Risk of Duplicate ICD Codes for Orthopedic and Injury Related Research

By Gregory Benes, BS

Abstract

The World Health Organization's International Classification of Diseases (ICD) has become the international standard diagnostic classification for reporting morbidity and mortality. In 2015, the United States transitioned from the 9th to 10th Revision. The update was necessary due to major structural limitations of the ICD-9 system. Concerns of the transition mainly centered around clinical usage and cost; however, there were concerns for overlapping codes with the same classification but different meanings between the two versions. Duplicate codes could pose an issue for big data retrospective studies that overlap between the two systems. Therefore, the goals of this study are to further explore and identify duplicate ICD codes between the systems. ICD-9-CM and ICD-10-CM code files were obtained from the Centers for Medicare & Medicaid Services. There were 14,567 ICD-9-CM codes and 91,737 unique ICD-10-CM codes tabulated. Duplicated items between the files were isolated. Four hundred sixty-nine duplicate codes were identified, consisting of 39 E Codes and 430 V Codes. These twin codes contain classifications for external causes of injury and factors influencing health status and contact with health services. Therefore, special attention should be drawn to retrospective research involving methods of injury spanning ICD-9 and ICD-10 systems.

Keywords: electronic health records, international classification of disease, retrospective research

Introduction

The World Health Organization's (WHO's) International Classification of Diseases (ICD) has become the international standard diagnostic classification for disease.[1] The classification system allows for the systematic analysis, interpretation, and comparison of morbidity and mortality data collected in different areas at different times.[2] Beginning in 1893 with the first version of international classification of diseases, the system for classifying diseases has evolved from 179 to over 120,000 total codes in the most recent version.[3,4]

On October 1, 2015, the US Department of Health and Human Services began requiring hospitals to report diagnoses and procedures using the 10th revision of International Classification of Diseases (ICD-10-CM/PCS). The ICD-9-CM coding system includes approximately 14,000 diagnosis code, whereas the updated ICD-10-CM coding system contains nearly 70,000 diagnosis codes.[5] The development of a 10th revision introduces alphanumeric codes and greater specificity than ICD-9.[6] The update was crucial because of major structural limitations of ICD-9-CM that could no longer adequately accommodate important disease and procedure concepts.[7] However, the transition from the 30-year-old ICD-9 coding system presented several concerns and challenges.[8-13] While most of the concerns were centered around clinical usage and cost, there were concerns for overlapping codes with the same classification but different meanings between the two versions.[14]

From 2014-2017, there have been 39 ICD codes identified as duplicates by the Centers for Medicare & Medicaid Services (CMS). Duplicate codes could pose an issue for retrospective studies that overlap between the transition of the ICD-9 coding system to the ICD-10 coding system. The identified codes involve external cause of injury classifications (e.g., car

accident); therefore, studies exploring injury research or evaluation of injury prevention strategies could be impacted. To date, no studies have investigated duplicate ICD codes and their influence on big data collection. The aims of this study are to: 1) provide background on duplicate codes published by the CMS, and 2) investigate if there are additional duplicate codes based on CMS classification.

Methods

Microsoft Excel files containing official ICD-9-CM and ICD-10-CM codes were downloaded from the CMS website.[15,16] The codes were compiled into one sheet and tabulated. A function was set up to only select duplicate codes. These codes were isolated and transferred to a separate Excel file. This study is exempt from review by the Institutional Review Board because the data is publicly available.

Results

Duplicate ICD-9-CM and ICD-10-CM Codes
14,567 ICD-9-CM codes and 91,737 unique ICD-10-CM codes were tabulated. Between the two coding systems, there were 469 duplicate codes.

E Codes
Of the 469 codes, there were 39 E Codes (**Table 1**). The ICD-9 codes classify external cause of injury, while the ICD-10 codes classify metabolic disorders.

V Codes
Four hundred thirty V Codes were identified as duplicates in addition to the E Codes (**Supplemental Table 1**). The ICD-9 V codes classify factors influencing health status and contact with health services, while the ICD-10 V codes classify external cause of injury. Examples are listed in **Table 2**.

Discussion

Several reports highlight the impact of the ICD-10 transition, including effects on productivity, costs, reimbursement, coding accuracy, and patient care.[17-22] However, there is a paucity of literature discussing the implications of the transition on research activities. In addition to the 39 ICD codes published by the CMS, there are 469 codes with the same classification but different code meanings between the two coding systems. All codes are within the E and V sections of the International Classification of Diseases. It is important for researchers and clinicians to be aware of the potential for duplicate codes, as discrepancies could lead to false information used for retrospective studies.

The discussion of possible "twinned" ICD codes began to surface around 2012 regarding the use of codes to classify the external cause of injury.[23] Among the ICD-9 system, external causes of injury codes (classified as E000-E030 and E800-E999) are used as supplemental information to diagnosis codes to provide data for injury research and evaluation of injury prevention strategies.[24] E codes capture how the injury, poisoning, or adverse effect happened, the intent, the person's status, the associated activity, and the place where the event occurred.[25] In ICD-10-CM, the E codes were moved to Chapter 20: External Causes of Morbidity (V01-Y99).[26] In both coding systems, the external cause of injury codes are intended to be used in conjunction with diagnoses codes from other chapters in the

corresponding ICD coding system to clarify or specify the nature/cause of diagnosis/condition. While there is no national requirement for mandatory external cause reporting, these codes can provide valuable data for injury research and evaluation of injury prevention strategies. Because of the overlapping nature of E and V codes (**Figure 1**), there is possibility of duplication between the two coding systems, specifically E800-E999 and V01-V99.

Our study findings of 39 duplicate ICD E codes are consistent with the ICD-CM Duplicate Codes posted by the CMS from 2014-2017.[27,28] Of note, there were three ICD-9-CM codes (E8311, E894, E8981) that are like ICD-10-CM codes (E83110, E8940, E89810). It is important to be aware of similar codes that could lead to errors in big data collection of electronic medical records.

The finding of 430 additional ICD V codes to the published CMS duplication list has not been discussed in previous literature. Within the ICD-9 system, V codes are utilized to classify occasions when circumstances other than a disease or injury are recorded as a diagnosis or problem, such as an encounter to act as an organ donor. As previously mentioned, the V codes among the ICD-10 system are a part of the external causes of morbidity and mortality. This includes environmental events and circumstances as the cause of injury, such as a motor vehicle accident. Most ICD-10-CM External Causes of Morbidity (V01-Y99) codes have a requirement for a seventh character (A, D, or S) to indicate whether the injury or condition being treated is the initial encounter (A), subsequent encounter (D), or sequela (S). For example, V41.7 encodes a diagnosis for person on outside of car injured in collision with pedal cycle in traffic accident. However, the code is invalid if it has not been coded to the full number of digits required for that code.[29] In this case, the full code would require seven characters, such as V14.7XXA. While the identified duplicate V codes among ICD-10-CM are considered invalid, this finding is important, as it is possible for incomplete codes to arise during the translation of codes depending on the conversion process utilized.

Moreover, this finding can have implications outside the realm of direct patient care with retrospective research projects that utilize ICD conversions. Studies that involve external cause of injury codes spanning both ICD systems can be implicated. For an example, a study aimed to examine hip fractures due to osteoporosis excludes fractures due to high velocity trauma. To accomplish this, all hip fractures associated with an external cause of injury code indicating high velocity trauma (V01-Y99) would be removed, such as V700 (driver of bus injured in collision with pedestrian or animal in non-traffic accident). If the dataset does not distinguish between ICD-9 or ICD-10, the code of interest might be removed by mistake. In this case, the ICD-10-CM definition of V700 is “routine general medical examination at a health care facility.” Routine medical examination is a much more common event than a bus driver being injured by colliding with an animal and would falsely inflate the ICD-10 code for that high-trauma event. Thus, not only would fractures be inaccurately excluded from the study, but a very large portion of the fractures would also be excluded. Because of this possibility, it is important for large-scale projects be able to differentiate between which codes are ICD-9-CM and ICD-10-CM. Being able to distinguish between ICD-9 and ICD-10 codes is necessary; however, this brings attention to another issue of using outside resources for code conversion and lack of consistency.

To ease the burden of researchers who need to translate their cohort from ICD-9-CM to ICD-10-CM, the CMS created and maintains the General Equivalent Maps (GEMs) as a tool for conversion between the two versions.[30] The GEMs provide information linking codes from

one system with codes in the other system, often times described as "crosswalks."[31] The GEM crosswalks are bidirectional with "forward maps" converting ICD-9-CM to ICD-10-CM and "backward maps" converting ICD-10-CM to ICD-9-CM. However, the complex relationship between the conversion ICD-9 and ICD-10 codes is not one-to-one mirror images of one another; therefore, the use of GEMs requires informed consideration.[32-36] As a result of the challenging nature of accurate ICD conversions, many researchers rely on automated conversions, such as coding conversion websites. There is variation among conversion website services, and even highly automated conversions require detailed review.[37] For instance, ICD-9-CM codes and ICD-10-CM codes, respectively, are generally referenced as numeric codes without a period (e.g., E030) and alphanumeric codes with a period between the numbers (e.g., E03.0). However, there is variable listing of both coding systems with and without periods. This study excluded periods from both coding versions to be consistent with the methodology utilized by the duplicate codes files published by the CMS.[38,39] The complicated translation between GEMs and variations between automated conversion systems highlight the importance of detailed attention as inconsistency can potentially have an impact on study findings.

There are several limitations of this study. First, we are unable to directly assess the impact of duplicate codes in other studies. As there are differences in the accuracy of conversions with forward or backward mapping,[40] our study findings encourage studies with overlapping ICD codes to disclose the methods of conversion. Furthermore, while there were several studies investigating the accuracy of conversions among specialties of medicine,[41,42] there is a lack of research regarding the impact of ICD-10 transition pertaining to injury related research. We postulate that this may be due to E and V codes being classified as supplemental codes and not necessary for diagnosis. Future studies are warranted to investigate the accuracy of the ICD-10 transition among injury related research, especially due to the potential for duplicate codes to impact the accuracy of findings among this area of research. Lastly, ICD-9-CM and ICD-10-CM codes were used without periods, which could impact the generalizability of the results to conversions utilizing periods among ICD-10-CM codes. However, we believe this should not limit our findings, as this method was consistent with the duplicate codes file published by the CMS.

With the implementation of another revision, ICD-11, it is important that all data is understood. This topic becomes even more important with the possibility of three different coding systems spanning bioinformatics and hospital administrative data.

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Data Availability

ICD-9-CM and ICD-10-CM can be obtained from CMS website with the following links, respectively, https://www.cms.gov/Medicare/Coding/ICD9ProviderDiagnosticCodes/codes and https://www.cms.gov/Medicare/Coding/ICD10/2015-ICD-10-CM-and-GEMs.

