Volume 20, Issue 2

Spring 2023 Introduction

The Spring 2023 issue of AHIMA's peer-reviewed research journal, *Perspectives in Health Information Management*, is now available. This issue's topics explore lessons learned from the transition to a new electronic health record (EHR) and the effect on workflow, insight on utilizing EHR data from patients with ADHD to spur educational support, and the role of clinical decision systems in preventing stroke.

Papers include:

- **Extracting Data from the Electronic Health Record of Patients with ADHD Reveals Pediatricians' Discussions of Educational Support and Document Collection**
- **Methods and Lessons Learned from a Current State Workflow Assessment following Transition to a New Electronic Health Record System**
- **The Role of Clinical Decision Support Systems in Preventing Stroke in Primary Care: A Systematic Review**

We hope you enjoy the Spring 2023 issue of PHIM.

Volume 20, Issue 2

The Role of Clinical Decision Support Systems in Preventing Stroke in Primary Care: A Systematic Review

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Abstract

Computerized clinical decision support systems (CDSS) are increasingly being used to facilitate the role of clinicians in complex decision-making processes. This systematic review evaluates evidence of the available CDSS developed and tested to support the decision-making process in primary healthcare for stroke prevention and barriers to practical implementations in primary care settings. A systematic search of Web of Science, Medline Ovid, Embase Ovid, and Cinahl was done. A total of five studies, experimental and observational, were synthesised in this review. This review found that CDSS facilitate decision-making processes in primary health care settings in stroke prevention options. However, barriers were identified in designing, implementing, and using the CDSS.

Keywords: Clinical decision support systems, electronic health records, prevention, primary health care, stroke, tools

Introduction

A clinical decision support system (CDSS) helps healthcare institutions to analyze data from electronic health records (EHRs) and make recommendations to physicians by sending prompts and reminders in real-time[1]. CDSS systems can be divided into three general types: diagnostic, patient management, and alerts and reminders[1]. The computer-based CDSS analyses EHR data and, as a result, transmits alerts and prompts to assist health care practitioners in adopting clinical guidelines throughout the provision of care. A CDSS platform leverages patient data to give health care practitioners with individualised assessments and interventional recommendations based on scientific evidence[1,2].

For example, CDSS can incorporate a reminder for overdue screening services for stroke risk factors[2]. This enables the system to use patients' history, results from clinical tests, and symptoms to assess their risk of having a stroke or one recommending treatment options to be considered by the healthcare provider depending on the patient's risk of stroke[2]. A CDSS tool may also suggest lifestyle modifications that the physician and patient can explore together[2].

This systematic review aims to identify available decision support systems or tools that have been developed and tested to support the decision-making process in primary healthcare to prevent stroke in primary care settings.

CDSS improves the screening of the risk factors that indicate the occurrence of a stroke[3, 4, 5]. The significance of using CDSS to improve stroke prevention is justified by the number of fatalities and morbidities due to stroke in the recent past. Saini et al. (2021) report in the analytical report of global epidemiology of stroke that cases have risen from 1990 through 2016[6]. In 2016, 80.1 million cases of stroke were reported worldwide. On gender-grouped data, there were 41.1 million (38.0–44.3) cases among women and 39.0 million (36.1–42.1) among men[6]. Feigin et al. (2017) reported that over time, the burden of stroke, that is the resultant health complications after stroke, has risen since 1990[7]. Even in small populations, the prevalence of stroke is observed at 2368 and 2967 per 100,000 (crude and age-adjusted respectively)[8]. This can be reflected in the global stroke burden as reported by the World Stroke Organization (WSO) in the 2022 stroke fact sheet[9]. Between 1990 and 2019, the fact sheet reported rises of 43.0 percent deaths from stroke, 70.0 percent increase in incident strokes, 143.0 percent disability-adjusted life-years (DALYs) lost, and 102.0 percent prevalent strokes)[10]. These numbers have climbed beyond 100 million cases annually, thus increasing the risk of patient death.

These increased risk levels demand more preciseness to help primary care providers prevent the occurrence of strokes and other fatal cardiovascular diseases. Computer-aided diagnostics and detection tools are therefore getting appreciated every day in the medical domain to improve the chances of patient survival in the most critical events.

Studies and other investigations have looked at the possibility of quality-of-care improvements by looking at clinical outcomes related to morbidity and mortality for numerous health conditions. Bright et al. (2012) reported that by looking at 148 randomized controlled trials (RCTs) assessing the implementation of CDSS systems, healthcare processes seemed to improve preventive, diagnostic, and prescriptive healthcare processes[11]. However, there was not enough evidence to warrant the conclusion that the clinical outcomes improved.

Additionally, the review focused on the application of CDSS against multiple processes such as cancer screening, immunization, and cardiovascular disease prevention. Three years after this review, Njie et al. (2015) carried out a review seeking to fill the gaps of evidence left by Bright et al. (2012). In their findings, Njie et al. (2015) confirmed the results of Bright et al. (2012) with an addition of the significance of CDSS in disease treatment[12]. The specificity of this review was lacking hence the recommendation that further research should concentrate on practice-based settings to better understand barriers encountered by implementers and challenges posed by generic, mass-produced EHR software not tailored to practices' needs.

Following the recommendation by Njie et al, (2015), this systematic review looked at the primary care setting and evaluated the performance of CDSS in preventing a single clinical outcome (first stroke). Therefore, the article is a systematic review carried out to identify the available decision support systems or tools that have been developed and tested to support the decision-making process in primary healthcare to prevent stroke in primary care settings. It also identified the barriers facilitators encountered during design, implementation, or using CDSS and summarized the core aspects of the decision aids.

Materials and Methods

Systematic Review Objectives

1. To identify available decision support systems or tools that have been developed and tested to support the decision-making process in primary healthcare to prevent stroke.

2. To identify any barriers or facilitators encountered during design, implementation or using CDSS.

3. To summarize the core aspects of the decision aids.

Key terms: Clinical, decision support system, tools, computerized, electronic health records, prevention, stroke

Search Strategy

The search of this systematic review started March 1, 2021 and finished in September 2021 and includes papers from the initiation of each database to 2021. The search was carried out using key terms and search terms outlined in **Table 1**. Keywords like clinical decision support system, tools, computerized, electronic health records, prevention, and stroke were used to build a search strategy. The databases of Web of Science (1970-present), Medline Ovid (1950 to present), Embase Ovid (1980 to present), and Cinahl (1981 to present) were searched. In addition, a manual search was conducted of the references to identify any missing papers. The search was repeated just before starting the analysis stage to avoid missing any new studies eligible for inclusion.

Inclusion and Exclusion Criteria

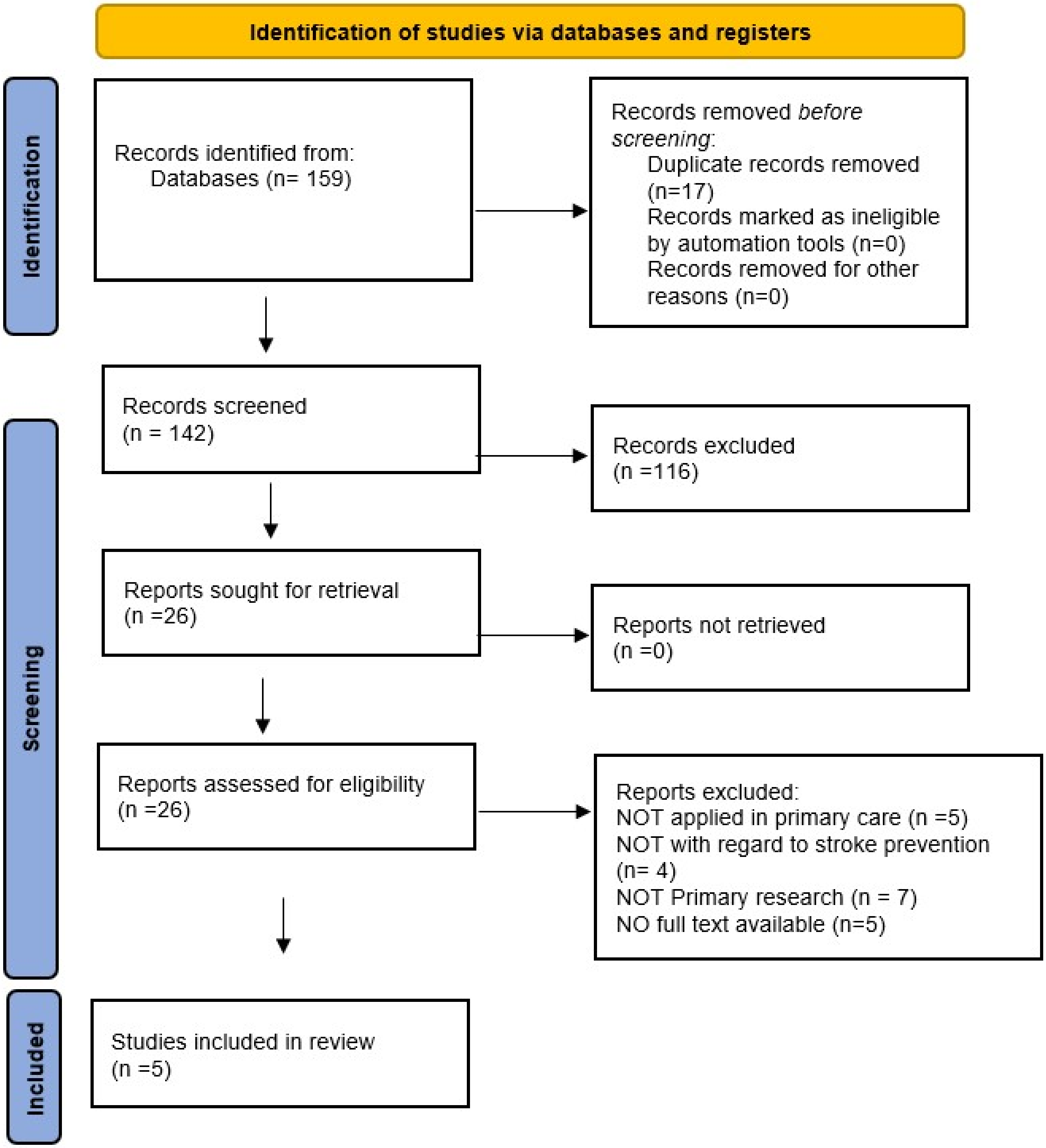
Inclusion considered studies focusing on the prevention of stroke in primary care using CDSS. These studies had to be original papers in English that implemented CDSS in primary care settings with the aim of preventing stroke. A study was only included if patients were adults who had visited primary care. Clinical management in the study had to have used CDSS systems, tools, or applications to manage these adult patients' risk factors.

