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Using Telehealth to Provide Behavioral Healthcare to Young Adults and College Students

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Abstract

The suicide rate remains the second leading cause of death for young adults and increased by 33 percent between 1999 and 2019.[1] Also, it is the fourth leading cause of death among people ages 35-44 and the fifth leading cause among people ages 45-54, making suicide a problem not unique to only the university community; it is problem all across the country.[2] The 2021-2022 academic year will also be mentally challenging to students returning to campus and those taking online classes due to COVID-19. The World Health Organization Situation Report published August 1, 2020, reported 4,456,389 confirmed cases and 151,265 deaths.[3] However, most universities reopened their campuses in the fall of 2021. As universities may have limited social events, some students, particularly freshmen, may feel isolated. Social distancing can also cause stress levels among students to increase. This research investigates the perception of students about the need and use of telehealth and virtual appointments to provide students additional opportunities to receive the care they need. Most students were born in the information age and welcome technology as a tool to solve problems.[4] The authors determined that providers can use mobile platforms to solve health problems. Regarding the full-scale replacement of health services with telehealth, the participants did not believe this was helpful and efficient. The authors determined that if healthcare providers implement telehealth, particularly in remote university campuses and rural areas, it will help to improve behavioral health on university campuses.

Keywords: telehealth, behavioral health, students, COVID-19

Introduction

Nature of the Problem

Within the United States, there has been a mental health crisis going on for years, and we continue to see its prevalence every day. The National Alliance on Mental Illness reports that approximately one in five adults experiences mental illness each year, equating to about 51.5 million people in 2019; the prevalence rate for young adults was the highest.[5] Even though nearly 13.1 million of the adult population suffers from severe mental health illness, 8.6 million received treatment, which is about 65 percent.[6] The implication is that not having access to care is a significant cause of not receiving the necessary treatment. In fall 2021, many schools are reopening, and some students will go back to campus. Most students may feel isolated while on campus. The older teens and young adults who are transitioning from their inherited families to their chosen families are mostly affected.[7] The isolation can lead to difficulty concentrating and decision-making because students may not have the needed face-to-face interaction with their instructors and peers. Some students may increase the use of substances, including tobacco, because they may believe in using such substances as a solution to their problems. Students with existing mental health conditions may experience worsened situations due to limited interactions. Healthcare stakeholders must make it possible for students to receive mental health treatment as colleges observe social distancing.

Purpose of the Research

This research aims to explore various health information and technology approaches and strategies to pursue high-quality medical care delivery for isolated and rural areas, particularly in college towns. Providers can create behavioral health facilities that will use telehealth platforms to help students access the mental health services they need. Telehealth services can be timely and cost-effective and still be able to administer high-quality behavioral healthcare. The primary reason for focusing on isolated colleges is because of a lack of accessibility to a continuum of care. Healthcare providers may not invest in establishing robust facilities in isolated areas where they cannot generate revenues for their investments. Technology, salaries, and other related costs drive facility location strategies. Telehealth might be economical to use in such areas.

COVID-19 can worsen mental health problems across all ages. The World Health Organization (WHO) Situation Report published on August 9, 2021, reported a global 202,138, 110 confirmed COVID-19 cases, and 4,285,299 associated deaths.[8] Many colleges and universities plan to have face-to-face lectures starting in fall 2021. Unfortunately, such a mode of delivery requires students to be on campus. Due to social distancing and strict rules to reduce the spread of the coronavirus, many students may feel isolated from friends and families. Mental health issues on campus can increase. This research investigates students' perceptions regarding the need and use of telehealth, particularly in the coronavirus pandemic period.

Hypothesis and Significance to Healthcare Providers

The null hypothesis is as follows: College students express no support for the use of telehealth for behavioral health care services. Due to legislative changes over the past few years, more people are being treated with telehealth and have insurance to help them receive the treatments they need. However, suicidal ideation and youth depression rates are still rising.[9] One of the reasons is due to a shortage of mental health professionals. The Health Resources and Service Administration reported 6,010 mental health professional shortage areas, and 6,849 practitioners are still needed.[10] While the amounts of uninsured have dropped, there is still limited access. Thus, the utilization of telemedicine can make a difference.

Background and Literature Review

Overview

A National Institute of Mental Health report shows that nearly half of all mental health illnesses begin by age 14 and 75 percent by age 24. The implication is that college students and young adults are the most likely age group affected by severe mental illness in the United States.[11] When the institute used demographic groups to classify mental health, the percentage of mental health patients in the lesbian, gay, or bisexual group was as high as 44.1 percent.[12] In 2018, the second leading cause of death for the age group 14-25 was suicide, which can happen due to mental illness.[13]

Current Environment on Campuses

Mental Health on College Campuses. Research conducted by the University of Michigan on nearly 65000 students at 81 universities and colleges suggests that 35.5 percent of undergraduate students met the criteria for at least one mental health problem. Of that population, only 39.4 percent have received treatment in the past year.[14]

Research conducted at Franciscan University concluded that of their student participants, 11 percent had severe or extremely severe depression, and 15 percent had severe or highly severe anxiety.[15]

Many factors cause suicidal ideation on campuses. Research suggests that there is an association between low social support and suicidal ideation. A feeling of hopelessness has a strong association with suicidal ideation.[16]

Ways to Combat Mental Health

Mobile applications. Current trends within behavioral health are showing that the use of telehealth and telepsychiatry is promising. Results of a study conducted by Hubley, Lynch, Schneck, Thomas, and Shore concluded that patients show satisfaction with telepsychiatry. Also, telepsychiatry is more cost-effective.[17]

The accessibility of mobile devices allows patients and providers to change the way behavioral health is delivered. The addition of human support on the back end of these applications expands access to care to those who previously could not do so.[18] In a review of 21 articles by Lui, Marcus, and Barry, findings suggest that the use of applications and mobile games focused on attention bias is associated with a significant anxiety reduction compared to controlled groups as well as a reduction in depressive symptoms. The review also suggests a substantial decrease in comorbid symptoms.[19] In a large-scale empirical research study, evidence suggests the use of mobile or internet-based care increases access to patients. Such mobile devices are a viable treatment for depression and anxiety and become more cost-effective as more patients use them.[20] Research conducted on the usability and willingness to suggest an online tool found that those in the treatment group would recommend the service to a friend. The authors found that participants were satisfied with the program, and it helped them deal with their issues.[21]

Methodology

The authors used a survey as the primary method to collect data on university students who reside on university campuses. The survey was anonymous and randomized. However, it was specifically delivered to college students in colleges isolated from cities. The survey was not tested prior to the distribution. However, the authors believe college students have adequate knowledge to respond to the survey questions correctly for the results to be valid and reliable. The survey focused on personal exposure to mental and behavioral health, usage and knowledge of existing services provided, and comfortability with a telehealth option if provided. The primary data gathered focused on the student perspective of undergraduate and graduate students. Five colleges from three states participated. Of the 200 targeted students, 72 students participated. The response rate was 36 percent. To assure the sample reflects the population, students who consented to participate in the survey provided their school email that was used. However, the survey was anonymous, and the participants' names and colleges were deidentified.

Students age 18 to 34 could participate. The survey was administered electronically to increase student participation, and the authors sent reminders. Age and gender are asked to be able to get population data of those that completed the survey. Questions about insurance coverage and knowledge on telehealth were helpful to determine the health literacy and insurance coverage of the students on campus.

Results

Seventy-two students randomly participated. Of the responses, 48 were female, and 24 were male, making a 2:1 ratio. The age range of the majority of the respondents was 19 to 21 years old at 55.6 percent. When asked about health insurance, 95.8 percent of respondents marked yes. Freshmen and sophomores made up the majority with 27.8 percent and 30.6 percent, respectively. The next largest group was graduate or nontraditional students at 18.1 percent. Getting into the survey information, 22.2 percent of students had heard of telehealth. Respondents answered that 12.5 percent (nine of 72) had been diagnosed with depression or anxiety (**Figure 1**).

When asked if someone close to them had problems regarding mental health in the last two years, the authors found that the majority of students, 52.8 percent, have had a friend or family member with mental or behavioral health problems in the last two years. Also, 30.6 percent had personally experienced a mental health issue within the past two years (**Figure 2**).

When asked if they had ever seriously considered harming themselves, 18.1 percent responded yes, and when asked about taking one's life, 6.9 percent answered yes. These results are represented in **Figure 3** and **Figure 4**.

Regarding knowledge of the services on campus available to students, they responded strongly at 69.4 percent that they knew what services were available, and 15.3 percent had attempted to schedule an appointment at the counseling center. The final questions were to look at the likeliness of speaking to someone at the center or virtually. When asked if they felt comfortable talking to someone at the counseling center, students responded at 37.5 percent for “yes,” 41.7 percent for “maybe,” and 20.8 percent for “no” (**Figure 5**). When asked about speaking to someone virtually, the “yes” answers increased to 38.9 percent, “no” increased to 30.6 percent, and “maybe” dropped to 30.6 percent (**Figure 6**).

The final question revolved around the students’ view on a mobile application to intervene with self-harm behaviors. The respondents answered “yes” for the majority at 65.3 percent, followed by “maybe” at 20.8 percent, and 13.9 percent at “no” (**Figure 7**).

Discussion

Of the responding students, we had 66 percent female and 33 percent male who participated. The result suggests that female students might be interested in solving health issues more than males. When we removed graduate students from the calculation, the ratio remains the same. However, further research and a larger sample size across campuses are needed to ascertain this research finding. When asked if they had heard of telehealth, the majority of students that had were graduate students. Only four of those who responded were undergraduate students. The outcome suggests graduate students are more knowledgeable about treatment options than undergraduate students. When asked if they had been diagnosed with depression, the nine “yes” responses comprised eight females; seven of those eight were either freshmen or sophomores. This population is most likely to be living on campus, so they will be the most critical population to monitor their mental health status. Besides, the outcome suggests some freshmen and sophomores have not yet been fully independent after graduating from high school. The academic rigor and research requirements from instructors might challenge these groups.

When asked about mental health within the last two years, nearly 64 percent have been around someone dealing with mental health problems or have personally had problems with mental health in the previous two years. Though students may know more about mental health, it is ideal for counselors to expose them to react appropriately to mental health situations they experience.

The following two questions were concerning self-harm and suicidal ideation. When asked about serious thoughts about self-harm, 18 percent of the students responded “yes,” and for just undergraduate students, it was 17 percent. This percentage is very close to the 19 percent reported by the National Alliance on Mental Illness. When asked about suicidal ideation, the percentage was 7 percent, which is two percentage points higher than the NAMI reporters of 4.6 percent and lower than the reported age group number of 11 percent for people ages 18 to 25. This lower percentage might be due to the nature of students who participated. Female students participated twice as much more than male students, and the suicide rate for females in the age group is lower than that of males.

When asked about willingness to talk to someone at the counseling center for behavioral health issues, there were 27 responses for “yes,” 15 for “no,” and 30 for “maybe.” That leads to a nearly 2:1 ratio for yes to no. The response demonstrates the desire for students to solve mental health problems when diagnosed. If colleges and universities plan to implement mental health counseling, it must be robust enough to attract most students’ attention. When asked if they felt the need to speak with someone about their mental health virtually when needed, it was split much more evenly at 38.5 percent “yes,” 30.5 percent “no,” and 30.5 percent “maybe.” This result is not very encouraging for the use of therapy sessions on a mobile application, but the result was much different when looking at crises. Students were very responsive to the use of virtual means to intervene in crisis situations, with 65 percent responding “yes” and 14 percent “no.” The response demonstrates that the students believe that virtual means can help someone considering self-harm.

Conclusion

While we do not know for sure that telehealth services would prevent suicide, it was evident that students will be interested in the services. However, some students are unsure about how telehealth will help improve behavioral health. If possible, colleges and universities could include a freshman class on mental health to help students become well-educated on this issue A limitation of the research consists of the low number of participants. The authors plan to increase the sample size to have more reliable findings. Including other colleges from many states could help make future research more valid and dependable. For future research, the authors plan to explore how students’ majors and fields of study influence their desire to use telehealth services.

We propose funding telehealth mobile technology to be a significant portion of federal budgets. Such budgets include those for improving public health informatics and technology. The results may vary as we expand the scope of our future research in other regions of the country.

Third-party payers, particularly the Centers for Medicare and Medicaid Services, could continue to reimburse telehealth providers even after the COVID-19 pandemic. However, government agencies must regulate such services to ensure they are similar to typical provider visits. The authors propose that colleges, universities, and providers could give preferences and more attention to the young adults in the lesbian, gay, bisexual, transgender, and queer group. As noted in the literature review, this group has a higher chance of having mental health issues. In addition to the telehealth treatment options, this group may need counseling and guidance, even on college campuses. The data provided by the National Alliance on Mental Illness was significantly high. If they experience isolation and intimidation on campuses, they risk having mental health issues.

There is also a need to exclude certain patients from participating in the services based on the need for thorough mental health assessments. Though any HCPCS or CPT code can safely and appropriately be rendered at a distance, the authors suggest the following services be excluded from telehealth services: G0425-G0427: Initial Telehealth Consultations

It is also ideal for universities to improve mental health counseling to reduce suicidal rates on campuses. The majority opinion showed that they believe that a crisis situation could be mitigated by using this type of service. We hope that the use of telehealth remotely will improve the treatment of behavioral health issues on isolated college campuses. The authors hope that patients and providers will eventually use telehealth intensively in healthcare if third-party payers approve reimbursements. If students embrace its use in remote areas, it can also become easier for their parents to embrace the services. The authors hope to expand the research by involving more young adult population.

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Using Health Information Technology to Create Pathways for Hepatitis C Treatment and Cure in West Virginia

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Abstract

This case study describes use of health information technology for enhanced team-based care and care coordination between primary care providers and infectious disease specialists for curing and eventually eliminating hepatitis C in West Virginia. This program, the West Virginia Hepatitis Academic Mentoring Partnership, aims to improve outcomes of West Virginians with chronic hepatitis C infection by training and supporting primary care providers to screen, diagnose, evaluate, treat, cure, and follow patients in the community rather than referring them to distant specialists with long wait times. This initiative supports health equity by increasing access to quality care in severely under-resourced rural areas. Primary care providers engage with hepatitis C experts in a web-based training and mentoring process, combined with informatics training in use of a customized Research Electronic Data Capture (REDCAP) platform for secure data tracking and bidirectional communication. This use of an informatics platform available to all partners supports shared decision-making between primary care providers and specialists, fostering a primary care learning network for improved hepatitis C care in West Virginia.

Keywords: health information technology, team-based care, hepatitis C, REDCap

Introduction

The burden of chronic hepatitis C virus (HCV) infection in West Virginia is severe, with an extremely limited number of specialists located in urban centers and none in rural areas. The West Virginia Academic Mentoring Partnership (WVHAMP) aims to improve the health outcomes of West Virginians with HCV by training and supporting primary care providers (PCPs) and addiction care providers to screen, diagnose, evaluate, treat, and cure people in the community rather than referring patients to distant specialists with long wait times. This case study describes the role of WVHAMP in supporting team-based care for curing HCV through optimizing health information technology (HIT) designed to support real-time communication between providers and specialists, develop provider-level patient registries, and facilitate statewide surveillance for the goal of HCV elimination. This initiative supports equity in healthcare access for more rural, geographically, and socially isolated patients. This study was reviewed by the West Virginia University (WVU) Institutional Review Board and granted exempt status (Protocol number 2109406918).

Background

HCV infection remains a significant public health problem globally despite recent advances in curative treatment.[1-5] Untreated, HCV can cause cirrhosis, liver cancer, end-stage liver disease and death. Worldwide, approximately 71 million individuals have chronic HCV,[6] with about half unaware they are infected.[7] Deaths due to HCV are staggering, with approximately 339,000 deaths globally in 2016 and approximately 16,000 deaths in the US in 2018;[8,9] in fact, deaths due to hepatitis C now outnumber deaths due to human immunodeficiency virus (HIV)/acquired immunodeficiency syndrome (AIDS) and is the most common infectious cause of mortality in the US. The public health burden of HCV is especially pronounced in more rural, socioeconomically challenged areas that have HCV infection rates double that of urban areas.[10] This substantial increase in infection rate is primarily due to transmission via shared use of equipment for injecting drugs.[11-13] Furthermore, HCV diagnosis can be elusive, as it is frequently asymptomatic until it progresses to more advanced stages in approximately 80 percent of cases.[14] Fortunately, combination antivirals can cure at least 95 percent of cases, significantly reducing the risk of associated morbidity and mortality.[15-17] Access to treatment remains limited, however, especially in under-resourced rural areas, resulting in significant healthcare inequities.[18] Increasing access to curative treatment is essential and not only benefits those who are infected but also limits ongoing transmission similar to the concept of “treatment as prevention” for HIV.[19,20]

West Virginia, the only state located entirely within Appalachia, is a critical area for innovative approaches to improving health equity regarding the treatment and cure of HCV. Approximately 45 percent of the state’s population lives in rural areas, and about 18 percent lives in poverty.[21] As of 2017, West Virginia ranks first in the nation in acute HCV incidence, with 9.1 cases per 100,000 (**Figure 1**).[22-24] HCV cases have been steadily increasing in West Virginia since 2010 at nine times the national average due to the prevalence of injection drug use, as West Virginia has had the highest US rate of fatal overdoses for the past decade—currently at 52.8 deaths per 100,000 population.[25] Medicaid costs alone for treating HCV exceeded $27 million from 2014-2016.[26] Rurality, mountainous terrain, lack of public transportation, and poverty all constitute significant obstacles to healthcare access. These challenges, coupled with a lack of available specialists to treat HCV, spur disparities in access to curative HCV treatment (**Figure 2**).[27-29] Enhanced use of HIT for team-based care in the successful management of HCV is essential.