Conflicts of Interest

The author declares no conflict of interest.

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Supplementary Materials

The following are available online: Table S1: Master List of Duplicate ICD-9-CM and ICD-10-CM Codes.

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Quality Assessment of the Road Traffic Health and Safety Apps with a Focus on the Five Rights of Information Management

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Abstract

Objective: The expansion of mobile applications as a tool for road traffic health and safety may develop several issues from the perspective of information management. Quality assessment of these apps, especially from an information system management perspective, appears inevitable, as their possible low quality may cause irreversible injury or fatal consequences. This study aimed to evaluate the quality of the apps in the three subcategories of road traffic safety apps (including Accident Record and Report (ARR), Distraction Management (DM), and Vehicle Operating, Fixing, and Maintenance (VOFM)) using the Mobile Application Rating Scale (MARS), which rates 23 evaluation criteria organized in five domains (Engagement, Esthetics, Information, and Subjective Quality) with particular attention to the five rights framework of health information system.

Method: The researchers retrieved road traffic health and safety mobile apps from Google Play. First, the domain expert panel (n= 7) (from disciplines of HIM and medical informatics) was formed. They scrutinized and discussed the MARS items and mapped them into the five rights framework of information quality. Moreover, the researchers assigned the apps to the information system or decision support system category. Two researchers independently reviewed the apps and conducted the qualitative content analysis to categorize them into ARR, DM, and VOFM classes. Finally, the quality of the apps was assessed using the MARS rating scale (max=5) in terms of 1) app classification category with a descriptive aim; 2) app subjective and objective quality categories comprised of engagement, functionality, esthetics, and information sections; and 3) an optional app-specific section. The mean scores for the subjective quality, objective quality, and app-specific sections were calculated separately for each mobile app. A score ≥ 3.0 was considered acceptable.

Results: A total number of 42 apps met the criteria for the assessment. The average objective quality scores were computed as 2.6, 2.2, and 3.0 for the ARR, DM, and VOFM apps, respectively. Therefore, the quality of the apps in the ARR and DM subgroups was not acceptable. Moreover, the quality of the apps in the VOFM subcategory was considered moderate. Furthermore, the subjective quality and app-specific sections of apps in the ARR and DM categories were less than moderate. Most apps had the potential of an information system or decision support system. Also, the criteria measured by MARS could be mapped to the five rights framework of information management.

Conclusion: The findings of this study revealed the existing gaps in three subcategories of road traffic safety apps. Considering the multiple criteria of the MARS and having in mind the framework of five rights, developers of the apps may develop better products in road traffic health and safety.

Keywords: five rights framework, mobile apps, traffic safety, information system, decision support, MARS, digital health, traffic accident

Introduction

Road traffic accidents and injuries are one of the global health challenges. The number of deaths due to road traffic has constantly increased from 1.15 million in 2000 to 1.35 million in 2018.[1] Therefore, road accidents are not only a road safety problem but also a public health issue.[2,3] E-health is one of the new approaches to support public health , and m-health has a great potential to expand e-health to the public due to the ubiquity of mobile devices and mobile technologies toward improving public health.[4] Mobile health covers medical and public health procedures supported by mobile devices, including mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices. Mobile health and wellness apps are expected to improve safety, health, and quality of life through behavioral feedback and targeted information.[5] The mobile application can be considered a specific subdomain of an information system and, in some cases, it can act as a decision support system.[6,7] Similar to other information systems, developing a health and traffic safety mobile app creates a system with input, processing, output, outcome, and impact. Data collection is the starting point of the information management process in mobile apps. Also, the quality of health information is an essential criterion of health information management: the right information should be available to the right person, in the right format, at the right time, and at the right place through the right channel to support health management decisions.[8] The five rights framework reflects the importance of tailoring the information provision to the user's needs.

Considering the public health aspect of road traffic issues, three main elements that can play a role in accidents are road infrastructure, vehicles, and drivers. Among these, the driver has the largest share of accidents. Therefore, if the right information (e.g., driving behavior, drowsiness alerts, hazardous areas, early warning of weather and road conditions, and vehicle condition) is given to the drivers at the right time at the right place through the right channel and in the right format, they can make better decisions and respond quickly to serious driving conditions.[9] Nonetheless, roads and vehicle traffic are an essential part of people's daily lives. Therefore, monitoring their situation has received much attention. For this purpose, intelligent transportation systems (ITS) have been built. Many of these involve the installation of dedicated sensors in vehicles (e.g., GPS-based tracking units) or on the road (e.g., inductive loop vehicle detectors and traffic cameras.), which can be an expensive proposition and usually limited to the busiest road routes.[10] From another point of view, the widespread penetration of mobile phones has dramatically improved communication in the community. Cellphones are like small multipurpose computers that, in terms of CPU power and RAM size, are similar to laptops found a few years ago. In addition, more and more users own these smart terminals, and their main use is gradually shifting to functions such as web browsing, social networking, multimedia streaming, online games, and

other applications. In this platform, new information and communication services can be introduced using smartphones in various fields.[11] Therefore, mobile applications could be used as public health information or decision support systems.

Although mobile phones seem to distract drivers and cause road accidents,[12-15] there are features in these devices that make them an opportunity to prevent accidents, such as lane detection, vehicle detection, vehicle distance estimation[16] and also drowsiness management, distraction management, and speed limit warning. In addition, with the prevalent use of smartphones, many companies have recently developed unique apps to improve public service quality, people security, and safety.[17] On the other hand, similar work has been proposed and implemented in connection with the development of mobile apps. Their primary focus areas have been traffic management, routing and navigation, driving behavior analysis, vehicle and road safety, and emergency services.[18,19] All these functionalities are possible in the context of information systems or decision support systems manifested in the mobile application form. One of the essential issues about these apps is their quality. Their evaluation is inevitable because their poor performance may cause irreversible injury or fatal results. Traditional systems used to test app quality, such as user star ratings (app ratings on a scale of 1 to 5 stars) and reviews, can provide fake or subjective reviews and give users the wrong signals.[20] Moreover, app descriptions in the Google Play Store are often incomplete or inaccurate and are not a valid tool for assessing the quality of an app, especially when dealing with sensitive issues such as road traffic safety.[21]

Because of the need to ensure better app quality for users, a Mobile App Rating Scale (MARS) has been presented by a multidisciplinary team of experts. “The MARS is a simple, objective, and reliable tool for classifying and assessing the quality of mobile health apps. It can also be used to provide a checklist for designing and developing new high-quality health apps.”[22] MARS is a 23-scale tool that provides an in-depth evaluation of app quality by testing and grading the app in several areas, including user engagement, functionality, aesthetics, information, and subjective quality. Each item is scored using a 5-point scale (1-Inadequate, 2-Poor, 3-Acceptable, 4-Good, 5-Excellent).[23]

In the previous study, the researchers grouped the road traffic apps into two categories using Haddon’s factors and public health approaches: Road Traffic Training (RTT) and Road Traffic Health & Safety (RTHS) apps. Each of these groups has some subcategories. The RTHS category has 11 subcategories, including (accident record and report; alcohol-free driving; distraction management; driving/driver behavior feed backing; drowsiness management; eco-driving and fuel saving; real-time traffic information/alerting; ridesharing service; safe driver service; speed camera and police detector; and speed limit warning). Furthermore, the RTT category has three subcategories: driving performance; traffic rules and road signs; and vehicle operating, fixing, and maintenance.[24] The researchers intend to use the features of three subgroups of apps (Accident Record and Report (ARR), Distraction Management (DM), and Vehicle Operating, Fixing, and Maintenance (VOFM)) to make a multipurpose mobile app for use in Iran as a part of the Ph.D. thesis. This study evaluated the quality of three subgroups of road traffic apps using the MARS with a focus on the five rights framework of information management**.**

Methods

The researchers used the MARS rating scale, a reliable tool for assessing the quality of m-health apps for assessing the quality of subgroups of apps (ARR, DM, and VOFM). One of the key

guidelines used in the development of MARS is Healthcare Information and Management Systems Society (HIMSS).[25] The HIMSS guidelines for evaluating the usability of m-health apps use a Likert scale of "strongly agree" to "strongly disagree" to rate each criterion. HIMSS criteria have usability measures for rating efficiency, effectiveness, user satisfaction, and platform optimization, but no measures of rating information quality have been included. The MARS rating scale is comprised of two sections. The first is the classification section, which collects descriptive and technical information about the app. This section has six items of descriptive and technical information for each app: 1) descriptive information (name, number, and type of ratings for all versions; developer; version; cost; platform; description; update); 2) focus; 3) theoretical background and strategies; 4) affiliations; 5) age group; and (6) technical aspects (social sharing, web access, app community, login, password protection, and reminder functions). The second section is the app quality category, divided into objective and subjective quality. The rating scale assesses app quality on four dimensions. All items are rated on a 5-point scale from "1. Inadequate" to "5. Excellent." Objective quality has four sections (engagement, functionality, esthetics, and information) with 19 items, while subjective quality consists of four items, for a total of 23 items. In addition to these two categories, there is an optional app-specific section with six items (awareness, knowledge, attitudes, intention to change, help-seeking, and behavior change). These added items can be adjusted and used to assess the perceived impact of the app on the user's knowledge, attitudes, and intentions to change as well as the likelihood of actual change in the target health behavior.[26]

Two authors independently reviewed each of the apps in the three subgroups: 1) ARR (three apps); 2) DM (25 apps); and 3) VOFM (24 apps). Also, the researchers installed apps when possible to better assess the apps. Before scoring each app, the reviewers used each app for at least one week to understand the app's functionality. They also learned how to complete the MARS. Data were analyzed using descriptive and analytical statistics. The mean score of each MARS section was calculated. The mean score of the four objective quality sections (engagement, functionality, esthetics, information) was calculated separately from that of the subjective and app-specific sections to strengthen the impartiality of the measure. Kendall's coefficient concordance was used to calculate the interrater agreement between two raters. The analysis was performed with SPSS Statistics version 21. Moreover, the researchers assigned the apps to the category of decision support system or other information systems.

Expert panel (n= 7) (disciplines of HIM and medical informatics) was formed. Then the panel scrutinized and discussed the MARS items and mapped them into the five rights framework of information management. The five rights is well-known in HIM. It has also been referred as the Five Rights of Clinical Decision Support (CDS) and has been used widely in public health and healthcare.[27]

Results

The MARS Items Mapped into the Five Rights of Information Management

Expert panel mapped the MARS items into the five rights of information management. **Table 1** shows the detail.

Evaluation Analysis of the Apps as a Type of Information System by the MARS

The Kendall coefficient for the agreement was 0.96 (p = 0.06), which indicates a good agreement between the two evaluators. Disagreements over each of the concessions were discussed and resolved by consensus.