Study Selection & Data Extraction

The search results were uploaded to Covidence, a web-based program designed to manage the screening process in systematic reviews. Titles and abstracts were initially screened by two reviewers (SA, ST) independently. Then, full paper evaluations were conducted by the two reviewers independently. In case of disagreement, the papers were sent to a third reviewer for solving the disagreement. Data extraction of the study type, country, settings, methodology (population and sample size, sampling methods, data collection, and data analysis), intervention, and outcome were carried out. These data were extracted using an Excel spreadsheet. Characteristic of studies and results and relationship was systematically summarized by narrative synthesis.

As shown in the PRISMA diagram, records Identified from the databases based on our search strategy were 159, the abstract and title screening was done for 141 studies, 18 duplicate papers were removed. One hundred and forty-two studies were screened by two reviewers independently where 116 studies were excluded, and only 26 were included for the full-text screening. Only five papers were included in the systematic review. The other 21 papers were excluded because of the following reasons they were not primary papers, they were not relevant to primary care, or they were not related to the prevention of stroke.

Figure 1


Identification of studies via databases and registers
Identification
Records identified from:
Databases (n= 159)
Records removed *before screening*:
Duplicate records removed (n=17)
Records marked as ineligible by automation tools (n=0)
Records removed for other reasons (n=0)
Screening
Records screened
(n = 142)
Records excluded
(n =116)
Reports sought for retrieval
(n =26)
Reports not retrieved
(n =0)
Reports assessed for eligibility
(n =26)
Reports excluded:
NOT applied in primary care (n =5)
NOT with regard to stroke prevention (n= 4)
NOT Primary research (n = 7)
NO full text available (n=5)
Included
Studies included in review
(n =5)

Quality Assessment QA (Risk of bias)

The default QA template in Covidence is Cochrane's Risk of Bias (RoB) and was used with the Critical Appraisal Skills Program (CASP) tool to assess the methodological quality of the RCT papers selected for retrieval by two independent reviewers before they were included in the review. The AXIAL tool was used to assess the quality of the cross-sectional studies.

From the qualitative data, a thematic synthesis was be used to identify significant categories and themes. The evidence from the SR of qualitative research methods was used to determine how much confidence can be placed in qualitative finding.

Tables 3, 4, and 5 represent the results of this assessment. Four out of the five studies considered as high level of quality, the remain considered average. The major methodological limitations were the lack of groups similarity and the risk-benefits analysis of the studies.

Results

Characteristics of the Studies Included

A sum of 470,392 patients at a high risk of stroke were assessed in the five studies[13-17] included in this systematic review. These patients were assessed in primary care settings distributed in various parts of the world, including the Netherlands (Arts et al., 2017), Sweden (Karlson et al., 2018), Italy (Mazzaglia et al., 2016), Denmark (Bonnevie et al., 2004), and Australia (Wang & Bajorek, 2016). Three of the studies were cluster randomized trials (Mazzaglia et al., 2016; Arts et al., 2017; Karlson et al., 2018), two were a cross-sectional studies (Wand et al., 2016; Bonnevie et al., 2004). The five studies had research investigations conducted in the years ranging between 2004 and 2018. Bonnevie et al. (2004) was the earliest study, while Karlson et al. (2018) were the latest. For additional details, see **Table 2**.

Core Aspects of the CDSS Tools

A typical CDSS tool should have three core aspects: the user interface, the processing layer or inference engine, and the data management layer, which acts as the system's base[18]. The three aspects work collaboratively to complete the architecture of a CDSS tool. Clinical data, patient data, and the system's knowledge algorithms are executed at the base. The inference engine then processes this information and relays it to the interface layer in the form of alerts, recommendations, and reminders [19]The user interface can be accessed on any device; mobile messages, mobile applications, web, or on the dashboard of an EHR system. In the five studies, the recurrent aspect of the CDSS tools used was the integration capability of the CDSS and the EHR system of the institution where the study was set.

CDSS Tools Developed

Knowledge-based CDSSs

Knowledge-based and non-knowledge-based are common classifications for CDSS in healthcare. The CDSS in the reviewed studies are all knowledge-based, where in these systems, rules are developed (IF-THEN statements), with the system obtaining data to assess the rule and providing an action or result [20].

Karlsson et al. (2018) looked to establish whether the CDSS tool increases adherence to guidelines regarding the prevention of stroke in atrial fibrillation (AF) patients[17]. In this research, Cambio Healthcare Systems built a computerised tool integrated into EHR with primary care providers and cardiologists. This CDSS predicts AF, a key stroke risk factor, using EHR data. The CDSS alerts the doctor of a risk factor and suggests a treatment.

For Wang & Bajorek (2016), the CDSS model was meant to facilitate the prescription of two antithrombotics, warfarin or NOACs. Wang & Bajorek (2016) did use an improved Computerised Antithrombotic Risk Assessment Instrument 2.0 instead of an interactive tool (CARATV2.0)[21]. Wang & Bajorek (2017) discovered promising results in optimising antithrombotic treatment, they found that CARATV2.0 increases antithrombotic usage and lowers stroke risk. A significant increase in antithrombotic was experienced in the first application of the NAOCs CARATV2.0 [22]

Bonnevie et al. (2004) used the PRECARD® program. The model was designed to test the preventive abilities of the tool against cardiovascular risks using the Copenhagen Risk Score. The recommendations are based on sex, age, previous heart disease, a familial predisposition to heart disease, systolic blood pressure, diabetes, lifestyles like smoking, body mass index (BMI), and high-density lipoprotein (HDL) cholesterol[14]. Previously, Thomsen et al. (2001) had published the development research of the PRECARD® program and approved its probability of improving the clinical prevention of stroke[23]. Despite its ability to improve the quality of cardiological risk preventiveness in primary care, the tool has been the response for a 14 percent increase in waiting time [14]

Similarly, Arts et al. (2017) developed a CDSS tool that drew patient data and based recommendations on the Dutch general practitioners' guidelines for atrial fibrillation. This CDSS tool was implemented to be non-obtrusive to the general practitioner's flow of activities to improve guidelines[16]. The increased effectiveness, in this case, is a result of non-interruptive recommendations and responses.

In the Italy-based study by Mazzaglia et al. (2016), the investigators used the Health Search Cegedim Strategic Data Longitudinal Patient Database (HS-CSD-LPD)[15]. It uses Health Search Network data to make recommendations to the medical practitioners involved in the study. The usage of HS-CSD-LPD has not been very widespread compared to other tools like the PRECARD® program and CARATV2.0.

The design of Mazzaglia et al. (2016) sought to ascertain the hypotheses that CDSS will increase the use of preventive therapies to cardiovascular therapies and, by so doing, reduce the dependency on drugs[15].

Effectiveness of CDSS to Prevent Stroke

The general usefulness of CDSS is to ease the work of the physicians as well as lowering the risk of various health conditions. The risk of stroke has been assessed on the fronts of diagnosis, treatment, and prevention and can be monitored and greatly lowered through timely and computerized decision prompts[14,21].

CDSS and Stroke Screening

CDSS tools have demonstrated abilities to lower the risk of stroke by monitoring most risk factors. However, Mazzaglia et al. (2016) found that the system's number of alerts sent is so large that it had to be discontinued from screening. Despite such decisions poking holes in the logic of useability, the larger health informatics literature can agree that such alerts cannot be ignored unless the functionality is not in use ()[24]. Karlsson et al. (2018) standardized the CHA2DS2-VASc tool to activate a patient with AF diagnosis[17]. The tool was, however, not very useful in diagnostics, despite relaying the risk traits of stroke, a CDSS cannot provide a certain diagnostic.