The goals of WVHAMP are to: 1) recruit and train PCPs and addiction care providers practicing in safety-net settings such as federally qualified health centers, community hospitals, and rural clinics in high-risk communities; 2) establish a primary care workforce throughout the state capable of curing persons with chronic HCV infection, including high-risk, low-resource rural settings, removing barriers to HCV care in the community; and 3) increase the number of West Virginians who are successfully linked to care and cured, thus advancing the goal of HCV elimination in West Virginia. Patients receive treatment in their own communities from familiar, trusted providers, overcoming transportation barriers to and costs associated with referral to care in urban settings and avoiding travel to distant specialists with long wait times for an appointment. Overall, this initiative is grounded in the need to improve access to HCV treatment and cure for individuals in high-risk, low-resource rural areas by removing long-standing barriers to care, including West Virginia Medicaid’s requirement that PCPs treat HCV under the guidance of a specialist.

Methods

WVHAMP,[30,31] an adaptation of foundational efforts developed in Kentucky,[32] aims to improve the health outcomes of West Virginians with chronic HCV infection by equipping safety-net primary care providers with web-based training and ongoing mentoring from infectious disease specialists to implement the “cascade of care” for HCV: from screening follow-up after cure. HCV cure is defined as a “sustained virologic response,” which means that a blood test done to detect the virus by a nucleic acid test is below the limit of detection 12 weeks after the patient completes treatment. This is termed SVR12. In terms of HIT and supportive analytics, WVHAMP is based on the use of a secure, HIPAA-compliant data system via Research Electronic Data Capture (REDCap)[33] that allows for consult submission, data tracking, and bidirectional communication between local providers and specialists via internet access from any location. REDCap, originally developed and supported by the National Center for Advancing Translational Sciences, offers a secure platform for building and managing online data collection and analysis. A specialized REDCap database for WVHAMP was constructed around four key data domains: 1) patient demographics and health history; 2) provider location; 3) initial consultation between provider and specialist; and 4) follow-up consultation for determining treatment outcome. At each stage of the data collection process, the data system provides auto-notifications and real-time reporting to ensure dialogue among the health care team members for care coordination. Automated triggers in the data system notify specialists of the incoming consult and, in turn, notify the provider submitting the consult when the review has been completed. Turnaround time is under 24 hours for response to consults. By virtue of using the system, both provider- and healthcare-system level patient registries are created, and statewide surveillance is supported for all individuals treated for HCV through WVHAMP. This informatics-based approach better positions safety net clinics to engage in team-based care as per the National Committee for Quality Assurance Patient-Centered Medical Home model[34] in which many primary care clinics are already engaged. The approach also supports evaluation of the effectiveness of the intervention through data collected at each interaction across the care team.

The multidisciplinary WVHAMP team includes health services researchers with expertise in data-informed quality improvement and practice-based research within the WVU School of Public Health Office of Health Services Research;[35-39] infectious diseases clinicians in the WVU School of Medicine Departments of Medicine and Behavioral Medicine and Psychiatry with expertise in the infectious diseases associated with injection drug use;[40-44] a nurse with expertise in HCV treatment and systems approaches to HCV healthcare delivery;[45] and leadership from the West Virginia Rural Health Association that provides infrastructure to support WVHAMP.[46] This study aims to describe the role of WVHAMP in supporting team-based care for curing HCV through optimizing HIT designed to support real-time communication between providers and specialists, develop provider-level patient registries, and facilitate statewide surveillance for the goal of HCV elimination.

Results

To date, 97 PCPs and addiction care providers have been trained as WVHAMP scholars. Among those trained, more than half are from West Virginia counties designated as rural by the Health Resources and Services Administration Federal Office of Rural Health Policy, underscoring the benefit of WVHAMP to health equity in rural communities. From April 2020 through September 17, 2021, 308 consults have been submitted by 25 scholars for review and case discussion. Of the 92 patients who have reached the time point to assess cure or “SVR12” after completing therapy, 90 have achieved an SVR12 for a 97.8 percent cure rate. Ninety percent of patients achieving cure have been West Virginia Medicaid enrollees. This success is among providers who have not previously treated HCV. This success rate is similar to that achieved by specialists,[47-49] demonstrating that WVHAMP provides a model for successful HCV care in rural communities and a step towards statewide HCV elimination. HIT-enhanced team-based care can improve equity in HCV treatment by facilitating cure in underserved rural areas.

Discussion

This case study describes use of HIT for enhanced team-based care and care coordination via bidirectional communication and data sharing between PCPs and infectious diseases specialists for curing and eventually eliminating HCV in West Virginia. The WVHAMP program emphasis is on provider education and mentoring, supported with secure informatics tools for data tracking, communications, and shared decision-making. The success rate in curing HCV is on par with that of specialists, making this program a viable model for treatment and cure in other rural and underserved areas.

WVHAMP is aligned with the current healthcare landscape of the state, and the strength of the initiative and its potential for sustainability is bolstered by the following factors. First, Medicaid expansion through the Patient Protection and Affordable Care Act[50] has increased healthcare coverage, allowing more patients the opportunity to access healthcare. Second, West Virginia has higher rates of primary care physicians, in particular family physicians, per capita than the national average who can be engaged in HCV care with appropriate ongoing education and support.[51] Third, West Virginia has a well-established network of federally qualified health centers (FQHCs) that act as a primary care safety net for underserved communities. The 31 FQHCs in WV encompass nearly 300 locations and serve approximately one in four West Virginians.[52] While knowledge of and experience with curative HCV therapy has been largely restricted to specialists (hepatologists, gastroenterologists, and infectious diseases physicians), their number is extremely limited statewide and concentrated in urban areas. WVHAMP provides an opportunity to overcome this disparity in access to HCV care. Lastly, West Virginia Medicaid requires PCPs who treat HCV to do so under specialist guidance and oversight. WVHAMP meets this need, while equipping PCPs with the knowledge and skills for successful HCV treatment. Given the success rate of WVHAMP scholars in curing HCV and the supportive environmental factors, it is reasonable to consider that this health informatics-supported team-based care model can not only be further disseminated within West Virginia but can also potentially serve as a model for other states aiming to improve health equity in treating individuals with HCV in underserved rural and urban areas.

Conclusions

WVHAMP has demonstrated that primary care and addiction care providers can deliver HCV treatment with the same success rate as specialists. HIT-supported team-based care is having a positive impact on the ability of rural PCPs to successfully treat and cure HCV in the community. In turn, patients can retain continuity in care at their medical homes and avoid the difficulties associated with referral to distant specialists. This use of an informatics platform available to all partners supports shared decision-making between primary care providers and specialists, fostering a primary care learning network for HCV treatment.

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Telehealth in Primary Health Care: A Scoping Review of the Literature

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Abstract

Background: The use of telehealth as a viable mobility to deliver quality services steadily increases in various levels of the health system. Despite the increasing use of telemedicine in secondary and tertiary health care services, there is a long way to go in the use of this technology in public health and primary health care (PHC). This study aimed to explore the features, approaches, and various dimensions of telehealth in PHC.

Methods: A scoping review was conducted using the Arksey and O'Malley framework. A search was conducted in three bibliographic databases including PubMed, Web of Sciences, and Scopus and in Google Scholar to collect papers published in November 2018 to 2000. Data were extracted according to a predefined form and check for completeness and accuracy by a second reviewer.

Results: Through reviewing papers, the authors extracted information on the general characteristics and features of telehealth services, kinds of PHC services delivered via telehealth, hardware and software facilities used for providing health care through telehealth services packages, as well as their benefits, outcomes and obstacles.

Conclusion: Telehealth can be used for different purposes of PHC through deploying a full range of communication channels available to the public. Due to the opportunistic use of existing devices and platforms, telehealth can provide scalable PHC services nationwide and worldwide. However, implementing telehealth in PHC faces challenges from technical, organizational, and human perspectives. Digital equity (in terms of technology access and e-health literacy) is required to expand telehealth services to the populations in underserved areas.

Keywords: telemedicine, telehealth, primary care, general practice, family doctor, services, guideline, package

Introduction

Advancement and accessibility of healthcare services are among the measures of a society's development. Recent progress in telecommunication technologies has further emphasized the global importance of access to healthcare. It has impacted the methods of medical care and healthcare delivery and, as a result, remote access to health-related services known as telehealth has emerged as one of the most effective paradigms to improve the accessibility of health services.[1-5]

National healthcare systems are under pressure to provide prompt, accessible, and high-quality healthcare in cost-efficient ways.[6,7] By bridging the distance between care providers and receivers, telehealth can provide healthcare to hard-to-reach areas and help solve some of the issues patients face within the healthcare system. Telehealth is a new approach to delivering remote health services via real-time communication between the patient and the healthcare provider, using electronic audio and visual means.[7,9-11] With telehealth, information is exchanged over communication networks to monitor the health status of patients and to offer clinical recommendations, consultations, treatment, education, and administrative services.[1, 2, 5,12-14]

Telehealth has various benefits in primary health care (PHC), ranging from seamless access to health services for people in remote places to self-management promotion, patient empowerment, cost reduction of unnecessary referrals, and decreasing the need for commuting to seek medical care. Physicians can share information via telehealth channels for better clinical education, faster diagnosis, disease prevention and quicker therapeutic interventions. [1,2,5,11-13,15-18] Telehealth services also open up a new way of communication among patients and family caregivers and improve the sharing of critical information and experiences.[14] Use of this technology can also incentivize physicians to recruit and retain in remote and rural areas by allowing them to remotely communicate with their colleagues and take advantage of long-distance education.[19] The health system can also overcome the issue of limited resources and facilities by utilizing telehealth.[20]

In PHC, telehealth can usually be offered when a patient is seeking the doctor's advice about a non-emergency medical problem. It does not replace face-to-face consultation, but complements it by offering timely PHC services in areas facing logistical hurdles to receiving secondary health care.[1-3] PHC as the first contact point of population with health system aims to achieve the equity in population access to the health services.[21,22] Telehealth can contribute to this aim and overcome the challenges.[23-25]

In this paper, we aim to determine the characteristics and components of telehealth packages through a scoping systematic review by answering the following questions:

1. What are the general characteristics of telehealth in PHC?

2. What kinds of PHC services can be offered in the form of telehealth?

3. What facilities are used for providing PHC through telehealth?

Methods

This study is a scoping systematic review, and the methodology for this review was based on the framework outlined by Arksey and O'Malley.[26] The researchers carried out a preliminary scoping search to determine a terminology for establishing the search terms of the study.

Data Sources and Search Strategy

We searched three electronic databases including PubMed, Web of Science, and Scopus. Google Scholar was also searched for relevant articles published in November 2018 to 2000. The combination of the following keywords, including Telemedicine, Telehealth, Primary Care, General Practice, Family Doctor, Services, Guideline, Package, Primary Health Care, Primary Healthcare, were used to find the studies.

Figure 1 shows the process of articles' selection.

Inclusion criteria:

- The focus of the study is on the telehealth in PHC
- All types of the study

Exclusion criteria:

- Non-English studies
- Papers where the full text was not available

Data Extraction

Two of the researchers (LB and LRK) examined the full text of all the included studies independently. They extracted data from fully eligible studies into a predefined form. The data extraction form was used including information on: title of the study, author(s)' name, study type, stud year, study population age, tools/equipment used to provide telehealth, telehealth mode (synchronous or asynchronous), providers involved in telehealth, period of the telehealth delivery, intervention group, control group/s if applicable, the reason for telehealth, intervention type, telehealth outcome, target group of telehealth, and clinical and non-clinical equipment parameters used in telehealth. Any disagreement about the extracted data was resolved by the third researcher (LD).

Results

Out of the 3,823 articles identified from the electronic literature search, 115 were duplicates and were therefore eliminated. After screening the title, abstract, and full text of the papers, a total number of 43 were included for the final review (**Figure 1**).

Table 1 presents the characteristics of all 43 included studies.[27-69] Fourteen out of all the studies were the randomized controlled trial.[33,36,37,40,41,44,47,49-50,52,54,57,62,69] The focus of the studies was the population with over the age of 18, except for one study that focused on children.[43]

The studies included in this review originated from 15 countries around the world. The majority of the studies originated from the United States (n=15)[34,36,39,41,42,44,46,48-51, 54,59-60,67,] and the United Kingdom (n=12).[28,35,37,43,52,55,57,58,61,65,66,68] Only three studies were from Asian and African countries.[27,30,45] Diabetes and hypertension were the most frequently targeted diseases[27,36,39,45,46,47,48,49,51,52,61,62,69] by the telehealth PHC services.[28,44,49,68]

In 26 studies, general practitioners were the primary providers of telehealth services.[28-31,34-38,44,46,51-53,57-59,60,61,63-69] A total number of 19 studies used the real-time (synchronous) approach for providing telehealth services.[27,28,30,32,34,35,37,39-42,52,53,57,61-63,65,66] Patients were found to be the primary receivers of telehealth services (n=32).[27-29,31-39,41-42,44, 46-54,57-63,68]

The aim of providing telehealth services was various. In some studies, the aim of telehealth was to follow up with patients[29,30] and monitor disease,[27,29,37,44,52,62] empower people,[43,44] train patients,[27,47] and provide quick and easy access to meet medical needs.[30,31,43,53,61] However, some telehealth services aimed to train and supervise healthcare providers and give a second opinion or consultation. The studies included in this review originated from 15 countries across the world.[45,53,56,64,65]

Equipment and devices used for delivering telehealth services included television,[27] telephone,[34,35,39,41,44,46,48,50,54,57,59,66] glucometer,[52,59,62] camera,[27,35,36,45,46,60,63] mobile phone, [40,43,48,52,61,68] spirometer,[29,64] pulse-oximeter,[29] heart rate monitor,[29] computer,[30,33,39,41,45,69] digital otoscope,[60] and telephonic stethoscope.[60]

Disease management,[28,36,62,69] healthcare support in rural areas,[30,41] self-management,[27,33,39,42,48,51,58,59,61] and cost reduction[35,38,46] were the most critical achievements of telemedicine services in the reviewed studies.

The critical challenges reported for implementing telemedicine services include lack of resources,[27,69] lack of awareness,[27,30,48] staff resistance,[38,50] lack of privacy criteria,[27,33,43] and lack of access to technology.[57,58,64] (**Table 2**)

Discussion

This study aimed to investigate telehealth at the PHC level. Our findings revealed that the adults (18-60 years old) were the target of telehealth services in most of the studies. It shows that people of these ages are more willing to use this method, have the necessary technological know-how, and can easily use the tools involved in telehealth.[17] The target group of telehealth services in some of the included studies were elderly adults. There is evidence that the telehealth applicability to the seniors has not been a barrier to receiving telehealth services, and older adults have an interest in using telehealth services. People in this age range are more likely to utilize telehealth services if they do not have an additional cognitive load.[70] The majority of the telehealth services provided in PHC originated from European and American countries. A possible explanation for this may be the leading position of this country in technical infrastructures and the equipment required for implementing such services.[71]

The results of our study revealed that the majority of telehealth services used various communication channels such as video conferencing, cellphones, telephones, the web, email, and Skype, considering the situation of the service receiver and the available tools. The variety of communication channels reveals the full range of options for delivering telehealth services. According to the findings of the study done by Dhillon et al., Skype and email were the most popular tools for receiving telehealth services among the participants.[70]

Most of the participants in the included studies suffered from chronic and non-communicable diseases such as hypertension and Type II diabetes. Patients suffering from chronic conditions usually place substantial financial burdens on the health care system so that the utilization of telehealth services can reduce these pressures.[72] Turning to the telehealth approach can act as a solution to the problem of managing care for chronic conditions among aging of the population in different communities. The investigation by Esperance et al. (2016) has concluded that self-management via telehealth services can improve patients’ access to physicians and the quality of care among diabetic patients. Despite being overall pleased with using the telehealth system, the patients in the mentioned study raised concerns on technical issues and the need to learn new information to use the system.[73]

Xu et al. (2018) conducted a study on the efficacy of telemedicine in providing care to diabetic patients in rural areas. The patients who had used the telemedicine system experienced lower blood sugar levels, better access to health care, less waste of time, and a high degree of satisfaction with the method.[74] The higher success rate of telehealth services in this domain can be attributed to the broader adoption of telehealth for managing diabetes compared to other diseases.