As shown in **Table 2**, the highest mean score in the accident record and report (ARR) subgroup for engagement (4.2), functionality (4.5), esthetics (4.0), information (2.6), and subjective quality (4.3) was related to AYS Accident Report and SafeDrive. The overall mean MARS objective quality score, which allows the evaluation of the general app quality (maximum of 5 points), was 2.6 points (SD 1.2); thus, the quality of the three included apps in the ARR subcategory was not considered acceptable (< 3.0). The score of the subjective quality section was 3.2 points (SD 1.6), and that of the app-specific section was 2.2 points (SD 1.3). When the scores of the six MARS sections (four objective, one subjective, and one app-specific) were compared, the score of the information section (mean 1.6, SD 0.9) was lowest than the others. In this subcategory, the highest Google Play Store user rating score was 4.1 points related to the SafeDrive app.
As it is evident from **Table 2**, all the apps categorized in the ARR subgroup act as the information system as well as the decision support system.

Play store user star ratings	Information management system
0	IS&DS"
1	IS&DS
4.1	IS&DS
1.7	
2.2	

The highest mean score in the distraction management (DM) subcategory for engagement (4.4), functionality (4.8), esthetics (4.3), information (2.7) and subjective quality (3.8) was related to Car Mode, MessageLOUD *and* TextDrive. The lowest total mean score of the DM subgroup was related to the information section (1.4). In addition, the highest total mean score of the DM subgroup was related to the functionality section (3.2). The total mean of the MARS objective quality score for the DM subcategory was 2.2 points (SD 0.7); therefore, the quality of the 22 included apps in the DM subcategory was not considered acceptable (< 3.0). The score of the subjective quality section was 2.7 points (SD 1.1), and that of the app-specific section was 2.4 points (SD 1.2). In this subcategory, the highest Google Play Store user rating score was 4.6 points related to the DriveCare app. More detailed information is presented in **Table 3**. All apps

in the subcategory of distraction management can be considered information systems; however, they can indirectly act as a decision support system in some sense.

The highest mean score in the VOFM subcategory for engagement (4.6), functionality (4.8), esthetics (4.7), information (3.4), and subjective quality (4.8) belonged to BMW Driver's Guide, MINI Driver's Guide, NISSAN Driver's Guide *and* Mercedes-Benz Guides. The highest total mean score of the VOFM subgroup was related to the functionality section (3.7). In addition, the lowest total mean score of the VOFM subgroup was related to the information section (2.2). The overall mean MARS objective quality score for the VOFM subcategory was 3.0 points (SD 0.9); thus, the quality of the 17 included apps in this subcategory was considered moderate. The score of the subjective quality and app-specific sections was the same (3.4 points, SD 1.0). In this subcategory, the highest Google Play Store user rating score was 4.6 points related to the Car Scanner ELM OBD2 app. As it is evident from **Table 4**, all three apps categorized in the VOFM subgroup act as the information system as well as the decision support system. See **Table 4** for more detailed information.

Figure 1 compares the mean scores of each MARS section in the road traffic safety apps of the three subgroups. The VOFM subgroup in all of the MARS sections has the highest score.

Discussion

The present study evaluates the objective quality (engagement, functionality, esthetics, and information) and the subjective quality of the available apps for the three subcategories of road traffic apps in the Google Play Store. Considering the apps' functionalities, the researchers assigned the apps to the information system or decision support system category. As such, it was possible to map the different aspects of the MARS tool into the five rights of information management.

Quality evaluation using the MARS tool showed that out of 42 apps in three subgroups (accident record and report; distraction management; and vehicle operating, fixing, and maintenance), the VOFM subgroup with 17 apps are qualitatively acceptable, concerning the MARS mean ratings of $\geq$3 out of 5 points.

Comparing the six sections of MARS (four sections of objective quality, subjective quality section, and the app-specific section) in the ARR and VOFM subgroups, the most significant results were related to the engagement, functionality, and esthetics of the apps because they were visually pleasing and descriptive enough. In contrast, the information section of these apps needs to be improved. A review of the DM subgroup apps with the MARS score showed that except for the mediocre performance section, all sections had low mean scores and should be reviewed by developers because these apps claim safety for users and their inefficiency and inadequate

information may cause hazards to users while driving. While a lack of up-to-date and scientific information about apps in road traffic health and safety could be a barrier to proper and reliable guidance for users, simple, high-performance aesthetics, including visual appeal, could encourage the use of mobile apps.[28,29] Also, the lowest mean score for the engagement was in the DM subgroup, evaluated based on the entertainment, interest, customization, interaction, and attractiveness of the target group and the esthetic scale, evaluated in terms of layout, graphics, and visual appeal. This finding is consistent with previous studies using the MARS to evaluate the quality of mobile apps for asthma management, where the esthetic score is lower, indicating that this factor is less considered in health and safety design.[30]

In addition, it is essential to evaluate the effectiveness of apps to help users become familiar with road traffic health and safety issues. Therefore, it is substantial to conduct studies examining road traffic apps' quality, efficiency, and reliability. Moreover, it is notable that traffic safety experts should evaluate such apps to provide better information to assist users in making safety-related choices.[31]

The subjective quality and app-specific sections in the ARR and DM subgroups were less than moderate, so they need to be improved by the app developers. This finding is in line with the results of previous studies using the MARS for quality assessment of mobile apps for food allergies.[32] The subjective quality and specific parts sections noted the general conception of users of the app, which, if positive, leads them to recommend and use it. Hence, more engagement can be needed to improve users' understanding. Therefore, it is vital to expand users' subjective quality view and impact of the app-specific, mainly affecting users' perception of the app.[33]

As the results show, in most of the apps surveyed in the three subgroups, the user star rating score is above average. When we compare these results with the total MARS score, especially in the two subgroups DM and VOFM, we see that the user star rating is higher than the total score of MARS. Similar to the previous studies, there is a clear difference between a quality assessment obtained by a researcher using a more objective tool such as the MARS and a real-world user who tends to rate the quality of the app by star rating in a very subjective way.[34] Therefore, the MARS quality evaluation is a more objective tool to provide more accurate app quality information and recommendations for developing future apps.

By definition, the right information provided to the end user must be evidence-based, derived from a set of recognized guidelines, or based on a standard of practice. If too much information is given to the end user, it may create too much cognitive load and cause him to ignore the warning.[35] One of the criteria of app objective quality of the MARS is the quality of the information provided in the app, which states that the developed app must contain quality and documented information.

Engagement and esthetics criteria of app objective quality are related to graphic design, overall visual appeal, color scheme, attractiveness, customizable, and interactive to the audience. These criteria correspond to the right intervention format of the five rights that it states. Decision support is implemented in various formats—such as alerts, order sets, protocols, monitoring systems, and information buttons. Therefore, it is essential to choose the best format to solve the problem.[36]

The right time in the workflow is related to the functionality of the MARS app objective quality, which involves the app's functioning, ease of learning, navigation, flow logic, and gestural design of the app. Also, subjective app quality and app-specific criteria are related to the right person, which caused users' knowledge, attitudes, and intentions to change and the likelihood of actual change in health behavior.

Conclusions

The moderate quality of MARS was identified for the VOFM subcategory from three subcategories of road traffic apps, although the objective and subjective quality of the reviewed apps should be improved, and the existing apps should be tested experimentally. Through mapping the MARS items into the five rights framework, it can be concluded that the five rights of information management are yet to be realized in the mobile apps targeting road traffic health and safety. The domain app developers can use these results to develop new reliable apps in the field of road traffic health and safety toward promoting public health.

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Privacy and Security Risk Factors Related to Telehealth Services – A Systematic Review

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Abstract

The objective of the study is to identify challenges and associated factors for privacy and security related to telehealth visits during the COVID-19 pandemic. The systematic search strategy used the databases of PubMed, ScienceDirect, ProQuest, Embase, CINAHL, and COCHRANE, with the search terms of telehealth/telemedicine, privacy, security, and confidentiality. Reviews included peer-reviewed empirical studies conducted from January 2020 to February 2022. Studies conducted outside of the US, non-empirical, and non-telehealth related were excluded. Eighteen studies were included in the final analysis. Three risk factors associated with privacy and security in telehealth practice included: environmental factors (lack of private space for vulnerable populations, difficulty sharing sensitive health information remotely), technology factors (data security issues, limited access to the internet, and technology), and operational factors (reimbursement, payer denials, technology accessibility, training, and education). Findings from this study can assist governments, policymakers, and healthcare organizations in developing best practices in telehealth privacy and security strategies.

Keywords: telehealth, telemedicine, privacy, security, confidentiality

1. Introduction

The extended lockdown as a result of the COVID-19 pandemic brought about increased demand for telehealth services.[1] Before COVID-19, telehealth services existed but were not widely used, mainly due to the lack of reimbursement. The use of telehealth services has been viewed as innovative and a solution for improving the delivery of healthcare as well as reducing costs and increasing access to care regardless of location.[2] Prior to the COVID-19 public health emergency (PHE), Mental and behavioral health providers utilized telehealth services most frequently. However, after March 2020, with the declaration of the PHE, the necessity for telehealth services sored in all disciplines, especially with primary care, mental and behavioral health and pediatrics.[1]

In a 2022 telehealth survey of physician participants conducted by the American Medical Association, 60 percent of respondents agreed or strongly agreed that telehealth enabled them to provide high-quality care. More than 80 percent of respondents indicated that with the use of telehealth, patients have better access to care.[3] However, putting telehealth services to use during the pandemic opened the door to multiple issues, including health care disparities.[4] With the increased use of telehealth and virtual care comes a plethora of new services, widening the gap of risks, which now include cyber and technology-related data security and privacy exposures.[7] Also, patients' lack of trust and expertise in using telehealth technology adds to their concerns for privacy and security.[5] The American Telemedicine Association, a leader in telehealth policy, advocates for telehealth and virtual care technology to be built on a foundation of protection of patient privacy, patient data, and the reduction of cybersecurity risks.[6] Despite telehealth being viewed as a valuable resource for providing quality healthcare services, data privacy and security

concerns continue to hinder the perception of benefits and influence the overall adoption and successful use of virtual care services.[2]

Healthcare professionals have become acutely aware of the obstacles to using telehealth technology, such as the performance of physical examinations as well as the lack of reimbursement parity and differences in state licensure and regulations.[8] Vulnerable populations struggle more than others with the use of healthcare technology, which raises privacy and security concerns.[9] Although there have been significant temporary changes in telehealth policies at both the federal and state levels, permanent changes to support telehealth services have been slower to manifest despite the continued demand.[10] To gain a better understanding of the challenges and barriers to the adoption and use of telehealth technology, the authors undertook this study to gather information that can be used to develop best practices and guidelines for telehealth privacy and security strategies.

Study Objectives:

1. Identify challenges and associated factors for privacy and security related to telehealth visits during the COVID-19 pandemic.
2. Categorize challenges into key factors in order to develop best practices and guidelines for telehealth privacy and security strategy.

