices and warning times. Traffic Characteristics (TC) encircles roadway and railway traffic operational characteristics. Environmental (EN) includes climatic condition and visibility, and Others (OT) covers license status, crossing time, the time between consecutive trains, vehicle lateral position, the distance between vehicle and train, and topography.

3.1.1. Driver behavior at active RRGCs

The effectiveness of the RRGC protection system is mainly reflected in the form of driver's response because often poor decision-making skills and improper awareness of the drivers perceived at RRGC lead to crashes (Meeker et al., 1996; Salmon et al., 2012; Berg & Oppenlander, 1969; Caird, 2002; Green, 2002). Many researchers have examined driver compliance at active RRGCs using videography tools. Aberg (1987) revealed that RRGCs installed with flashing lights are 10 times riskier than those equipped with gates. Therefore, RRGCs equipped with only flashing lights should be designed in such a manner so that all necessary information can be gathered by road users against the approaching train (Tey et al., 2012). Descriptive statistical analysis of collected data by Meeker et al. (1996) revealed that around 67% and 38% of drivers crossed the RRGC equipped with flashing light and gates before the approaching train, respectively. Larue et al. (2018a) investigated errors, rising risks, and interactions among various road users using videotaped data for two days. The authors observed a high non-compliance rate and high congestion was

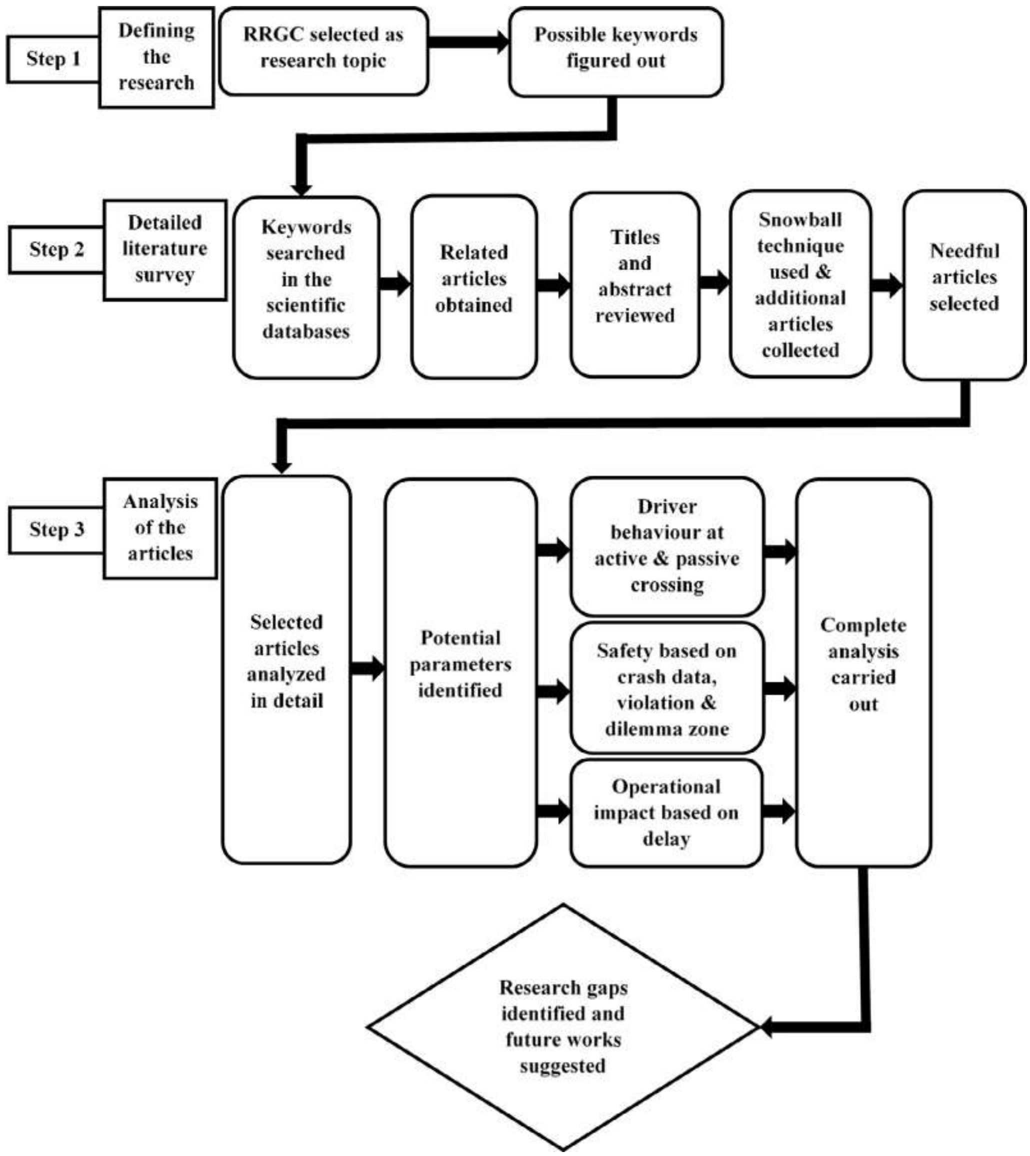


Fig. 2. Flow chart demonstrating the proposed review methodology.

observed due to high train frequency, short stacking issues, fewer options for pedestrians to traverse, and synchronization-related issues. The color of the flashing light was found to affect the compliance rate. Tenkink and Horst (1989) observed that red light compliance shown by car drivers against white light was relatively on the better side as all drivers stopped their cars after 6 seconds from the onset of the red signal at RRGCs. Various countermeasures such as speed breakers and posted speed limits can effectively lower vehicular speed (Radalj & Kidd, 2005; Oh et al., 2006; Peltola, 2006; Park, 2007). These countermeasures enable the road users sufficient time to understand the situation and respond accordingly. To force drivers to slow down and become careful on approach to RRGC, Cale et al. (2017) developed three cognitive designs: lines with distance shortening, bottleneck, and pictogram with safety blue carpet. The driving simulator results indicated that drivers do reduce their speed significantly concerning each intervention. Moon and Coleman (1999) concluded that a significant reduction in vehicular speed is observed as the driver moves toward RRGCs, and speed reduction in the case of the platoon is relatively more than that of a single-vehicle.

Tey et al. (2012) reported that a micro-simulation tool (VISSIM) with some modification could be employed effectively to investigate traffic-related safety indicators, including collision likelihood and temporal collision at RRGCs. The authors also concluded that active RRGCs are at least 17% safer than passive RRGCs. Simulation results of dual gated RRGCs by Coleman and Moon (1997) showed that aggressive drivers traversing the crossing against the approaching train generally cross the safe stopping distance and penetrate beyond the railway track, which can lead to a serious collision. The driving simulation tool is effective in evaluating behavioral parameters, including stress level, secondary activity while driving, and familiarity with RRGCs (Lenne et al., 2011; Tey et al., 2011;Tung & Khattak, 2015; Young et al., 2018) and the use of driving simulator has been validated for RRGC (Larue et al., 2018). Young et al. (2018) revealed that drivers spend more than 50% of their time texting without looking ahead on driving through RRGCs, which could make them unaware of the instant situation. Additionally, Tung and Khattak (2015) reported that around 33% of drivers traversing the crossing were engaged in secondary activities such as operating cellular phones and talking to car passengers. Likewise, Russo et al. (2020) conducted an observational study utilizing videotaped data and reported that 9.5% of pedestrians and 7.7% of bicyclists were distracted while traversing RRGC, and most of these distractions were observed using headphones. Larue et al. (2019c) suggested that the installation of illuminated lights in the footpath can be effective in attracting the attention of distracted pedestrians engaged with smartphones while crossing the RRGC.

Moreover, Young et al. (2015) examined novice and experienced drivers' attention on approaching urban RRGC. The authors reported that most of the drivers, including novice and experienced, were less focused on RRGC and relied on the behavior of surrounding drivers. Lenne et al. (2013) utilized instrumented vehicle to explore the factors that affect the driver behavior at active RRGC equipped with flashing lights with or without gates and at passive RRGC with stop and give way controlled. The authors revealed that the number of head checks decreases as sight distance decreases, and the number of head checks increases with the provision of rumble strips. Larue et al. (2019a) used an advanced driving simulator to examine the impact of waiting time on risky behavior and frustration level of road users. The findings revealed that waiting time greater than 3 minutes makes the road users frustrated, and hence, they involve themselves in risky action by crossing illegally in different gate operation phases.

A comprehensive questionnaire survey revealed the improper understanding of the commuters of various control devices installed at RRGC. Richards and Heathington (1988) concluded that safety at the crossing could be enhanced by installing lifting barriers, flashing lights, or both, educating the road users, and replacement by grade separators. Basacikl et al. (2013) utilized a user perception survey to estimate road users' understanding in context to signs and signals at RRGC. The authors revealed that the road users well understood the significance of flashing red lights, but most of the respondents failed to distinguish between danger warning signs for RRGCs with gates and other RRGCs. Furthermore, Stanton et al. (2013) conducted a user perception survey for two weeks to quantify how road users make their decision at RRGC. The authors observed the variation among the experience and behavior of different classes of road users. The findings revealed that in order to be alert about the presence of an approaching train, motorists and car drivers mostly relied on flashing lights, whereas, pedestrians and bicyclists mostly relied on audible warning signs. Moreover, Davey et al. (2008) revealed that heavy vehicle drivers experience visibility and vehicle clearance issues. Most of the drivers rush through the RRGC to save time and are less aware. Mulvihill et al. (2014) utilized a two-week diary study and implemented a decision ladder technique to compare road users' decision-making process during their compliance and non-compliance state. The main finding from the study indicated that drivers engaged in non-compliance at the crossing were less concerned of safety. Later, Mulvihill et al. (2016) observed some differences in decision-making among various road users groups. The authors concluded that engineering countermeasures such as flashing lights, intended to improve decision-making, may have an adverse effect on few road users as the system allows high flexibility for intervention. Also, Metaxatos and Sriraj (2016) conducted interviews with the railway experts and reported that collision at RRGC can be reduced by enhancing certain areas such as: (a) advancing consistent standards for warning devices and treatments; (b) advancing consistent approaches for managing non-motorist risk; and (c) progressive commitment to education, engineering, enforcement, and evaluation efforts by enabling stakeholders to provide adequate resources.