Our findings implied that the healthcare providers who made the most use of telehealth services were family doctors. Telehealth can undoubtedly improve the quality of PHC offered by general practitioners through increasing access to physicians. General practitioners can use telehealth to perform examinations and provide consultations to their patients in any place and at any time without even having to go to their offices. This approach can reduce waiting times in doctors' offices, deliver healthcare services to people living in remote areas, and allow physicians to increase their income through reimbursement systems intended for telehealth services.[75]

The results revealed the most dominant approach to telehealth services was the synchronous form.[27,28,30,32,34,35,37,39- 42,52,53,57,61,62,63,65,66] Real-time communication is considered an effective way of delivering telehealth services in PHC. In the synchronous mode of telehealth, there is a stronger sense of communication between patients and providers. What determines the suitable mode of delivering telehealth services are the patients and the type of disease they have. Moreover, telehealth is a technological phenomenon[76] and a directed approach for meeting individuals' needs.[75]Therefore, choosing between one-way or two-way as well as synchronous or asynchronous methods must be made accordingly.

Most of the included studies in this review have focused on investigating the effects of these services on rural and underserved areas since those are the areas facing problems with access to healthcare.[7] Increasing accessibility and improving patient health can happen by establishing telehealth services in rural areas. However, the rollout of the technology in rural regions is usually slower due to the lack of technical support and lower budgets. Lack of adequate resources can be another barrier to deploying telehealth in underserved areas since they do not have dedicated technical support teams of experts like the large urban areas. Moreover, it should be noted that even though innovation is considered a competitive advantage, rural systems are usually resistant to change.[77]

According to the findings of our review, it seems the clients mostly received the telehealth services directly by themselves. However, the study by Dhillon et al. found that the elderly preferred to receive telehealth services through the help and support of their families.[70] There is evidence that patients whom a supervisor supported were more successful in using this technology.[77]

Reviewing the main obstacles to the implementation of telehealth revealed that lack of coverage by healthcare insurances and payment plans are among the primary problems holding back the adoption of telehealth networks.[11,78] Barriers also ranged from difficulty in acquiring permits to concerns about privacy[3,11,13] and the lack of enough information, user perception, skill, education, initial costs, and the providers' reluctance toward new approaches of health care delivery.[9,79] The study by Souza et al. identified additional factors such as low bandwidth, unsuitable networks, low signal quality, picture quality, and organizational issues as barriers to the implementation of telehealth services.[80] Furthermore, a study conducted by Fatehi reported technical, organizational, cultural, sociological, economic, and ethical obstacles.[81] The barriers reported by Nesbitt et al. also are similar to the ones identified in our study.[78] Regardless of the disadvantages, there were a variety of advantages reported for telehealth services in primary healthcare. They range from self-care promotion to patient empowerment, decreased patient visits, cost reduction, and access improvement to the services. Additional benefits include patients' time savings, higher commitment to showing up for appointments,[75] better clinical results, better access to specialist services, less need for travel, and better screening rates.[82]

Conclusion

Telehealth can be used for different purposes of primary health care through deploying a full range of communication channels available to the public. Due to the opportunistic use of existing devices and platforms, telehealth can provide scalable primary health care services nationwide and worldwide. However, the implementation of telehealth in PHC faces challenges from technical, organizational, and human perspectives. It seems inevitable to transform the policy context and regulation if telehealth approach is a part of health system agenda. Respect for privacy and confidentiality principles is also crucial. Moreover, digital equity is required to expand telehealth services to the populations in underserved areas. Digital equity can be achieved through addressing existing disparities in internet and technology access and improving e-health literacy among low-income and underserved communities. Under such conditions, telehealth can strengthen primary health care system toward universal health coverage. Since no guideline was reported for implementing telehealth services in primary health care, future research may utilize the findings of this study as a basis for developing the guideline. Analysis of telehealth policies for primary healthcare in different countries could shed light on a deeper understanding of our findings. The current study is limited in this regard and future research may explore this to complement the findings of this study.

Declarations

Ethics approval

Ethical approval for conducting this study has been obtained from the Research Ethics Board at Tabriz University of medical science, Tabriz, Iran (No: IR. TBZMED.REC.1396.1251).

Competing Interests

The authors declare that there is no competing of interest.

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Authors’ Contributions

LB: Data extraction, data organization, treatment of data, and drafting a manuscript. LRK: Data analysis, and manuscript writing, scientific revision and approval. LD: Data examination, writing of manuscript and scientific criticism as well as approval. MF: Data examination, scientific review and approval. All authors have read and approved the final manuscript.

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Notes

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Opportunities for Using Health Information Technology for Elderly Care in the Emergency Departments: A Qualitative Study

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Abstract

Introduction: Recently, several technologies have been developed for being used in the field of geriatric emergency medicine. As a large number of elderly patients visit emergency departments, the use of health information technology in this department can help to improve patient care and control the outcome of diseases. The present study aimed to identify opportunities for using various health information technologies for elderly care in the emergency department.

Methods: This qualitative study was conducted in 2020. The participants included geriatricians, geriatric nurses, emergency medicine specialists, and nurses who worked in the emergency department. In total, 33 semi-structured interviews were conducted, and data were analyzed by using framework analysis method and MAXQDA software.

Results: The findings of the qualitative study included four main themes, nine subthemes, and 20 categories. The main themes were the common process of elderly care in the emergency departments, data required for elderly care in the emergency departments, the elderly treatment team, and current information technologies used in the emergency departments for elderly care. Overall, the results showed that there was no specific workflow for elderly care in the emergency departments; the great workload of this department prevents the clinicians to conduct cognitive and functional assessments; geriatricians were not involved in the care process; and none of the current information systems were designed specifically for elderly patients. It seems that using specific heath information technology for elderly care in the emergency department can help to overcome current challenges.

Conclusion: Identifying opportunities for using health information technologies for geriatric patients in the emergency department can lead to better use of financial, physical, and human resources, and improve staff performance. These systems can be designed and used for different purposes such as reducing work load, readmissions, and hospitalization. Improving access to data and better collaboration between different specialties are other benefits of using these systems. However, more research is required to evaluate the effectiveness of technology in this area.

Keywords: health information technology, medical informatics, emergency department, elderly

Introduction

As the number of elderly people is increasing in different countries, hospital emergency departments have been faced with more challenges than other departments in providing healthcare services for this age group. However, current emergency care facilities may not meet the requirements of the elderly.[1,2] In emergency departments, the elderly usually have the longest waiting time for treatment and discharge, and the difficulty of obtaining a history due to their hearing and mental impairment makes the evaluation of elderly patients complicated and time-consuming.[3] On the other hand, the number of admissions of the elderly in the emergency department is increasing every year.[4] For example, in some countries, such as Turkey and the United States, more than 24 percent of emergency patients are the elderly,[5-9] and they spend more time in emergency departments than other age groups.[10,11] Therefore, emergency care processes need to be improved for this group of patients. The lack of care optimization for the elderly can lead to adverse outcomes of care and increase readmission, mortality, and morbity.[12,13] It is notable that, according to the World Health Organization (WHO), indviduals who are 65 years old or older are considered elderly from a chronological perspective.[14]

As the field of geriatric emergency medicine evolves, the use of various health information technologies (HIT) in this area has been found of particular importance.[15] The application of health information technology in geriatric emergency medicine can be useful in various aspects, such as prevention, care support, and process management mainly by providing adequate data at the point of care.[16-18] Moreover, the availability of information—especially via information technologies—can help clinicians to make better decisions at the right time.[19] Generally speaking, health information technology includes a variety of Information and Communication Technologies (ICT) that are used to collect, store, transmit, and display patient data.[20] A wide range of products and services such as electronic health records (EHRs), telehealth, mobile health (mHealth), remote monitoring tools (telemonitoring tools), assistive technology, and sensors are some of the examples of heath information technologies.[21,22]

Recently, several technologies have been developed for use in the field of geriatric emergency medicine.[23] For example, the use of a clinical decision support system (CDSS) has helped to improve pain management. This system was designed based on the guidelines for the prompt management of geriatric pain and is aimed to enhance physician awareness about geriatric pain assessment and treatment.[24] Vital signs monitoring systems have helped to reduce waiting time and mortality, accelerate diagnosis, and improve health outcomes by providing adequate data at the point of care.[25] The use of computerized physician order entry (CPOE) and EHRs in emergency departments have reduced the number of radiographic and laboratory test requests and saved costs by preventing repetitive diagnostic procedures.[26,27] Nurses can use different methods of electronic documentation for elderly patients to reduce errors and overlaps in the documentation.[28] Telemedicine is another widely used technology that has the potential to facilitate care processes in geriatric emergency medicine.[29] To date, the mentioned systems have been used for different groups of patients, and there is a large literature support for their effectiveness. However, few studies have focused on the use of health information technologies in geriatric emergency medicine, and in particular in emergency departments. As the requirements of elderly patients can be different from other age groups who visit emergency departments, the purpose of this study was to identify the opportunities for using various health information technologies for elderly patients in emergency departments.

Methods

This qualitative study was conducted in 2020 and, before conducting the research, ethics approval was obtained (IR.IUMS.FMD.REC 1396.9323563001).

Participants

The participants were selected using the maximum variation purposive sampling method and included geriatricians and geriatric nurses who worked either in the medical universities or geriatric clinics, and emergency medicine specialists and emergency department nurses who worked in emergency departments. A criteria of having at least three years of work experience in geriatric medicine, emergency medicine, or geriatric emergency medicine was considered for all participants.

Setting

The settings of the study were four medical universities (Tehran, Shahid Beheshti, the Iran University of Medical Sciences, and the University of Social Welfare and Rehabilitation Sciences) that had geriatric medicine or geriatric nursing departments, and three hospitals affiliated with the medical universities in which the number of ED visits per month was higher than other emergency departments. These hospitals were responsible for providing patients with the secondary care services.

Data Collection

Data were collected through in-depth, semi-structured interviews with 33 informed individuals in January 2020 through February 2020. Interviews continued until data saturation was reached. Prior to the interviews, an interview guide was developed based on literature review[30-35] and consisted of 10 open-ended questions (**Appendix I**). The questions were related to the current clinical pathway for elderly patients in emergency departments, current challenges, differences between this group of patients and other emergency department patients, and current status of, and opportunities for, using heath information technologies for geriatric patients in the emergency departments. To refine the questions of the interview guide, initially, three interviews were conducted, and problems in terms of ambiguity of questions in the interview guide were identified and corrected for subsequent interviews. The validity of the interview guide was assessed by six experts in the field of geriatrics, emergency medicine, and geriatric nursing.

To collect data, potential participants were contacted by one of the researchers (GS), and a convenient time was proposed by those who agreed to take part in the interview. All interviews were conducted in the workplace of the interviewees by one of the researchers (GS), and in a crowded environment, such as an emergency department, a quiet room was selected and interviews were conducted in that room. All of the interviewees signed a consent form before conducting the interviews; however, they could leave the interview whenever they needed. The interviewees were also provided with adequate information about the research objectives and the contact information of the researchers. The interviews were digitally recorded with the interviewee’s permission, and notes were taken whenever it was necessary.

Data Analysis

In order to analyze data, the thematic analysis method and MAXQDA software (version 10) were used. In this method, themes are identified, organized, described, and reported. The focus of this method is on the inductive rather than deductive coding and provides a flexible approach that can be modified for different studies.[36]

In this study, the interviews were transcribed verbatim and studied by one of the researchers (GS) several times. After getting familiar with the content, the researcher (GS) identified the key concepts, coded, and adjusted them based on the thematic framework. To codify the interviews, first the common concepts were identified and then the main categories and subthemes and themes were determined. The results were reviewed by other researchers, (HA) and (MH), to avoid inconsistency in reporting the results and misinterpretation. Finally, a summary of the results were sent to the interviewees to check the credibility of the findings and all of them approved the content.

Results

In this study, 33 clinicians participated in the interviews, and the average time of the interviews was 50 minutes. **Table 1** shows the demographic characteristics of the participants.

As Table 1 shows, about half of the participants were men (n=17, 51.5%), and the highest frequency (n=13, 39.4%) was related to the age group of 40-49 years old. Regarding the educational level, specialists had the highest frequency (n=18, 54.5%). Their specialties included emergency medicine and geriatrics.

Overall, four main themes, nine subthemes, and 20 categories emerged from data analysis. The themes included the common processes for elderly care in the emergency departments, required data for elderly care in the emergency departments, the elderly care team, and the current information technologies used for elderly care in this department (**Table 2**). Each of the themes, subthemes, and categories are described below in detail. It is notable that to respect the confidentiality issues, we de-identified the interviewees' personal information and used the letter "P," which indicates a participating interviewee and the number following that indicates the specific interviewee who provided the quote.

Theme 1: Common Processes of Elderly Care in the Emergency Departments

Elderly care in emergency departments is different from caring for young patients, and more time is required to assess various aspects of their health status. Most of the interviewees noted that the emergency department of a hospital is divided into different sections, including triage, resuscitation, green, yellow, and orange units. The names of these units may vary slightly depending on the physical space of the emergency departments, but all emergency departments cover five levels of care for patients. It is notable that these colors are used based on the standard triage color coding, and they are used in all emergency departments. According to the interviewees, the severity of the disease and the urgency of receiving treatment were determined in the triage unit for every patient who entered to the emergency department. Then, the patient was transferred to the relevant unit according to the triage score.

The green unit included outpatients who did not need special counseling and would be discharged in less than six hours. The yellow unit included patients who were clinically stable and waiting to be transferred to inpatient or intensive care units. The orange unit included patients with heart and respiratory problems or patients who needed isolation or relaxation. Patients with a high risk of cardiac arrest or poor general condition were also taken directly from the triage to cardiopulmonary resuscitation unit (P 21).

According to the interviewees, there was apparently no specific workflow for the elderly care in the emergency departments, and this group of patients was admitted to the emergency department just like other people. Regarding the work processes associated with the elderly care, one of the nurses who worked in the emergency department stated: "… We do not consider any specific workflow for the elderly and do not have any separate section for them. The patient who enters is triaged and the triage level (from one to five) is determined, then the patient is referred to the appropriate unit for his/her condition …" (P 31).

Workload

Most of the interviewees believed that, due to several reasons, such as the availability and cheap health care services, the number of emergency patients is high in general, and one of the main groups of emergency patients is the elderly. It seems that more than half of the emergency patients are the elderly and brought to the emergency departments for various reasons such as fall, lung infection, kidney infection, heart attack, stroke, and sometimes accident. Another reason for the large number of elderly referrals to emergency departments is receiving insufficient care at home along with low public awareness about the proper use of healthcare resources and facilities, which leads to unnecessary referrals of the elderly to the emergency departments. In this regard, one of the emergency medicine specialists stated: "… If we look closely, we find that about 50 to 60 percent of the elderly who refer to the emergency room do not need emergency care services, but they are just old and suffer from chronic conditions …" (P10).

According to some of the interviewees, the proper use of the referral systems, in particular via a family physician, can prevent the elderly from unnecessary referrals to the emergency department. Moreover, it is possible to prevent acute conditions and reduce the number of referrals to emergency departments just by modifying and applying small changes to the elderly life style. Such a workload can also be managed by using different types of health information technologies like telemedicine.

Clinical Assessment

According to the interviewees, the method of care in the emergency department is disease-based, and the elderly, like other patients in this department, receive healthcare services based on the severity and urgency of their disease. According to the interviewees, all patients are categorized according to the triage guidelines, and emergency severity index (ESI), which cover all age groups, are used for them (P 20).

As the elderly patients may not be able to move or get out of the bed on their own, clinicians are required to obtain a sufficient history of the cognitive and functional status of them. However, the nature of the emergency department processes prevents any time-consuming operations. Therefore, it is necessary to conduct a quick clinical assessment of the elderly in a concise manner and based on the priorities in the emergency room. The rest of the additional actions should be done after the patient's condition is stabilized (P 3). This process can be facilitated by using health information technologies, such as clinical decision support systems.