2. Methods

2.1. Search Strategy

This systematic review was undertaken using a comprehensive literature search to find all published work identifying privacy and security challenges in telehealth. The search strategy was developed with the assistance of a college librarian. The search terms included a combination of Medical Subject Heading (MeSH) and advanced terms such as privacy, security, and telehealth. The six databases of PubMed, Science Direct, ProQuest, Embase, CINAHL, and the Cochrane Library were selected for the search using database-controlled vocabulary terms for telehealth, privacy, and security.

A protocol was established before the search, data gathering, and analysis using the Population, Interventions, Comparison, and Outcomes (PICO) Framework. This protocol outlined the search strategy, selection process, and data collection. This approach allowed the reviewers to frame this research based on the PICO methodology, which include the following:

- Population: Includes all providers using telemedicine; all consumers of healthcare using telehealth, excluding insurance companies
- Interventions: Includes all types of telehealth services such as live video, store-and-forward, remote monitoring, and mobile health; excludes face-to-face encounters
- Comparison: Privacy and security challenges 2020-2022 with challenges prior to 2020
- Outcomes: Best practices for privacy and security

2.2. Inclusion and Exclusion Criteria

Inclusion Criteria

- English-language only
- Peer-reviewed empirical studies
- January 2020 to February 2022
- Search terms: telehealth, telemedicine, privacy, security, confidentiality

Exclusion Criteria

- Studies conducted outside of US
- Study design issues: non-empirical studies (systematic review, literature review, commentary)
- Non-telehealth related studies (mobile health, eHealth)

2.3. Review Process

The selection strategy of abstracts for full review was divided among three reviewers. First, each reviewer independently reviewed abstracts for inclusion. Then, each reviewer presented their findings to the full group, and all discrepancies were reconciled.

A total of 1,224 study abstracts were identified through online databases. Upon review, 47 studies were duplicates; the reviewers eliminated 750 studies based on inclusion criteria dates; and 122 were eliminated due to wrong study design. A full-text review was selected for 305 articles. Upon examination, 77 studies were excluded due to wrong study design, 29 were mobile health, 10 did not include privacy and security, 31 were foreign studies, and 140 studies were wrong publication type. Eighteen studies were found acceptable for analysis, as decided by the three reviewers. A summary of the selection process is shown in **Figure 1**.

3. Results

3.1. Study Design and Data Collection Methods

Eighteen studies were identified and included in this study. Quantitative studies were the most cited study design (n=8), followed by qualitative study (n=5), four mix-methods (n=4), and one pre-post design (n=1). The collection methods included a host of approaches from interviews (both semi-structured and focus group) to surveys eliciting both qualitative and quantitative measures. **Table 1** contains the study design and data collection methods in the review.

3.2. Participant Types and Characteristics

The characteristics of the 18 studies, including the participant level, participant types, and a sample description, are summarized in **Table 2**.

Ten studies (56 percent)[9,11-17,25,26] included patients, parents, or consumers, with the most common participant type being patients or parents utilizing telehealth services in an outpatient setting[9,12,13,15,16,26] such as ambulatory surgery, clinics, or physician practices. Two studies[11,17] included participants from the community while one study[16] examined remote monitoring.

Overall, a total of 3,324 patients, parents, or consumers of telehealth were included in the 10 studies.

Six studies (33 percent)[18,19,21,22-24] included a range of provider types from athletic training, emergency room providers, pediatricians, and mental health. A total of 626 participants were providers of telehealth services.

Two studies (11 percent)[4,25] included both provider (clinical personnel, physicians, and nurses) and parent types as participants. A total of 24 providers or parents were participants.

3.3. Privacy and Security Challenges and Risk Factors

Table 3 summarizes all papers analyzed for telehealth's privacy and security challenges and risk factors. Three risk factors associated with privacy and security in telehealth practice include: environmental factors (lack of private space for vulnerable populations, difficulty sharing sensitive health information remotely), technology factors (data security issues, limited access to internet and technology), and operational factors (reimbursement, payer denials, technology accessibility, training, and education).

Unsurprisingly, most cited challenges included privacy and security. Twelve studies[4,9,11-17,20,25,26] cited patient privacy and confidentiality challenges, seven studies[18-21,22-24] cited provider privacy and confidentiality challenges, and age-related patient challenges were mentioned in four studies. The presence of parents during a pediatric/adolescent telehealth visit was an example of an age-related privacy concern. Additionally, the elderly population sometimes presented with limited digital literacy. However, age-related challenges were not noted for providers.

Seven studies identified the use of technology as a risk to telehealth.[9,11,13-15,20,25] The technology risk includes health/digital literacy (language, medical terminology), patient awareness and communication, patients experiencing technical errors, perceived information incompleteness, lack of interest and comfort in using internet-capable devices, and the need for patient assistance with technology. Five studies[19-21,23,24] included technology issues for providers, such as limited access to the internet and telehealth-specific technology, financial cost of technology, implementation of technology, staffing, information technology personnel to implement and support technology, reliability of internet connections to support telemedicine, access to video services, lack of digital devices, cellular data, or Wi-Fi.

The patient's environment as a privacy risk was identified in five studies[4,9,12,15,20]. For example, being overheard in the patient's or provider's home, navigating disruptions in their living space, lack of proper equipment such as headphones, unwarranted visualization of patient's living conditions, large households not having adequate space for confidential conversations, and lack of a private room for the vulnerable population such as the homeless. In two studies,[20,22] providers cited the lack of private workspace for personnel and difficulty in maintaining awareness of the surroundings to protect patient privacy as challenges.

Three studies identified patient's trust as a challenge to the use of telehealth.[11,13,14] Participants noted that to be successful, providers or other trusted individuals should describe and show

patients how to use the technology; identifying a suitable space may be another reflection of trust, acceptance of remote video consultation to improve measures and gain trust, and perceived trust in the competency of telehealth platforms. Three studies identified professional development and training for telehealth as a challenge.[19,20,22] However, providers' studies did not list trust as a challenge or risk.

Three studies identified limitations of quality assessment and diagnosis as a provider challenge and a risk only.[4,18,23] Individuals with HIV, pregnancy, or mental health diagnoses have special privacy concerns and two studies[15,17] identifying special privacy issues for these patients. Liability, legal, and regulatory challenges were found in two studies,[21,23] and reimbursement challenges[19] and burnout from telehealth use[21] were noted in one study for the providers only, respectively.

Discussion

Key Findings and Best Practices

This study identified the challenges and three key factors associated with telehealth privacy and security: environmental, technology, and operational factors. The authors developed and categorized these factors based on the identified issues and risks, and **Table 4** illustrates the summary of each three factors and examples. To address these risk factors, best practices and recommendations are discussed below.

Environmental Factor Implications

Environmental conditions play an essential role in telehealth privacy and security, which refer to an individual's surroundings, living conditions, and social connections that directly or indirectly impact privacy and security protections. Vulnerable populations such as the homeless, elderly, adolescents, and those who struggle with mental health are often concerned about the lack of private space for telehealth visits. Telehealth patient visits also create difficulty sharing sensitive health information remotely for people with certain conditions or diseases, such as HIV/AIDS, behavior health, and contraception requirements. The space, location, and accessibility to the use of telehealth are also a concern for healthcare providers.

For best practice, providing a safe, accessible environment should be a major concern when performing telehealth practice. Providers should check the availability and suitability of the patient location before and during the telehealth services. Provide guidance and resources to patients for finding a private place for the appointment when necessary. Use email, chat, or messages through the patient portal if a private location is unavailable or reschedule and suggest a better place for the telehealth visit. Explain to a minor patient whether parents or guardians should or should not be present at the appointment. Obtain informed consent or fill out a release of information before the visit begins.

Technological Factor Implications

Technology and digital literacies are other factors in telehealth privacy and security concerns. Technology factors include data security issues such as hacking of video visits, limited access to the internet and technology, lack of digital devices, cellular data use, or Wi-Fi, digital literacy such as limited knowledge and understanding of the technology use, and poor quality of audio or video output. Knowledge of technology use and digital literacy limiting the quality of assessments and diagnosis is another issue in telehealth use.

For best practice, when sharing information online, identify steps to protect patient information, and only enter personal information on secure websites with a lock icon in the URL bar. Require passwords for all online meetings and verify information while the patient remains in the "waiting room." For patients with telehealth visits, do not set up a telehealth appointment or share personal information with an unknown provider; use the provider's main phone number to confirm their identity. Keep devices protected with updated antivirus software. Avoid using public Wi-Fi to access telehealth services, and avoid accessing telehealth on devices shared with people outside of the home or family. Improve the quality of audio and videos by working with IT staff to ensure adequate bandwidth. Utilize the network, quality of service, and other measures to enhance the speed of the internet. Provide resources and training to patients with low health digital literacy. Consider the needs of vulnerable populations, such as English as a second language, disabilities, minors, and the elderly population.

Operational Factor Implications

The operational factor is also important in telehealth privacy and security practice. Reimbursement, payer denials for telehealth services, technology accessibility for all patients, training, and education for both staff and providers, maintenance and updating of devices and software are all related to the operational factors.

For best practice, the healthcare provider should incorporate telehealth services into privacy and security policies, procedures, and workflows, as well as integrate telemedicine into the Notice of Privacy Practices. Conduct thorough training modules with multiple sessions, manually rehearse steps, and ensure workflow integration is in place prior to beginning sessions. Ensure all staff and providers have received telehealth-specific privacy and security training. Include telehealth equipment, software, and devices in the organization's security management plan and annual security risk assessment. Determine the need for business associate agreements.

Healthcare professionals should review insurers' coverage determinations for telehealth services. Perform coding updates in the chargemaster to ensure billing codes meet payer requirements. Provide coding education for providers and office coding and billing staff. Ensure documentation for telehealth services is standardized and meets billing requirements. Use documentation templates or checklists for payer-specific requirements and use automatic time tracking within the organization's electronic health record for CPT code selection if available. Smart and dot phrases with predefined, modifiable snippets, which allow for standardization and timesaving documentation. Be aware of potential fraud or identity theft. At the start of each visit, verify a patient's identity using a government-issued ID and confirm their name, address, and device location.

Limitations and Future Studies

There are several limitations to this study. First, the search and review only included English-speaking languages, and studies conducted inside of the US; this limited comparison of any studies published in non-English and conducted in other countries. Second, the search only included peer-reviewed empirical studies; therefore, those non-peer-reviewed non-empirical studies, such as reports, case studies, and commentary published non-peer-reviewed, may be missed. Third, this review study included only publications from January 2020 to February 2022 intended to capture information beginning and during the COVID-19 pandemic. Therefore, the studies published before and after this period are excluded.