CDSS and Clinical Guidelines Adherence

Clinical guidance adherence was assessed by two of the included studies (Arts et al., 2017; Karlsson et al., 2018)[16,17]. Notably, the use of CHA2DS2-VASc by Karlsson et al. (2018) produced significant results indicating adherence differences after 12 months of follow-up between groups using the tool and the control. The difference in findings between the CDSS group and the control was (73.0%, 95% CI 64.6%–81.4%) versus (71.2%, 95% CI 60.8%–81.6%) $p = 0.013$. Echoing these results, Arts et al. 2017 reported a 10 to 20 percent absolute effect size and adherence rate of the randomized groups in the study whose prompts are ignored with a reason; and whose prompts are ignored without reason). In a subsequent study, Arts et al. (2017) could not establish a significant difference between the interventional (55 percent) and control (50 percent) groups in terms of sticking to the therapeutic prompts[16,17].

Discussion

The use of Clinical Decision Support Systems (CDSS) in stroke prevention has the potential to bring about significant benefits to patient outcomes. These benefits include enhanced accuracy and efficiency in identifying high-risk patients, improved adherence to evidence-based guidelines for stroke prevention, and earlier diagnosis and intervention. However, the implementation of CDSS in clinical practice is not without potential risks. This paper explores the possible downsides of CDSS in stroke prevention, including the increased workload for healthcare providers, potential loss of personal interaction between providers and patients, and the risk of overreliance on the CDSS, leading to overdiagnosis or overtreatment.

In an effort to enhance the pharmacological management of high-risk cardiovascular patients in primary care, Mazzaglia (2016) created CDSS. The findings of their study were encouraging, demonstrating that the implementation of CDSS led to a positive impact on the quality of care for diabetic patients[15].

Wang (2016) developed a decision support tool called the Computerized Antithrombotic Risk Assessment Tool version 2.0 (CARATV2.0) to help doctors decide whether to use novel oral anticoagulants (NOACs) or warfarin to prevent strokes in older patients with AF[21]. While the tool improved the use of antithrombotic treatment, it also led to more frequent prescription of blood thinners than what general practitioners typically do. This suggests the potential for overtreatment, where patients receive unnecessary or excessive treatment, and highlights the importance of optimizing treatment utilization to prevent potential harm to patients.

In terms of adherence to clinical guidelines, Karlsson et al. (2018) discovered that integrating a clinical decision support (CDS) tool for stroke prevention into the EHR has the potential to enhance adherence to stroke prevention guidelines for patients with AF. AF is associated with significant morbidity, especially in stroke patients. Karlsson et al. (2018) demonstrated that the use of a CDS could improve adherence to guidelines for anticoagulant therapy in patients with AF. The automated CDS tool integrated into EHRs functioned by producing an alert for AF patients at risk of stroke if they did not receive appropriate treatment. This intervention is straightforward and ultimately increased the utilization of anticoagulants in patients with atrial fibrillation. Nevertheless, Karlsson et al. (2018) noted that the difference is small in comparison to cases where the CDS tool was not used, the capability of CDS cannot be underestimated[17]. It actually indicates the potential for further enhancements that might lead to compounding beneficial effects on patient care.

Bonnevie et al. (2005) conduct a study on the implementation of a program (PRECARD®) used for electronic cardiovascular disease risk assessment and management by general practitioners in Denmark[14]. They not only access its usage but also attitudes towards the program. It was reported that by using the program, there was a favourable effect on the interaction between general practitioners and patients. Even so, there were some general practitioners that were reported to have stopped using the program citing reasons such as technical problems and incompatibility of routines with the program.

Despite the potential benefits of CDSS in stroke prevention, studies such as that conducted by Arts et al. (2017) have shown that CDSS are not always effective in increasing adherence to clinical guidelines. Specifically, the study found no significant difference in guideline adherence between patients where a CDSS was used and control groups. Interestingly, both the intervention and control groups showed an increase in guideline adherence during the trial period. In light of these findings, Arts et al. (2017) recommend that future efforts to implement CDSS in clinical practice should focus on improving multi-domain CDSS to address challenges in implementation and facilitate their effectiveness in real-world settings[16].

Implications

The findings from various studies on the effectiveness of CDSS in preventing first stroke in primary care are inconclusive, highlighting the need for further research in this area. While some studies have shown promising benefits, the variability in CDSS characteristics and the heterogeneity of results indicate that more investigations are necessary to draw stronger conclusions.

Therefore, future studies should focus on identifying ways to improve CDSS effectiveness in preventing stroke, particularly by exploring the pre-implementation and implementation processes and the human factor, which can play crucial roles in determining the effectiveness of CDSS in real-world settings. Given the potential for CDSS to enhance stroke prevention in primary care, it is important to continue studying and improving the effectiveness of these systems.

This systematic review carries significant implications as it underscores the potential benefits of CDSS in preventing stroke in primary care, emphasizing the possibility of substantial advantages that such systems may offer and their ability to enhance the communication and collaboration between patients and general practitioners.

Limitations

The scarcity of data stemming from the analyzed studies impedes the formation of definitive conclusions regarding the efficacy of CDSS in preventing stroke in primary care. Furthermore, the presence of heterogeneous results, characterized by varying degrees of beneficial outcomes, underscores the urgency of additional investigations aimed at attaining more consistent and robust results. Additionally, the absence of pre- and post-intervention measurements to evaluate the role of CDSS in stroke prevention poses another obstacle that necessitates further exploration in subsequent studies.

Conclusion

CDSS can improve primary care outcomes and prevent disease occurrence. While most interventions achieve only small to moderate improvements in patient outcomes, some studies demonstrate the potential benefits of CDSS in preventing strokes and enhancing primary care. However, designing reliable CDSS remains a challenge. Future research should explore new ways of designing such systems to ensure reliability.

Acknowledgments

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Supplementary Tables

Table 1: Search Strategy Table

Database	Search Strategy
Ovid (Medline and Embase)	Clinical? Decision? Support? Systems Or Computerized Decision? Support? Tools Or CDSS AND prevent AND Stroke AND Primary care
Science Direct	TS=("Clinical? decision? support? systems" OR "Algorithm" OR decision OR tool)" OR AND TS= "Prevention" TS= Stroke TS= primary care
Cinahl	Clinical decision support systems Decision Support Systems, Clinical CDSS TX prevent TX Stroke TX Primary care

Table 2: Studies characteristic

Lead Author, Year: Yishen Wang MBBS, 2016

Study Title: Clinical pre-test of a computerised antithrombotic risk assessment tool for stroke prevention in atrial fibrillation patients: giving consideration to NOACs

Country: Australia

Aim of Study: The study wanted to pre-test a CDSS tool that would help clinicians in selecting antithrombotics.

Study Design:A cross-sectional study

Setting: 369 general practice patients with atrial fibrillation (AF) participating in the previous study (2012) were involved here. Their age was ≥65 years with a confirmed diagnosis of AF New South Wales. Their information was available in the former study database.

Participants Characteristics: 393 patients with AF [mean age 78.0 (±7.0) years], 54.5% were male and 45.8% (n = 180) were aged ≥80 years.

Type of CDSS Tools Utilized: An updated version of CARATV2.0 based on latest clinical evidence.

Outcomes: CARATV2.0 recommended warfarin for 360 (91.6%) patients, NOAC for 5 (1.3%) patien ts, either rivaroxaban or apixaban for 6 (1.5%) patients, andapixaban for 9 (2.2%). This was in the ca se where warfarin was recommended as first-line therapy.

Lead Author, Year: Lise Bonnevie, 2004

Study Title: The use of computerized decision support systems in preventive cardiology-principal results from the national PRECARD@ survey in Denmark

Country: Denmark

Aim of Study: Conduct a cardiovascular disease risk assessment and management in Danish patients since 1999 using the PRECARD® program.

Study Design: A cross-sectional study

Setting: 3568 general practitioners registered in Denmark were contacted. An online survey conducted on 592 general practitioners in Denmark.

Participants Characteristics: 400/3568 took the postal survey and 291/400(73%) responded. The participants were subdivided into users 60(22%) [males 45(75%)] and mean age 49.7 years, ex-user 28(10%) [males 18(64%)] and mean age 51 years, and never user 191(68%) [males 126(66%)] and mean age 51.7 years.

Type of CDSS Tools Utilized: The PRECARD® program for CVD risk assessment and management.

Outcomes: 21.5% GPs use the program, 10% have used it before, and the program is utilized at a rate of 64% weekly. The usage of the program affects the patients favourably by enhancing the dialogue between them and the practitioner. However, it also prolongs consultation time.

Lead Author, Year: Lars O. Karlsson, 2018

Study Title: A clinical decision support tool for improving adherence to guidelines on anticoagulant therapy in patients with atrial fibrillation at risk of stroke: A cluster-randomized trial in a Swedish primary care setting (the CDS-AF study)

Country: Sweden

Aim of Study: To assess whether adherence to guidelines regarding the prevention of stroke can be increased by using a CDSS tool.

Study Design: A cluster randomized trial

Setting: 444,347 Swedish patients obtained from 43 primary care clinics county of Östergötland will be into CDSS and control groups for the randomized study.