3.1.2. Driver behavior at passive RRGCs

Many researchers have made efforts to investigate the understanding of drivers towards warning signs at the passive crossing. The findings revealed that, although many drivers can figure out and distinguish the different warning signs, most of them have inadequate knowledge regarding their responsibility and application of various warning signs and pavement markings at RRGCs (Richards & Heathington, 1988; Picha et al., 1997; Global Exchange, 1994; Beanland et al., 2017). The user perception survey conducted by Picha et al. (1997) revealed that around 81% of the drivers identified the distinct warning signs. Still, only 18% of them were able to figure out the exact position of signs. A similar survey report by Fambro et al. (1994) observed that around 30% of the drivers were unaware of conventional and advanced warning signs' location. Turner et al. (2013) reported that a decision point marker should be provided before the passive RRGC so road users have to make their own judgement to safely cross the RRGC. Mounce (1981) collected the field data using videography and reported that the compliance rate of drivers increases with a decrease in road traffic volume. Beanland et al. (2017) identified factors associated with driver's compliance and non-compliance level at rural RRGC with stop signs. The findings revealed that most of the participants complied with the stop sign, but those who did not comply either failed to detect stop sign or overestimated the sight distance. In contrast to the videography technique, Larue and Wullems (2017) introduced an effective and reliable method to examine driver behavior at passive RRGC for a longer time. The authors installed pneumatic tubes on both side of roadway linked to RRGC to measure approach speed and compliance rate of the drivers. Larue et al. (2015) utilized a driving simulator tool to access motorist's acceptance of distinct intelligent transport systems developed to minimize crashes. Fifty-eight participants actively participated in the study where three intelligent transport system devices, namely, an in-vehicle visual intelligent transport system, an in-vehicle audio intelligent transport system, and an on-road valet system were tested. The overall findings of the study revealed that most of the drivers intended to use road-based valet system at passive RRGC.

Driving through the passive crossing needs considerable attention from road users as it is quite challenging to predict the train arrival time at the crossing. At passive RRGC, around 95% of accidental cases have been reported due to careless driving (Serbian Rail Administration, 2009; Ward & Wilde, 1995, 1996; Hauer, 1984; Raslear, 1996; Russell et al., 2007; Meeker & Barr, 1989; Kumar, 2012; Larue et al., 2018b). Larue et al. (2017) examined the veracity of motorist's perception in judging the speed of an approaching train and their decision to enter the crossing zone. The findings suggested that motorists were highly sure with their speed judgement and would have entered the crossing zone if the crossings were actively protected. Limited lateral visibility faced by the drivers approaching the crossing compels them to alter their usual behavior, and as a result, they commit risky action (Ward & Wilde, 1996; Caird, 2002; Wigglesworth, 1976; Moon & Coleman, 1999). Statistical descriptive analysis by Kasalica et al. (2012) revealed that trains running at high speed possess less safety margin for road users, and drivers find it difficult to guess the speed of approaching trains at passive crossings with low lateral visibility. For this reason, drivers engage in risky operations, which results in a high number of accidents. Larue et al. (2019b) introduced road vehicle activated advanced signage to improve the attention of road users about the approaching RRGC. The authors observed that a high range of advantages could be achieved using such advanced signage as making the drivers aware of the level crossing, improved drivers' attention towards road signs, gaze behavior, and distinct speed choice. The in-vehicle warning system helps the driver draw attention to the approaching train (Osemenam, 1998; Carroll et al., 2001; Smailes et al., 2002). Kim et al. (2015) employed three intelligent transport system interventions (visual in-vehicle, audio in-vehicle, and on-road marker system) and observed that these interventions mostly influence driver behavior at passive RRGCs compared to those of passive to active RRGCs.

3.2. Safety evaluation

Catastrophic outcomes of accidents at RRGCs have captivated researchers and transport planners to resolve the safety aspects of them (Lu & Tolliver, 2016). Safety at RRGCs is commonly reflected in the form of repeated accidents/crashes with varying levels of severity and generally evaluated utilizing available crash data of past few decades (City of Greater Dandenong, 2007; Dodgson, 1984; Powell, 1982; Liang et al., 2017a; Liang et al., 2017b; Liang et al., 2020). Apart from historical crash data, safety at RRGCs can also be evaluated by examining violations of road users utilizing collected field data through videography techniques. Violation at RRGC is significantly responsible for crashes with a range of severity in injuries to road users (Freeman & Rakotonirainy, 2015; Khattak & Luo, 2011; Liang et al., 2017a). Moreover, drivers trapped within the dilemma zone on traversing the intersection may experience orthogonal or rear-end collision, which adversely affects road users' safety (Papaioannou, 2006; Liu et al., 2007; Zhang et al., 2014). The safety-related aspect based on crash data, violation, and dilemma zone is discussed in the following subsections. Also, studies pertaining to safety are portrayed in Table 2 in chronological order. Variable types under the OT category include centerline barrier length, punishment, annual crash frequency, injury level, violation type, and land use. The remaining variable types contain the same parameters, as mentioned in Section 3.1.

3.2.1. Accidents analysis

Road users can experience severe injuries and fatalities if a crash occurs on traversing the RRGC. Approaching high-speed train, concrete pavement, senior citizens, risky actions, observational mistakes, heavy vehicle, high speed limit at passive crossings, times of the day, foggy environment, free space, and number of tracks are the potential factors associated with crashes with serious injuries (Meiers et al., 2012; Haleem, 2016; Hu et al., 2009; Hao et al., 2017; Zhao & Khattak, 2014; Laapotti, 2015; Hao et al., 2016; Keramati et al., 2020). A study conducted by Evans (2011) in Greater Britain (based on crash data of 26 years) reveals that the total reported fatalities at active, passive, and railway controlled RRGCs are responsible for 52%, 43%, and 5% fatalities, respectively, and pedestrians alone contributed 60% of total fatalities. Liu et al. (2015) performed path analysis utilizing crash data of 10 years and concluded that the severity of injury at active crossings is 16% lesser than passive crossings.

Austin and Carson (2002) reported that the frequency of fatality increases with an increased number of accidents and can be reduced by upgrading crossbuck with a stop sign. Various mathematical models can be used for analyzing crash-related safety aspects. Lu and Tolliver (2016) observed that the Poisson regression model could be effectively used to analyze the frequency of crashes at RRGCs and also to overcome the crash data-related issues, including over dispersion where the mean of the sample is smaller than the variance. Further, Hao and Daniel (2014) reported that the ordered probit model could be employed to determine the factors responsible for crashes and prioritize the severity of injury outcomes at RRGCs. Moreover, a mixed logit model was reported to have the advantage over multinomial logit, nested logit, and ordered probit models to trace the effect of unobserved predictors like driver behavior during the crash (Haleem & Gan, 2015).

Stratified tree-based regression was reported to be useful in analyzing and forecasting crashes at passive RRGCs (Yan et al., 2009). Millegan et al. (2009) reported that negative binomial regression could be utilized for developing alternate prediction models. Tjahjono et al. (2019) analyzed four years of crash data using the ordered probit and logit model and revealed that waterlogged surfaces, two-wheelers, low traffic volumes, and male drivers are among the prime promoters responsible for fatal accidents at RRGCs. Zhang et al. (2018) developed an ordered logistic regression to quantify the severity of rail-pedestrian crashes at RRGC and revealed that out of total crashes, 60% were fatal. Additionally, Stephens and Long (2003) treated urban and rural RRGCs with noticeable road markings (X inscribed in a box) and reported a significant reduction in crash rates. Gitelman and Hakkert, (1996) suggested that unification of limited crash data can be done to develop hazard indices, and accordingly, several RRGCs can be prioritized based on the development indices; hence, safety can be ensured.

3.2.2. Violation studies

Gated RRGCs are believed to have a significant impact on lowering the collision rate when compared to RRGCs with different protection system, including flashing lights, audible bells, warning signs, and pavement markings (Ogden, 2007; Lenne et al., 2011; Austin & Carson, 2002; Park & Saccomanno, 2005; Elvik et al., 2009; Raub, 2009). But, violation at gated RRGCs could be the most dangerous behavior as road users, including drivers, expose themselves to the high-risk accidental zone by traversing through and around the gates in the course of gate operations (Cooper & Ragland, 2012; Liu et al., 2015). The violation is observed for all the modes of transport like motorized, non-motorized, and pedestrian (Larue et al., 2018a; Larue & Naweed, 2018; Liang et al., 2017a; Liang et al., 2018a,b). Investigations pertaining to motorist violation and pedestrian and bicyclist violations are presented in two separate sections below. Moreover, the studies on safety evaluation based on the dilemma zone are given separately.