There are several opportunities for further research and investigation. First, although there have been significant temporary changes in telehealth policies at both the federal and state levels, permanent changes to support telehealth services have been slower to manifest despite the continued demand. Further research in developing and strengthening telehealth policies and regulations to better guide practice. There is also a lack of in-depth studies that address privacy and security concerns with the use of telehealth services and shows a need for continued research. In addition, the growth of telehealth and the use of technology has exposed digital health inequity and identified the need for digital health literacy education to the vulnerable populations. Finally, challenges such as provider telehealth burnout opens an avenue for further investigation.

Conclusion

The growth of telehealth use has inadvertently created challenges and issues for privacy and security. A multidimensional approach is needed when developing the best practices to incorporate and resolve the issues and tailor the needs of patients, providers, and operational managers. Building best practice guidelines and policies to address technology, digital literacy, accessibility and minimize privacy and security risks are necessary.

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Medical Scribes: Symptom or Cause of Impeded Evolution of a Transformative Artificial Intelligence in the Electronic Health Record?

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Abstract

Studies have quantified various specific benefits related to the use of medical scribes, finding physician workflow and productivity improvements, with some demonstrating marginal value or detrimental impact. However, this evidence base misses a critical underlying issue with the expanding number of physicians using medical scribes routinely. There are an estimated 28,000-33,000 peer reviewed biomedical journals worldwide, currently publishing an estimated 1.8-2 million scientific articles every year. Over a typical physician's career from the 11-13 years of undergraduate through medical school and specialty/residency training as well as 34-36 practice/care delivery years beyond (to age 65), this yields 84-94+ million peer reviewed journal articles that are published in the global medical literature and to be potentially consumed/ considered over a roughly 47-year career. Clinical trial results in various stages of peer review, with 409,000 clinical trials registered in 2022, augment this massive volume of new clinical and bioscience information that clinicians might utilize to advance their care delivery by over 19 million bioscientific reports over a lifetime of training and care delivery.

Inclusive of clinical trial reports and peer reviewed journal articles, a physician might derive clinical care value from an expanding career-long evidence base of 103-113+ million scientific communications. Even if only 0.1 percent of the global output of biomedical science has clinical relevance to a highly specialized physician, the narrowed career-long total remains a staggering 103,000 journal publications and clinical trial reports. For physicians with a more general and diverse clinical focus such as family medicine, emergency medicine physicians, and hospitalists, if 1 percent of newly published evidence-based literature is pertinent, the total career-long estimate is over 1 million journal articles and clinical trials to be reviewed and clinically integrated.

As a result, a challenging issue created by the increasing role of medical scribes is not just evaluating their value (or lack thereof) for practicing physicians in their workflows and productivity. Rather it concerns the impact that medical scribes may be having by decoupling physicians from the iterative technological and cognitive progression of the electronic health record (EHR) and its evolving artificial intelligence (AI), which can facilitate the integration of the year-over-year proliferation of clinically pertinent new scientific evidence into a physician's practice of medicine. This commentary addresses the challenge to the evolution of the AI of the EHR posed by physicians' increasing use of and reliance upon medical scribes, and highlights how medical scribes may also, inadvertently, isolate and insulate physicians from their essential role in continuous refinement and advancement of EHR AI. Consideration is given to the broader challenge of inadequate focus and resources needed across sectors to drive the evolution of AI in the EHR, and associated health informatics research, as a US national priority.

Keywords: medical scribes; electronic health record; artificial intelligence; medical/health informatics; EHR evolution; health informatics research; health IT research

Introduction: Looking Beyond Clinician Value Derived from Medical Scribes to a Systemic Impact of Medical Scribe Use on the Advancement of EHR AI

Over the last decade in the United States, as the use of the electronic health record (EHR) has become ubiquitous, the medical scribe industry has grown dramatically. The medical scribe industry seeks to fill the understandable need and desire of some physicians to liberate and unburden themselves from extremely time-consuming EHRs with poor usability, insofar as safely possible, by having a clerical scribe complete a substantial part of the documentation component of physicians' EHR workflow. One desired major benefit of medical scribe use is to reduce EHR-related as well as general professional burnout of physicians, nurses, and other clinicians. Current estimates suggest that there could be as many as 100,000 medical scribes employed within the US, serving the nation's roughly one million professionally active physicians.[1] However, medical scribe training remains defined primarily by the industry itself—scribes are frequently medical or nursing students, but no minimum educational background or training requirement have been defined nationally. Further, medical scribe certification, as well as scribe clinical and operational performance, are, just like the industry itself, unexamined and largely unregulated.

Published studies have quantified specific outcomes produced by the use of medical scribes, some finding broad improvements, and others detrimental impact.[2-7] However, these studies mostly omit consideration of a critical underlying issue associated with the expanding and increasingly pervasive use of medical scribes by physicians. An estimated 28,000-33,000 peer reviewed biomedical science journals worldwide are currently publishing a collective annual output of an estimated 1.8-2 million peer reviewed journal articles.[8,9] In a single decade of a physician's career, therefore, the scientific literature and evidence base intended to progress the clinical effectiveness and safety of their care of patients may expand by 18-20 million reported studies.

Over the course of a typical physician's training and delivery of patient care, often about 47 years, if the growth rate of journal articles published annually in the scientific literature remains at current levels—unlikely given recent trends—the evidence base underlying the contemporary practice of medicine may expand by 84-94 million new journal articles. In addition, as of 2022, there were 409,000 clinical trials registered globally, a prolific rate of growth from the 2,119 trials that were registered annually just 22 years ago in 2000.[10] If this level of clinical trial growth sustains, this adds over 19 million scientific studies to the literature over a typical physician's 47-year career length. For physicians seeking to follow the emerging and dynamically changing evidence base to inform and evolve their delivery of patient care, this remains an impressive volume of new journal literature and clinical research to assimilate, even excluding the substantial majority of which may have little or no direct bearing on any given physician's clinical care and specialty focus.

Thus, inclusive of clinical trial reports and peer reviewed journal articles, a physician confronts an expanding evidence base in excess of 103-113 million scientific communications over the course of their career. Aside from primary care, family medicine, and emergency medicine physicians and hospitalists whose clinical scope is very wide, most specialty and subspecialty physicians are potentially impacted by a far narrower evidence base, given their focus on

clinically managing an often much delimited, finite range of pathologies within a clinical scope where they are “learning more and more about less and less” in terms of consumption of new medical science reporting. Nonetheless, when one adds in the imperative for all physicians to keep apprised of certain epidemiological reports issued regularly by municipal, county, state, and federal health agencies/departments about the local incidence of prevalent or highly transmissible communicable diseases, and other advisories of clinical or public health importance, these numbers remain impressive and daunting. Few career endeavors require such a level of continuous integration of newly discovered specialized knowledge and practices over the course of a career.

If only 0.1 percent of articles within the global output of biomedical science has clinical relevance to a highly specialized physician, their career total information integration burden remains a staggering 103,000 reports and journal publications; or 2,191 articles or clinical trial reports per year, every year over 47 years; or six scientific articles/trial reports per day, every day of the year. If only one in 10,000 reports are pertinent to a particular narrowly focused specialist, that drops the annual consumption—including cognitive integration and potential clinical practice application—of their emerging evidence base to 219 articles or reports per year, or 4.2 per week, every week, year-round. For physicians with a more general, diverse, and broader clinical care focus such as family and emergency medicine physicians and hospitalists, if one percent of newly published evidence-based literature is pertinent, potential total career consumption is over 1.03 million journal articles and clinical trials, almost 22,000 articles and reports per year, or 423 articles and trials per week, every week, year-round.

The above estimates assume that global journal article and clinical trial report quantitative output or generation remains at current levels, which, based on trends observed during the last decades, seems counterintuitive and highly unlikely. These metrics convey only crude volumes of information to be integrated and do not consider how effectively individual clinicians can differentiate a journal article or clinical trial report with a strong methodological design and adequate statistical power from one that is weaker. For physician consumers of scientific evidence, even with the support of systematic evidence reviews, meta-analyses, and specific evidence-based clinical guidelines, integrating into practice only the most pertinent clinical implications of global evidence growth is arguably already (or will soon be) beyond human capability and capacity. In effect, the successful progression of medical science and knowledge has outpaced our individual and collective ability to systematically and comprehensively evaluate, integrate, and exploit the massive daily and annual production of biomedical science. Only an artificial intelligence (AI) can coherently and comprehensively keep up with the expansion of medical knowledge and drive its integration into the EHR in an expedited, timely manner so that it can inform every physician’s care.

Given these challenges, an issue to consider about the expanding integration of medical scribes into physician care delivery is not solely what value or negative effects scribes do or do not convey in the context of physician practice and clinical workflow per se. An unexamined question concerns the impact of medical scribes in directly undermining the influence of critical physician EHR end users, stakeholders, and resultant physician/hospital market pressure on a heavily market saturated, highly (financially) successful EHR industry. An imperative exists for the EHR industry to invest in the improvement of not just the usability of EHRs, but in efforts to

drive their technological, cognitive, and scientific evolution and progress them to a level where embedded artificial intelligence can real-time surveil for and integrate the enormous year-over-year production of new scientific and clinical evidence, applying it in a clinically meaningful, physician-usable and impactful way in patient care.

AI can potentially integrate and apply this expanding evidence and knowledge base in near real time at the patient level to inform specific episodic patient care delivery, while also informed by what will soon be decades of individual patient (and populational) past medical history EHR data. This is central to the future of EHR AI. How can this AI be developed in the absence of physicians using the full capabilities of the EHR? This commentary endeavors to explore this query and address the challenge to EHR and EHR AI evolution posed by physicians' increasing reliance on medical scribes, which effectively isolates and insulates them from both the problems—and the opportunities—implied by routine physician EHR use and engagement in continuous EHR refinement. As will become clear, while medical scribes may reduce physician EHR engagement, the rise of the scribe industry is primarily a symptom of a far greater problem in the lack of US national private and public sector investment in advancing the AI of the EHR, and its consequent stagnation.

The EHR as a Delivery Vehicle for the Evidence-Based Transformation of Medicine

The adoption of EHRs, while eliminating paper from clinical workflows and making electronic one of the last major global industries to resist digitization, was only partly about these objectives. The primary and essential value of EHR adoption has been its acceleration of the global practice of evidence-based medicine through science-driven standardization of clinical order set content and order issuance, clinical workflows, and clinical decision support, along with electronic documentation, organization, and leveraging of patient health information. Evidence-based medicine, after decades of systematic meta-analyses of the peer review medical literature led by global collaborative initiatives like the Cochrane Collaboration, revealed that many contemporary medical practices were not based on robust evidence. Substantial clinical care was supported by methodologically flawed and weak studies, many inadequately powered statistically. Yet the adoption and impact of evidence-based medicine was slow, languishing in impact on and use by physicians. Other than issuance of evidence-based guidelines, there was no vehicle to drive and ensure ubiquitous adoption of care exclusively defined by the evidence base into the practice of every physician.