Participants Characteristics: Patients with atrial fibrillation at risk of stroke, 43 primary care clinics in the county of Ö stergö tland, Sweden (population 444,347, patients with AF

Type of CDSS Tools Utilized: A CDSS embedded in a standard electronic health record (EHR) and uses medical record data to identify patients with AF and one or more risk factors who have not yet been prescribed anticoagulant medication, according to the CHA2DS2-VASc algorithm.

Outcomes: CARATV2.0 suggested any NOAC for 279 (70.9%) patients, rivaroxaban or apixaban fo r 80 (20.4%) patients, apixaban for 9 (2.3%) patients, and warfarin for 12 (3.1%) patients. This was i n the case of where NAOCs were recommended as first-line therapy.

Lead Author, Year: Giampiero Mazzaglia, 2016

Study Title: Effects of a computerized decision support system in improving pharmacological management in high-risk cardiovascular patients: A cluster-randomized open-label controlled trial.

Country: Italy

Aim of Study: Testing if using CDSS can favourably affect the prevalence of preventive therapies according to the recommendation guidelines and check whether the number of days of drug interactions will reduce among patients with a high risk of cardiovascular diseases.

Study Design: A cluster randomized controlled trial

Setting: 197 general practitioners were randomly assigned to groups that will either receive alerting computerized decision support system integrated into standard software (intervention arm) or the standard software alone (control arm)

Participants Characteristics: Diabetic patients, 21230 patients with diabetes, 3956 with acute myocardial infarction, and 2158 with stroke were analysed, 197 Italian general practitioners, high-risk cardiovascular patients.

Type of CDSS Tools Utilized: A CDSS embedded in a standard EHR and uses medical record data to identify patients with AF and one or more risk factors who have not yet been prescribed anticoagulant medication, according to the CHA2DS2-VASc algorithm.

Outcomes: For 279 (70.9%) patients, CARATV2.0 recommended any NOAC, rivaroxaban or apixaban for 80 (20.4%) patients, apixaban for 9 (2.3%) patients, and warfarin for 12 (3.1%) patients. When NAOCs were suggested as first-line therapy, this was the situation.

Lead Author, Year: Derk L. Arts, 2017

Study Title: Effectiveness and usage of a decision support system to improve stroke prevention in general practice: A cluster randomized controlled trial

Country: The Netherlands

Aim of Study: Using a non-obtrusive CDSS integrated into the workflow to increase guideline adherence. Also, to figure out why people don't follow guidelines.

Study Design: A cluster randomized controlled trial

Setting: A randomized control experiment on the Dutch general practices. To prevent contamination bias, randomization was done at the GP practice level. The allocation ratios were 2:1:1 and 1:1:1. The 'sample' function was used to generate a random sequence from the list of GP practices provided by DA in the statistical environment R. GPs were aware that they were assigned to a system variant, but they were unaware of their assignment and how the variants differed.

Participants Characteristics: 781 patients were included randomized into post-study control (259 patients) [mean age(SD): 73.73 (14.7)] and post-study intervention (522 patients) [mean age(SD): 72.79 (12.61).

Type of CDSS Tools Utilized: Real-time, non-interruptive, and based on data from electronic health records were all attributes positively associated with effectiveness when a decision support system was established. The recommendations were based on the CHA2DS2-VAsc for stroke risk stratification, which is used in the Dutch general practitioners guideline for atrial fibrillation.

Outcomes: There was a decreased utilization of the system (5%) which dropped over time. There was a 58% rate of dismissal and 42% rate of acceptance to notifications (76 were responded to). Acceptance had improved in both groups by a factor of 8% and 5% but the difference was not significant between the analysed groups.

Table 3: Cochrane's Risk of Bias (RoB)

Table 4: The CASP assessment table below represents the appraisal of three RCTs included

QUESTIONS	Mazzaglia et al. (2016)	Arts et al. (2017)
Did the study address a clearly focused research question?	Y	Y
Was the assignment of participants to interventions randomised?	Y	Y
Were all participants who entered the study accounted for at its conclusion?	CT	CT
Were the participants, investigators, and the people assessing/analysing outcome/s 'blind' to intervention they were given?	Y	CT
Were the study groups similar at the start of the randomised controlled trial?	Y	N
Apart from the experimental intervention, did each study group receive the same level of care (that is, were they treated equally)?	Y	N
Were the effects of intervention reported comprehensively?	Y	Y
Was the precision of the estimate of the intervention or treatment effect reported?	CT	CT
Do the benefits of the experimental intervention outweigh the harms and costs?	N	N
Can the results be applied to your local population/in your context?	CT	CT
Would the experimental intervention provide greater value to the people in your care than any of the existing interventions?	Y	Y

Table 5: The AXIAL assessment table below represents the appraisal of all the two cross-sectional studies included

	Wang & Bajorek. (2016)	Bonnevie et al. (2004)
Introduction		
Were clear aims and objectives of the study used?	Y	Y
Methods		
Was the study design appropriate for the stated aim of the study?	Y	Y
Was the sample size justified?	Y	Y
Was the target/reference population clearly defined? (Is it clear who the research was about?)	Y	Y
Was the sample frame taken from an appropriate population base so that it closely represented the target/reference population under investigation?	N	N
Was the selection process likely to select subjects/participants that were representative of the target/reference population under investigation?	NA	NA
Were measures undertaken to address and categorise non-responders?	N	Y
Were the risk factor and outcome variables measured appropriate to the aims of the study?	Y	Y
Were the risk factor and outcome variables measured correctly using instruments/measurements that had been trialled, piloted or published previously?	Y	Y
Is it clear what was used to determined statistical significance and/or precision estimates? (e.g. p-values, confidence intervals)	N	Y
Were the methods (including statistical methods) sufficiently described to enable them to be repeated?	N	N
Results		

Were the basic data adequately described?	NA	NA
Does the response rate raise concerns about non-response bias?	N	Y
If appropriate, was information about non-responders described?	N	N
Were the results internally consistent?	Y	Y
Were the results presented for all the analyses described in the methods?	Y	Y
Discussion		
Were the authors' discussions and conclusions justified by the results?	Y	Y
Were the limitations of the study discussed?	Y	N
Others		
Were there any funding sources or conflicts of interest that may affect the authors' interpretation of the results?	N	N
Was ethical approval or consent of participants attained?	Y	N

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PERSPECTIVES
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Methods and Lessons Learned from a Current State Workflow Assessment following Transition to a New Electronic Health Record System

Claire Hayes Watson, PhD, MPH; Anthony Masalonis, PhD; Tim Arnold, PharmD; Neale R. Chumbler, PhD; William Plew

Abstract

The transition to a new electronic health record (EHR) system requires an understanding of how the new system addresses the needs, business processes, and current activities of a healthcare system. To address such requirements, a multidisciplinary team conducted a current state workflow assessment (CSWFA) of clinical and administrative functions to elicit and document business processes (via process diagrams), requirements, workarounds, and process issues (i.e., user interface issues, training gaps) at one healthcare facility. We provided a novel method of evaluating the implementation process to ensure that a CSWFA was documented with key stakeholders. In this analysis, we describe the CSWFA approach and expected outcomes with a specific emphasis on how a qualitative approach can be integrated to explore underlying patterns and relationships in the data. Overall, this methodology enables practitioners to deliver data-driven support initiatives that optimize EHR implementation while considering user experience, productivity, and patient safety.

Keywords: Workflow assessment, electronic health record, user experience, EHR transition, EHR implementation

Introduction

As healthcare systems work to facilitate clinical and administrative processes, care delivery, and decision-making activities while at the same time improving quality and reducing medical errors[1],[2], there continues to be an uptick of the implementation of electronic health records (EHRs) throughout the United States. In fact, many healthcare systems are now replacing or converting their existing EHRs to improve workflow, efficiency, and quality.[3] Waiting to evaluate an EHR until after it has been implemented creates many challenges and impacts the delivery of optimal care after transition to the new system.[3] Thus, it is imperative to understand what, if any, barriers may have existed in terms of workflows and processes. Such an evaluation is especially important because distinct processes to ensure patient care quality were already in place and such behaviors may be challenging to modify after the implementation of a new system. A systematic review of EHR implementation found that documentation time increased significantly after a new EHR was put in place, but workflow (defined as the sequence of physical and mental tasks performed by end users within and among work environments) improved after staff became more familiar with the new system.[4]

Common post-EHR implementation issues include those that involve end users, such as workarounds in workflows and processes after the EHR vendor or its designees were unable to resolve it, as well as user interface issues and staff training needs.[2,4,5,6] Following EHR implementation, managers and informatics staff need a user-friendly data collection tool to better understand if system end-users are able to effectively use the EHR system. This data will inform decision makers on whether workflows are running smoothly and the extent to which workarounds exist.[5] To date, there is limited information tailored for health information managers and planners that not only collects but evaluates the needs of the end user.