3.2.2.1. Motorist violation. In general, drivers and road users traversing the gated RRGCs commit three types of violations: flashing light violation, gate descending violation, and gate blockage violation. Fitzpatrick et al. (1997) analyzed the videotaped data and revealed that around 48% of drivers violated in the flashing light phase, 47% in the gate descending phase, and 5% in the gate blockage phase. Khattak (2014) developed the Poisson regression model and concluded that protracted waiting time and greater accessibility of freedom at dual gated RRGCs result in a higher violation rate. Liang et al. (2017a) analyzed the data through descriptive analysis and observed that the violation rate increases during peak hours. Path analysis is efficient in investigating the factors associated with gate violation and in correlating gate violations with the severity of injury at RRGCs (Liu & Khattak, 2017, 2018). The results from path analysis utilizing crash data of nine years indicated that if a driver crashes during violation at dual gated RRGC then his/her probability of survival reduces by 7.47%. Carlson and Fitzpatrick (1999) explored the contributing geometrical and operational parameters responsible for the violation and developed two models based on regression to determine whether the driver violates in the flashing light phase or the gate descending phase. Risk analysis performed by Liang et al. (2017b) at two and four half barriers equipped with flashing lights revealed that various factors (including presence or absence of nearby railway station, vehicular density, and duration of gate blockage) significantly influence the violation rate. Zhang et al. (2017) performed driver's behavioral analysis utilizing an artificial intelligence-based computer vision tool having the ability to analyze the database of near-miss events in diverse climatic and visibility conditions at RRGCs. The authors reported that the tool is capable of tracking, capturing, and aggregating near-miss events due to trespassing with adequate reliability in context to real-world scenarios. The flexible centerline barrier system is effective, economical, and promising in demotivating the drivers to violate at RRGCs (Ko et al., 2007; Khattak & McKnight, 2008). The results from descriptive statistical analysis and negative binomial model revealed that the violation rate reduces by around 25 times with the introduction of treatment with centerline barriers.

3.2.2.2. Pedestrian and bicyclist violation. Safety issues encompassing non-motorized road user groups, pedestrians, and bicyclists, in particular, have collected significant attention in the past few years due to their vulnerability (Barić et al., 2017). Collision of pedestrians or bicyclists with motorists or trains even at low speed is more likely to result in severe injuries or fatalities when compared to motorists or train passengers (Freeman et al., 2013). Although there are multiple factors responsible for the rising number of fatalities of pedestrians and bicyclists, with violations among the prime factors (Larue et al., 2018). Pedestrians and bicyclists engage themselves in violations at RRGCs in multiple ways such as crossing before the approaching train, during gate descending, and in the course of gate blockage after the train passes the intersection (Federal Highway Administration, 2007; Nelson, 2008; Sochon, 2008). Most of the road users fail to detect the RRGC and fail to notice the approaching train and misjudge train speed. Hence, they traverse the crossing with high risk (Cooperative Research Centre for Rail Innovation, 2010; Wallace, 2008). Relatively more pedestrian and bicyclist collision cases have been reported than that of motorists, and out of the total train-pedestrian collision, approximately 67% of the cases are fatal (Lobb et al., 2002; Australian Transport Safety Bureau, 2004). The leading cause of illegal crossing of pedestrians at RRGC could be due to purposeful violation or by mistake. Freeman and Rakotonirainy (2015) conducted a user perception survey and revealed that 25% of pedestrians intentionally violated the crossing, and 3.5% of them crossed by mistake. Many researchers have suggested that investigating risky behavior in association with multiple parameters would be more beneficial (Iorio et al., 2012; Read et al., 2013; Read et al., 2015; Werkman et al., 2012).

In order to understand the crossing behavior of non-motorists at RRGCs, Stefanova et al. (2015) developed a system-based non-motorist unsafe crossing framework and concluded that time of the day, gender, and age group of the road user significantly contributes to the pedestrian's risky activities, such as violations. Males of the younger group and peak hours, as well as other parameters such as a cluster of pedestrians in haste, undue attention, types of protection devices, and lateral visibility, are primarily responsible for such behaviors (Clancy et al., 2007; Edquist et al., 2011; McPherson & Daff, 2005; Metaxatos & Sriraj, 2013; Searle, 2012; Sposato et al., 2006). Khattak and Luo (2011) reported that children and younger non-motorists (bicyclists and pedestrians) violate 1.25 times more than the old group non-motorists. Educational and access prevention mediation programs can be employed to enhance awareness of pedestrians on the illegal and unsafe crossing (Lobb et al., 2000). A study by Lobb et al. (2002) revealed that although education program is effective in lowering the unsafe traversing of the pedestrian at RRGCs, punishing the road users on illegal crossing would reduce the risky crossing a greater extent. Siques (2002) revealed that pedestrian treatments (including automatic barriers, warning devices, and various signboards such as look both ways and stop at RRGCs) are promising in reducing the violation rate significantly. Also, Barić et al. (2017) utilized videotaped data and observed that the violation rate of pedestrians and bicyclists can be reduced up to 59.23% with the presence of policemen and installed cameras at RRGCs.

3.2.3. Dilemma of drivers

The dilemma zone concept was first explored by Gazis et al. (1960). Subsequently, various researchers studied the dilemma zone at RRGCs (Crawford, 1962; Herman, 1963; Olson & Rothery, 1972; Zegeer, 1977; Sheffi & Mahmassani, 1981). Many studies have been undertaken in context to dilemma zone at highway signalized intersection, but, to the best of the authors' knowledge Moon (1998), Coleman and Moon (1997), and Moon and Coleman (2002) are the only researchers who explored dilemma zone at four-quad gated RRGCs. The authors addressed that motorists that were heading towards the gated RRGC experience almost the same situation as when approaching a signalized highway intersection. For identifying the static dilemma zone, the formulation of stopping distance and continuation distance was suggested by Moon and Coleman (2002). Also, Larue and Naweed (2020) utilized videotaped data and revealed that most of the drivers entering the dilemma zone during the onset of flashing light violated the dual gated RRGC due to insufficient warning time for drivers to respond and to stop before traversing the RRGC. However, the authors did not reveal how the dilemma zone was identified for dual gated RRGC.

Simulation technique can be utilized to model the vehicular dynamic characteristics and contributing factors in context to motorists stopping at gated RRGCs to figure out the dilemma zone. Accordingly, gate operations time can efficiently be computed (Coleman & Moon, 1997). Moon and Coleman (2002) employed a car-following model to introduce the concept of a dynamic dilemma zone at four-quad gated RRGC. The authors reported a relatively higher value of gate delay and gate interval in the case of platoons than that of single vehicles approaching the crossing. In contrast to the dilemma zone, an option zone is also identified where a motorist has an option to stop or drive through the intersection. The option zone leads to a probabilistic approach and defines the zone as the region where at least 10% and at most 90% of motorists tend to stop before the intersection, which reflects the dynamic nature of the zone (Zegeer, 1977).

3.3. Operational impact assessment

Most road users suffer from congestion and delay in traversing the signalized intersection. Therefore, the improvement of such intersection zones is the primary concern of researchers, traffic planners, and traffic management authorities (Shahi & Choupani, 2009). Delay is the prime measure to quantitatively evaluate the Level of Service (LOS) of any intersection (Zhang & Prevedouros, 2010). RRGCs are analogous to signalized intersections where road users face bundles of operational problems (Moon, 1998; Coleman & Moon, 1997; Moon & Coleman, 2002). Among the operational parameters, significant studies have been undertaken to encompass vehicular delay at RRGCs (Powell, 1982; Chandler & Hoel, 2004; Rilett & Appiah, 2008; Hakkert & Gitelman (1997). Motorists are likely to face delay when the vehicle is stopped or traveling at a speed of less than two kmph and do not exceed five kmph (Tey et al., 2012). A survey by VicRoads (2010) reported that travel time decreases significantly (around 22%) in rush hours on upgrading the RRGC with grade separators. Travel time can be defined as the total time elapsed for a particular vehicle to travel from one point to another over a specified path in association with lost time during the stops, queuing delay, and intersection delay (Mori et al., 2014). Hakkert and Gitelman (1997) developed a modified delay model using the model proposed by Ryan and Erdman (1985).

The authors revealed that motorists traversing the RRGC face delay not only during gate operations but also during gates open to traffic due to roughness at the intersection zone. Trivedi and Gor (2017) examined the impact of lane discipline on the delay faced by motorists at RRGCs using a modified Webster model of delay. The authors reported that the delay faced considering lane discipline is on the lower side when compared to the delay without lane discipline. Unlike signalized highway intersection, it is very difficult to compute the delay faced by motorists at RRGC due to non-cyclic train arrival and gate operation times. Therefore, the microsimulation technique can be effectively employed to determine vehicular delay (Chandler & Hoel, 2004; Cline et al., 1987; Powell, 1982; Mitrovic, 2011; Tey et al., 2012). Powell (1982) utilized a microsimulation tool for vehicular delay analysis at RRGCs in the United States and reported an average weekly delay of 46 hours. Chandler and Hoel (2004) employed a microsimulation tool (VISSIM) and concluded that vehicular delay increases with increased road traffic volume and approaching train frequency at RRGCs. Another study utilizing VISSIM encircled a total of 152 RRGCs in Melbourne, Australia, by Nguyen-Phuoc et al. (2017). The study revealed that the aggregated effect of all RRGCs in the city increased the travel time by 0.3%, congested links by 0.9%, and total delay by 0.7%. Delay at RRGC affects the traffic flow performance and contributes significantly to economic loss (Protopapas et al., 2010). Another study by Hasnat et al. (2016) revealed that a single RRGC is responsible for an annual economic loss of around 5,491,430 USD in association with vehicular operating cost and value of travel time. Mitigation measures, including various treatments and cost-effective design solutions, effectively optimize the traffic operation condition at RRGCs. Beanland et al. (2018) proposed three cost-effective design solutions for active and passive RRGCs: GPS, average speed interface, and ecological interface design crossing. The authors used a driving simulator to compare these designs with conventional RRGCs and revealed that ecological interface design crossing performed the best. Moreover, Larue et al. (2020) examined the effectiveness of treatments utilizing simulation technique and concluded that reducing warning time by 10 to 40 seconds could result in overall travel time reduction by 7–57%.