That is, until the near ubiquitous adoption of the EHR in nations with moderately mature health system information technology infrastructure, initially by the most digitally advanced nations but later across a growing spectrum of nations. The EHR, through its computer-based standardization of clinical order issuance, clinical decision support, and electronic documentation functionality, serves as a highly effective mass distribution vehicle for the practice of evidence-based medicine. The order sets within computer patient order entry (CPOE) and management are driven exclusively by peer-reviewed evidence, as is the integrated clinical decision support (CDS). As millions of physicians around the world adopt the EHR, they will practice continually evolving and refreshed evidence-based medicine, and today at least a half a billion patients are realizing clinical effectiveness and safety benefits as a result. However, all the patient data captured in the EHR promises a future impact as well, where data-driven analytics and the

integration of new science and evidence merge seamlessly with CPOE, e-documentation, and CDS to yield an evolution in early detection, sensitivity and specificity of disease diagnosis, and improved clinical effectiveness and safety achieved in part by the clinical integration of peer reviewed global science to benefit every patient.

The objective of advancing clinical AI in the EHR, which is to imitate, emulate, and ultimately exceed the abilities of human intelligence, including inference, decision-making, and prediction, is more complex than in many other fields.[11,12] Already, AI has been utilized effectively in medicine, delivering value and advancements in speech recognition, image recognition, expert systems, intelligent tutoring, predictive clinical guidance and decision-making, adaptive neural networks, deep and symbolic machine learning, natural language processing, and complex statistical analyses for varied healthcare uses.[13-21] AI has demonstrated value in disease assessment, diagnosis, clinical problem resolution, and prognostics. Illustrations include AI prescriptive and predictive analytics that improve inpatient care and reduce clinician workload,[22] virtual counseling AI for training nurses in enhanced communication skills,[23] AI standardized electronic care handover that improves patient safety/quality and efficiency,[24] and AI medical information processing in emergency care.[25] These examples only hint at the great promise of AI in the EHR, if it can systematically evolve and be harnessed.

Growth in Biomedical Science has Exceeded Human Cognitive Capacity: EHR Adoption as Just the Beginning of a Journey that Progresses Through Artificial Intelligence

No human mind or multidisciplinary, multispecialty team of minds can complete the critical integration and clinically meaningful application of the tsunami of continuously expanding medical science evidence base and soon-to-be decades of individual patient EHR/medical history data. But AI can help accomplish and accelerate this imperative to deliver effective patient care through and based on the integration of the rapidly expanding, evolving evidence base. EHR AI can only continue to grow and thrive if physicians continue to use EHRs, personally and directly, so their expertise, user experiences, and learning, including dissatisfactions as well as inspired care improvements and creative refinements, drive EHR evolution. Medical scribes, by reducing or eliminating physician interface and use of the full EHR, interrupt and eliminate physician-driven input and advancements in EHR and EHR AI functionality. This viewpoint was first articulated eight years ago,[26] and in the interim, medical scribe use—and the scribe industry—have continued to grow significantly, disconnecting an increasing number of physicians from the EHR as its most critical end users and as essential drivers of EHR improvement and evolution of its AI.

The Meaningful Use of EHRs era, initiated and funded by the Obama administration, achieved its objectives of driving EHR adoption in the United States, resulting in 92 percent of American hospitals and 75 percent of office-based physicians currently utilizing EHRs. EHRs are being adopted internationally as well across Europe, the Middle East, and in parts of Asia and Latin America. However, the last decade of adoption was only the beginning, not the end, of physicians' journey with the EHR. Now that EHRs are more widely adopted, this and subsequent generations of physicians need—or one could argue have a responsibility—to drive improvements and refinements to the EHR, and its emerging AI, with knowledge and insight that can only be derived from their clinical training and experience. This evolution of the EHR must

involve physicians' personal/individual and collective use of the EHR as clinicians. Medical scribes fundamentally disrupt the physician-EHR-AI ecosystem and the technology advancement lifecycle that are essential to driving advancement of EHR AI. The medical scribe industry is effectively relegating the clinician's training and experience to the background through reduced EHR use in favor of use by individuals who lack the training, depth of understanding and experience needed to identify and distill the gaps, weaknesses, imperatives, and opportunities that can drive EHR advancement.

Why Physicians Are Essential to the Evolution of EHR AI

The evolutionary development of AI within EHRs cannot occur with physicians disconnected from the EHR and instead deploying college students and other clinically untrained individuals working as medical scribes. By effectively isolating and insulating the EHR's most critical users—physicians—from its technological progression, medical scribes are contributing to the stagnation of EHR innovation. When physicians can relegate EHR interface and use to others, and when they are completely uncoupled from the current crude state of the EHR, their unique ability to drive EHR vendors unwilling to invest in improving their product vanishes. The fundamental question about medical scribes is not how well they capture information or ease and expedite physician workflows; rather, it is how any complex, highly advanced interactive technology can evolve without its primary intended end users engaged and using it.

Medical scribes have neither the training nor the experience to drive the evolution of EHR AI; only physicians, nurses, and other clinicians can do so. Continuous improvement and refinement of the contemporary EHR can only be meaningfully driven by the most critical generators and users of patient clinical information as it evolves during care delivery; by those who originate and most frequently implement clinical care orders: physicians and nurses, respectively. Thus, physician, nurse, and other clinician insights into how current EHRs are not optimized for their workflows can only be rendered by those clinicians, not by individuals such as scribes who have little or no clinical training (and no role in clinical care delivery to patients). Furthermore, as employees of medical scribe vendors, individual scribes who might perceive problematic EHR workflows or other issues face an inherent conflict of interest, because in identifying poor EHR performance, navigation, usability, or disruption in clinical workflows, they risk effectively biting the hand that feeds/pays them: medical scribe vendors. As regards evolving EHR AI, medical scribes are not only untrained and under-skilled, but financially conflicted.

Thus, while studies of medical scribes deliver insights into their impact and utilities in clinical settings and workflows,[27-32] they do not address the central objective and imperative of rapidly advancing AI within EHRs so that machine capacity and intelligence can help integrate the expanding evidence base and enable it to be increasingly actionable and valuable to physicians in their care of patients. As the populations of many nations age, as a greater percentage of patients will present complex chronic comorbidities to manage clinically, and as medicine innovates and the evidence base continues to expand voluminously, physicians will need their individual—and inherently limited—clinical intelligence augmented with the EHR's artificial intelligence more than ever. Thus, every physician who chooses, for understandable personal professional reasons, to opt out of using the EHR by employing a medical scribe is, effectively, choosing to disregard

the immense need—one could argue every physician's professional obligation—to advance the EHR and its evolving AI to provide more clinically effective and safe care to their patients.

Recognizing and Reducing the Contribution of Current EHR Technology to Clinician Burnout

As a chief medical information officer working to support and improve 15,000 physicians' work lives with EHRs, our team captured every concern, issue, and unmet need physicians articulated about the EHR.[33] Some we could resolve, many we could not, as only the EHR vendor could do so, but often not until a next version or release of its platform, if then. Current and future generations of physicians and nurses have been forcibly placed on a kind of heroic journey not only to work with the rudimentary EHR of this early period, but to advance it. Massive improvement in the technology is coming, and we asked physicians to recall that only 15 years separated the first generation of single (and poorly) functioning mobile telephones in the 1990s and the beginning of the smartphone era that connected us to the internet, placing the digital world in our pockets. The technological evolution of the smartphone has conveyed almost limitless applications and value, transforming how we live, work, and play through an elegant, intuitively navigable, mobile device at lesser cost.

Of course, 15 years or longer is a substantial part of any individual physician's career life. Nonetheless, it is only through capturing clinicians' individual and collective frustration with EHRs, where their time is lost and where their diagnostic/treatment and cognitive workflow needs are unmet, that the opportunities for point-of-care AI-driven clinical enhancement of the EHR's potential to empower physicians can be realized. It is through physicians sharing their actionable insights and recommendations that today's EHR AI will evolve. Physician EHR users have a critical role to play in working collaboratively with medical informaticists, data and AI scientists, and the EHR industry to drive the evolution of the EHR and its emerging AI. This future AI will not only make medicine more clinically effective, safer, and cost-effective; it will evaluate, distill, integrate, synthesize, and inform physicians of the clinical care application derived from the massive continuing expansion of medical science evidence and best practices. EHR AI will empower physicians in a way that they are unable to accomplish as individuals, and that the existing healthcare system and medical science infrastructure is unable to convey.

Evolving AI within the EHR will also help make the practice of medicine more satisfying and can potentially eliminate the EHR as a contributor to clinician professional and EHR burnout. Advancing EHR AI will make use of the EHR more intuitive, less clerical, faster, and more efficient. It will make future physicians more clinically powerful and enable precisely what physicians using medical scribes are seeking: more time to deliberate about patient diagnosis and care, and to engage with patients and their families. But evolution of EHR AI is threatened by the increasing decoupling of physicians from the EHR as its primary user due to reliance on medical scribes. By deploying a new professional role to shield physicians from the EHR, we are throwing out the baby with the bath water, giving up at the precise moment when EHRs have achieved ubiquity in the US, and handing over a major part of EHR functionality to a clerical scribe who is inherently unable to improve the technology.

Much as the test pilots of supersonic jets in the post-WWII era facilitated the evolution of subsequent engine design technology that was used in the exploration of space, generations of physicians will need to be in the pilot's seat of the EHR to truly evolve AI that clinicians increasingly need and that their patients deserve. Is this analogy overly drawn? Perhaps, but less so if one considers not physician-EHR pilot lives lost, but those of their patients in an era when an estimated 110,000 to 400,000 patients in the US are killed annually due to medical errors,[34] arguably the third leading cause of death in the nation prior to the COVID-19 pandemic.[35] One of the greatest obstacles to the evolution of AI within the EHR is the increasing abandonment of the EHR by the expanding number of physicians who have rationalized giving up on it, dismissed their duty to use it and through that use, drive the continuous refinement and evolution of what should and must become one of the most powerful innovations in medical history.

Recommendations: Converging Critical Imperatives and Opportunities to Move Forward

Given the above factors and realities, what is the best way forward? There is little doubt that a substantial component of EHR utilization by physicians and other clinicians is work well below the scientific and clinical "top of license" functioning of these care providers. Given the volume of data captured by EHRs—some of which mediates the financial reimbursement of care delivery and revenue cycle management not directly pertinent to patient clinical care—a role for "new data occupations" in healthcare around the EHR such as medical scribes may have emerged.[36] While information capture and clerical coding of care delivery processes are central to the transactional financial components of healthcare, and are driven by decisions and orders issued by physicians, this must be disaggregated from efforts to advance the artificial intelligence embedded within EHRs that can improve clinical care effectiveness, cost-effectiveness, and patient safety.