Discharge Recommendations

The majority of the interviewees stated that a lack of trained staff in the field of geriatric emergency medicine, a large workload, and the time limit to provide the elderly or their companions with discharge recommendations may cause many unnecessary visits to the emergency department in future. The discharge recommendations, which were given to the patient or their companion, were in two sheets like a checklist. The interviewees believed that the continuation of care is one of the important factors that should be taken into account for elderly patients. Otherwise, any deficiency in treatment will lead to the elderly referral to the emergency department. They need to be communicated properly to follow their treatment and medication adherence, for example via telemedicine services.

Theme 2: Data Required for Elderly Care in the Emergency Department

The elderly have special characteristics that are different from other age groups, and it is necessary to pay attention to their requirements in emergency departments. This theme included clinical and supportive data required for elderly care in emergency departments.

Clinical Data

Due to the various problems that the elderly have, it is necessary to take a medical history, do screening tests, and use appropriate questionnaires to obtain adequate clinical data about them in order to facilitate their treatment process. Most of the interviewees stated that the elderly visit emergency departments for various reasons such as lung or kidney infections, heart attack, stroke, accidents, and falls. Loss of consciousness, weakness, and lethargy are common causes for these conditions. Some geriatricians believed that if the elderly refer to the emergency room for any reason, it is better to perform the necessary screenings tests for them.

Unfortunately, the characteristics of emergency departments, such as overcrowding, a large number of referrals, and staff shortage, have left few opportunities to pay attention to the screening tests of the elderly. Therefore, it seems that the presence of geriatricians in the ED can help other clinicians. These people may have sufficient time and adequate knowledge to perform necessary screening tests for the elderly and can provide a complete medical record for these patients. Although using some questionnaires, such as Activities of Daily Living (ADL), Identification of Seniors at Risk (ISAR), and Instrumental Activities of Daily Living (IADL), is very helpful to assess the health status of the elderly, it seems that completing these questionnaires depends upon the presence of geriatricians or nurses trained in geriatric emergency medicine. These people have adequate knowledge and can spend more time on patient assessment. Sometimes the use of these questionnaires can lead to identifying at-risk people as well as dysfunction syndromes before discharge, thus preventing the subsequent re-referral of the elderly to emergency departments. Obviously, collecting these data in different systems such as electronic medical records, electronic health records, and personal health records can facilitate getting access to the right information at the right time and place.

Supportive Data

According to the interviewees, elderly patients who refer to the emergency department need supportive data about insurance coverage and self-care education in addition to medical treatment. The findings showed that, sometimes, there is no special insurance coverage for the provision of services by geriatricians. Moreover, identifying the patient’s family and the presence of the elderly patients’ companions in the emergency department are very important. In the absence of such persons, the elderly should be introduced to the welfare organizations. Some interviewees noted that volunteers can also be employed to help the elderly in the emergency departments (P1, P24), and without training, self-care education, and strong communication with the elderly family, successful treatment will not be provided (P26).

Theme 3: The Elderly Care Team

The findings showed that the elderly care team was limited to the ED clinicians, and there was no plan to add the geriatricians to this team in the emergency departments. In this regard, one of the nurses said: “… The basis of the emergency medical team is emergency medicine; if they need to consult other specialists, they will ask infection, heart, internal medicine, and other specialists in the inpatient department. We do not have geriatric medicine in the emergency room…” (P16).

It seems that geriatricians were busy with the outpatients, clinics, and nursing homes. Also, there was not a positive attitude regarding collaboration with geriatricians in the emergency departments. The interviewees believed that involving other specialties in the elderly care team depends on the positive attitudes of senior managers, organizational facilities, and financial supports. According to the interviewees, the elderly care team included the main health care providers and medical consultants.

Main Health Care Providers

The findings showed that, generally, the main healthcare providers in the emergency departments were emergency medicine specialists and nurses, and there was no specific care team for the elderly in this department. However, in an ideal situation, this team could include geriatricians, emergency medicine specialists, geriatric nurses, elderly sports specialists, geriatric nutritionists, and physiotherapists (P 8). Some of the interviewees stated that the presence of trained geriatricians and geriatric nurses in the emergency medical team as well as adequate space in the emergency department for the elderly care can help to improve health outcomes of the elderly.

Medical Consultants

According to the research findings, in case of necessity, consultants in different medical fields such as internal medicine, surgery, infectious diseases, neurology, cardiology, or other required specialties would be asked to help in elderly care. These medical consultants were either available in the inpatient or in the outpatients departments. According to some interviewees, the involvement of specialists such as physiotherapists, geriatricians, clinical pharmacists, psychiatrists, and geriatric nurses in the emergency medical team would result in better health outcomes for the elderly, but basic coordination and planning need to be considered at the higher organizational levels. In this case, even telemedicine technology can be used to facilitate collaboration between different specialties.

Theme 4: Current Information Systems Used for Elderly Care in the Emergency Departments

The results showed that in the emergency departments, information systems were used jointly for all ED patients, and there was no specific system for the elderly care. As noted by an interviewee: “…We do not have any specific health information technologies for the elderly. We have picture archiving and communication system (PACS) and hospital information system (HIS) in the emergency department or emergency department information system that can be used by all patients and are not specific to a specific age group…” (P 23).

This theme included emergency department information system and the challenges of using it and other health information systems, which are described below.

Emergency Department Information System and the Challenges of Using It

The results of the interviews showed that the emergency department information system was used as a subsystem of the hospital information system, and there was no specific information system for elderly care. Regarding access to patients' information, one of the interviewees said: “…Previous history, medications, and problems of elderly patients along with a medical history should be accessible in the hospital information system…” (P 27).

According to the results, despite the use of information systems in the emergency departments, there was no connection between the hospital information systems of different hospitals, and the lack of integration between these systems made the treatment process difficult. According to the interviewees, the accessibility of patients’ medical history and the results of previous diagnostic tests can accelerate the provision of appropriate healthcare services and reduce related costs. Error reduction as a result of the system integration and improving the completeness of patients’ records are other benefits of using emergency department information systems.

Other Health Information Systems

The interviewees believed that in order to use technology, it is necessary to provide appropriate infrastructure, and users should receive necessary training in this regard. In fact, the technology will not be very effective if it is used improperly or imposes additional workload. Most of the interviewees believed that access to a variety of technologies such as electronic health records, integrated information systems, telemedicine, electronic questionnaires, trackers, as well as clinical decision support systems would be very useful, if they are supported by senior managers. In this regard, one of the geriatricians noted: “… Clinical decision support systems and reminders work well to provide elderly care, and other technologies can help reduce emergency readmission …” (P 9).

Some specialists expressed their interest in electronic prescriptions and technological products such as airbag belts and trackers for the elderly, which would prevent serious injuries in case of a fall, and Alzheimer’s patients would be tracked effectively.

The interviewees believed that using all parts of the hospital information system and launching an electronic health record system would have far-reaching benefits. The picture archiving and communication system was another technology used in the emergency departments, and the emergency medical team was able to access the results of medical imaging of the elderly and other patients via computers in the emergency departments. According to the interviewees, access to this system via a wireless network could also be useful for physicians (P 31). The interviewees also stated that although there was no specific information system for the elderly in the emergency rooms, all emergency rooms were equipped with vital signs monitors for different groups of patients including the elderly.

Discussion

The use of health information technologies for the elderly in emergency departments is a new approach that is used in many countries. These technologies can be applied for different purposes, such as patient care, department management, treatment, follow-up, and training.[37] As the speed of diagnosis and treatment is important in emergency departments, the use of technology can help to expedite the care processes. In the present study, the opportunities for using various health information technologies for elderly care in emergency departments were investigated.

The results showed that although the care requirements of elderly patients are different from other age groups, and they are a major group of patients who visit emergency departments, there was no specific workflow for caring and providing them with appropriate emergency care services. In addition, a great part of the workload in the emergency departments was devoted to elderly care. Similarly, Lyons et al. found that, compared to other emergency department patients, elderly patients may have multiple active diseases that need to receive different types of treatments. It seems that health information technologies can be used to provide them with better emergency care services and reduce the workload. For example, electronic screening and assessment can provide an overview of the health condition of elderly patients, and clinical decision support systems can be used for these purposes to support clinical decision-making.[38] There are also opportunities to continue treatment for the elderly who are discharged from emergency departments by using telemedicine technology, such as tele-follow-up services.[39] However, users may experience difficulty in integrating the technology into their routine clinical practices or changes in patient care processes due to a modification of data flows and task sequences. As a result, the uptake of these systems should be aligned with clinicians' tasks to achieve the desired outcomes. Similarly, in terms of elderly care, the context of use and key activities should be initially investigated to be able to design and use information systems efficiently.[40]

According to the findings, emergency department clinicians need to have access to both clinical and supportive data of all patients, especially for the elderly.[41,42] This is another opportunity to use information technologies such as hospital information systems, emergency department information system, electronic health records, and personal health records to improve health care services. These technologies can also help managers and decision-makers to control adverse effects of treatments such as death, long-term stay, and frequent emergency visits of the elderly.[43] Other benefits of using these systems are easy access to the current and past patient information, decreasing practice variability, and ensuring legible communication between health care providers, which can save time for them.[44] However, it is important to consider data exchange standards,[45] as a lack of information sharing may limit the possible benefits of using information technology in care processes.[46]

In terms of the elderly care team, the findings showed that medical staff in the emergency departments (physicians, nurses, etc.) and medical consultants in the hospitals were the main members of the care team. However, this team should also include geriatricians, geriatric emergency medicine specialists, geriatric nurses, geriatric nutritionists, and physiotherapists. Similarly, Devriendt et al noted that in most geriatric emergency care models, collaboration between the emergency department team and geriatricians has been highlighted to reduce the emergency department workload. These models can help to reduce unplanned readmissions, hospitalization, and health outcomes.[47] To access medical consultants or geriatricians at any time and place and to expand the elderly care team, the use of technologies such as telemedicine and teleconsultation is recommended.[48]

The results showed that current information systems in the emergency departments included hospital information systems, emergency department information systems, vital signs monitoring systems, and picture archiving and communication systems, which were used for all patients; there was no specific information system designed or used for elderly patients. These systems facilitated multidisciplinary task management and a quick overview of patients, staff, and processes was available for the system users.[49] However, according to the literature, many other information systems can be designed and implemented to support the elderly care processes in emergency department. The use of telemonitoring systems for the elderly with multiple health problems,[50] asking the elderly in the emergency department to provide clinical information by using a tablet computer,[51] and predicting hospital readmission for elderly patients by using machine learning algorithms[52] are some examples of using information systems to facilitate screening and monitoring patients outside the emergency department, reduce the workload of this department, and improve care processes.

Limitations of the Study

With an increase in the elderly population, many emergency departments need to visit more elderly patients. This group of patients presents unique challenges to the healthcare team. However, the use of health information technology can help to improve quality of care by improving the accessibility of data and healthcare services, for example, via telemedicine. Although the current study helped to identify opportunities for using health information technology for the elderly in the emergency departments, it has some limitations.

In this study, only three emergency departments were selected, and their emergency medicine specialists and nurses were interviewed. However, these emergency departments had a high number of patient referrals per month compared to other similar settings. Moreover, the number of geriatricians and geriatric nurses was limited, as the field of geriatric medicine was relatively new in the country. We tried to include a variety of expertise and explore specialists’ opinions; however, there might be other people or specialties, such as psychologists, who may have different opinions about using health information technology for elderly patients in the emergency departments.

Moreover, as the main users of the information systems were clinicians in the emergency departments, we did not interview elderly patients or their caregivers. These people may have their own perspectives about using information technology in the emergency departments.

In this study, although a number of opportunities were identified for using health information technology in geriatric emergency medicine, the application of these technologies depends on many other contextual and organizational factors in different countries. Therefore, the feasibility and benefits of using different types of health information technologies for elderly care in the emergency departments can be investigated in different countries to address the limitations of this research.

Conclusion

The findings of the present study showed that there are a number of opportunities that health information technologies can be used for elderly patients in the emergency departments to improve clinical practices and quality of care. Identifying these opportunities and using the technology can also help to better use of financial, physical, and human resources and improve staff performance. These systems can be designed and used for different purposes such as reducing work load, readmissions, and hospitalization. Improving access to data and better collaboration between different specialties are other benefits of these systems. However, to implement the systems successfully, aligning the views of the key medical staff, such as emergency department specialists, nurses, geriatricians, and geriatric nurses, about using these systems is necessary. Healthcare policymakers may also benefit from getting access to high-quality reports about the elderly care processes and can use them in future planning and better management of resources. However, more research is required to evaluate the effectiveness of technology in this area.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Observing Provider Utilization of Electronic Health Records to Improve Clinical Quality Metrics

By Kevin Brooks, PhD; Molly Polverento, MSEd, CPH; Laura Houdeshell-Putt, DPH; Erin Sarzynski, MD; and Sabrina Ford, PhD

Abstract

Introduction: This study compared changes of healthcare quality in a Michigan Medicaid population before and after physician adoption of electronic health records (EHRs) via the Meaningful Use (MU) program for selected Healthcare Effectiveness Data and Information Set (HEDIS) quality of care measures.

Methods: Healthcare measures included well-child visits, cancer screening, and chronic illness quality measures. Utilization data were obtained from Medicaid paid claims and encounter data with providers (N=291) receiving their first MU incentive in 2014 and at least one HEDIS-defined outpatient visit with a Michigan Medicaid enrollee. Paired t-tests with a repeated measures design were utilized to analyze the data.

Results: Improvements in quality of infant well-child visits (mean difference = 10.2) and colorectal cancer screening (mean difference = 8.0 percent) were observed. We found no change or slight decreases for the other selected measures.

Conclusion: These outcomes inform the performance and ability of EHRs to improve quality of healthcare standards particularly as technology continues to evolve under the Centers for Medicare & Medicaid Services (CMS) Interoperability and Patient Access final rule.

Keywords: meaningful use, health information technology, electronic health record, clinical quality metrics

Introduction

Electronic health records (EHRs) have become standard in over 90 percent of physician practices.[1] One goal of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 was to improve the efficiency and quality of patient care through increased use of certified EHRs.[2-4] The Meaningful Use (MU) component of the HITECH Act incentivized EHR adoption and use by physicians to accomplish specific tasks (e.g., referrals and screenings) and increase patient and provider access to health information.[5,6] Now, EHR use has become a clinical standard, and interoperability aims to improve health information technology (HIT) communications for physician and patient. Initially, the Centers for Medicare & Medicaid Services (CMS) provided monetary incentives and to physicians who adopted EHRs.[7-9] In turn, physicians were required to demonstrate MU by reporting clinical quality measures (CQMs) to indicate more efficient and equitable patient care processes, and improved patient outcomes.[10]

Nationwide, providers participated in either the Medicare EHR Incentive Program managed by CMS or the Medicaid EHR Incentive Program managed by each state.[11,12] To qualify for an incentive payment under the Medicaid EHR Incentive Program, a provider had to meet one of the following criteria: 1) have a minimum 30 percent Medicaid patient volume; 2) have a minimum 20 percent Medicaid patient volume as a pediatrician; or 3) practice predominantly in a Federally Qualified Health Center or Rural Health Center having a minimum 30 percent patient volume attributable to medically underserved individuals.[13]

There are very few studies reporting the associations between EHR adoption and healthcare quality in Medicaid beneficiaries, specifically in primary care outpatient settings. Further, there is limited research on the impact of EHR adoption related to promotion of health quality for chronic disease management, recommended prevention and screening services, and medication management.[14] Instead, most studies have examined EHRs' impact on inpatient settings or productivity and efficiency in data quality and management.[15,16] We assert that additional research is justified to examine the impact of MU and the adoption of EHRs on the delivery of health services to outpatient Medicaid populations. It is warranted to ascertain that MU achieved quality improvement goals in a variety of settings and for diverse patient populations as the EHR interoperability is in full operation.