Through a partnership with a large integrated healthcare system in the United States, the purpose of the present study was to examine the business and operational processes that occurred at a single hospital after the implementation of a new EHR. The objective of this study is two-fold. First, we describe and disseminate a technique, Current State Workflow Assessments (CSWFA), that quantifies process issues (e.g., workarounds) that end-users may perform after the implementation of a new EHR. Second, we describe the data that was generated from a CSWFA at a single hospital after implementation of the new EHR. Findings from the CSWFA capture the as-is operational understandings that support EHR conversion or implementation. The results are designed not only to inform process improvements, but also to identify components for workflow optimization and information-system redesign.[3]

Methods

This assessment engaged leaders and technical teams from multiple informatics-related divisions within a large healthcare system. More specifically, an informatics project team comprised of clinical informaticists, human factors engineers, business process analysts, process architects, requirements analysts, and business process re-engineers, collaborated to deliver a current state assessment of primary care services at one health care facility following deployment of a new EHR. This process, referred to as CSWFA, included the documentation of business processes for six primary care service areas, as well as gaps and pain points reported by end users who had transitioned to the new system. Creating, populating, and managing a repository allowed human factors engineers to generate a dataset for quantifying and categorizing captured gaps and pain points based on the nature of each issue and the impact of each on job satisfaction, productivity, patient safety, and other related factors. All activities associated with CSWFA were conducted virtually using Microsoft Teams. The virtual environment enabled diverse participant involvement from medical facility staff and project team members facilitating the sessions, which was key considering the multidisciplinary approach.

CSWFA Planning

Based on the number of service areas targeted, and the complexity of these services, multiple planning sessions occurred, allowing the site and project team members to convene to identify "deep dive areas" or focus areas of interest that would be prioritized in preparation for the workflow assessment. Focus areas were identified by site staff and leadership based on clinical domains that were experiencing issues, barriers, or unclear definition of processes. Moreover, the team deliberated prior to these sessions to develop preliminary "as-is" process models. Existing workflows provided by the EHR vendor were leveraged to create the as-is models using Business Process Model and Notation (BPMN) [7], a standardized graphical notation that uses shapes, symbols, and rules for creating process models that are easy to understand. Additional documentation such as existing site-level workflows, Standard Operating Procedures (SOPs), clinical practice guidelines, and policies were also leveraged in the development of As-Is models prior to the beginning of each Workflow Elaboration Session.

Workflow Elaboration Sessions

One, 90-minute Workflow Elaboration Session was conducted for each "deep dive" area in order to clarify and/or confirm the steps associated with the business process being reviewed. An informaticist, a process architect (modeler) and human factors engineer facilitated the session with a specific focus on tasks; user roles responsible for completing tasks; data objects or artifacts associated with tasks; pain points; workarounds; and systems or software being used. Subject matter experts (SMEs) interviewed were system end-users including providers, nurses, managers, pharmacists, and local informatics staff. During sessions, as key details on the process flow were elicited[7,8], as-is workflows (developed during CSWFA planning) and Current State Workbooks were simultaneously updated to document changes and key details shared by facility staff. Human factors engineers asked specific questions to probe into each SME's experience using the new system with a specific emphasis on the system interface, as well as the challenges experienced when using the system. Sample questions used by engineers as guides during Workflow Elaboration Sessions can be found in **Figure 1**.

Questions posed during Workflow Elaboration Sessions enabled the capture of narrative data that could be leveraged to perform qualitative analytics and to answer questions that inform problem identification and issue resolution. This included elements such as systems used, devices required to perform the task, user roles, and triggering events, while also allowing the team to identify and document gaps, inefficiencies, pain points, manual processes, and workarounds implemented by the site.

Workbook Normalization and Review Sessions

Following each Workflow Elaboration Session, one Workbook Normalization and Review Session was conducted to review data captured and validate findings. The overarching goal of each session was to confirm each captured gap/pain point, while leveraging the expertise of at least one clinical informaticist and at least one human factors engineer to classify each line item by the nature of the specified issue and the impacts it has on the user. This discussion, facilitated by a human factors engineer and a business process re-engineer, encouraged collaborative communication and allowed the informatics team to concur on definitions for elicited pain points before coming to a consensus on the classifications. For each step in the model, the human factors engineer reviewed all captured gaps and requested feedback from at least one clinical informaticist to validate that the pain point was captured accurately. This approach also ensured that expertise from critical areas such as human factors, cognitive engineering, and/or safety engineering was acknowledged in the assessment of each gap.[9]

Qualitative Analysis

We used text-based analytic visualizations to explore the body of text within each Workbook Elaboration Session and to identify themes. We used several approaches for viewing how important a word was to the content in the corpus.[10] Lists of simple word frequencies and other ways to view word significance were viewed by the team. The team also viewed other NLP visualizations as we began to conceptualize themes. The team manually reviewed the list of remaining keywords excluding single characters and function words along with general and nonapplicable words decided upon by the team. With the remaining words, a co-occurrence network was created to help visualize themes. The thematic analysis of key data insights further allowed researchers to understand patterns, relationships, and commonalities among recurring terms. *For more information on processes for designing co-occurrence networks, see Arnold (2022).[11]*

Orange data mining toolbox[12] was used to create a pipeline for interactive word co-occurring network visuals. In Orange, we used the preprocess text widget to tokenize the text; connected and configured the corpus to network widget to create co-occurring word networks; used the network visualization widget to view the results; and explored network visualizations while iteratively configuring.

Results/Findings

The Co-occurrence Network (**Figure 2**) illustrates the frequency of use of terms in the narratives captured in the Workflow Elaboration Sessions and further refined in the Workbook Normalization/Review Sessions. Co-occurrence networks and other Natural Language Processing (NLP) visualizations can be displayed dynamically to systems studies and design teams to support exploration. These visualizations can be configured during the tokenization process, by tailoring frequency or significance assignment or tailoring thresholds of visualization features and relationships. The co-occurrence network in Figure 2 represents the visualization based on one set of thresholds.

There are many visualizations available in text analytics and NLP software including word tree representations, corpus and topic model viewers, and clustering visuals. Exploring options for and iterating on some combination of visualizations for viewing text may help with discovery activities. Approaches should be tailored to the context of work and analyst team's preferences. Mihalcea and Radev (2011) provide insight on and uses for graph-based NLP.[13]

The linguistic features and relationships depicted can prompt the review team to further explore the context of specific narratives captured in the Workflow Elaboration Sessions. It can be seen that "medication(s)" and "order(s)" were frequently used terms that often co-occurred. More specifically, the high frequency of "order(s)" led us to focus our deep dive on this topic, guided also by "hypotheses" derived from the connections between "order," "options," and "lists." We examined the Workbooks with a focus on these topic areas, synthesizing qualitative data from different comments where appropriate. Select key insights from this analysis were distilled into **Table 1**.

The deep dive topics derived from examining the co-occurrence network often turned out to be frequent themes in the synthesized insights. For orders, the issue suggested by the network visualization that ordering options may be a pain point, was verified by detailed examination of the data. Exploring order-related issues in greater detail also revealed other pain points that were *not* apparent from the co-occurrence network, including a description of a workaround, even though the words "workaround" and "order" were not shown as associated in the network. Thus, the deep dives are guided but not dictated by the themes highlighted in the co-occurrence network. The findings of the deep dives led to specific recommendations, which are described briefly in the Discussion section below as an illustration of the types of recommendations that this methodology can produce.

Discussion

The CSWFA methods employed in the present study provided the agility to comprehensively identify user-described obstacles (i.e., "pain points") that emerged during the implementation of the EHR in a primary care workflow context. Moreover, the techniques used in our study enabled the analysts to propose solutions (not described in detail in this paper), thus pointing to the method's utility for improving the efficiency and accuracy of orders and the medication use process in primary care workflows. Specific insights and lessons learned included:

Personnel and Process

- CSWFA should be a multi-professional team approach including most or all the following: clinical staff, informaticists, architects (both process and information), requirements analysts, human factors engineers, and implementation experts who have proficiency with and exposure to the specific new EHR being deployed. This multidisciplinary team can cross-check the findings of the other disciplines and offer new perspectives.
  - The importance of having a team with diverse expertise was especially important due to the documentation and training needs prevalent with new EHR deployments.[1,3,4] The multi-professional nature of the team facilitated an understanding and analysis of the barriers to efficiency and workflow created by these documentation and training gaps.
  - In addition, program management office stakeholders and facility leadership who are consumers of the new EHR should be engaged at all stages of the process, to help define more accurately the high-level workflow definitions and mission-level considerations that drive the task being analyzed.

- Content and data fields that emerged from the Workbook Normalization and Review Sessions should be tailored to goals of CSWFA, while at the same using caution not to include extraneous fields (i.e. Devices Used, Handoffs, Hard Stops, etc.) that may not be used or that will unnecessarily increase workload for a project team.

- Workbook data fields should remain modifiable. The team should remain flexible and open to adapting tools based on the site/service line. In addition, the toolkit's usability must be considered. The Microsoft Excel implementation of the workbooks described in this paper offers the advantages of using a tool with which most users will be familiar. It should be noted that intermediate-level Excel functionality is used in our tools, and future efforts would benefit from developing a reference card or training guide to assist users, especially those facilitating meetings and updating workbooks in real time, with Excel filtering and formatting operations beyond the basic level.

Data Analysis

- Data analysis should be comprehensive. That is, stakeholders should leverage qualitative content analysis results to identify themes. In the context of our study, these included order-related issues around which integrated deep-dive assessment and improvement efforts were constructed, as opposed to a series of unrelated and isolated improvements.