The better ultimate answer to the problems of poor EHR navigability, excessive physician time consumption/inefficiency, physician EHR burnout, and others that clinicians rightly have with the contemporary EHR is to improve the technology so these problems are mitigated, not to divorce physicians from the EHR. If physicians disengage from the EHR, their use-based dissatisfactions, critical perceptions, and insights toward advancing AI in the EHR will be lost and thus unable to drive progress of the EHR and its AI toward its potential to enable better, more scientific and evidence-based, clinically effective, and safer care. Medical scribes partly close the door of this opportunity for advancement of EHR AI to converge and distill the expanding medical science evidence base to empower physicians in improving patient outcomes and safety.

Almost a decade into its existence, the medical scribe industry remains a rapidly growing frontier business that is unregulated, where training and performance standards are defined and monitored not by independent and objective third parties but by the industry itself and specific medical scribe vendors. This conflict of interest is not tolerated in any of the healthcare professions and must be eliminated. Medical scribes remain an ill- and undefined, industry-trained healthcare system role held to no objective performance standards beyond satisfying the clinicians and care delivery organizations who "rent" them, and meeting what medical scribe companies deem the minimum necessary skill level and training to sell their services to physicians and care delivery organizations. Furthermore, while the impact of medical scribes has

been and continues to be studied with respect to patient throughput, cost-effectiveness, easing physician work burden and burnout, no system of monitoring for EHR inaccuracies and clinical errors caused by medical scribes exists, and our understanding of who medical scribes are professionally and with respect to competencies remains very limited.

In order to differentiate the clerical roles of medical scribes from the critical role physicians must play in experiencing/using the EHR with its clinical decision support and AI and advancing it, the following is recommended:

1. *Differentiating What Medical Scribes Can Contribute Without Undermining Advancement of EHR AI*

A national multicenter and evidence-based process should systematically examine the role and function of medical scribes in the continuous development of AI within the EHR, involving the multidisciplinary expertise and insights of physicians, health informaticists, data and AI scientists. The objective and focus of this process should include defining critical areas where direct EHR utilization by clinicians is imperative to advancing EHR AI, and where medical scribe use should be prohibited and physician engagement required, versus those areas that are comprised purely of non-clinical clerical functionality and impact that can be relegated to a new role such as medical scribes (with standardized appropriate training, certification, performance evaluation, and continuing education requirements).

2. Funding Needed for Research Driving Accelerated Development and Deployment of EHR AI

Minimizing the negative impact of medical scribes on the development of EHR AI by ensuring essential engagement by clinicians can mitigate detrimental effects introduced by medical scribes, but does not by itself ensure rapid evolution of EHR AI. The value proposition of the EHR at the outset of the Meaningful Use era was at least threefold. The EHR was to take the last major American industry electronic, seizing the varied efficiencies and utilities gained through digitization, including advancing health information management and access, as well as facilitating healthcare financial transactions. Second, the EHR was to enable—and has enabled—the mass distribution and effective enforcement of and compliance with the science and practice of evidence-based medicine as it continuously evolves through the EHR, which, prior to EHR ubiquity, no such pervasive or systematic vehicle existed. And third, the immense volume of individual patient and population data captured by the EHR was to drive a transformative human/patient outcomes, safety and financial return on investment by enabling valuable analytics and precision in healthcare delivery in general, and at the point of care hitherto not possible.

The first two of these objectives have been achieved. However, the third area of value delivery, which focuses on enabling advanced data aggregation, synthesis, analysis, and evidence-based clinical care guidance, is linked inextricably to the development of the AI within the EHR, whose fruition has been unacceptably slow. Despite a plethora of health IT industry actors, including and beyond the EHR industry, trying to achieve and/or claiming achievement of this critical objective, the transformative advancement of healthcare precision, patient outcomes, and safety envisioned to emerge from EHR ubiquity have not substantially materialized. How can

this be in an era when AI is trusted to fly aircraft, drive road vehicles, perform robotic surgery, and land exploratory devices on other planets?

After investing massively to achieve EHR adoption in more than 90 percent of US hospitals, increasing EHR vendor growth to remarkable levels, investment in the next critical phase of AI advancement—of driving/evolving EHRs to deliver their greatest potential value—has dwindled. We continue to be slow in recognizing that because health information technology is so central to everything that occurs in a modern healthcare system at all levels—national and institutional—engagement and investment in health IT research on the digital transformation of healthcare should be equal to that which supports laboratory basic biomedical research and clinical trials. The ongoing evolution and expansion of telemedicine, virtual health, wearables and remote monitoring, and how these will be integrated with EHR AI, have ensured the centrality of IT in the US healthcare system—in its performance and outcomes at all levels. Moreover, health IT and informatics research constitute a discrete and critical area of population health and public health research. Just as the conduct of clinical trials research benefits hospitals, health IT and informatics research should as well.

What is required to enable this potential transformation is a systematic, multidisciplinary, multicenter, and well-funded national research investment to advance EHR AI to achieve improved clinical impact on diagnostic accuracy, diagnostic and care timeliness, and improved therapeutic and patient outcomes, as well as operational and financial efficiencies. The longstanding year-over-year impact of healthcare-related errors as a leading cause of death in the US,[37] as well as unacceptably high levels of avoidable morbidity, care utilization and human suffering across the nation—despite the cliché—warrants a Manhattan Project or Apollo Moonshot level of US national commitment, focus, intensity, and resourcing.

This research effort should be managed and implemented by a consortium of academic medical centers, non-academic public and private community hospitals, and health IT, informatics, data and AI scientists and thought leaders, with the integral participation of EHR vendors. It is quite clear, however, that the critical imperative of advancing AI within the EHR is not actively being driven solely or even primarily by the EHR industry/marketplace and market forces. Despite years of high EHR industry revenues and growth, with hospitals and health systems often spending tens or hundreds of millions of dollars on the purchase, implementation, and maintenance of EHRs, the industry has not demonstrated it can drive meaningful advancement of EHR AI. Indeed, there appears to be little or no financial incentive and/or sense of urgency within the EHR industry to advance the AI within its technology product. Perhaps it is unreasonable to expect that industry alone could accomplish such a massive evolution of technology, as the task likely demands cross-sector and public-private partnership and collaboration.

The rise of the medical scribe industry has also insulated or shielded the EHR industry from the kind of consumer dissatisfaction and resulting market pressures that normally drives innovation in industry by systematically eliminating the most important, demanding and disenchanted customers-end users of their product—physicians—from the impact of consumerism and usual market forces. Given the ongoing national crisis in healthcare related errors and patient safety, and the modest impact thus far of the EHR broadly on patient care outcomes, as well as ongoing

physician dissatisfaction with EHR demands and performance, a multi-billion dollar, independently operating fund should be developed to invest in advancing the AI of the EHR.

This fund should be financed in part by the EHR industry, along with US federal government investment of its institutional medical science and population/public health research assets, capabilities and resources at the National Institutes of Health (NIH) and the Centers for Disease Control and Prevention (CDC). Its goals should be to drive multicenter research and government-industry collaboration to evolve EHR AI and advance the technology in a non-proprietary manner that will benefit all EHR vendors, patients, and physicians across the US and the globe. American industry, medical and public health science, and government are well positioned to collaboratively foster a technological transformation that will eventually touch the lives of people everywhere with impact and value equal to that of the personal computer, the internet and smartphones, its forbearers and component vehicles. Developed in tandem with the ongoing disruption brought by telemedicine, remote monitoring and wearables, and embraced creatively by multilateral organizations such as the World Health Organization (WHO) and major donors, a truly intelligent and personalized/personally connected EHR can potentially be deployed encompassing the Internet of Medical Things (IOMT) to also help overcome the entrenched and resistant health inequities and outcomes disparities existing in most nations.

3. Preparing and Educating Physicians and Population Health Scientists to Understand and Engage Their Critical Role in Advancing the AI of the EHR

The central and pivotal role of physicians in advancing the AI in the EHR should be a focus in the undergraduate and professional training of physicians in the medical school curriculum, complemented with efforts dedicated to preparing them for their roles in EHR use and advancement so that they can contribute to their resolution. The appropriate and inappropriate uses of medical scribes, as determined by the above discussed research, should be an element considered within such curricular content.

For graduate students in public health and related population health sciences, a training focus on the EHR as both a vehicle for capturing population data, and for potentially for program development aiming to achieve and document improved population health outcomes, is similarly warranted. Along with physicians, these domain experts and stakeholders will help the nation mine value from the EHR as a strategic public health improvement capability/vehicle, and as a population outcomes data source and asset. There is a population/public health AI to be developed in the EHR in addition to a clinical AI, including in areas such as expanded, heightened disease/risk surveillance, earlier detection of population health/disease trends in both infectious and chronic non-communicable diseases, systematic population health engagement and behavioral change/risk reduction, and population impact outcomes evaluation.

4. Evaluating Patient Safety When Medical Scribes are Used

At present, we have no systematic data collection to evaluate the extent to which problems in communications or clinical workflows, or other factors, can be attributed to the use of medical scribes. Because medical errors occurring where malpractice has been claimed often end in negotiated settlements which are sealed from scrutiny, we have no objective sense of the extent

to which medical scribe use contributes to errors or negative patient outcomes. Thus, we have inserted a new element in care delivery across the nation interposed between physicians and their EHR documentation—and between physicians and patients some might argue—without monitoring for and assessing its downside risks, in addition to its upside benefits. Systematic research is needed to compare the patient safety performance of care delivery organizations using medical scribes versus those that do not.

5. Medical Scribe Industry and Practice Oversight

Healthcare regulatory organizations and authorities such as The Joint Commission and local, state and federal healthcare agencies focused on the healthcare professions should ensure that their evaluation and oversight of healthcare delivery performance and standards includes review/assessment of the appropriateness of medical scribe use and performance, once the parameters of appropriate scribe use are identified and standardized.

6. Standardizing Medical Scribe Training Curriculum and Minimum Competencies

Statewide and nationally consistent or standardized training, and a curriculum with defined minimum competencies, needs to be defined for the role of medical scribes in assuming the purely clerical functions of EHR documentation, and clearly differentiating the latter from any scribe EHR engagement/use that contributes to critical clinical care workflows and executive clinical decisioning of physicians in the diagnosis and treatment of patients. While the input, knowledge, and experience of the medical scribe industry can be utilized in defining this training curriculum, its definition, implementation and monitoring should be completed by a third party, independent agency, and organizations with no vested financial interests in the scribe industry.