Objective

This study evaluates the impact of physicians' participation in MU on select CQMs for Michigan Medicaid enrollees. It builds upon our initial work in a previously published study[17] reporting that providers' participation in MU may have varying degrees of influence on select clinical quality metrics. Although MU attestation has ended, the effectiveness of provider use of EHRs is still highly relevant. Therefore, using a retrospective design, this study examines physician performance on specific CQMs before (pre) and after (post) MU participation on a cohort of Michigan Medicaid enrollees, a vulnerable patient population. The pre-post MU measures studied here are highly relevant to primary care providers and those working to improve care for vulnerable and underserved populations.[18]

Methods

Study Design

As part of a larger evaluation effort on the impact of HIE/HIT in Michigan, this project was determined to be non-human subject research by the Michigan State University Institutional Review Board. This retrospective analysis of Michigan Medicaid claims and encounter data examined the impact of physicians' adoption of EHRs on CQM and beneficiaries' health services. Physicians who first participated in the program in 2014 were selected as the cohort of interest. Select outcome measures for patients attributed to these physicians were then grouped into either pre-MU (2013) or post-MU (2015). Thus, the selected cohort of patients were enrolled in the Michigan Medicaid program continuously in 2013 through 2015.

Data Source

The Michigan Office of Health Information Technology provided summary data on all eligible MD and DO physicians who participated in its Medicaid MU program for the time period 2011 through 2016. Data elements for providers included payment year, age, name, gender, geographical location, and ethnicity. Then, the Michigan Medicaid data warehouse was accessed to identify: 1) the patient population and 2) the administrative claims data summarized into quality of care metrics by a rate-generating software (Optum® Symmetry®).

Attribution Logic

Physician MU enrollees with at least one outpatient visit (as defined by Healthcare Effectiveness Data and Information Set (HEDIS)) were accessed via the Michigan Medicaid data warehouse. The primary logic attributed beneficiaries (patients) to the physician based on a plurality of outpatient visits. If two or more physicians had the same number of outpatient visits for an enrollee, a secondary logic was established to break ties based on which provider submitted the most recent claim.

Participants

Providers: The study population of providers was restricted to MDs and DOs in Michigan with receipt of their first Medicaid MU incentive program attestation payment in 2014. Providers such as podiatrists, chiropractors, occupational therapists, midwives, etc. were excluded to establish a consistent cohort of providers who could impact primary care sensitive quality measures.

Medicaid Enrollees: This study included enrollees 1) age 64 and younger; 2) with full Michigan Medicaid healthcare coverage and no other insurance or spend down; 3) attributed to one of the study providers in 2014; and 4) qualified for at least one selected quality measure in 2013 or 2015. This rendered a fluctuating member cohort for the pre- and post-measurement periods.

Measures

We assessed 12 objective CQMs across three categories of care, including 1) five measures for preventive care visits (well-child visits for infants, primary care visits for younger children, primary care visit for older children, primary care visit for adolescents, and adults' access to preventive care); 2) three measures for cancer screening (breast, cervical, and colorectal); and 3) four measures for chronic illness (asthma medication management, spirometry test for COPD, HbA1c test for diabetes, and serum creatinine check for hypertension).

We compared providers' performance on these measures in 2013 (pre-MU) to their performance in 2015 (post-MU). For physician characteristics, we quantified age, gender, practice type (primary versus specialty), and geographic practice location (urban versus rural). For uniformity across 2013 and 2015 data, we utilized a consistent cohort of patients attributed to study physicians in 2014. For enrollee characteristics, we quantified age, gender, geographic location (urban versus rural), and race.

Data Analysis

Significant differences (alpha 0.05) between time periods was determined using a paired t-test. To control for potential confounding effects, a repeated measures design was used to account for the fact that observations (outcomes) are not independent and therefore required modeling of correlation structure.[19] This method allowed us to model changes in outcomes between 2013 and 2015 while allowing errors to be correlated and adjusting for all covariates. All statistical analyses were conducted using JMP® Pro, Version 13.1.0. (SAS Institute Inc., Cary, NC.)

Results

Provider and Patient Characteristics

Of the 366 MD and DO providers that received their first MU payment in 2014, 291 had at least one HEDIS-defined outpatient visit with a Michigan Medicaid enrollee in 2014 making them eligible for the study. These providers were predominately male (60.2 percent), located in an urban setting (75.5 percent), with a median age of 49 years, and white (57 percent). The Michigan Medicaid beneficiaries (patients) attributed to the 2014 provider cohort were predominantly female (56.5 percent), live in an urban setting (79.9 percent), with a median age of 16 years, and more likely to be white (54.1 percent). These provider and patient demographic characteristics are displayed in **Table 1**. Demographic proportions in pre/post years, 2013 and 2015, were similar to those during the attribution year except for patients' age. Age difference was expected and recognized as an artifact of the study design where those in the pre-study period would be younger. Additionally, age, gender, and enrollment restrictions applied to individual CQMs in accordance with national specifications may be responsible the observed age difference.

Overall comparisons and mean difference (MD) for each measure for the same provider in 2013 (pre) and 2015 (post) revealed significant increases ($p<0.05$) in three CQMs: 1) well-child visits (six or more) for infants (MD=10.2); 2) primary care visits for adolescents (MD=1.7); and 3) colorectal cancer screening (MD=8.0). Conversely, four measures: 1) primary care visits for younger children (MD= -3.0); 2) primary care visits for older children (MD= -3.0); 3) breast cancer screening (MD= -3.7); and 4) cervical cancer screening (MD= -7.3) demonstrated significant ($p<0.05$) decline between 2013 and 2015 (**Table 2**).

Significant differences were noted for some CQMs based on physician characteristics. For female providers, we identified a significant decrease for primary care visits for the adolescent measure [MD = -2.4; 95% CI (-4.1 – -0.7)], and significant increase in the spirometry test for the COPD measure [MD = 12.4; 95% CI (3.5–21.2)]. Providers who practiced in rural areas had a significant increase for well-child visits for infants [MD = 10.3; 95% CI (4.2–16.4)], adults' access to preventive care [MD=2.2 (0.5–3.8)], and HbA1c test for persons with diabetes [MD=7.4; 95% CI (3.7– 11.2)]. Finally, we identified significant inverse relationships between the providers' age and two measures: primary care visit for older children [MD = -0.1; 95% CI (-0.2–0.0)] and spirometry test for COPD [MD = -0.9; 95% CI (-1.6 – -0.2)]. The remaining measures showed no significant difference between 2013 and 2015 for measures dependent on provider characteristics. Results are shown in Table 2. For several CQM, we note improvements for rural geographic characteristics attributed to EHR-MU.

Discussion

Results showed the use of EHR-MU garnered varied outcomes for patients across multiple categories of care. Improvements for infant and adolescent well-child visits were observed, but decreases in childhood well-child visits were shown. These findings could be a function of fewer well-child visits in middle childhood as documented in the literature.[20] Thus, EHRs could be used to increase consistent and sustained well-visits across the childhood developmental milestones to improve child health overtime. Given that EHRs have identified this as clinic/system gap, interventions should be implemented to increase child well-visits.

Likewise, cancer screening outcomes showed mixed results with improvements in colorectal cancer screening and decreases in breast and cervical cancer screening attributed to EHR-MU. It should be noted that breast and cervical cancer screening guidelines changed during the study period recommending fewer screenings for low-risk patients. Thus, the decrease in breast and cervical cancer screening rates could be a considered improvement as a result of adherence to the new guidelines but warrants further investigation. The study revealed no changes in chronic disease management, again, indicating a need for provider attention regarding utilization of EHRs to improve patient management. Chronic disease management is complex and requires multifactorial input including patient education on the importance of regular visits, improved provider-patient communication, and utilization of the EHR (physicians as well as patient portals) to increase follow-up rates that are imperative for chronic disease management.

Although we know that this cohort of physicians first participated in the Michigan Medicaid MU Incentive program in 2014, we do not know if they had prior experience or administrative support in using EHRs. This is an important consideration because studies suggest that provider initiation to EHRs can affect efficiency and performance[21,22] as well as contributing to physician burnout[23-25] that could account for inconsistencies in observed screening and prevention outcomes here. Inconsistent findings have important implications for evaluating the success of the EHR utilization on quality of patient care, particularly for Medicaid populations that often experience health disparities.[26,27] Although improvements for infant well-child visits, adult preventive care, and HbA1c test for persons with diabetes were observed for rural geographic characteristics, further examination is needed to make a full interpretation of the outcome.

Limitations of the study include restriction to physicians who participated in the Michigan Medicaid MU Incentive Program and to Michigan Medicaid participants who received care from these physicians, which limits generalization to broader populations who are enrolled in Medicare or private insurers. In addition, CQMs were assessed using only claims data, so there could have been improvements in outcomes not fully captured from these data. Furthermore, we did not have information about practice workflow and provider EHR education that could influence provider MU performance. Finally, we limited our comparison to one year before and after adoption. Additional years of follow-up are necessary to fully identify improvements in care linked to EHR adoption.[28] We plan to address this in future studies.

Conclusion

As supported by previous studies in the literature, EHRs play to mixed reviews.[29-32] For this Medicaid population in Michigan, improvement in healthcare delivery was found for infant and adolescent well-child visits and colorectal cancer screening but apparent decreases in childhood well-child visits and breast and cervical cancer screening. No significant changes were observed for chronic disease. While our results did not have ability to explain patient outcomes, other sources have suggested that improving EHR software design and updates, as well as effective physician training, would make improvements in patient quality of care more consistent.[33] Given that EHRs are now considered a standard of clinical care process, it is necessary to keep physician capacity in mind (e.g., workflow, burnout). Outcomes of this study can shed light on effective physician EHR use and improving patient outcomes.[34,35]

Notes

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The Next-Generation Electronic Health Record in the ICU: A Focus on User-Technology Interface to Optimize Patient Safety and Quality

By Laleh Jalilian, MD, and Saif Khairat, PhD

Abstract

As a knowledge-based field of medicine, critical care medicine has benefited from the use of the electronic health records (EHRs) in daily practice, as intensive care unit (ICU) patients generate thousands of pieces of clinical data each day.1 ICU teams must review, interpret, and take action on these data points when managing multiple patients in a time-constrained environment. The increasing number of available data facts to be processed by ICU clinicians for decision-making surpasses human cognitive capacity. ICU physicians described the current display and representation of patient data in the EHR as suboptimum. Performance dashboards are an information delivery system that display the most important information about performance objectives to ICU directors, allowing them to monitor and manage their ICU performance more effectively. The development of visualization dashboards that monitor ICU performance will still need to adhere to usability principles such as Jakob Nielsen's heuristics. The goal of improving EHR interfaces will directly enhance provider well-being, patient outcomes, and quality of care.

Introduction

More than a decade has passed since the passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, which incentivized health systems to adopt electronic health records (EHRs).[2,3] By accruing digitized clinical data, EHRs now impact nearly every decision in patient care. As a knowledge-based field of medicine, critical care medicine has benefited from the use of EHRs in daily practice, as ICU patients generate thousands of pieces of clinical data each day.[4,5] ICU teams must review, interpret, and take action on these data points when managing multiple patients in a time-constrained environment. Since its implementation, the EHR has demonstrated capability in improving quality and efficiency of ICU care processes,[6] improving communication, and becoming a platform for clinical decision support.

However, studies also suggest that unintended consequences with EHR use in the ICU have simultaneously emerged. These include decreased job satisfaction, fatigue, and burnout among clinicians.[7-9] The current state of EHR usability—or the extent to which this technology can be used efficiently, effectively, satisfactorily, and safely—has been a source of increased clinician cognitive workload[10] and has been associated with patient safety risks.[11] The Institute of Medicine recognizes that these current inefficiencies associated with EHR use threaten the quality and safety of healthcare delivery, and that improving the quality and safety (QS) performance of hospitals has become increasingly important in recent years.[12,13] In the upcoming decade, a focus on visual analytics on EHR data—utilizing tools from improvement science, safety science, implementation, and system safety science—may help ICUs improve on care delivery at the level of the patient and the processes of ICU care. In this paper, we discuss the current challenges with representing ICU patient data in EHRs and the potential of data visualization dashboards, and we provide insights into possible technology and policy solutions.

ICU Data Representation: Challenges at the Patient Level

The increasing number of available data to be processed by ICU clinicians for decision-making surpasses human cognitive capacity.[14] Clinicians are presented with more than 1,300 data points during the evaluation and planning of a single patient visit.[15] ICU physicians monitor approximately 2.5 million data points during a given month, and they respond to an average of 187 EHR alerts per patient per day.[16-18] The optimum human cognitive capacity averages five sets of facts per decision, and the current EHR screens present more data than our cognition needs, which can have unintended consequences on clinicians, patients, and the overall quality of care.

ICU physicians described the current display and representation of patient data in the EHR as suboptimum.[19] Physicians report that finding information in the EHR is a major challenge, which they attribute to data-busy screens and to layers of menus. Data redundancy and inconsistent data among EHR screens are major barriers to timely and accurate decisions. For instance, patient vital signs data presented in the flowsheet screen presents real-time patient data compared to the vital signs screen that presents relatively older data facts because it is not refreshed as frequently as the flowsheet. Such data discrepancy creates frustration and confusion for providers attempting to make time-sensitive decisions for critically ill patients. As a result, providers have reported not using screens that are known to have a data lag, which poses the question of why present the same patient data in two separate EHR screens? An effective and usable system should seek to reduce data redundancy and discrepancies, ensure minimalistic menu design, and present patient data in consistent and user-friendly fashion.

Data display is another area of frustration among ICU providers. Many EHR systems did not adopt a user-centered design (UCD) approach when designing their EHR interfaces.[20] UCD approaches ensure that a system is designed to meet the expectations of the user and increases the likelihood of delivering a product that is satisfactory to the user.[21] The lack of UCD approach led to data display in the EHR that does not align with the way physicians were trained to read and interpret data. For example, while EHR systems may use color-coding to label a lab value, when graphing values over time, providers may have to read the results in a different way than they are trained (left to right, every eight hours, etc.). Clinicians eventually adapt to the way data is displayed, but it remains a pain point, especially among physicians with more years of practice in the pre-EHR era. Data representation needs to meet user requirements rather than user needs. User requirements distinguish the required functionality for the user to achieve specific tasks in the system, while user needs describe the end result of a given task.

Currently, IT applications provide little support for the cognitive tasks of clinicians. However, a nascent area of research investigates the use of artificial intelligence in prioritizing relevant patient information in order to minimize the time and effort that physicians spend in identifying relevant information. Machine learning-based systems have been demonstrated to directly learn the relationship between data and visualizations by training models on analyst interaction and show promise in reducing the cognitive load in seeking ICU data.[22] However, it is unknown the effect of using visualization dashboards on clinician decision-making abilities and fatigue levels, which is an area of further investigation using subjective and objective measurements.

ICU Data Representation: Challenges at the ICU System Level

The data currently captured in the EHR reflects ICU processes of care but is underutilized in helping ICU directors assess whether their ICUs are performing effectively. The measurement of these ICU processes of care, or process measures, are meaningful to ICU directors because they evaluate the actions and behaviors of ICU teams and may identify modifiable targets to improve patient care. Tracking process measures allow ICU directors to ask questions such as “Is my ICU meeting benchmark quality and safety metrics?” or “Is care in this ICU adhering to approved institutional guidelines?” With the voluminous amounts of tracked data, there is an increasing focus on the development of ICU performance dashboards to continuously assess ICU care processes in order to support ICU teams in delivering a consistently high level of clinical performance.

Performance dashboards are an information delivery system that display the most important information about performance objectives to ICU directors, allowing them to monitor and manage their ICU performance more effectively. Performance dashboards support data-driven situational awareness and show promise in reducing variations in healthcare quality by stimulating quality improvement (QI).[23-27] They may assist in identifying deviations from clinical best practices and monitoring of compliance to professional practice standards and can improve care quality through fewer errors, improved efficiency, and enhanced situational awareness.[27-29] Challenges, however, arise when developing performance dashboards; these include initially identifying process measures through discussion with stakeholders or through academic measures in the literature. Early involvement of health IT may also help in defining a real-time process measure and its appropriate data element in the EHR, which may then require changes in clinical processes in order to record the correct data. Additionally, a challenge in the past to the use of performance dashboards has been their inability to reflect ICU performance in real time, in part because key data elements may be inconsistently reported, absent entirely, or stored in different databases.

Finally, the development of visualization dashboards that monitor ICU performance will still need to adhere to usability principles such as Jakob Nielsen’s heuristics principles.[30] More specific information visualization guidelines highlight the importance of providing flexibility for users to control display configurations such as time periods and baseline measurements.[31] Data set reduction, the elimination of data elements rarely used, is a challenge in the current EHR and remains a riddle in the development of data visualization for performance dashboards. Additionally, the type of information and its representation varies among clinicians based on their role and patients based on their condition. Creating “personas” based on professional role has been one way to mitigate the differences in user needs.[32] However, creating a comprehensive and sustainable persona remains a challenge given the changes in staffing and with the continuous EHR upgrades. A nascent area of research surrounds itself with the development of machine learning algorithms to create personas based on what EHR screens and data clinicians use the most, derived from EHR log data.