Various studies pertaining to operational impact have been portrayed in Table 3 in chronological order. Variable types under OT category include detector location and length, lost time, weekdays, weekends, speed limit, the distance between the stop line and rail, and lane discipline. The remaining variable types contain the same parameters, as mentioned in Section 3.1. A critical review of published literature revealed that efficient traffic management plays a vital role in enabling smooth traffic flow at an intersection in general and at RRGCs in particular. But, at bottlenecks like RRGCs, vehicular delay, formation of queue length, drop-in capacity leads to congestion during various gate operation phases, which ultimately deteriorates the service level. If the issues mentioned above are not resolved, it would create numerous operational and safety-related problems and result in deterioration of the overall performance and safety of RRGCs. Therefore, to manage the traffic efficiently at RRGCs: (a) delay faced by road users during and after various gate operation phases needs to be computed, (b) drop in capacity is required to be evaluated during various gate operating phases, (c) queue formation during gate closure time and queue dissipation time after gate ascending need to be quantified, and (d) based on the delay and user perception, level of service has to be estimated. Once all these parameters are determined, various geometrical and operational attributes could be varied utilizing simulation tools to check how the overall performance of the RRGC could be improved. Accordingly, suitable mitigation strategies could be implemented to enhance the overall performance of RRGCs, such as:

a) Educating the road users to comply with traffic rules and making them aware of crossing controls at RRGCs may reduce the risky action taken by road users.
b) Pavement markings to guide the road users about the safe available space for their smooth movement may reduce the collision likelihood between the different classes of road users to some extent.
c) Installation of centerline flexible barriers on the roads linked to RRGC to force them to stay at their assigned lane may ensure the smooth dissipation of queue.
d) Marking "X" shaped symbol after the RRGC may help the road users judge whether there is enough space to drive through the RRGC or stop moving until complete "X" is visible. It could help in reducing the queue length formation.
e) Augmentation of road width at the area surrounding RRGCs could accommodate more traffic and may reduce congestion and overall delay to road traffic.
f) Construction of foot over bridge at RRGC could result in uninterrupted pedestrian movement regardless of different gate operation phases. Further, this strategy could diminish the interaction between vehicle and pedestrian traffic, leading to a reduction in vehicular traffic delay during queue dissipation. Moreover, this mitigation measure could result in enhanced pedestrian safety at RRGCs.
g) Reducing RRGC crossing roughness by making a paved surface or installing a rubber pad may significantly reduce the additional delay faced by road users due to the rough crossing surface.
h) Optimizing warning, gate descending, and gate blockage time by utilizing artificial intelligence systems could reduce the delay faced by road users and promote safety by demoralizing the violators.
i) Integrating traffic signals at signalized intersections near RRGCs with train signals may reduce congestion to road traffic to some extent.

Subsequently, before and after studies could be carried out, and the outcome from the before and after studies would give suitable directions to achieve efficient traffic management at RRGCs.

4. Critical observations and future direction

This study investigated three potential parameters (driver behavior, safety, and operational impacts) that greatly influence the performance of RRGCs. To date, RRGCs have received substantial attention from researchers, and most of the studies have been undertaken in context to safety and driver behavior. Whereas, few investigations have been carried out on the operational aspects prevailing at RRGCs. A decade-wise analysis covering the number of studies on various parameters is shown in Fig. 3. A country-wise study (Fig. 4) depicts that around 49% of the studies on RRGCs have been undertaken by United States researchers whereas, Australian researchers have devoted approximately 29%, and contribution from the researchers of other developing countries is minimal. Among the mentioned three parameters, 41%, 45%, and 14% of studies have been undertaken to date concerning safety, driver behavior, and operational impacts, respectively, as shown in Fig. 5.

This study has made a synthesis of available literature and identified the critical parameters affecting the performance of RRGCs in detail. From a comprehensive review of published research, the following critical observations have been made.

1. Driver behavior is among the prime determinant attributes reflecting the effectiveness of the protection system and governing safety-related aspect of RRGCs. The decision made by a road user while traversing the RRGC primarily depends on his/her experience, education, self-judgment ability, reaction time, perceived situation, state of mind, and other psychological

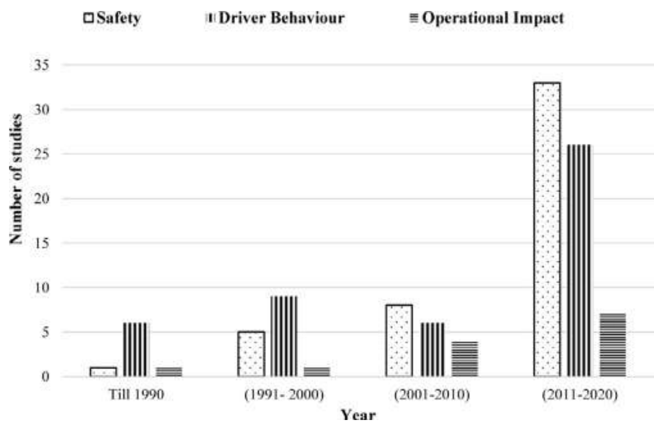


Fig. 3. Decade wise global analysis of parameters influencing RRGC performance. (Source: Authors' synthesis).

factors. In addition, the disability of road users, usage of alcohol and drug, and fatigue not only cap the perceptual performance and decision-making skills of the driver, but also enhances the risk of fatal incidents. Therefore, the evolution of a pertinent risk management approach incorporating driver behavior could result in more efficient planning and better execution of safety reform at RRGCs.

2. Careless driving can be catastrophic as it may result in severe injuries and fatalities (Berg & Oppenlander, 1969; Caird, 2002; Green, 2002; Fambro et al., 1994; Ward & Wilde, 1995, 1996; Hauer, 1984; Raslear, 1996; Russell et al., 2007). The prime reasons for careless driving could be due to a high-stress level, gender, age group, and aggressive driving habits of the road users. Moreover, frustration due to long waiting times at RRGCs, times of the day, overestimated sight distance, low / non-audible train horns, and climatic conditions could be the attributing factor for careless driving. Many studies have been carried out on driver

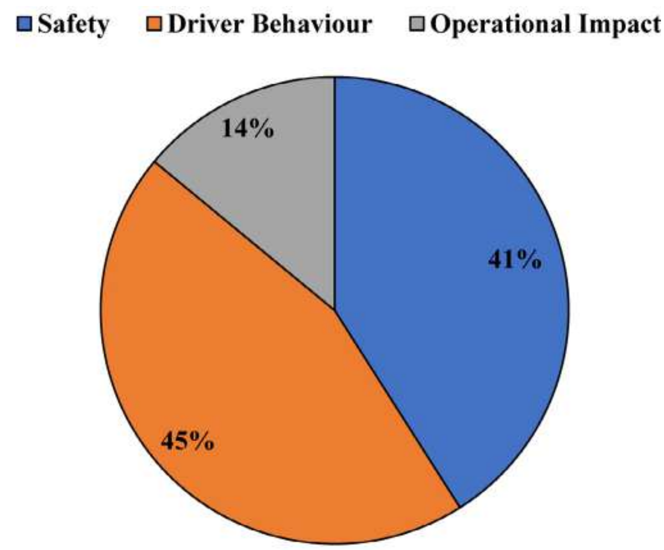


Fig. 5. Parameter wise study on RRGC in the global context. (Source: Authors' synthesis).

behavior at active and passive RRGCs incorporating various attributes related to traffic characteristics, crossing features, visibility factor, and driver characteristics such as age and gender. But there is a lack of research on investigating factors associated with decision-making skills and the self-judgment ability of drivers. For example, the careless driving behavior at RRGCs with poor train horn audibility could be scrutinized by installing roadway side horns in the vicinity of RRGCs. If the installation is found efficient in reducing the risky action taken by road users, roadway side horns can be installed at other RRGCs with