7. Standardizing Medical Scribe Certification, Continuing Education, and Performance Monitoring

A certification examination and process for individuals who have completed a nationally defined and standardized curriculum of training for medical scribes should be established in order to ensure that all medical scribes in the US have achieved and maintain minimum required competencies. The training, evaluation, professional certification, and periodic re-certification of medical scribes should be completed by an organization that is not funded or sponsored exclusively by the medical scribe industry, and rather by a fee or other financial mechanism, much as the examination and certification processes of physicians, nurses, and other professions in healthcare are funded. As patient facing and impacting roles within healthcare delivery, medical scribes should be required to engage in continuing education and recurrent examination and certification, much as other clinical care roles in healthcare delivery are required to (such as physicians, nurses and ancillary care providers).

Conclusion

In sum, with respect to the evolution of EHR AI, it is clear that the rise of the medical scribe industry is both a cause of—but also a symptom of—the current slow progress toward this goal. While medical scribes may be of value to some physicians by narrowing or delimiting their EHR

use, it is in the ultimate interest of patients and physicians to evolve the AI within EHRs such that medical scribe use is not regarded as, and does not become, a long-term solution filling existing critical needs. During this transition period, and until EHR AI and general EHR usability/efficiency achieves its required performance level and potential, the use of medical scribes should be highly circumscribed, and must abide by evaluation, monitoring and regulatory standards similar to other professional healthcare roles that impact patient outcomes and safety. It is imperative that medical scribe use must not decouple physicians' critical engagement in evolving the AI of the future EHR, and thereby impede the realization of its potential and implicit promise to improve healthcare delivery and clinical as well as population/public health outcomes.

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Best Practices for the Design of COVID-19 Dashboards

By Dillon Malkani, Melina Malkani, Neel Singh, and Eesha Madan

Abstract

Since 2020, health informaticians have developed and enhanced public-facing COVID-19 dashboards worldwide. The improvement of dashboards implemented by health informaticians will ultimately benefit the public in making better healthcare decisions and improve population-level healthcare outcomes.

The authors evaluated 100 US city, county, and state government COVID-19 health dashboards and identified the top 10 best practices to be considered when creating a public health dashboard. These features include 1) easy navigation, 2) high usability, 3) use of adjustable thresholds, 4) use of diverse chart selection, 5) compliance with the Americans with Disabilities Act, 6) use of charts with tabulated data, 7) incorporated user feedback, 8) simplicity of design, 9) adding clear descriptions for charts, and 10) comparison data with other entities. To support their findings, the authors also conducted a survey of 118 randomly selected individuals in six states and the District of Columbia that supports these top 10 best practices for the design of health dashboards.

Keywords: health dashboard, health informatics, health information management, COVID-19, public health, data visualization

Introduction

A health dashboard is a visual display of health information used to highlight data for individuals and organizations for decision-making. Numerous types of health dashboards are accessible to the public for various diseases worldwide. These health dashboards provide individuals with essential information that can help increase safety, policies, and behavior. Several of the well-known dashboards include the Johns Hopkins COVID-19 dashboard, the Centers for Disease Control and Prevention (CDC) COVID-19 dashboard, the state of Maryland COVID-19 dashboard, and the Madison & Dane County COVID-19 dashboard.

A few of the authors presented their findings to the COVID-19 dashboard team in Montgomery County, Maryland. Through this presentation, the authors learned about several key elements essential to designing a COVID-19 dashboard at the county level. The authors continued their survey of COVID-19 dashboards by reviewing over 100 US city, county, and state government COVID-19 dashboards. Thereafter, the authors developed and performed a survey to help identify and confirm the top 10 best practices of COVID-19 dashboard design.

Background

The number of COVID-19 cases has rapidly increased over time. As of November 2022, there were over 98 million COVID-19 cases and over 1 million deaths in the United States alone. COVID-19 and long COVID has affected many individuals in countless ways. Although COVID-19 vaccines have recently been introduced, COVID-19 dashboards are still vital for everyone. The rampant infectious disease continues to spread despite the vaccine, and it is

essential for everyone to be able to make healthcare decisions for themselves. The literature review on this topic found very few academic articles on the best practices for the design of COVID-19 dashboards and, even more importantly, health dashboards.

Methods

The authors systematically examined over two years of data from 100 available US city, county, and state health dashboards related to COVID-19. The authors also provided recommendations to the COVID-19 dashboard team in Montgomery County, Maryland. Through this exercise and review of 100 COVID-19 dashboards, the authors identified 10 key design elements for public-facing health dashboards. Thereafter, the authors surveyed 118 individuals on COVID-19 dashboards to identify the top 10 best practices of any health dashboard. Demographic data were not collected for the first group of 58 individuals, but demographic data was collected for the second group of 60 individuals (**Table 2**). The 10 characteristics of creating and understanding COVID-19 dashboards design were incorporated and confirmed in the survey, and the results were collected (**Table 1**).

The authors conducted a survey of 118 (n=118) individuals above the age of 18. The survey consisted of 10 questions. Responses of "yes" counted as one point, while responses of "no" counted as zero points. The authors calculated a total of 1,181 responses, including 995 responses of "yes" and 186 responses of "no." Incorporated user feedback had the lowest percent agreement of "yes" responses of 74 percent, whereas ADA compliance had the highest percent agreement of "yes" responses of 92 percent (**Table 1**).

Results

Based on the two surveys, the authors identified the top 10 design attributes of health dashboards (**Figure 1**) as noted below:

1. Easy Navigation

An essential feature of a dashboard is to allow the user to easily navigate through the various pages and elements of a health dashboard. Upon the authors' review of 100 COVID-19 dashboards, it was noted that some were difficult to navigate from one page to another due to various navigation issues. Thus, several changes were implemented in terms of the location and size of the navigation features that are more in line with the current practices of other dashboards. In addition, a health dashboard may allow the user to hover over a data element to review additional information regarding that element, known as a "focus mode."

2. High Usability

Another important element of a health dashboard is the ease of use. Key factors in usability are fast loading times, simple layouts, and readability when using the dashboard. Faster loading times, for example, allow for more user engagement, allowing the opportunity for people to look further into the data given in the dashboard. Furthermore, it is critical that the data is easily accessible, and the text is large enough for viewers to visualize the data clearly.

3. Use of Adjustable Thresholds

Interactive adjustable thresholds are an important attribute in dashboards because they can be beneficial to users to better understand the data. With adjustable thresholds, users can interact with the dashboard and change parameters for example from 14 days to 60 days for COVID-positive cases. By changing a parameter in a dashboard, the user can view the data in different ways that ultimately help them make better healthcare decisions. Additional thresholds for example based on percentages as opposed to numbers allow for more versatility for the user. This is more effective than a static dashboard, as the percentage of COVID cases decreasing during a certain period of time would inform the user of important, relevant data**.** One could even for example change from a monthly to a daily statistic to better understand a data trend (**Figure 2**).

4. Use of Diverse Chart Selection

The use of multiple chart types is advantageous for a health dashboard. In order to increase the heterogeneity interest, diversity, and range in a health dashboard, it is important to provide different types of charts, graphs, and other data visualization options. Given the range of users that may visualize data, the addition of elements other than line charts that appeal to various groups, such as a heat map, will provide a variety to a dashboard. Studies show that users prefer to visualize different types of charts, such as bar charts or pie charts. Having graphs that interact with the viewers is helpful to have included so that they are capable of viewing the data from multiple different angles (**Figure 3**).

5. Compliance with the Americans with Disabilities Act (ADA)

Given that data visualization often requires the use of color, it is important to ensure charts and graphs using color are compatible with the Americans with Disabilities Act (ADA). One in 12 men and one in 200 women are colorblind, and it is essential that everyone has an equal opportunity to fully understand the data being displayed. The most common form of color blindness includes the colors of red-green color blindness, and the avoidance of red and green should be considered. The use of standard colors that are ADA compliant is highly recommended.

6. Tabulation of Data Into Charts

Although it is essential to frequently demonstrate data and numbers in charts and graphs, it is equally important to avoid over-compression and summary of such data by providing the actual tabulated data. Furthermore, tabulating the data presented by charts allows easier access for individuals or companies seeking to use the statistics. Charts allow one to interpret the data in a different way, allowing one to visualize the data while tabulated data provides the actual numbers that may inform the user in a different way (**Figure 4**).

7. Incorporated User Feedback

While a designer of any system will go out of their way to anticipate issues for the end user, it is essential to have an easy and simple way for users to provide feedback for a health dashboard. This feedback then must be incorporated into the health dashboard, as shown in **Figure 5**. Giving the option for users to leave remarks on a dashboard will immensely improve the effectiveness of a dashboard for the needs of individuals.

8. Simplicity of Design

Users for any COVID-19 dashboard will have a range of education and the ability to interact with an online dashboard. Thus, based on the authors' review of 100 dashboards and a survey of 118 adults, the complexity of displaying data should be minimized. This can be achieved by presenting data more simply and compactly while also providing layers where the most important information is displayed on the initial pages of the dashboard. Additional pages may allow the user to achieve greater levels of detail in reviewing dashboard data (**Figure 6**).

9. Adding Clear Descriptions

Based on the authors' survey, they found that clear descriptions of the charts are necessary for the user to grasp a full understanding of the data being presented. Clearly describing what data is being shown in a chart or graph is imperative. Especially for certain people who don't understand how charts and dashboard works, clear descriptions are vital. Clear labels for the x-axis and y-axis, for example, help the user better understand the data. Beyond charts, tables, figures, and other data, visualizations should be apparent to all users (**Figure 7**).

10. Comparison Data with Other Entities

When providing any type of data, it is crucial to allow it to be placed within a greater context. Thus, dashboards should have a feature to compare their data to similar entities. For example, Montgomery County data or any county's data should be reviewed in the context of other counties so that a user can determine whether one county has fewer or greater cases than another. This gives users the ability to make healthcare decisions based on their area's current situation as well as its surrounding situation (**Figure 8**).

Discussion

The COVID-19 pandemic is the most impactful, significant, and researched event of our generation. COVID-19 is a disease process that potentially affects our entire population of over 7.8 billion worldwide, over 330 million in the United States, or simply 100,000 in the average county within the United States. It is essential that the best practices can be followed to enhance and optimize data visualization, as various cities, counties, and states develop dashboards for reporting COVID-19 data. The authors determined that 10 specific elements should be considered during the design of a COVID-19 dashboard. Further study is required to better validate the impact of each of these individual elements and to conduct a larger nationwide survey with demographic data. This study's limitations include a limited geographic area in a few states.

Conclusion

The COVID-19 pandemic is ongoing and continuously increasing in a number of cases and deaths. With the public seeking data regarding COVID-19 cases, deaths, vaccine usage, etc., accurate and effective dashboards are necessary for the public health information process. To ensure the dashboards are effective in the best ways possible, the authors have come to a conclusion with the 10 best practices to consider while creating a dashboard. These best practices will provide counties, states, and other designers with a set of guidelines for effective communication of COVID-19 statistics to the public. As these practices are in use, they will provide better health information while also improving public health.

Conflicts of Interest and Support

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