- The CSWFA approach should not be primarily quantitative, instead it should provide a starting place and flexible guide for walking through a collection of narratives as the team seeks to interpret data from the Workflow Elaboration and Normalization/Review sessions. Co-occurrence network, topic model, and other natural language visualizations should be configurable and explored interactively by a multi-professional community. By moving between the parts and whole or greater context, this exercise can facilitate interpretation and inform thematic analysis. This approach can be particularly useful when themes have not formally been predetermined or when the team is challenged by analyzing narratives to identify themes. Additionally, walking through a range of visualizations can help illuminate topics that may otherwise be overlooked. These collaborative activities can contribute to the hermeneutic process as priorities and timelines shift. To this end, narratives from the collection are highlighted in this paper for exemplar purposes. Their inclusion is not intended to provide quantitative information; rather, they are described here to characterize the approach to this work.

- Although it would not be the main focus of data analysis, the evaluation should incorporate a quantitative component. Several of the issues identified in Figure 2 and Table 1 related to system shortcomings that affected EHR user workload and the time it took to complete the tasks. Future efforts could be improved by deriving — through structured lines of questioning and ideally augmenting the questioning with time-motion studies — distributions of times that key activities take, and how different tasks and decisions in the model interact. This information can be subjected to computational modeling to identify and quantify measurable improvements of recommended solutions.

- Cognitive and decision modeling should be considered to improve the process. To more explicitly capture elements of the workflow that contributed to cognitive workload, decision making uncertainty, and potential for error, analysis of mental workload and decision processes and factors modeling should be conducted. The information derived from this analysis can also be incorporated into the aforementioned computational models.

Follow-On

- A plan should be provided to each site by the analysts to guide site personnel with integration and leveraging of findings generated by CSWFA. It will also be important for each site to communicate back to the analysis team how the results are used for training and implementation. This feedback will help the project team understand if Workflow Elaboration Sessions are eliciting the right level of data.

- Develop a training program for CSWFA project teams. The program should include informatics and workflow modeling training as well as the Microsoft Excel workbook training and documentation noted above to build capacity for CSWFA and to support larger-scale implementation rollouts for the EHR.

Much of the work on workflow analysis in healthcare IT has focused on improving the automation to develop and construct workflows[14] or on study of the impacts of EHR or other changes on the general process[15,16]. However, there is a dearth of past work on process improvement in the context of a formally modeled business process coupled with formal thematic analysis of the content. Some work has been conducted involving both modeling and analysis, conducting extremely useful high-level categorizations of challenging features of current-state workflow models[17]. The present study incorporates the entire process of modeling a workflow, subjecting its content to more rigorous qualitative analysis, and deriving actionable conclusions to be leveraged for near-term process improvement.

Conclusion

This study provides the overall methodology and lessons learned for conducting a current state workflow assessment and qualitative analysis following the implementation of a new EHR. Although the examples included describe a post-go live CSWFA, our methodology is replicable to all phases of EHR implementation. In fact, our previous engagements conducting CSWFA include those medical facilities that are preparing for transition to a modernized system. These assessments assist teams in identifying inefficiencies, as well as identifying areas where bottlenecks or productivity can be improved. CSWFA results and their application contribute to compliance and quality and may even inform job aids for system end users.

Limitations This study was conducted with healthcare personnel from one facility. Although the large integrated health system studied here has achieved an elevated level of national standardization, facility differences may be inevitable due to factors such as site organizational culture, facility size, and regional variations. Not only do these differences necessitate caution in generalizing the findings of one facility's CSWFA assessment to other facilities, but they also raise the point that conclusions regarding the CSWFA methods themselves will be strengthened – or revised – following the conduct of these assessments in other locations. Furthermore, we acknowledge that not all organizations may have access to the interdisciplinary expertise described in the Methods section.

Impact. The issues identified through the CSWFA process are reviewed following the assessment and routed to the appropriate party to be addressed, whether this entails workflow reengineering, system bug fixes/enhancement requests, or training/documentation solutions. A number of issues identified in the present assessment have already been addressed and are beginning to result in process improvements that positively impact the site studied and other sites. As the large integrated health system that participated in the present work continues deployment of new EHR systems across the United States, lessons learned about workflow and tooling – after being vetted for applicability across sites as noted above – can be applied to improve the current state at other sites in preparation for an EHR rollout.

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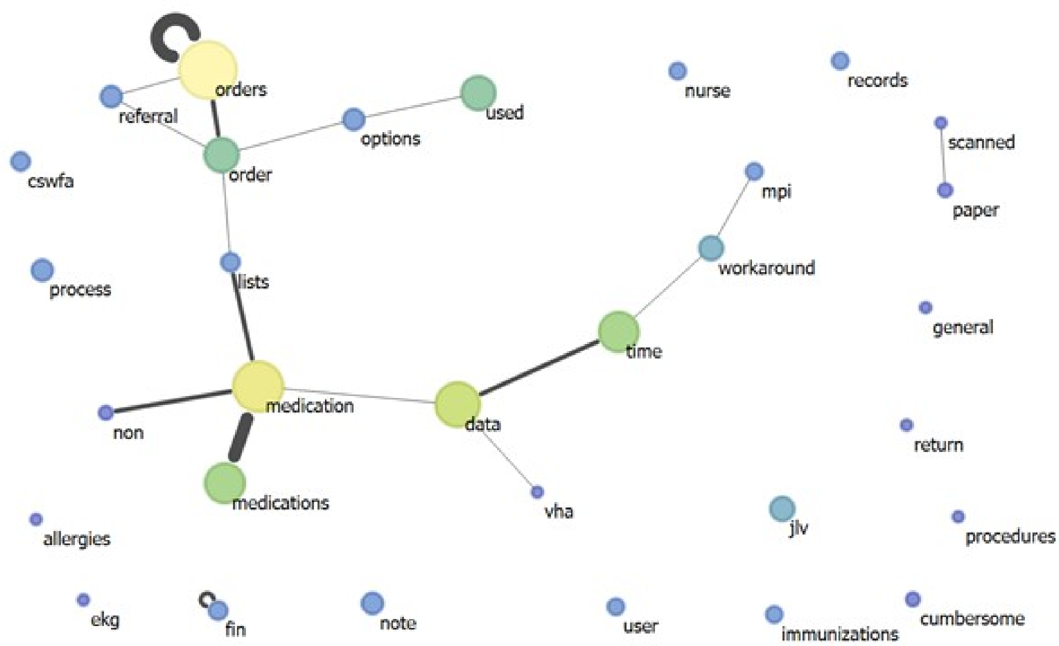
Figure 1 Guiding Questions for Workflow Elaboration Sessions

Sample Guiding Questions

- What roles/actors participate in this process?
- What information from activities lives in a system and which system? How are different systems harmonized? What is the core reason for duplication of information?
- What activities are performed outside of a system and are human driven?
- What initiates each transition of work between roles (electronic, verbal order, paper, other)?
- Are there any workarounds involved in completing an activity?
- Are there any Timing events (Hard stops/Hand offs) for the activities?
- What are the inputs and outputs of the work steps? Where are they recorded?
- Are there any devices used to complete a step?
- Are there any relevant policies for this activity/workflow?
- What type of critical information are you consuming and/or producing?
- What IT solutions are being utilized?
- What are your expectations of an ideal workflow?
- What are the most challenging aspects of the workflow?

Figure 2. Co-Occurrence Network of Key Terms from Primary Care Workflow Analysis



Note: Network visualization created using Orange: Data Mining Toolbox in Python[12]

Comment: threshold = 3; window = 1; frequency threshold = 3 in corpus to network widget

Table 1. Select Key Insights from Orders Management

Theme	Description
Inactive Order Options	Providers had more options to select than what was actually available. If the "wrong" orders were transmitted to the lab, then it was conveyed as an error. There are other options that can be selected and signed by providers in the system, but they cannot actually be acted on or moved forward for the patient.
Disappearing Orders	The "Manage Orders" module removed open orders from the provider's work queue that are pending physician approval. These orders disappeared from a patient's order list at midnight. When nursing re-ordered a medication, it re-appeared as a duplicate.
Nomenclature/ Naming of Orders	Providers faced incorrect orders/nomenclature issues. A return to clinic order can also be placed with other departments, but there was confusion because appropriate naming/nomenclature must be referenced.
Placing Orders	Overall, there was confusion in how providers placed orders. For example, Prosthetic and Sensory Aid Service (PSAS) assistive devices required orders from either a physical therapist or occupational therapist. However, the type of equipment was not linked with the provider. At present, some providers employed workarounds (i.e., used a working list via Microsoft Teams) to navigate the system to place the orders.

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Extracting Data from the Electronic Health Record of Patients with ADHD Reveals Pediatricians' Discussions of Educational Support and Document Collection

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Abstract

Primary care physicians (PCPs) have an important role in the identification and management of Attention Deficit Hyperactivity Disorder (ADHD). There is a paucity of research on PCPs' practices related to the discussion of educational interventions. We conducted a retrospective chart review using Natural Language Processing to extract data on how often PCPs in an outpatient clinic: 1) discuss educational support with patients and caregivers; and 2) obtain educational records. About three-quarters of patients had at least one term related to educational support included in at least one note, but only 13 percent of patients had at least one educational record uploaded into the electronic health record (EHR). There was no association between having an educational document uploaded into the EHR and inclusion of a term related to educational support in a note. Almost half (48 percent) of these records were unclearly labeled. Further education of PCPs is warranted to increase discussions of educational support and obtaining educational records, as is collaboration with health information management professionals around labeling.