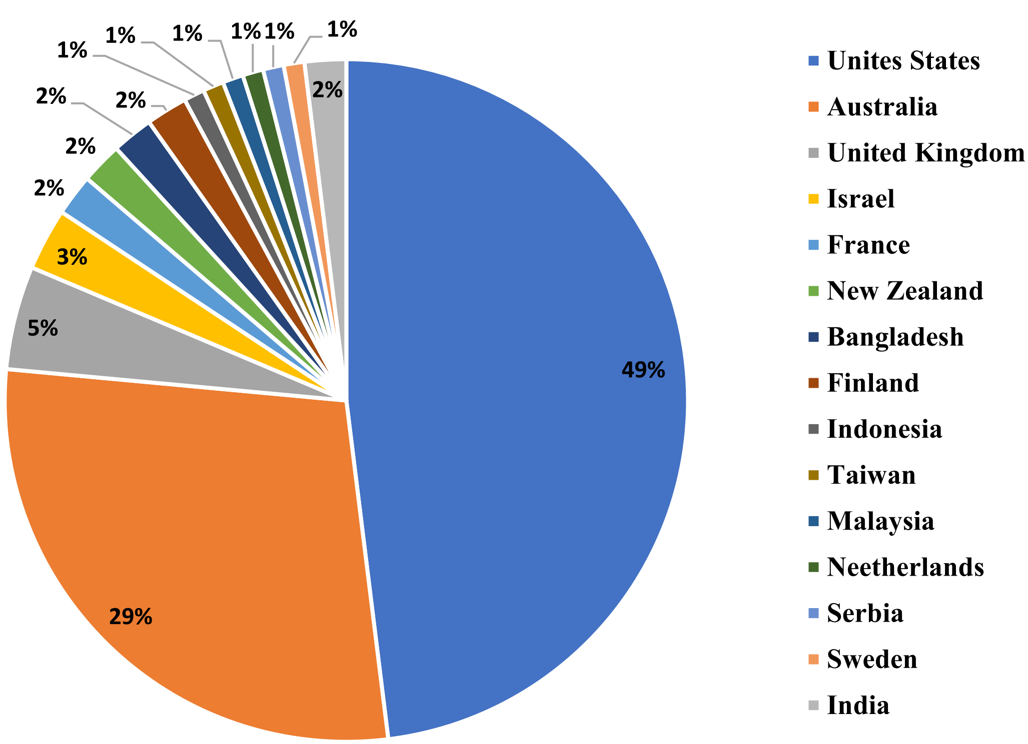


Fig. 4. Country wise studies on RRGC. (Source: Authors' synthesis).

train horn audibility issues. Therefore, future work exploring various strategies to diminish careless driving habits will assist in providing a clear vision on the comprehension of change in driver behavior at active and passive RRGCs.

3. Safety at RRGCs and its associated factors are mostly examined by historical crash data (City of Greater Dandenong, 2007; Dodgson, 1984; Powell, 1982). Considering various geometrical, operational, and environmental factors, many researchers have investigated road users' injury severity levels by developing accident prediction models utilizing historical crash data. But, none of the researchers have utilized the historical crash data to address driver behavior, operational aspects, and effectiveness of warning devices equipped at RRGC. Therefore, historical crash data could further be utilized to compare the crash rate of RRGC equipped with traffic signals to that of RRGC with no traffic signals. Also, the efficacy of the second train warning sign could be assessed by investigating crash histories at RRGC, and the effect of such warning signs on road user behavior could be analyzed. Safety assessment through crash data may not be efficient as it is inclusive of multiple drawbacks, including randomness and the rare occurrence of an accident, lack of empirical evidence, inaccurate accident reports, and an improper spot of an accident by the respective administrative officers, which in turn affects the reliability and veracity of safety analysis (Paul & Ghosh, 2018). Therefore, collision likelihood, the severity of the injury, and driver behavior can be integrated to develop models to frame risk management to a large scale.
4. Violation is another crucial aspect contributing to the RRGCs safety as road users expose themselves into the high-risk accidental zone by traversing through and around the gates in the course of gate operations (Cooper & Ragland, 2012; Liu et al., 2015). Many violation studies have been undertaken to incorporate multiple factors, but limited studies have examined the effect of varying warning times and train occupancy time on violation rate. Also, limited before and after studies have been carried out with the introduction of treatments based on artificial intelligence tools. Furthermore, research is needed for RRGCs with high accident rates to examine whether such RRGCs have high violation rates during the warning phase. If so, the cause of the violation should be investigated. It could be due to false alarms, long warning time, deliberate violation, or other demographic attributes. In addition, there are several questions that need to be answered in order to understand the cause of the violation. Some of them are: (a) Whether the road users violate deliberately or by mistake? (b) What parameters are needed to develop efficient psychological models? (c) Under what climatic condition likelihood of violation increases? (d) Does the distance between the gates affect the rate of violation? (e) What countermeasures are needed to slow down the violation rate? Therefore, future research in this context will assist the transport planners and agencies in optimally allocating resources and funds and ensuring safety by discouraging the violators.
5. The dilemma zone also plays a vital role in addressing the safety-related aspect of RRGC safety. If not identified and eliminated, the dilemma zone can lead to motorist entrapment between the gates (Coleman & Moon, 1997). Studies on dilemma zone have been undertaken considering four quad gated RRGCs, and none of the studies has explored the dilemma zone at dual gated RRGCs. Hence, it is needed to identify the dilemma zone at dual gated RRGCs and compute optimal gate delay and gate interval time to reduce collision likelihood and vehicle entrapment between the gates. Once the dilemma zone is identified, it is also required to examine how the road users

Table 5
Summary of research gaps and future work.

Parameters influencing RRGC performance	Research Gaps	Future work	Significance
Driver behavior at active RRGC	Lack of research on factors associated with driver's decision making concerning compliance level	Identify various factors associated with diverse driving style by incorporating cost-benefit analysis and establish some technique to improve compliance	Weightage of cost and benefits significantly influences the decision-making process of drivers
Driver behavior at passive RRGC	Inadequate consideration over driving experience level, land use, geometrical attributes, psychological factors and educational status in context to driving behavior	Develop models based on factors contributing to the self-judgement ability of drivers	Self-judgement ability of drivers plays a vital role in ensuring their safety as passive RRGCs are mostly unprotected.
Safety evaluation based on crash data	Limited safety-related attributes and lack of empirical evidence	Integrate collision likelihood, the severity of injury and driver behavior to build mixed effect models	Outcomes from the research incorporating these attributes can assist in framing risk management to a large scale.
Safety evaluation based on motorist violation	Limited study has been carried out to examine the violation rate on varying warning time and train occupancy time	Use simulation technique to optimize warning time and check whether variation in warning times affect the violation rate	Warning time optimization can contribute significantly to enhance safety by discouraging violators
Safety evaluation based on pedestrian and bicyclist violation	Limited before and after investigation to suggest mitigation measures in context to safety effectiveness	Introduce various intervention measures including artificial intelligence techniques and examine pre and post-treatment effects	The investigation can assist the transport planners and various agencies in allocating resource and funds in optimal manner
Safety evaluation based on dilemma zone	No research has been carried out to identify dilemma zone at dual gated RRGC	Use empirical models and simulation technique to identify the dilemma zone and optimize gate delay and gate interval time to eliminate dilemma zone	Elimination of the dilemma zone can ensure the safety up to a greater extent by reducing collision likelihood and vehicle entrapment between the gates
Operational impacts	Lack of evidence over the impact of lane discipline on delay faced by drivers, and various operational attributes including the level of service, capacity and queue characteristics is under explored	Use empirical models and simulations technique to examine the impact of lane changing behavior of drivers on delay and evaluate the level of service based on user perception	A better understanding of travel time variability and quality of RRGC can be achieved

behave in the dilemma zone: whether they choose to safely stop or illegally traverse the RRGC at the onset of the warning phase. Also, geometrical and operational attributes can be varied, and road user behavior at the dilemma zone can be examined utilizing simulation tools during the warning phase of RRGCs. Numerous research has been undertaken in context to dilemma zone at signalized intersection but this area, in particular, is underseen by the researchers at RRGCs in past few decades. Therefore, further work on the dilemma zone incorporating a dual gate assembly can ensure greater safety by reducing collision likelihood and vehicle entrapment between the gates.

6. Operational attributes are measures of effectiveness to evaluate an intersection's performance (Kyte et al., 1991). Among the operational parameters, significant studies have been undertaken encircling vehicular delay at RRGCs (Powell, 1982; Chandler & Hoel, 2004; Rilett and Appiah, 2008), but other attributes (including the level of service, queue characteristics, and capacity) are underseen by the researchers to date.
7. There is a lack of evidence over the impact of lane discipline on delays faced by drivers. Lane changing behavior of motorists has a significant effect on the safety and the capacity of any traffic facility (Ji & Levinson, 2020). Additionally, due to the multiple-gate closure cycle at RRGCs, highway users cannot utilize full capacity. Therefore, it is needed to compute the highway's drop in capacity, considering the possible factors. Future work in investigating the aforementioned operational parameters and their related aspects will provide a better understanding of travel time variability and quality of a RRGC in terms of its performance.

In the purview of the above-mentioned critical observations, the observed research gaps, future directions for research encompassing issues related to driver behavior, safety evaluation by crash data and road user violation, and operational impacts have been collated in Table 4.

Moreover, in context to mixed traffic conditions prevailing in the developing world, the research on RRGCs related aspects is underexplored. In mixed traffic conditions, the traffic operation at RRGCs becomes very complex and risky as it is associated with a high degree of heterogeneity in vehicular dimension with varying operating speed, absence of lane discipline, and diverse decision-making skills of motorists and pedestrians. Therefore, further to the above-mentioned research gaps and future scope, all these aspects could be investigated, emphasizing mixed traffic conditions.

5. Conclusion

Available literature reveals that due to an increase in the number of RRGCs due to burgeoning transportation networks and the associated complexity of driver behavior, the severity of safety concern and the allied operational and economic impacts has spurred a growing interest in many researchers to model and analyze the traffic performance at RRGCs. These efforts have resulted in many publications related to performance evaluation at RRGCs. This article presents a comprehensive systematic critical review of the published research pertaining to the performance of RRGCs and addresses critical research gaps in the context of this field. This study provides a critical review of identified potential parameters influencing the RRGC performance, namely, driver behavior, safety, and operational impacts, including significant findings, used variables, analysis methods, research gaps, and recommendations. Subsequently, the identified parameters were segregated into various possible components such as driver behavior at active and passive RRGCs, safety evaluation using crash data, motorist violations, pedestrians and bicyclist violations, and dilemma zone, to analyze the research findings in depth with adequate veracity. A total of seven critical research gaps concerning identified parameters were recognized, facilitating a comprehensive agenda for further research pertaining to RRGC performance. The proposed future research would be beneficial for enhancing the performance of RRGCs and will result in safer and sustainable transportation.