A Call to Action

Evidence from other industries suggests that value derived from information technology comes from the ability to analyze and share real-time data.[33-35] In the next decade, a priority on the meaningful use of data in the EHR will advance its use as an effective tool towards high quality, efficient, and safe healthcare. As described by the Healthcare Information and Management System Society (HIMSS), the presentation of clinical data must strive to adhere to the five “rights”: deliver the *right* information, to the *right* person, in the *right* intervention format, through the *right* channel, and at the *right* time in the workflow. Current real-time data presentation for clinical assessment poses a risk to patient safety, with limitations that include alerts that do not deliver information in a timely manner. A focus on developing meaningful data visualization and EHR user interface and design that better supports clinical care and cognitive tasks may improve front-line user efficiency and effectiveness. Additionally, an emphasis on the development of ICU performance dashboards with effective real-time data visualization will advance digital quality improvement, helping ICU teams be more effective through ongoing outcomes feedback. Finally, adding EHR user design standards and usability criteria, especially pertaining to information layout, into current EHR certification standards through the Office of the National Coordinator for Health Information Technology IT Certification Program, may help to prioritize improving EHR usability moving forward.[36]

Conclusion

ICU teams continue to express frustration with the current representation of patient data in the EHR. The widespread adoption of EHRs and advances in information technology and data analytics offer an opportunity to improve the quality of care through real-time clinical feedback that leads to quality improvement of in-hospital processes. Visualization dashboards present a unique opportunity to visually represent patient data in meaningful ways that enable providers' decision-making processes. ICU performance dashboards show promise in assisting health systems in tracking their performance against benchmarks, revealing areas to processes that may become more efficient and more effective through behavioral change in order to achieve quality targets. Dashboards will need to follow UCD principles to ensure minimalist design and eliminate data redundancies. For a properly functioning and sustainable real-time dashboard that will enable automated monitoring of ICU performance, quality, and safety, a robust healthcare data analytics and information technology platform will be required. More research is needed to investigate the impact of visualization dashboard on providers' cognitive load, fatigue, and performance levels. The goal of improving EHR interfaces will directly enhance provider wellbeing, patient outcomes, and quality of care.

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Improvements for the Prior Authorization Process for Elective Surgical Procedures at an Academic Medical Center

By Karen Y. Marble, MHS; Genie R. Briggs MHS; and Xiaoshan Z. Gordy, PhD

Abstract

Prior authorization is an approval process to ensure that services provided by healthcare organizations will be reimbursed by insurance carriers. Prior authorization denials can result in revenue loss. Due to multiple prior authorization issues, over $21 million in charges was denied, and $291,217.63 was ultimately written off as uncollectible in a one-year period at the Department of Surgery at Hospital X. This paper aimed to design an improved process to reduce, or eliminate, the issues causing charges to be written off. Three divisions with the most prior authorization denials within the department were identified. A comprehensive review of the current prior authorization process was conducted. Each division was found to have a unique prior authorization issue that was causing charges to be written off. Barriers were identified, educational training was provided accordingly, and process changes were implemented thereafter. When comparing the results pre- and post-interventions, these interventions resulted in these charges no longer being denied or written off. The processes utilized here can be easily replicated for organizations with similar barriers.

Keywords: prior authorization, denials, revenue loss

Introduction

The reimbursement landscape of the healthcare industry is complex, and claim denials create a considerable obstacle for health care organizations (HCO) that strive to collect timely and accurate payments for services. The constant evolution of reimbursement rules and regulations from legislative statutes and healthcare insurance payers complicate the already difficult reimbursement process. The American Health Information Management Association (AHIMA) conducted an analysis of numerous hospitals' payment transactions in 2017 that revealed that initial denial rates among five national payers ranged from 7.5 percent to 11.1 percent of net revenue from patient services, which means one-tenth of revenue is at risk for nonpayment.[1] The cost of unproductive claims processing, reimbursement, and reconciliation can significantly impact HCOs' ability to remain financially stable. In an effort to pursue every dollar for the services provided to their patients and reduce administrative waste, HCOs must design processes to streamline claims management for revenue cycle departments. A hot topic in healthcare reimbursement today is prior authorization, a process put in place to ensure that services provided by healthcare organizations will be reimbursed by insurance carriers.

A prior authorization process is designed to ensure high-quality care while simultaneously regulating healthcare spending. The process accomplishes two main goals: 1) HCOs can provide high-quality patient care supported by appropriate payment; and 2) payers can maintain their own benefit plan designs and payment levels. Though insurance companies believe that prior authorizations improve efficacy and ensure patient safety,[2] the process is labor-intensive, imposing administrative and financial burden on clinicians and support staff. Bendix reported that prior authorization activities for physicians totaled $69 billion annually based on a 2011 study.[3] Experts suggest that HCOs must find ways to minimize the burden of prior authorizations without affecting the quality and efficiency of patient care.[4]

To meet prior authorization requirements, proposed patient care paperwork must be filled out and submitted to the payer prior to a procedure; however, the information entered onto the prior authorization paperwork may be different from the procedure that is ultimately performed in the operating room (OR). To further complicate matters, the staff responsible for filling out the prior authorization paperwork are often clinical staff who do not possess knowledge of billing and coding guidelines. The lack of such knowledge can result in incorrect data being placed onto the prior authorization paperwork, and some payers will not allow a retro-authorization to be done after the surgery.

For healthcare organizations, the prior authorization process is wearing down physicians as prior authorization regulations are becoming more and more cumbersome. Ultimately, payers have become the gatekeeper in determining if a patient will receive the medical services prescribed by the physician. Additionally, prior authorization rules are leading to patients deviating from the suggested course of treatment. These administrative deferments and limitations influence patients’ ability to access needed care in a timely manner. In a recent study, the American Medical Association (AMA) found 30 percent of physicians polled reported that PA has led to a serious adverse event for a patient in their care.[5] Most payers have independent prior authorization policies within sub-plans, making it difficult for HCOs to streamline prior authorization procedures.[6] Furthermore, it is common for providers to be unaware of which services require prior authorization.

Figure 1 illustrates an example of a current prior authorization process for a HCO.[7] While this process is time-consuming for HCOs, the payer also utilizes considerable time and resources addressing prior authorization requests. A standardized, automated workflow could prove to be beneficial to all parties: HCOs, payers, and patients.

Revenue loss related to the prior authorization process for HCOs was estimated to be between $23 to $31 billion annually, and future predictions expected the impact of the prior authorization process to grow substantially.[8] In the Department of Surgery at Hospital X, claims denials related to prior authorizations have been identified as a primary cause of revenue loss. Prior authorization denials make up 16 percent of the claim denials. This HCO utilizes a centralized billing office, which has resulted in there being a separation between what prior authorization processes are handled by the billing office and which processes are handled in the department of surgery. The HCO’s current system lacks a universally adopted process and exchange of data, resulting in duplicated manual approaches and no consistent method of processing and obtaining a prior authorization.

The purpose of this paper was to identify prior authorization issues that could be handled completely within the Department of Surgery without having to engage HCO employees that were not under our control. We wanted to find the root cause of these prior authorization denials, improve the accuracy of these processes, and minimize such denials in order to prevent revenue loss.

Methodology

The setting of this project was the surgery department at Hospital X. Surgical divisions of the department include general surgery, urology, plastic surgery, cardiothoracic surgery, surgical critical care, hand surgery, pediatric surgery, and vascular surgery. The participants involved in this project included clinical and administrative staff in the department. Additionally, relevant billing and coding staff were included in the educational sessions for this project.

The high volume of prior authorization denials for the department necessitated a change in the prior authorization process. The Plan-Do-Study-Act (PDSA) framework, a performance improvement tool, was utilized to guide and design the implementation process of this project.

During the “plan” stage, a retrospective audit of the procedures performed by clinicians in the surgery department were conducted by the revenue cycle manager (RCM). Between July 1, 2018, and June 30, 2019, the number of denials by division, dollar amount of denials by division, and number of denials by denial code were reviewed. Based on the reports done during the phase, the top three divisions with the most past denials and the largest financial impact related to prior authorization claim denials were identified for investigation in this project. These three divisions were plastic surgery, urology, and vascular surgery.

During the “do” phase, the three divisions mentioned above were investigated for specific prior authorization “target areas” that we could focus on for process improvement. It was found that plastic surgery had a large number of denials for not completing prior authorization requirements that were unique for one payer and for excisional debridement done in the wound care clinic; therefore, this issue was chosen as our target area for improvement. The clinical staff received education on how to pre-authorize these services. In urology, it was found that the clinic was also failing to pre-authorize clinic procedures such as prostate biopsies and medication; therefore, this issue was chosen as our target area for improvement. The clinical staff were provided with educational sessions on which procedures and medications required pre-authorization, and they were shown how to perform these. Vascular surgery issues were related to cases being posted incorrectly prior to the procedure; therefore, this issue was chosen as our target area for improvement. Due to the unique process of posting OR cases, the “do” phase for this division required a different action. All elective cases posted to the operating room (OR) and catheterization lab were reviewed by the department of surgery RCM for coding including the CPT codes posted for the OR case, and the information entered onto the clinic note or progress note when the procedure was ordered to verify that accurate codes were being placed onto the OR case. Education for vascular staff included some coding education on various procedures that were found to have errors, and the “cheat sheet” that staff was using to post cases was updated and expanded.

The “study” phase involved an audit to evaluate whether the educational sessions (plastic surgery and urology) and the multidisciplinary review (vascular surgery) for elective surgical procedures achieved the desired outcomes by comparing the pre- and post-implementation audit data. Coding and billing practices of the clinical and administrative staff for certain elective procedures performed by the top three divisions between July 1, 2018, and June 30, 2019, were identified in the retrospective audit. Services performed from September 1, 2019, through January 31, 2020, were included in the post-implementation audit. In total, 2,052 procedure charges were reviewed. The audit data were documented within an excel spreadsheet. The categories included date of service, primary surgeon, procedure name, service line, location, initial CPT code(s) posted, CPT code(s) billed, charges, accuracy of billed CPT code(s), and financial impact.

Finally, during the “act” phase, a trained medical coding professional was assigned to review the prior authorization process as well as surgical case postings for prior authorization information. The desired outcome for this project was an improvement in coding accuracy, increase in reimbursement, and reduction in resources for the coding and billing of elective surgical procedures related to prior authorization processes.

Institutional Review Board (IRB) approval was not required for this project as it was a quality improvement project conducted within the Department of Surgery. No identifiable patient data were used in reporting the outcomes of this project.

Results

The retrospective audit revealed that between July 1, 2018, and June 30, 2019, the Department of Surgery received denials related to prior authorization equated to $3,444,773. Total denial amount during this same period was $21,358,805.60, meaning that authorization related denials were responsible for 16 percent of revenue loss. During the same period, $291,217.16 in prior authorization denials were written off as uncollectible.

Three divisions with the highest financial impact from these denials were: plastic surgery with $343,839 in denials and $84,191.42 written off; vascular surgery with $309,891 denied and $25,468.67 written off; and urology with $263,841 denied and $85,034.83 written off. The plastic surgery wound care clinic received denials for in clinic excisional debridement by one specific insurer. The urology clinic procedure charges also received denials from the same specific insurer due to no pre-authorization. The clinic staff was unaware that prior authorization was required for some insurance companies. In vascular surgery, the operating room cases were often created and posted by a resident, nurse practitioner, or office employee with little to no coding or billing experience. These cases had incorrect CPT codes placed on the case, which was the information used by pre-arrival to request prior authorization. When the case was incorrect, it meant the prior authorization was incorrect as well. After review of the encounters linked to prior authorization claim denials, it was determined that one of the biggest concerns was the CPT code not matching the procedure that was authorized. Other identified challenges included registration errors and payer regulation constraints. It was determined that all three of these issues were preventable and all process changes necessary to prevent these denials could be contained within the Department of Surgery without having to involve other departments.

During the post-implementation period, 2,052 procedure charges related to this study were performed (plastic surgery, 1957; urology, 84; vascular surgery, 11). The error rates leading to prior authorization denials were determined and categorized for each division. The financial impact of the errors on reimbursement was assessed as well. Details on number of denials and revenue loss can be found in **Table 1**.

Plastic Surgery

It was found that plastic surgery experienced 88 charges that were written off as uncollectible due to prior authorization denials during the pre-implementation audit, The charges associated with these write-offs were $84,191.42. Of these write-offs, the charges related to the pre-authorization issues we chose to work on were $22,624.75 and a total of 62 charges. The main area identified for improvement included excisional debridement services performed by plastic surgery providers at Hospital X’s wound care clinic. Authorization denials in these cases occurred due to referral information that was not specific enough for correct prior authorizations to be done prior to the patient being seen by the plastic surgery provider. Patients were often referred to the plastic surgery division with a general reason such as “chronic wound,” and an office visit was scheduled. Once patients were evaluated by the provider, it was determined that excisional debridement needed to be done that visit. However, because this encounter was set up as a clinic visit, the procedure had not been pre-authorized, which some insurers require it for reimbursement. CPT codes billed for these services were 11042, 11045, and 15275.

After the educational sessions on payer rule differences, which payers required prior authorization on clinic procedures, and what the deadline was for each payer were completed, a process for reviewing the prior authorization for the relevant insurance companies in the clinic on the day of procedures was developed and instituted. During the post-implementation period, charges written off for prior authorization denials totaled $13,946 with a total of eight charges; of these write-offs, none were charges in our target area.

Vascular Surgery

It was found that vascular surgery experienced 42 charges that were written off for prior authorization issues during the pre-implementation audit The charges associated with these write-offs were $25,468.67. Of these write-offs, the charges related to our chosen improvement target area were $23,354 with a total of 12 charges. The main area identified for improvement included the process for posting vascular surgery cases accurately and a review of the prior authorization process for these services. When surgical cases are posted in the EHR at this institution, the CPT codes placed on the case are viewed by centralized billing office staff that then used these codes to request prior-authorization. Nursing and office staff determined which CPT codes to place onto the case by referring to an old cheat sheet of surgical codes. They were not aware of how these code assignments affected the authorizations being obtained by the centralized billing office, nor were they aware that some payers will not allow retro-authorization for elective cases if the charges on the claim differ from what CPT codes were chosen to post the case. The CPT codes for these cases varied greatly from case to case, so no specific CPT codes were singled out for the division.

The nursing and office staff in vascular surgery received training on payer preference for elective operative room postings. The cheat sheet that office was using was updated with current payer information as well as new codes. Staff was instructed to call the revenue manager with any coding questions prior to posting a case. After the educational sessions were completed, the project team audited vascular surgery procedures performed during the post-implementation date range. Of the 11 vascular surgery cases audited, zero were denied for prior authorization. Other write-offs for prior authorization issues totaled $35,902.30 with a total of 22 charges; of these, none were charges in our target area.

Urology

It was found that urology experienced 92 charges that were written off for prior authorization issues during the pre-implementation audit. The charges associated with these denials were $85,034.83. Of these write-offs, charges related to our chosen target improvement area were $73,527.09 and a total of 43 charges. The main area identified for improvement included education on which urology procedures required prior authorization and an update on the process for completing prior authorizations. The CPT codes that were being written off in this division were J9217 – leuprolide acetate (for depot suspension), 7.5mg, J9031 – BCG (instillation), and 55700 – prostate biopsy. These codes required prior authorization to ensure payment; however, the clinic was not performing this.

After the educational sessions were completed, the project team audited the urology procedures performed during the post-implementation period. During this period, charges written off for prior authorization denials totaled $7,698.62 with a total of eight charges; of these, none where charges in our target area.

Discussion

Many providers still report a large burden related to prior authorization, with 85 percent describing the burden as “high or extremely high” in 2020.[9] Periodical reviewing denials and staying current on payer rules is critically important to preventing prior authorization denials that would otherwise result in lost revenue. Through comprehensive review, we were able to identify three separate prior authorization issues that could be prevented through process changes and education. Prior authorization write-offs were completely eliminated for these target areas in all three division. Continual training and education are essential to safeguard an organization from multiple types of prior authorization denials. Overall, between pre- and post- implementation, multidisciplinary coding and billing education and training resulted in a significant decrease in resources utilized to collect payment for procedures performed.

Similar to research by Menger et al,[10] this project found that provider practices should take time to research and analyze such data to make sure that they are not losing revenue that could have been prevented. The real-life implications of this study is that payer guidelines can change and differ among payers. Consistent, ongoing review of denial data helps adjust policies for each payer and ensures that practice policies stay current and meaningful.[11]

With the implementation of this project, a decrease of claim write-offs was actually observed in all divisions in target areas. The plan was to continue streamlining the process utilized in this project so that it could be applied in other divisions of the surgery department at Hospital X. It is important to know that there is still a considerable amount of work for the department to complete, with each different type of prior authorization issue needing to be identified and analyzed for solutions.