Key words: Attention deficit hyperactivity disorder; educational records; electronic health record; primary care pediatricians; natural language processing

Background

Attention Deficit/Hyperactivity Disorder (ADHD) is among the most highly diagnosed and treated mental health disorders in children and adolescents[1]. To diagnose ADHD, data from multiple sources (including educational records) are needed to demonstrate that symptoms cause functional impairment[2]. For youths who have ADHD, impairment in academic performance often warrants educational interventions and related instructional supports[3]. School supports may include environmental accommodations, modifying assignment presentation, and positive behavior support plans, to name a few[4]. Some youths require a greater level of support under either the Individuals with Disabilities Education Act[5] or Section 504 of the Rehabilitation Act of 1973[6]. Primary care physicians (PCPs) are expected to be knowledgeable about these programs and services[7], and have an important role in counseling caregivers of patients with ADHD on obtaining such support[8].

In this study, we determined the extent to which PCPs in a single outpatient clinic bring up school supports during office visits for their patients with ADHD, and the extent to which they obtain educational records for their patients (e.g., report cards, 504 Plans, individualized education plans, etc.). We examined PCPs' documentation within the electronic health record (EHR) to approximate their behavior in patient encounters. Previous studies have examined the EHR for PCPs' medication prescribing practices[9,10] and recommendation of behavior therapy[11], additional mainstays of ADHD management. To screen PCPs' documentation for mentions of school support, we used Natural Language Processing (NLP), which systematically breaks down text into components using algorithms, methodologies, and tools[12]. Previously, NLP has been used in a wide range of clinical specialties, primarily for the purposes of disease classification[13].

While the aforementioned studies have involved examination of the EHR to understand PCP practices in medication and therapy recommendations for patients with ADHD, the extent to which PCPs address educational supports in patient encounters, and collect educational documentation, is unknown. Previous studies of PCPs' practices in recommending school support have focused on different patient populations or relied on self-report of practices, for example [14,15]. Given the crucial role for educational support in ADHD management, we sought to better understand PCPs' practices in this area.

Methods

We conducted a retrospective chart review of patients, ages 6-18, with an ADHD diagnosis using the Western Michigan University Homer Stryker M.D. School of Medicine EHR, Epic (Epic Systems, Verona, WI). The list of eligible patients was queried through the Virtual Data Warehouse using ICD-10 codes and SNOMED terms for ADHD. To be eligible, patients needed to attend at least two appointments for an ADHD-related or well-child office visit at a single outpatient clinic during the date range of July 1, 2018 to Dec. 31, 2019. We examined an 18-month timeframe to have the greatest opportunity of capturing multiple visits during the school year when educational documents are renewed and more easily obtained.

Patient descriptive data were extracted, including age, sex, race, ethnicity, insurance type, language preference, prescription of an ADHD-related medication, and whether they saw one of the institution's mental/behavioral health specialists (i.e., pediatric psychology or developmental-behavioral pediatrics [DBP]) during the study period. We also determined whether patients had neurodevelopmental disorders with high rates of comorbidity to ADHD, including autism spectrum disorder (ASD), specific learning disorder (SLD), and intellectual disability (ID). These were queried using the relevant ICD-10 codes.

To review provider notes for documentation of ADHD-specific educational support terms, encounter notes were electronically extracted from the EHR for analysis using Canary Natural Language Processing (NLP) Software. Canary was selected due to its performance compared to other software and NLP models[16]. Testing of the NLP algorithm was completed using a test sample of 50 notes (outside the timeframe of the study) known to include at least one of the search terms. The analysis was run iteratively until all instances of the chosen study terms were identified. For the full study data set, we reviewed appointment documentation for 25 percent of the subjects (15 percent of total notes) for accuracy of the NLP algorithm.

From these data, we determined the frequency with which educational support terms were documented in providers' notes. Dependent on sample size, the following categorical variables were analyzed using Chi square or Fisher's tests: gender, race, ethnicity, ADHD medication prescription, specialist involvement, comorbid diagnoses, insurance category, and presence of uploaded educational support documents. Age was the only continuous variable. It was not normally distributed; therefore, a Wilcoxon Rank Sum analysis was performed. All NLP-related analyses were performed using SAS v 9.4.

In addition, we manually screened all uploaded documents in patients' EHRs within the study period for educational documents, including those related to special education. We then determined whether the pertinent documents had been assigned clear titles in the EHR for ease of identification by clinicians. Clearly labeled documents were defined as those that had a match between the title on the originating document and the file upload title. To ensure data validity, a senior author cross-checked 10 percent of the data set. A concordance rate of 77.42 percent was achieved and the discrepancies were reconciled through consensus.

We used multivariable logistic regression models to determine patient factors associated with having at least one educational record uploaded into the EHR. The logistic regression model was fit with seven patient factors including sex, age, ADHD medication prescription, specialist involvement, and comorbid diagnoses (ASD, SLD or ID). Insurance, race, and ethnicity were not included in the model due to the small sample size in certain categories. We also calculated the odds ratios (OR) for interpretation of the results. Logistic regression analyses were conducted using R software (version 4.0.0).

The Western Michigan University Homer Stryker M.D. School of Medicine Institutional Review Board approved the study and informed consent was waived as the study involved no more than minimal risk to the subjects and appropriate steps were taken to ensure confidentiality.

Results

During the 18-month timeframe, 314 unique patients were identified with a total of 1,459 ADHD-related visits. On average, each patient had 4.6 visits (SD=2.4). The mean age was 11.2 years (SD=3.39 years), 69.7 percent were male, 99.4 percent indicated their preferred language was English, and 76.4 percent had public insurance. Approximately 90 percent of the patients were prescribed an ADHD medication, 64.3 percent had seen a behavioral health specialist at our institution, and 13.4 percent had a comorbid neurodevelopmental diagnosis. See **Table 1** for details of the patient sample.

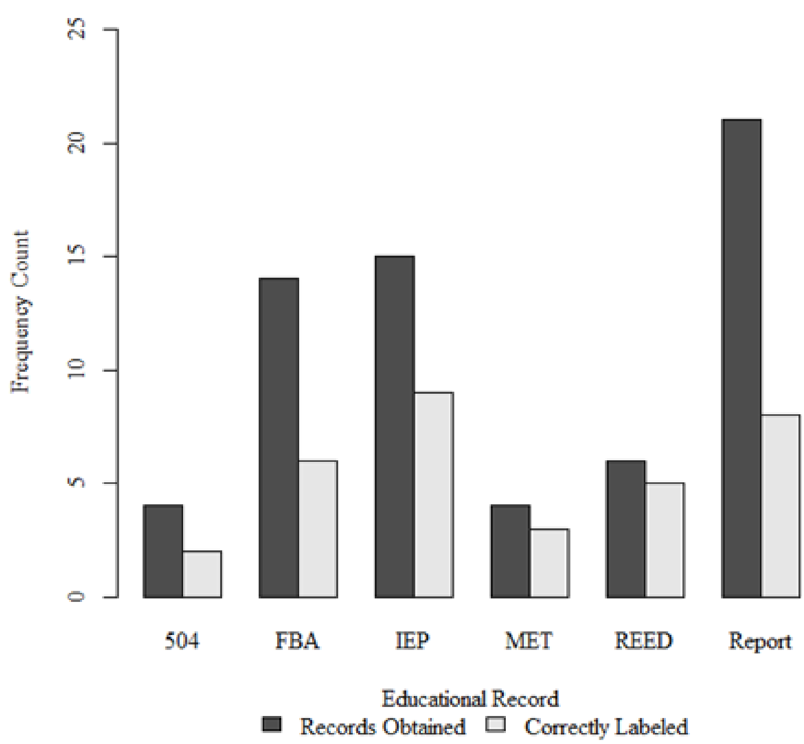
Overall, 231 (73.57 percent) patients had at least one mention of educational support in a clinical note during the study timeframe. The most frequently used educational terms for each patient are listed in **Table 2**.

Engagement with a behavioral health specialist increased the odds that a patient had at least one educational term included in at least one note ($p<0.01$). Race was significant with more White patients than Black patients having a mention of educational support in their notes ($p<0.05$) (**Table 3**). There was also a significant difference in age, with younger children more likely to have educational terms documented (M=10.94 years, SD=3.31 years for those with documentation compared to M=11.98 years, SD=3.53 years for those without; p<0.05). There was no association between inclusion of an educational support term in the encounter note and having an educational record uploaded into the EHR (p=0.4852).

A total of 64 uploaded educational records were identified in the EHR (see **Table 4**). Forty-one patients (13 percent) had at least one type of educational record uploaded into the EHR. Engagement with a behavioral health specialist increased the odds that a patient had at least one educational record uploaded to the EHR by 2.7667 times (p<0.05). One-unit increase in age decreased the odds that a patient had at least one educational record uploaded into the EHR by 0.9844 times (p<0.05).