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Seasonal variation in fall-related emergency department visits by location of fall – United States, 2015

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ABSTRACT

Introduction: In the United States, fall-related emergency department (ED) visits among older adults (age 65 and older) have increased over the past decade. Studies document seasonal variation in fall injuries in other countries, while research in the United States is inconclusive. The objectives of this study were to examine seasonal variation in older adult fall-related ED visits and explore if seasonal variation differs by the location of the fall (indoors vs. outdoors), age group, and sex of the faller. *Methods:* Fall-related ED visit data from the National Electronic Injury Surveillance System-All Injury Program were analyzed by season of the ED visit, location of the fall, and demographics for adults aged 65 years and older. *Results:* Total fall-related ED visits were higher during winter compared with other seasons. This seasonal variation was found only for falls occurring outdoors. Among outdoor falls, the variation was found among males and adults aged 65 to 74 years. The percentages of visits for weather-related outdoor falls were also higher among males and the 65–74 year age group. *Conclusions*: In 2015, there was a seasonal variation in fall-related ED visits in the United States. Weather-related slips and trips in winter may partially account for the seasonal variation. *Practical Implications:* These results can inform healthcare providers about the importance of screening all older adults for fall risk and help to identify specific patients at increased risk during winter. They may encourage community-based organizations serving older adults to increase fall prevention messaging during winter.

1. Introduction

Fall-related emergency department (ED) visits among older adults (65 years and older) in the United States increased from 2.2 million in 2009 to 3.0 million in 2018 (Centers for Disease Control and Prevention [CDC], 2003). Each month an estimated 250,000 older adults were seen in an ED for a fall in 2018 (CDC, 2003). Studies in other countries found that a higher number of fall-related ED visits (Al-Azzani & Mak, 2016; Beynon, Wyke, Jarman, Robinson, Mason, & Murphy, 2011; Jung et al., 2018; Wareham et al., 2003) and fractures (Bulajic-Kopjar, 2000; Grønskag, Forsmo, Romundstad, Langhammer, & Schei, 2010) occur in the winter months when compared with other seasons. Findings on the seasonal variation of falls and related injuries in the United States are inconsistent. One study found that between 1986 and 1990, a higher rate of fall-related fractures was observed during winter compared with other seasons (Bischoff-Ferrari, Orav, Barrett, & Baron, 2007). In another study, there were no noted seasonal differences in the rate of fall-related ED visits during 2001–2002 (Stevens, Thomas, & Sogolow, 2007). While these outcomes differ (i.e., fall-related fracture and fall-related ED visit), there were no consistent findings of seasonal variation in fall-related injuries.

Past studies that examined winter falls focused on those that occurred outdoors due to weather-related factors (e.g., slips or trips on ice, snow, or freezing rain) (Bobb et al., 2017; Dey, Hicks, Benoit, & Tokars, 2010; Gevitz, Madera, Newbern, Lojo, & Johnson, 2017). These studies found that there was a higher risk for fall injuries during (Dey et al., 2010; Gevitz et al., 2017) and immediately after periods of snowfall or freezing rain (Bobb et al., 2017).

Irrespective of season, older adult falls and fall injuries occur more often indoors than outdoors (Boye et al., 2014; Leavy et al., 2013; Moreland, Kakara, Haddad, Shakya, & Bergen, 2020; Schiller, Kramarow, & Dey, 2007). Studies that find seasonal variation in falls or fall injuries often propose that, in addition to outdoor weather-related events, prolonged periods of time spent

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indoors during winter could be a cause for increased falls (Campbell, Spears, Borrie, & Fitzgerald, 1988; Jacobsen, Sargent, Atkinson, O'Fallon, & Melton, 1995; Leavy et al., 2013; Qian, Chau, Kwan, Lou, & Leung, 2019; Stevens et al., 2007; Wareham et al., 2003). A potential consequence of staying indoors for extended periods of time that could increase fall risk include low physical activity, which leads to diminished muscle strength and bone loss (Jacobsen et al., 1995; Leavy et al., 2013; Mondor, Charland, Verma, & Buckeridge, 2015; Qian et al., 2019; Stevens et al., 2007; Wareham et al., 2003). Other consequences may include seasonal affective disorder, a form of depression due to low light and isolation (Jacobsen et al., 1995; O'Hare, O'Sullivan, Flood, & Kenny, 2016), tripping over objects inside homes and disturbance in circadian rhythms due to low natural light in winter (Johansen, Boulton, & Neuburger, 2016; Vikman, Nordlund, Näslund, & Nyberg, 2011). However, there is limited research examining seasonal variation by location of fall to support this discussion. Understanding seasonal variation by location could help us identify the factors driving seasonal variation, if any.

The objectives of this study were to examine seasonal variation in ED visits among adults age 65 and older and to explore if seasonal variation differs by the location (indoors vs. outdoors) of the fall, and the age and sex of the faller.

2. Methods

Data and narratives from the 2015 National Electronic Injury Surveillance System-All Injury Program (NEISS-AIP) were reviewed to determine the season and location of nonfatal falls that led to an ED visit among adults age 65 and older (NEISS, 2021). The NEISS-AIP is a nationally representative data system operated by the United States Consumer Product Safety Commission. It includes data from a sample of about 66 of 100 NEISS-participating hospitals in U.S. states and territories. NEISS-AIP captures data from a patient's initial ED visit for an injury. The data are then weighted to represent the U.S. population using the inverse probability of hospital selection in each stratum and adjusted for non-response (Schroeder & Ault, 2001). For each ED visit, the date of treatment, age, sex, primary diagnosis, precipitating cause of injury, intent of injury, and a 2-line free-form narrative describing the circumstance of injury are abstracted from the medical record. Only ED visits made by adults over the age of 65, and whose precipitating cause of injury was an unintentional fall, were included in this analysis making the initial sample size 38,654 ED visits. Date of treatment was used to define the season in which the fall occurred. Seasons were defined as spring (March – May), summer (June – August), autumn (September – November), and winter (December – February).

The narratives were used to create three additional variables: place of residence, fall location, and weather-related fall. This was done by dividing the 38,654 ED records into four groups. One of four researchers then reviewed each group. A codebook was developed (Appendix A) by reading 100 narratives and then updated for every 2,000 narratives read. A second researcher reviewed 10% of all narratives and the four researchers discussed coding discrepancies until they reached a consensus. Previous narratives were recoded based on changes made to the codebook.

Place of residence – If a narrative indicated that the fall occurred in a residential facility such as a nursing home, assisted living facility, or another type of facility, the person was considered non-community dwelling. If the narrative did not mention these keywords, the person was assumed to be community dwelling. There were nine cases where a fall occurred in a prison. These nine were excluded from the analysis reducing the sample size to 38,645.

Fall location – The location of the fall was then assessed for older adults who resided in the community (n = 34,336). Location was coded as either indoor (n = 14,131) or outdoor (n = 6,485). Cases where the narratives did not have sufficient information to identify indoor or outdoor location were coded as unknown (n = 13,720) (e.g., falls on stairs without any additional information were difficult to determine if indoor or outdoor). Events classified as unknown were excluded from location-based analyses. Location was not analyzed among non-community dwelling adults given the small number of events that occurred outdoors (n = 51).

Weather-related fall – Weather was classified for ED visits among community dwelling adults who sustained a fall outdoors. The ED visit for a fall was coded as potentially weather related (n = 1,092) when a term indicative of weather (e.g., rain, snow, ice) was mentioned in the narrative or non-weather related (n = 5,393) in their absence. Additional information on how narratives were coded for place of residence, fall location, and weather are included in the Appendix A.

Percentages and 95% confidence intervals were calculated for season in which the fall-related ED visit occurred, by place of residence, sex, and age group. For community-dwelling older adults, percentages were calculated for fall-related ED visits by location (indoor vs. outdoor), sex, and age group. For weather-related fall injuries, percentages and 95% confidence intervals were calculated for each sub-group of season, sex, and age. Percentages for each sub-group used the number of fall injuries sustained outdoors for that sub-group as the denominator. All analyses were weighted to be representative of the 2015 U.S. population. The conservative method of non-overlapping confidence intervals was used to estimate significant differences between categories. All analyses were performed using Survey Procedures in SAS version 9.4 (SAS Institute, Inc., Cary, NC, USA).

3. Results

The 38,645 narratives represented 3.04 million fall-related ED visits among older adults in 2015. Around 65% of these visits were made by females (data not shown). Fall-related ED visits were more common in winter (26.2%; 95%CI = 25.7, 26.8) than in spring (24.8%, 95%CI = 24.3, 25.4), summer (24.7%, 95%CI = 24.1, 25.2), and autumn (24.3%, 95%CI = 23.7, 24.8) (Table 1). When examined by place of residence, both community and non-community dwelling older adults had more ED visits due to a fall during winter. However, a statistically significant difference was found only among the community dwelling adults. Among community-dwelling males, the percentage of fall-related ED visits was highest in winter (27.3%; 95%CI = 26.3, 28.4) compared with spring (24.8%; 95% CI = 23.9, 25.8), summer (24.3%; 95%CI = 23.3, 25.2), and autumn (23.6%; 95%CI = 22.6, 24.5).