One strength of this project was that this was one of the first prior authorization denial prevention initiatives in our organization. The literature search also showed that very few organizations had made such efforts. Another strength was the use of the PDSA cycle, which permitted the planning and implementation of the rapid change processes and offered the opportunity for future revisions and re-implementation of this process. As to limitations, one was the lack of previous peer-reviewed research on this topic. Also the number of divisions of the department of surgery reviewed were limited to three divisions. Other divisions will be evaluated to further prevent revenue loss.

Conclusion

Prior authorization denials caused over $21 million revenue loss in a one-year period in the department of investigation. This project aimed to design an improved process to reduce the financial impact of such denials. Three divisions within the department that had the highest prior authorization denial rates and the largest financial impact were targeted for intervention. A comprehensive review of the existing prior authorization process was conducted. Problems were identified, accordingly educational sessions were provided, and changes were implemented. The comparison of pre- and post-intervention results showed that process changes eliminated any charges from being written off in the target areas of this study. The Plan, Do, Study, Act process that was used in this project could easily be replicated by other organizations to help prevent revenue loss. Because prior authorization issues are so complex, this process should be performed on a routine basis to continually review prior authorization issues as they arise.

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Healthcare Fraud Data Mining Methods: A Look Back and Look Ahead

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Abstract

Healthcare fraud is an expensive, white-collar crime in the United States, and it is not a victimless crime. Costs associated with fraud are passed on to the population in the form of increased premiums or serious harm to beneficiaries. There is an intense need for digital healthcare fraud detection systems to evolve in combating this societal threat. Due to the complex, heterogenic data systems and varied health models across the US, implementing digital advancements in healthcare is difficult. The end goal of healthcare fraud detection is to provide leads to the investigators that can then be inspected more closely with the possibility of recoupments, recoveries, or referrals to the appropriate authorities or agencies. In this article, healthcare fraud detection systems and methods found in the literature are described and summarized. A tabulated list of peer-reviewed articles in this research domain listing the main objectives, conclusions, and data characteristics is provided. The potential gaps identified in the implementation of such systems to real-world healthcare data will be discussed. The authors propose several research topics to fill these gaps for future researchers in this domain.

Keywords: Medicaid, fraud detection, class imbalance, machine learning, health insurance claims

Healthcare Fraud Introduction

Background and Significance

Caring for health has become more expensive, making both private and public administrators more cost conscious in recent years. Therefore, health decision-makers are actively looking for ways to reduce costs. One such avenue of saving potentially billions of dollars is to avoid and detect healthcare fraud. The National Health Care Anti-Fraud Association[1] conservatively estimates that about 3 percent of our healthcare spending is lost to fraud ($300 billion approximately) yearly. Fraud is a complex and difficult problem. It is important to acknowledge that fraud schemes constantly evolve, and fraudsters adapt their methods accordingly. The earliest account[2] of “fraud” in the healthcare literature is from the 1860s when railway collisions were a frequent occurrence, leading to a controversial condition called “railway spine,” which later became a leading cause of personal injury compensation in rail accidents. These accidental events were made profitable by means of insurance settlements in-court or out-of-court by opportunistic claimants, and these events laid the groundwork for fraud definitions and fraud management in the insurance industry.

Healthcare fraud has evolved in the 21st century and has a varied set of profiles ranging from simple fraud schemes to complex networks. The twin objectives of fraud management have always been fraud prevention and fraud detection[3] (see the definitions section below). The consequence of submitting a fraudulent claim remains the same: the fraudster is prosecuted by means of sanctions and prosecutions in a court of law. However, the methods used in both prevention and detection have evolved since the 1800s, and so have the methods of detecting fraudulent claimants. With the advances in computing, and the more rapid availability of aggregated datasets in the healthcare domain, there are several opportunities for potential advancements in healthcare fraud management. Despite these advancements, it is very difficult to quantify the number of undetected fraudulent cases that do not get prosecuted. The identified limitations[4] in achieving these advancements are manifold, including using legacy systems in claims processing; processing systems that are siloed due to involvement of multiple entities (e.g., enrollment, approvals, authorizations, claims adjudications); having sensitivity related to healthcare data privacy (e.g., sensitive healthcare domains such as family planning and mental health); and difficulty in proving intent of fraud in litigation settings.

The objectives of this review article are to summarize the methods and approaches used in healthcare fraud detection and to discuss the implementation gaps between the academic literature and real-world use by industry settings. Fraud detection in the literature encompasses data mining (rule-based to advanced statistical methods), over-sampling, and extrapolation techniques. The literature concerning overpayment and sampling estimation are important steps in fraud detection's business workflow and are addressed by Ekin et al. (2018).[5]

Definitions

There are many definitions in the literature and social media regarding what constitutes a healthcare fraud incident. Healthcare fraud is defined as an individual, a group of people, or a company knowingly misrepresenting or misstating something about the type, scope, or nature of the medical service provided, which, in turn, results in unauthorized[6,7] payments.

There is a vast amount of literature[8,9] available on fraud management techniques and models in different industries, such as healthcare, telecommunications, credit card services, insurance, and finance. Fraud management,[10] in theory, is divided into two goals: fraud prevention and fraud detection. Fraud prevention in healthcare can be defined as any action or policy that is in place to prevent any system abuse. For example, there is a Medicaid policy in the state of Texas[11] for outpatient mental health services where certain types of providers, such as psychologists and licensed professional counselors, are limited to billing a combined maximum of 12 hours per day, regardless of the number of patients seen. This policy requirement is in effect to prevent fraud (by means of overbilling in this case) before it occurs. Fraud detection, on other hand, is defined as identifying fraud as quickly as possible once a fraudulent scheme has already been perpetrated.

Fraud Actors, Types, and Facts

Healthcare fraud takes many forms. Some of the more prevalent forms[12,13] are traditional fraud schemes implemented by shell vendors, ghost employees who obtained access to bill payers, and employees who continue billing with expired licensures. Some of the main actors committing or involved in fraud are providers (those who are authorized to provide services to beneficiaries), beneficiaries (those who receive medical or associated services), medical equipment manufacturers, drug manufacturers, and agencies authorized to provide special services, such as home healthcare.

Some of the healthcare fraud schemes commonly discussed in literature and used often to develop fraud detection algorithms or analytics within regulatory entities such as the Office of Inspector General (OIG), the Department of Justice (DOJ), and the Centers for Medicare and Medicaid Services (CMS) are as follows:

- Diagnosis Related Groups (DRG) creep – when actors manipulate diagnostic and procedural codes to increase reimbursement amounts in an institutional setting
- Unbundling and fragmentation of procedures – billing individual service codes versus group service codes
- Up-coding of services – billing for a higher level of service than provided
- Phantom billing – billing for services not rendered to clients
- Excess number of services – billing unnecessary services that could lead to client harm
- Kickback schemes – actors might improperly pay for or waive the client's out-of-pocket expense to make up for that cost in additional business
- Billing for mutually exclusive procedures
- Duplicate claims
- Billing errors

Figure 1 illustrates the percentages of improper payments in the United States Health & Human Services (HHS) government programs from 2012 to 2019. Such improper payments include any kind of underpayment, overpayment, fraud, and any unknown payments. The government healthcare programs that were included from the original data source[14] are the following HHS agency programs: Children's Health Insurance Program (CHIP), Medicaid, Medicare Fee-For-Service (FFS), Medicare Part C, and Medicare Part D. As seen in **Figure 1**, the Medicaid and CHIP programs have generally shown a steady increase in the percentage of improper payments.

Figure 2 reports the recoveries from the False Claims Act[15] in years 1985 to 2020. In 2020 alone, $2.2 billion was recovered by the government, out of which $1.8 billion was from the healthcare industry. The recoveries are estimated to be significantly higher for 2021-2022 considering the ongoing difficulties in litigations in closed-court settings due to COVID-19.

Scope and Objectives

The scope of this article is twofold: to provide a comprehensive review of current healthcare-related fraud detection methods and to provide a discussion on implementation gaps in the application of such methods to real-world settings in the US. Related work section entails a comparative evaluation of review studies in literature. This is followed by a review of study methods section, which details selected fraud detection methods with discussions around gaps in applying these methods to real-world data. The next section focuses on implementation gaps, followed by conclusions and future research section, which summarizes the main points and future research directions for healthcare fraud detection. **Table 1** includes an extensive (not exhaustive) tabulated summary of healthcare fraud literature for prospective researchers in this area.

The literature reviewed here does not incorporate articles that included holistic healthcare as an objective, such as those of disease prediction, readmission, or length of stay, in which fraud identification is not necessarily the primary objective. In addition, only articles pertaining to healthcare fraud in the US were considered. In contrast to prior review articles,[16-19] this article discusses the literature from a business workflow perspective starting from a data-driven lead to the end point of litigation/recoupment, and provides recommendations to address the research gaps in existent methods.

Related Work

The value of this review is not only for comparative purposes on the methods employed in the literature but, more importantly, to start a discussion of how relevant current academic healthcare fraud detection methods are to the downstream process of proving intent of fraud by investigators in an industry setting. An understanding of the implementation gaps and overall fraud detection process (i.e., starting from data leads provided by a model to a conviction phase in a legal setting) will help leverage the already available collective knowledge to help improve practical fraud detection methods.

Several articles discussed healthcare fraud data-mining methods in the literature with similar goals but from different perspectives. Li et al. (2008)[20] categorized the three different actors in healthcare fraud—namely, providers, patients, and the payers—and focused on the provider fraud literature. They further highlighted the scarcity in the data pre-processing methods (from raw claims datasets to flattened datasets) and commented on the importance of this step in identifying healthcare fraud using supervised and unsupervised methods. They also highlighted the two main types of classifier performance metric categories; 1) the error-based methods and 2) the cost-based methods, with error-based classifiers being more common in healthcare fraud literature. An article by Bauder et al. (2017)[21] focused specifically on up-coding fraud in several healthcare domains using medical claims data. They highlighted the lack of literature pertaining specifically to using supervised techniques in up-coding fraud detection.

Ekin et al. (2018)[22] provided a comprehensive discussion of statistical methods in healthcare fraud, including sampling, over-payment estimation methods, and data-mining methods such as supervised, unsupervised, and outlier detection methods from the literature. The authors focused on describing unsupervised methods in more detail, such as using concentration functions and Bayesian co-clustering. Both Ekin et al. (2018)[23] and Li et al. (2008)[24] highlighted the lack of literature in identifying the potential drivers of fraud.

The most recent review by Ai et al. (2021)[25] discussed medical fraud detection methods in the literature using qualitative methods. They provided a methodological literature search using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines on the methods, number of peer-reviewed articles and a qualitative analysis of statistical methods, model performance, using evaluation metrics (when available) for health care domain. Their research is quite comprehensive, with a focus on being able to assess the strength of model performance and accuracy of existent fraud detection methods in the literature. They concluded that the evidence to provide a consolidated best method to identify healthcare fraud was inadequate considering the literature models were applicable to different domains within healthcare and therefore not directly comparable. They also highlighted that there was no literature available to estimate the cost of investigations in order to estimate potential cost savings using a fraud detection model.

Healthcare administration and payments have changed in the last two decades, especially from a data quality and data integration perspectives. Although the standard forms, such as the CMS-1500 or the UB-04 used for data collection (for payment processing), have not changed significantly over time—except for the volume increase in electronic submissions in the past two decades—there is still a significant gap in the application of literature methods to real-world settings. Other published review articles in this domain focused on the overall state of healthcare fraud literature and methods. This review extends the available literature by focusing on the applicability of these methods to real-world claims data and highlights the research gaps in the practical implementation of these methods.

Policy Statutes Overview

A range of civil, criminal penalties and laws exist within healthcare fraud.[26,27] Government agencies such as the US Department of Justice (DOJ) and the HHS Office of Inspector General (OIG) are the enforcers of such laws and penalties. A quick overview of these laws would aid the understanding of the end goals of the fraud detection business workflow in real-world cases.

The business workflow starts from converting data-based fraud leads to a civil or criminal case indictment, depending on the path an investigation takes, followed by legal proceedings on a case-by-case basis. Data-driven fraud detection tools are only a piece of the complete fraud puzzle; nevertheless, it is an important part considering this is a targeted methodological means to find fraud leads. A simplistic business workflow of how a fraudulent case progresses through a normal course of an investigation/audit is shown in **Figure 3**. The pictograph identifies the most relevant and helpful analytical methods used to identify fraud, waste, or abuse among provider or client or payer.

The common statutes under which fraudulent cases are prosecuted include both civil statutes (the False Claims Act and the Physician Self-Referral Law) and criminal statutes (Anti-Kickback Statute and Criminal Healthcare Fraud Statute).

False Claims Act[28,29] – Many of the fraud cases are lawsuits filed under the False Claims Act (FCA). This is a federal statute originally enacted in the 1800s, and penalties could include recovery of up to three times the damages sustained by the government, in addition to financial penalties for each falsely submitted claim. Most fraudulent recoupments reported by DOJ are claimed under this act.[30]

Physician Self-Referral Law or Stark Law[31] – Under this law, a physician is prohibited from referring patients to receive "designated health services" to an entity in which the physician or immediate family member of the physician has an investment.

Anti-Kickback Statute[32] – Under this law, a medical provider is prohibited from soliciting or receiving any remuneration or rewards directly or indirectly for patient referrals or business generation from anyone.

Criminal Healthcare Fraud Statute[33] – Under this law, any service provider is prohibited from executing a scheme in connection with delivery of health care benefits or services to defraud a health care program.

Data Sources

Healthcare data, in general, are broadly categorized as practitioners' data, administrative claims data, and clinical data.[34] The three sources of data together form a near-complete picture of the fraud data puzzle. However, it is extremely difficult to be in possession of all three data sources under one entity. Second, even if data are available from all three sources, integration of these sources of data can be extremely challenging in real-world practice due to the varied systems and identifiers involved in the data collection and ETL (extract, transform, and load) process. For purposes of fraud detection, the most commonly used data source in the literature is administrative claims.

The collected administrative claims data among insurers do not differ much in their basic structure because of the standard template used in the electronic claims processing. For example, the CMS 1500 form is used in the adjudication process of all professional claims. However, not all collected data are utilized for purposes of adjudication; hence, some data/field values can be considered informational. The data collection and utilization of such informational column values are also dependent on the payer (e.g., fee-for-service versus managed care organization in different state and federal programs). In the next section, the current state-of-the-art fraud detection and prevention methods is briefly described.

Most fraud detection/prevention models discussed in literature are based on either synthetic data or data collected in a de-identified manner and made available as open-source or agency-specific data, such as Veterans Affairs TRICARE, Health and Human Services, or Texas Department of State Health Services. For example, aggregated Medicare/Medicaid data are now made available through the CMS.gov[35] website. The Medicaid Analytic eXtract contains data collected by CMS from all states on a quarterly basis. Such data are available for researchers to study utilization patterns such as healthcare resource utilization or disease-based utilization. The fraud detection models developed using such aggregated data extracts are difficult for relevant parties to adopt due to the many logistical issues involved, such as the difficulty in linking results tied to the identified provider back to specific claim-line level data.

Rule-Based Fraud Detection

One of the most common approaches to identify fraud is to use domain or expert knowledge to identify anomalies in billing practices. Expert knowledge is often used and is very effective in keeping common fraud schemes in check.

Some common healthcare fraudulent claims as seen in literature fall into the categories mentioned earlier. Simple to medium-complex rules are developed to identify billing errors or duplicate claims to identify fraud categories such DRG creep or up-coding.[36] These are not to be confused with edits and audits in a claims processing system, as these rules are developed based on schemes rather than policy. These rules can be developed at a transaction level or actor level. This is a straightforward and effective approach even though static in nature.

The inherent limitation with such rule-based detection is that once the fraudster becomes aware of the rules—either due to unpaid/rejected/held out claims, or due to a retrospective inspection or audit of adjudicated claims—their fraudulent patterns could change, and these rule-based detection programs cannot quickly adapt to the fraud pattern modifications. Other limitations to having a rule-based detection system are that these engines are very expensive to build, as they require constant inputs from fraud experts and are quite difficult to maintain and manage in the fast-changing healthcare landscape. It is thus very difficult to keep a rule-based system lean and up to date.