Fifty-two percent of educational records were clearly titled within the EHR. See the Figure for details on the number of records obtained and labeling for each type of document. Unclear or incorrect titles were most often "outside correspondence" or an arbitrary document identification number. Some were also incorrectly labeled as a different type of educational document.

Figure: Educational Records Correctly Labeled in Electronic Health Record



Legend:

504=504 Plan

FBA=Functional behavioral assessment or behavior plan

IEP=Individualized education program

MET=Multidisciplinary evaluation team report

REED=Review of existing evaluation data

Report=Report card or progress report

Discussion

We examined PCPs' notes for pediatric patients with ADHD at an outpatient clinic to determine the extent to which they addressed educational support and obtained educational records during patient encounters. Overall, one-quarter of patients did not have any terms related to educational support in any of their notes, suggesting their PCP did not discuss this in either initial or ongoing treatment planning. This is concerning as educational interventions are recommended by the American Academy of Pediatrics (AAP) as part of the treatment of ADHD. Furthermore, only a minority of patients had any educational records uploaded to their EHR. There was no association between the presence of an educational document in a patient's chart and the inclusion of an educational support term in at least one note.

White patients and younger patients were more likely to have at least one educational support term included in a note, suggesting PCPs in our clinic addressed supports more with these populations. Younger patient age and involvement of a mental/behavioral health specialist increased the odds that educational records were uploaded. This may reflect PCPs' assumptions that older patients already have established educational supports so therefore do not discuss supports or solicit updated educational records. Studies on race and disproportionality in special education have yielded inconclusive results[17], but our small study would suggest that PCPs are less likely to counsel caregivers of Black youths on obtaining educational support, thus resulting in an incomplete discussion of ADHD treatment components. Future research could investigate the relationship of patient race, age, and PCPs' practices in recommending educational supports.

To our knowledge, this is the first study to investigate the presence of educational records in the EHR. This involved manual screening of each document uploaded during the study timeframe. This reflects the burden on investigators as well as clinicians; the EHR can contain many records, which may be either unclearly labeled or comprise hundreds of pages without clear document boundaries, making it hard to find specific records[18,19]. Another limiting factor of conducting research on uploaded documents in the EHR is that such documents are often viewable only in a specific institution's context, and not to researchers in other institutions who may share an EHR[20]. Often, the documentation is stored as a PDF or another image format, which does not export easily for database inclusion/analysis[21].

Our study also revealed the challenges of identifying records due to inconsistent health information management (HIM) standard labeling practices when adding documents into the EHR, necessitating manual search through numerous uploaded documents. In our study, only about half of the relevant documents had upload titles congruent with the originating document. In the future, appropriate training of HIM staff on the labeling of received educational records will allow more efficient access for clinicians (and researchers). Another approach would be using NLP approaches to reduce the burden of having to manually name and add individual educational records, though it is easier to conduct NLP with text than uploaded documents as the latter may require both NLP and optical character recognition with machine learning[22]. It may also help to provide a separate "tab" for educational information, like that which exists for laboratory and radiologic information.

Some limitations to our study include the fact that data were only from a single, small institution in the Midwest, and therefore reflected local practices that may not be generalizable to other locations or organizations. Also, given the retrospective chart review design, we assumed PCP behavior by their EHR documentation where inclusion of terms was used as a proxy for discussion of such topics during the actual encounter, which may not have reflected all actions or discussions that occurred during the encounter. There may be some instances when a PCP did obtain educational records and review them, but they were not saved to the EHR due to the PCP returning them to the family without obtaining a copy, or due to an uploading error.

Future studies should evaluate methods of care coordination that may enhance the number of records obtained. Often the burden of coordinating care falls to the caregiver, which is challenging to navigate for those unfamiliar with such processes or coping with multiple stressors and limited resources[23]. Teachers and caregivers both express an interest in sharing educational documentation with PCPs, and there have been some efforts to integrate medical and educational records[24]. However, school districts' electronic management systems for educational documentation are not always interoperable with medical EHRs. There is also the issue of the two privacy laws, Health Insurance Portability and Accountability Act (HIPAA)[25] for medical settings, and Family Educational Rights and Privacy Act (FERPA)[26] for school settings, which may be perceived as a barrier to sharing information. We suggest that while PCPs have tools available for ongoing treatment monitoring (e.g., follow-up rating assessments for parent and teacher), collection of educational information should be considered another "vital sign" of treatment as it provides valuable information about child academic and behavioral functioning. Pending any efforts for interoperability between school electronic systems and EHRs, this will require care coordination and system-level efforts as current ADHD portals also are unable to import educational data other than teacher rating scales (e.g., mehealth for ADHD tool)[27].

Conclusion

Our study demonstrates that PCPs do not appear to consistently address educational supports during visits with patients with ADHD based on NLP analysis. Furthermore, PCPs do not obtain educational records for most patients with ADHD, though involvement of specialists did increase the likelihood the records were obtained. There are currently several barriers to obtaining and locating educational records in the EHR, which need to be addressed for PCPs to advocate for families and optimize the care of pediatric patients with ADHD. Additionally, while NLP improves the efficiency of EHR analysis, caution should be exercised when interpreting results of these analyses as documentation may not be a true reflection of topics discussed at the visit.

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Tables & Figures

Table 1: Patient Characteristics (N = 314)

Characteristic	**Variable**	**n (%)**
Sex	Male	219 (69.7)
	Female	95 (30.3)
Race	White or Caucasian	186 (59.2)
	Black or African American	99 (31.5)
	Multiracial	16 (5.1)
	Unknown	5 (1.6)

	Other	8 (2.5)
Ethnicity	Hispanic/Latinx	21 (6.7)
	Not Hispanic/Latinx	285 (90.8)
	Unknown	8 (2.5)
Preferred Language	English	312 (99.4)
	Sign language	1 (0.3)
	Unknown	1 (0.3)
On ADHD Medication	Yes	283 (90.1)
	No	31 (9.9)
Insurance	Commercial	70 (22.3)
	Public	240 (76.4)
	Self-Pay	4 (1.3)
Seen By Specialist	Yes	202 (64.3)
	No	112 (35.7)
Has an Additional Diagnosis	Autism Spectrum Disorder	20 (6.4)
	Specific Learning Disorder	16 (5.1)
	Intellectual Disability	6 (1.9)

Note: "Specialist" refers to developmental behavioral pediatrics or pediatric psychology

Table 2. Frequency of educational terms in notes by patient.

Term	Patients with mention in note, N (# patients)	Percent of patients with mention in note, % (N/231)
1:1 Aide/One-to-One Aid/Aide	13	5.63%
Accommodations	5	2.16%
Paraprofessional/Parapro	4	1.73%
Academic Intervention Service/AIS	1	0.43%
Academic Learning Plan/ALP	2	0.87%
504 Plan/504	99	42.86%
Individualized Education Plan/IEP	179	77.49%
School Assessment	1	0.43%
School Testing	1	0.43%
School Evaluation	5	2.16%
School Support	0	0.00%
School Programming	26	11.26%
Special Education	32	13.85%
Resource Room	3	1.30%
Behavioral Intervention Plan	12	5.19%
Functional Behavioral Analysis	0	0.00%
Psychoeducational	1	0.43%

Table 3. Frequency of educational support note documentation by characteristic.

Characteristic	**Variable**	**Educational support term included in note** **n (%)**	**Educational support term not included in note** **n (%)**	**p-value**
Sex	Male	165 (75.3)	54 (24.7)	0.2787
	Female	66 (69.5)	29 (30.5)	
Race	Multiracial	9 (56.3)	7(43.8)	0.0198*
	Black	73(73.7)	26 (26.3)	
	White	140 (75.3)	26 (14.0)	
	Other	6 (75.0)	2 (25.0)	
	Unknown	3 (60.0)	2 (40)	
Ethnicity	Hispanic	19 (90.5)	2 (9.5)	0.1688
	Not Hispanic	206 (72.3)	79 (27.7)	
	Unknown	6 (75.0)	2 (25.0)	
Prescribed ADHD Medication	Yes	211 (74.6)	72 (25.4)	0.2823
	No	20 (64.5)	11 (35.5)	
Seen By Specialist	Yes	163 (80.7)	39 (19.3)	0.0001*
	No	68 (60.7)	44 (39.3)	
Comorbid Diagnosis	Yes	33 (84.6)	6 (15.4)	0.0945
	No	198 (72.0)	77 (28.0)	
Insurance	Public or Self-pay	185 (75.8)	59 (24.2)	0.0910
	Commercial	46 (65.7)	24 (34.3)	

Uploaded Educational Record	Present	32 (78.0)	9 (22.0)	0.4852
	Not present	199 (72.9)	74 (27.1)	

Note: *****Significance at $p<0.05$

Table 4. Educational records upload frequency.

Document Type	**N**
Review of Existing Evaluation Data	6
Eligibility Recommendation	0
Multidisciplinary Evaluation Team Report	4
Individualized Education Program Report	15
IEP Progress Report OR Report Card	21
504 Plan	4
Functional Behavioral Assessment	14
Behavior Support Plan	0

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