Fall injuries were two times as common indoors (n = 14,131) as outdoors (n = 6,485) (Table 2). However, a higher percent of ED visits occurred due to a fall sustained outdoors during winter (29.8%, 95%CI = 28.4, 31.2) compared with spring (25.8%, 95%CI = 24.5, 27.1), summer (22.2%, 95%CI = 20.9, 23.4), and autumn (22.2%, 95%CI = 20.9, 23.5). Males had a higher percentage of outdoor injuries during winter (31.4%, 95%CI = 29.2, 33.6) compared with spring (26.4%, 95%CI = 24.3, 28.4), summer (20.7%, 95%CI = 18.8, 22.6), and autumn (21.5%, 95%CI = 19.6, 23.4). Older adults in the age group 65 to 74 had more ED visits due to an outdoor fall in winter compared with other seasons (Table 2).

Out of the 6,485 fall injuries that occurred outdoors, 1,092 were reported to be weather related. Around 97% of all weather-related injuries were attributed to slips or trips on ice or snow (data not shown). The remainder were due to rain. Fig. 1 shows that, out of all fall injuries sustained outdoors, 34.4% in the winter were

Table 1
Characteristics of older adults with a fall-related emergency department visit by season and place of residence – National Electronic Injury Surveillance System – All Injury Program, 2015.

Characteristic	Total	Spring (March-May)		Summer (June-August)		Autumn (September-November)		Winter (December-February)	
	n	%	95%CI	%	95%CI	%	95%CI	%	95%CI
Total	38,645	24.8	(24.3, 25.4)	24.7	(24.1, 25.2)	24.3	(23.7, 24.8)	26.2	(25.7, 26.8)
Community Dwelling Older Adults									
Total	34,336	24.8	(24.3, 25.4)	24.8	(24.3, 25.4)	24.2	(23.6, 24.7)	26.2	(25.6, 26.8)
Sex									
Male	12,083	24.8	(23.9, 25.8)	24.3	(23.3, 25.2)	23.6	(22.6, 24.5)	27.3	(26.3, 28.4)
Female	22,253	24.8	(24.1, 25.6)	25.0	(24.3, 25.8)	24.5	(23.8, 25.2)	25.6	(24.9, 26.4)
Age Group									
65–74	12,591	25.0	(24.0, 25.9)	25.1	(24.1, 26.1)	23.4	(22.5, 24.4)	26.5	(25.5, 27.5)
75–84	11,716	25.6	(24.6, 26.6)	24.0	(23.0, 24.9)	24.3	(23.3, 25.3)	26.2	(25.1, 27.2)
85+	10,029	23.8	(22.8, 24.8)	25.3	(24.2, 26.4)	24.9	(23.8, 26.0)	26.0	(24.9, 27.1)
Non-Community Dwelling Older Adults									
Total	4309	24.7	(23.0, 26.3)	24.0	(22.4, 25.7)	25.1	(23.4, 26.8)	26.2	(24.5, 27.9)
Sex									
Male	1271	25.2	(22.1, 28.3)	26.9	(23.7, 30.1)	20.5	(17.6, 23.4)	27.5	(24.2, 30.7)
Female	3038	24.5	(22.5, 26.4)	22.9	(21.0, 24.8)	26.9	(24.9, 28.9)	25.7	(23.7, 27.7)
Age Group									
65–74	530	25.6	(20.7, 30.4)	20.7	(16.3, 25.1)	24.3	(19.6, 29.0)	29.5	(24.2, 34.7)
75–84	1184	25.9	(22.7, 29.1)	24.4	(21.2, 27.6)	25.9	(22.7, 29.2)	23.8	(20.5, 27.0)
85+	2595	24.0	(21.9, 26.1)	24.4	(22.3, 26.5)	24.9	(22.8, 27.0)	26.7	(24.5, 28.9)

n - Unweighted sample size.
% - Weighted percent.
95%CI - 95% Confidence interval.

Table 2
Characteristics of community dwelling older adults who sought emergency department care for a fall by season and indoor/outdoor location – National Electronic Injury Surveillance System – All Injury Program, 2015.

Characteristic	Total	Spring (March-May)		Summer (June-August)		Autumn (September-November)		Winter (December-February)	
	n	%	95%CI	%	95%CI	%	95%CI	%	95%CI
Fall Injury Occurred Indoors									
Total	14,131	24.4	(23.6, 25.3)	25.4	(24.5, 26.3)	24.6	(23.7, 25.5)	25.6	(24.7, 26.5)
Sex									
Male	4392	23.8	(22.2, 25.4)	25.5	(23.8, 27.1)	24.1	(22.5, 25.7)	26.7	(25.0, 28.3)
Female	9739	24.7	(23.7, 25.8)	25.3	(24.2, 26.4)	24.8	(23.7, 25.9)	25.1	(24.0, 26.2)
Age group									
65–74	4334	25.0	(23.4, 26.6)	25.7	(24.1, 27.3)	24.5	(22.9, 26.2)	24.8	(23.1, 26.4)
75–84	4880	25.3	(23.8, 26.8)	24.6	(23.1, 26.1)	24.3	(22.8, 25.8)	25.8	(24.2, 27.3)
85+	4917	23.0	(21.6, 24.5)	25.9	(24.3, 27.4)	24.9	(23.3, 26.4)	26.2	(24.6, 27.8)
Fall Injury Occurred Outdoors									
Total	6485	25.8	(24.5, 27.1)	22.2	(20.9, 23.4)	22.2	(20.9, 23.5)	29.8	(28.4, 31.2)
Sex									
Male	2794	26.4	(24.3, 28.4)	20.7	(18.8, 22.6)	21.5	(19.6, 23.4)	31.4	(29.2, 33.6)
Female	3691	25.4	(23.6, 27.1)	23.2	(21.5, 24.9)	22.7	(21.0, 24.4)	28.7	(26.9, 30.5)
Age group									
65–74	3001	26.1	(24.1, 28.1)	21.7	(19.9, 23.6)	20.8	(18.9, 22.6)	31.4	(29.3, 33.5)
75–84	2253	26.1	(23.8, 28.3)	22.4	(20.3, 24.6)	22.5	(20.3, 24.6)	29.0	(26.7, 31.3)
85+	1231	24.5	(21.6, 27.5)	22.7	(19.8, 25.6)	25.2	(22.1, 28.2)	27.6	(24.5, 30.7)

n - Unweighted sample size.
% - Weighted percent.
95%CI - 95% Confidence interval.

weather related compared with 14.5% in spring, 0.9% in summer, and 1.5% in autumn. Out of all fall injuries sustained outdoors by males, a higher percentage (17.2%, 95%CI = 15.5, 18.9) were weather related than that for females (12.7%, 95%CI = 11.4, 13.9). Out of all fall injuries sustained outdoors by 65–74 year olds (18.9%, 95%CI = 17.2, 20.6), a higher percentage were weather related than for those who were 75–84 (11.6%, 95%CI = 10.1, 13.1) and 85 years and above (9.8%, 95%CI = 7.8, 11.7).

4. Discussion

In 2015, there was seasonal variation in fall-related ED visits among older Americans, with a higher percentage of visits occurring in winter compared with any other season. By location, this seasonal variation was found only among falls sustained outdoors. That is, the percentage of ED visits due to falls that occurred outdoors was higher in winter than other seasons.

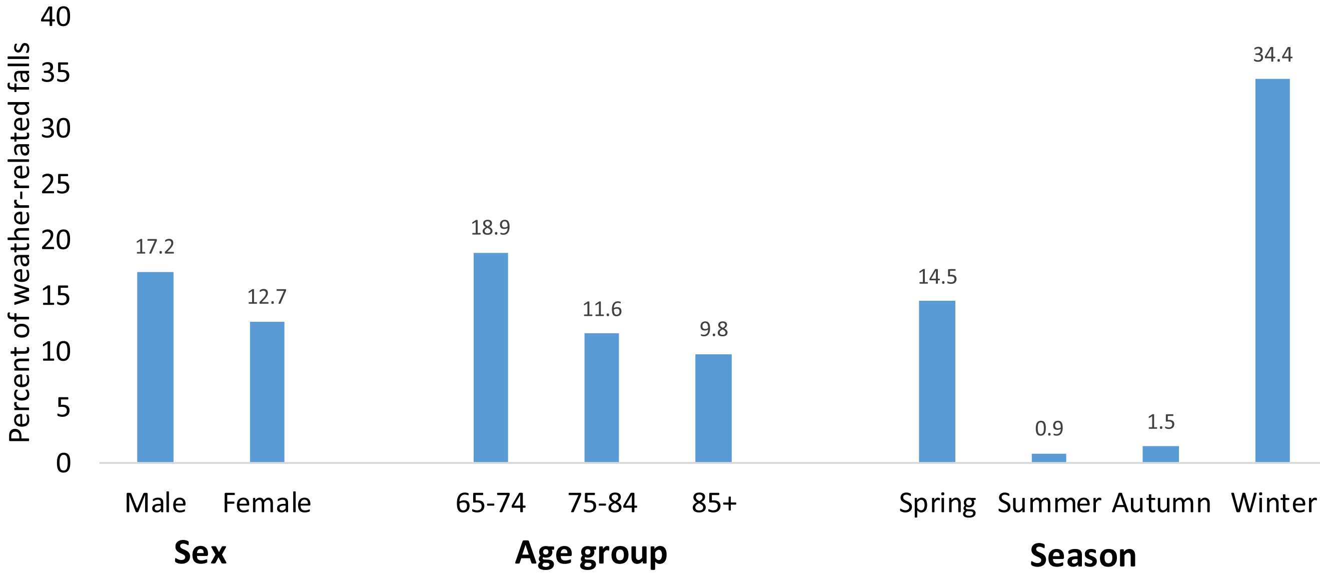

Fig. 1. Characteristics of community dwelling older adults who sought emergency department care for weather-related falls - National Electronic Injury Surveillance System – All Injury Program, 2015.
Sample for this figure includes only those older adults who made an ED visit due to a fall sustained outdoors (n = 6,485).
Percent for each sub-group was calculated with the denominator as the number of older adults who made an ED visit due to a fall sustained outdoors in that sub-group. E.g., Out of all the fall injuries sustained by males in the outdoors, 17.2% were weather-related and 82.8% (not shown) were not weather-related.

Previously, the two studies that investigated seasonal variation in the United States found conflicting results (Bischoff-Ferrari et al., 2007; Stevens et al., 2007). Bischoff-Ferrari et al. found that between 1986 and 1990, there was a higher incidence of all types of fractures during winter. Stevens et al. studied fall-related ED visits using 2001–2002 NEISS data. Though they found that the rates of fall-related ED visits were higher in winter, no statistical difference was found between the seasons. From 2001 to 2015, the age-adjusted rate of fall-related ED visits in NEISS-AIP increased by 37% (CDC, 2003). This relative increase in the number of fall-related ED visits could have powered the current study sufficiently to identify a statistical difference between the percent of fall-related ED visits in winter and other seasons.

The percentage of ED visits made due to a fall injury that was sustained outdoors, was higher in winter compared with other seasons. This may be due to adverse weather conditions. In the current study, about one-third of outdoor fall-related ED visits in winter were due to slips or trips on ice, in snow, or rain. No seasonal variation in ED visits from indoor falls was observed suggesting that prolonged periods of time spent indoors during winter may not be a contributing factor for seasonal variation. This is in line with a 2013 Swedish study that examined seasonal variation by location of falls. The study found that fractures sustained indoors tended to peak in February but the findings were not statistically significant (Leavy et al., 2013).

Among ED visits made due to an outdoor fall, seasonal variation was found in the 65–74 year age group with the percentage of such ED visits being higher in winter compared with other seasons. The percentage of outdoor falls related to a weather event like a slip or a trip on ice, in snow, or rain was also higher in this age group compared with older age groups. While we could not measure the amount of time an older adult spent indoors or outdoors, it might be that 65–74 year olds are more likely to go outside during adverse weather. The percentage of older adults in the labor force increased drastically in the past few years (Centers for Disease Control and Prevention, 2015). The largest increase occurred in the younger age groups (Kromer & Howard, 2013). Twice as many 65–74 year olds were in the labor force in 2016, compared with those in the 75–84 year age group (Roberts, Ogunwole, Blakeslee, & Rabe, 2018). In addition, this subgroup of older adults tends to be more physically active than adults 75 and older (Keadle, McKinnon, Graubard, & Troiano, 2016). Therefore, they may have more exposure to weather-related risk factors whether it may be getting to and from work, shoveling a driveway, going out to purchase groceries, or other activities.

Similar to the 65–74 year age group, males had a higher percent of ED visits from outdoor falls in winter than in other seasons. Such a difference was not found among females. Additionally, a higher percentage of males sustained a fall-related injury during a weather-related event compared with females. In relation to this finding, studies have found mixed results. Some studies found that older males were more likely to fall and have fractures in winter and on snowy and icy surfaces than older females (Bischoff-Ferrari et al., 2007; Duckham et al., 2013), others found no differences between the sexes (Leavy et al., 2013; Morency, Voyer, Burrows, & Goudreau, 2012), and one found females had a higher percentage of fall-related fractures on ice or snow when compared with males (Al-Azzani & Mak, 2016).

Our study has at least six limitations. First, state or region variables were not available in the NEISS-AIP data so we could not examine seasonal variation by geographical weather patterns. Second, fall location was unknown for over a third (38.5%) of the sample. There was no seasonal variation observed in this subset of ED visits. No seasonal variation was found in any of the three age-groups or among the sexes (Appendix B). Third, only narratives that mentioned a weather-related event in the notes were considered weather related. Therefore, weather-related injuries may have been underestimated. Fourth, these data do not include all falls but only those that warranted ED care. Fifth, the amount of time an older adult spent indoors or outdoors could not be measured. Sixth, this analysis being descriptive in nature, used non-overlapping confidence intervals to describe differences. A formal hypothesis test could have identified additional differences that would have been overlooked by comparing confidence intervals.

5. Conclusion

In 2015, over 3 million older adults went to the ED for a fall injury. This study found that there was seasonal variation with 26.2% of these ED visits occurring in winter. This may be in part due to adverse weather in winter such as ice, snow and rain that could increase fall risk. Interventions to reduce the risk posed by weather such as removing snow, treating sidewalks with salt or sand (Al-Azzani & Mak, 2016; Morency et al., 2012; Stansbury et al., 1995), promoting work closures or delayed openings during bad weather (Gevitz et al., 2017), utilizing weather alerts as a public health tool (Mondor et al., 2015), and encouraging the use of gait stabilizing footwear (McKiernan, 2005) have been proposed by others. Except for the use of gait stabilizing footwear (McKiernan, 2005), these interventions have not been evaluated for fall prevention.

6. Practical Implications

While it is important to consider potential risk factors such as adverse weather, fall risk increases as the number of risk factors increase (Ambrose, Paul, & Hausdorff, 2013). Therefore, it is important to identify all modifiable fall risk factors such as impaired vision, medications that increase fall risk, and gait and balance difficulties. CDC's STEADI (Stopping Elderly Accidents, Deaths, and Injuries) initiative (www.cdc.gov/steadi) recommends a physician-directed approach to identify older adult patients who may be at increased risk for a fall. Acknowledging the potentially increased risk of an outdoor fall during winter, for some segments of the older adult population, may help providers address and intervene to reduce their patients' unique fall risk. These results may encourage community-based organizations serving older adults to increase fall prevention messaging during winter.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Disclaimer

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

Appendix A. Seasonal variation by location of fall narrative codebook

Residential status (3 options)

- Residential facility (non-community), includes:
  - o nursing home, skilled nursing facility, extended care facility, long term care, assisted living, hospice, rehab, detox, or Alzheimer's unit, convalescent home, group home, then these are coded as nursing home. If it doesn't mention this assume it didn't happen in a nursing home
- Community, includes:
  - o Doesn't specifically mention nursing home.
  - o Adult day care or senior center
  - o If visiting a family member in a nursing home then community
- Prison, includes:
  - o Jail, prison or corrections facility

Location (3 options)

- Indoor, includes:
  - o Rooms in a house or apartment: bedroom, kitchen, living room, bathroom
  - o Stairs: any mention of stairs or steps where evident they are indoors, otherwise outdoors or unknown. If stairs have carpet then indoors, if stairs have baseboards then indoors.
  - o Public places: restaurant, store, hotel, jail, church, work, lobby/lounge, stairs in public place, escalator, elevator (had to be apparent that these occurred inside) If "at public place", for example fell "at restaurant" assume inside.
  - o Recreation area: bowling alley, gym, sports courts where evident they were inside
  - o Unspecified: Any mention of cabinets, sink, lamp, AC, heater, cleaning house, Hoyer lift, or fall out of a window assume indoor. Falls to the floor or carpet is indoor, except concrete/cement floor
- Outdoor, includes:
  - o Yard, porch, garage, balcony, ramp, and stairs if evident they are outside.
  - o Recreation area: parks, lakes, camping, rivers, outside sports courts, RV/camper, tent, national park, tree stand, beach, and farm.
  - o Public places: sidewalk, parking lot, curb, outdoor work place, bus, subway, metal grate, stairs outside a public place, street, and driveway.
  - o Any mention of falls to grass, gravel, rocks, ditch, shed, mud, ice, snow, rain, falling off ladder or a platform that is greater than 7 feet, uneven concrete.
- Unknown: Can't tell if location is inside or outside, or if stairs are inside or outside. When a fall happens on a concrete/cement floor, ground. While coming in or out of a place (and can't determine whether the fall happened inside or outside), playing pickle ball, at train station/catching train. When fall is associated with electric cord (unless more context provided), window sills, and ramps in public places.

Weather: If any mention of ice, snow, rain, hail, heat or any other term related to weather, then mention the term.

Appendix B

Characteristics of community dwelling older adults who sought emergency department care for a fall by season and unknown location – National Electronic Injury Surveillance System – All Injury Program, 2015.

Characteristics	Total	Spring (March-May)		Summer (June-August)		Autumn (September-November)		Winter (December-February)	
	n	%	95%CI	%	95%CI	%	95%CI	%	95%CI
Total	13,720	24.8	(23.9–25.7)	25.4	(24.5–26.4)	24.7	(23.8–25.6)	25.1	(24.1–26.0)
Gender									
Male	4,897	24.9	(23.3–26.5)	25.2	(23.7–26.8)	24.3	(22.7–25.8)	25.6	(24.0–27.2)
Female	8,823	24.7	(23.6–25.9)	25.5	(24.4–26.7)	24.9	(23.8–26.1)	24.8	(23.7–26.0)
Age-group									
65–74	5,256	24.3	(22.8–25.8)	26.7	(25.1–28.2)	24.0	(22.6–25.5)	25.0	(23.5–26.6)
75–84	4,583	25.6	(24.0–27.2)	24.1	(22.5–25.6)	25.3	(23.7–26.9)	25.1	(23.5–26.7)
85+	3,881	24.5	(22.8–26.2)	25.4	(23.7–27.2)	24.9	(23.1–26.6)	25.2	(23.4–26.9)

n - Unweighted sample size.
% - Weighted percent.
95%CI - 95% Confidence interval.

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