Data-Driven Fraud Detection

Data-driven fraud detection is becoming commonly popular in all domains, and the healthcare domain is no exception. Implementing data-driven fraud detection methods offers a higher fraud detection power along with operational and cost efficiencies. The fraud literature regarding the applications of advanced statistical techniques in various healthcare domains (medical, dental etc.) covers three main aspects of the business process: fraud detection, statistical sampling, and oversampling estimation methods. Fraud detection methods[37-42] all have one common motivation, which is to mine data to assess patterns.

Data-driven methods can be categorized broadly as supervised, unsupervised, and hybrid learning methods. These techniques can be summarized from a fraud perspective as below:

- Supervised learning methods employ samples of previously known fraudulent and legitimate transactions or providers.
- Unsupervised learning methods do not require a prior knowledge of fraudulent transactions or providers. They focus more on anomalies based on distributions of a provider’s billing behavior. They also use descriptive statistics to help learn such patterns in some cases.
- Hybrid learning is where a mix of both supervised and unsupervised techniques are used.

It is also worth mentioning that these data-mining methods are dependent on a well-defined problem statement and the acquisition of relevant, adequate, and clean data. The process flow of modeling (irrespective of the learning methods used) involves a sequence of steps as it relates to fraud and is described in **Figure 4**. The different level of complexities involved in a data-driven fraud models from literature are discussed in the next section.

Review of Study Methods in Healthcare Fraud

This section presents selected study methods and discusses practical implementation gaps of these methods. The studies were screened from a structured database search using search terms such as “fraud,” “healthcare,” “secondary data,” “prescriptions,” “Medicaid management information system,” “Medicaid,” “Medicare,” and any possible combinations of these search terms. From this, the studies were further narrowed down focusing on the data, methods, and implementation of fraud algorithms. A subset of such studies are discussed in this section, as they attempt to address some implementation gaps such as class imbalance in real-world data, missing fraud labels, and data pre-processing techniques before applying algorithmic models to data.

Supervised Learning

A supervised learning task is to learn a function that maps response variables to the inputs based on the available labeled response data. Researchers using supervised learning methods in fraud detection have the following in common: a labeled dataset (i.e., fraudulent: yes or no), a domain-specific justification to choose one algorithm versus another, and a performance metric of choice to determine the best algorithm. The general concept that stands out in the development of such supervised models is the identification of features that can discriminate a fraudulent provider from legitimate providers. The methods of identifying such features vary between researchers and are mostly focused from a provider-level rather than a transaction-level.

Considerations in Defining Ground Truth

It is important to acknowledge that any supervised technique application is inherently dependent on the validity of the labeled dataset used to categorize the data to their corresponding classes. Supervised learning algorithms thus require confidence in the correct classification/labeling of the providers. The fraud labels for the reviewed providers are classified to one of two categories: fraudulent or not fraudulent (legitimate). But it is not known if providers who were never reviewed did or did not commit fraud. Some published studies[43-45] address this uncertainty partially by having a varied range as an estimate for class distribution of the “never reviewed” providers. Thus, there will always be cases where fraud is mislabeled as non-fraud. Binary classification of providers as fraudulent or legitimate does not allow for uncertainty to remain after providers are investigated. In contrast, the confidence that a provider committed fraud (“fraud” confidence) could be used for supervised learning in lieu of a binary ground truth.

The labeled fraud dataset is skewed in nature, irrespective of methods used for label associations in a dataset. The skewness arises from the practical fact that only a small number of the reviewed providers are categorized as fraudulent while the majority of the reviewed providers are legitimate. This nature of skewness in a categorical label assignment is called “class imbalance” and has its own literature[46] stemming from computer science and its applications to real-world problems.

Review of Supervised Learning in Healthcare Fraud Detection

Bauder et al. (2018 and 2018, May)[47,48] categorized different supervised learning techniques (Random Forest, C4.5 decision tree, support vector machine, and logistic regression) to find the effect of class imbalance in fraud detection. The authors used publicly available claims data (Medicare Provider Utilization and Payment Data: Physician and Other Supplier) from CMS. The labels for known fraudulent medical providers across all specialties, and provider types were obtained from the OIG's publicly available database of List of Excluded Individuals/Entities (LEIE) in 2017. The final merged Medicare dataset (claims and labeled fraud data) was highly imbalanced (about nine out of every 100,000 providers were marked fraudulent). The performance metrics used were area under curve (AUC); false positive rate (FPR is the ratio of non-fraud cases incorrectly categorized as fraudulent cases to the total number of non-fraudulent cases); and false negative rate (FNR is the ratio of fraud cases incorrectly categorized as non-fraud cases to the total number of fraudulent cases). Two main conclusions were:

- The C4.5 (decision tree) algorithm had the best performance on the AUC metric (0.883).
- As the minority class distribution was varied from 20 percent to 50 percent, the learners became worse on their performance metrics.

Herland et al. (2018 and 2019)[49,50] also investigated the effects of class imbalance on supervised learning for fraud detection using the same publicly available datasets (claims and fraud labels) as Bauder et al. (2018, May). The authors concluded that a logistic regression model followed by gradient tree boosting performed well based on the AUC metric (0.828) evaluation.

Fan et al. (2019)[51] focused on physician fraud detection combining the different open datasets on claims (CMS data), social media ratings on physicians (Healthgrades.com), and ground truth fraud datasets such as LEIE and Board Actions. The different classifiers that were trained included logistic regression, naïve Bayes, and a decision tree classifier. The board action dataset features did not prove to be beneficial to their classification model, although it is not clear which features from the dataset were included in the modeling process. Some feature engineering was performed to determine the final set of features resulting in a best classifier. The authors concluded that their classification performance was highest using a decision tree with features (based on rating) from social media, open payment, and prescriber (CMS) datasets.

Ekin et al. (2021)[52] provided an overview of pros and cons in addressing three steps of the statistical fraud detection modeling process. In their experimental design, they manipulated the claims data to address the variance in the model performance from:

1. Correlated features – e.g., principal component analysis (PCA) on the features to address multicollinearity

2. Classifier type – nine supervised classification algorithms such as random forest, naïve Bayes, and neural networks.

3. Class imbalance – this effect was addressed by using four sampling techniques (e.g., random walk oversampling (RWO))

They utilized a wide range of evaluation metrics to assess the different model's performance with the aggregated public (CMS's Part B, CMS's zipcode to carrier locality file, and CMS's Geographic Variation Public Use File) datasets. To simulate an adjustment to the well-known method of considering LEIE data as the only source of ground truth for fraud labels, they performed an experiment with a range of possible fraud proportions (0.06 percent to 45.76 percent). The combination of these data manipulations led to a total of 405 different trained models. Based on their AUC metric (0.84) performance, their conclusions were:

1. As class imbalance becomes higher, AUC becomes lower. [This is in contrast to the first three articles that were discussed above and more in agreement with the imbalanced data literature].

2. The best sampling approach with the highest AUC was RWO. [This has not been previously reported in literature by any other published studies and is an important addition to the fraud literature].

3. Overall correlated features did not affect model performance for most of the algorithms; however, the authors do report a slight improvement in performance using PCA for random forest algorithms. [This is slightly inconsistent to the familiar belief in data science that correlated features affect model stability for some algorithms and will need a larger training data set].[53]

One common theme among these methods is that these authors used publicly available datasets and LEIE or expert opinions as their ground truth. However, the ground truth was considered binary for all these studies. Another major limitation in these studies was that the features used to train the models did not extend beyond what is available in the aggregated data extract, which limits feature engineering. Lastly, the evaluation metrics used were all error-based rather than cost-based. However, no prior research exists to make an estimate on cost and resources needed for an investigation.

Unsupervised Learning

Unsupervised learning refers to techniques that are used to identify patterns or structure in data. These descriptive techniques are used when no labels or class markers are available for the algorithm to learn from. The K-means clustering technique is a commonly seen example of unsupervised learning. These methods can also be a precursor to use before descriptive outlier techniques can be implemented. A more detailed overview of such methods can be found in Konjin (2017).[54]

Ekin et al. (2013)[55] proposed a novel Bayesian co-clustering framework to detect healthcare fraud. In this theoretical framework, the authors identify a co-cluster (defined as a dyadic grouping of provider and beneficiary) as fraudulent depending on the posterior probability assigned to the co-cluster. A Dirichlet distribution prior and Beta distribution prior for the random variable were proposed to arrive at the posterior probability distribution of each co-cluster. Any co-cluster containing unusual membership of either provider or a beneficiary was identified as fraudulent. The authors only used simulated data to test the feasibility of this framework. Nevertheless, this is an important step in the direction of investigating conspirator fraud involving two parties.

Sadiq et al. (2017)[56] used CMS Medicare Part B, Part D and durable medical equipment, prosthetics, orthotics (DMEPOS) datasets to develop a fraud claim detection system using the Patient Rule Induction Method (PRIM) based bump hunting method. PRIM starts with all of the training data and peels/removes regions followed by paste/addition of regions, thereby gradually zooming into regions with high values for target variables. At each step of the peel or paste, only a small set of observations are excluded or included in this heuristic search. For example, when a physician prescribed eye drops, they calculated the conditional probability of the prescriber being an ophthalmologist. A low probability indicated a higher likelihood that the prescription was improper. The homogeneity of prescriptions (overused medications for conditions such as headache, cold) was accounted for by using an analysis of variance (ANOVA) test and F score calculations. The identified bump regions were validated by comparing the number of observations in bump region with that not in the bump region using a confusion matrix. It is unclear from the article how the ground truth for the bump region was determined. This method may help in identifying potential fraudsters who may go unidentified when using other popular classifiers.

Sadiq et al. (2019)[57] used propensity matching and clustering for fraud detection using CMS's 2012-2015 Medicare Part B, Part D and DMEPOS dataset. They term this temporal learning framework as Cascaded Propensity Matching (CPM) Fraud Miner. Their primary goal was to see if a deliberate fraudulent action causes a perturbation in the observational data, accounting for any co-variates (X) that could lead to that fraudulent outcome. A weighted propensity score e(X) was used to compare the treatment group (T=1, indicating patients were treated by other physicians for a given condition) with the other-treatment group (T=0, indicating patients were not treated by other physicians for a given condition). For example, a condition such as a cataract is never treated by retinoblastoma removal surgery, but there could be situations or clients where such a condition is treated by this expensive surgery. The reason for such an expensive option billed in the data could be twofold: due to sheer neglect of the condition by the clients for many years, including other medical conditions leading to have the surgery, or due to a high reimbursement amount to providers for expensive surgeries. However, the method used to arrive at the ground truth or how these database results were incorporated to determine their performance metrics/values was unclear.

Zafari and Ekin (2019)[58] devised an unsupervised framework for prescription fraud using 2015 Part D Medicare data. The prescribing specialty code was used as a co-variate to control for the deviations normally evident in prescriptions due to the prescriber's specialty. These authors proposed a novel approach to detect associations between prescribers and drug group (topics) billings from transactional data, accounting for specialty differences that could lead to different billings. They used structural topic modeling concepts (from natural language processing literature) to group drugs into different topics (synonymous to grouped drug categories) for all prescribers. These groupings were then used as benchmark groups to detect outliers by means of concentration functions or distance-based measures that capture deviations from expected billing patterns. Their fraud framework can be summarized as consisting of two main steps: Step 1 involves identifying associations between prescribers and their drug billing utilization, followed by Step 2, which uses these groupings to detect outliers within a specialty.

Ekin et al. (2019)[59] outlined a novel unsupervised Bayesian hierarchical model to help untangle the relationship between medical procedures and billing provider using CMS's Part-B data. The joint distributions of these variables were derived, and a Gibbs sampler was used to draw samples from the posterior density function of this joint distribution. Their unsupervised hierarchical Bayesian framework implementation using real-world data identified anomalies in billing among providers who could be outliers considering only the billing procedure code and frequency of billing by the provider. One possible limitation that might explain some of the anomalies could be the lack of consideration for billing modifiers (modifiers allow a provider to indicate special circumstantial usage of a performed procedure) in a claim, but Part-B data does not contain modifiers, which is an inherent limitation of the data source.

Such outlier detection techniques allow for real-world implementation without having to rely on a labeled fraud dataset; however, the burden of proving intent of fraud lies with the investigators or experts in these cases. Identification of the claim line details that are the root causes for such provider billing anomalies is difficult considering that aberrant behavior of billing exists for the provider as a whole. These methods used, along with rule-based outlier detection techniques, could overcome some limitations of unsupervised techniques. Another major limitation of these methods in the real world is the governing business workflow for a fraud examiner.

Hybrid Learning

Hybrid learning includes a mix of both supervised and unsupervised techniques that are used at different stages of the model.

Shin et al. (2012)[60] proposed a tree-based segmentation model and scoring using outlier techniques and a method that unifies these different techniques to provide a final score. Eldardiry et al. (2013)[61] used rules to identify features, followed by rule-based feature extraction and risk score computation using the term frequency-inverse document frequency method that reflected how important or unimportant a particular rule violation is for a provider. In summary, Eldardiry et al.[62] applied a probabilistic outlier detection technique by combining features from a set of fraud rules to design a risk score computation, which would allow an investigator to tease out the specific rule a provider violated in the course of an investigation.

Identified Recommendations and Implementation Gaps

The literature justifies the applicability of machine learning and statistical techniques to healthcare provider fraud detection. Most research describes the process of utilizing open source aggregated transactional health data merged with some kind of ground truth (e.g., OIG exclusion list, expert opinions) database and validates their model using known performance metrics such as F-score, or recall. Some authors focus on specific areas such as prescription medications or DMEPOS as their data source. Different authors use different techniques ranging from a rule-based technique to advanced statistical models using algorithms such as multinomial naïve Bayes or logistic regression.

In spite of the extensive literature in this area, there is no unifying process that bundles these research methods together to identify healthcare fraud. There is, however, a need to have a unified framework to provide a solution to the problem of retrospective fraud detection in healthcare domains such as prescription claims, dental claims, long-term care service claims, and professional claims. This process should facilitate easy integration into an investigator or auditor’s workflow so as to meet the business and real-world needs of investigations.

Second, feature engineering is highly dependent on the data sources. This dependency on data sources inherently poses limitations on the number of co-variates considered as being associated with our response variable (provider fraud) in different domains. For example, provider specialty is a covariate that is usually considered in professional claims analysis, while provider specialties in the case of pharmacies such as chain, independent, mail service, and wholesalers are not considered in prescription claims analysis. There is a need for algorithms to be adaptive to the number of features available in different state or private payer systems and data sources within a domain. The model needs to be able to accommodate and degrade gracefully, dependent on the feature space considered for the focused healthcare domain. “Graceful degradation” here is defined as the ability of a model to maintain limited functionality even when a portion of data, or some variables, are missing. Most healthcare fraud literature does not discuss further feature engineering or data pre-processing from raw line-level claim element attributes. This is a common gap seen in this literature. Feature engineering is a key factor known to affect algorithmic performance to a great extent in the computer science literature. This is an inherent limitation of the aggregated data sources often used in fraud literature.

Third, fraud models in the literature seem to start with aggregated data before using a predictive algorithm on the collected or processed data. It is unclear how certain components of claims were dealt with in these aggregations. For example, in prescription claims, the quantity dispensed and whether or not the product was compounded are variables available for each claim (each prescription dispensed), but the method of aggregation of these variables remains unclear. A new train of thought is needed here to explore the idea of extracting patterns or meaning from de-aggregated claims. This will help build into the existing body of fraud literature and help build models that can be used for real-world investigations.

Lastly, the fraud literature does not address the actions or processes that happen beyond fraud-detection. Prospective researchers in this domain have the opportunity to follow the results beyond detection. Qualitative analysis, employing focus groups, and interviews with investigators, auditors, and litigators who play a very important role beyond the stage of fraud identification (using advanced statistical methods) is crucial to improving algorithms that will provide results that can be integrated into the business workflow process.

These gaps in healthcare fraud research are portrayed pictorially in **Figure 5** for one healthcare domain (pharmacy) for demonstration purposes.

Conclusions and Future Research Directions

Even though the academic literature on statistical methods used to identify healthcare fraud is substantial, there are very few states in US that implement these advanced methods in real-world practice. Possible reasons for the lack of application are discussed below:

1. The structure of such teams focused on fraud detection from a business workflow standpoint consists of a team of trained and credentialed auditors, administrative/criminal investigators, statisticians/analysts/both, and investigative attorneys within any state or federal integrity programs. Considering this business workflow (see **Figure 3**), there is a strong need for collaboration of the data team (statisticians/analysts/both) and the examiner's (auditors, investigators, and attorneys) team to identify and convert fraud leads to recoupments (fraud conversion rate).
2. There is also a strong need for closing the feedback loop on what worked and what did not from an investigation and litigation standpoint. This information collected in a quantitative or qualitative fashion (e.g., focus groups, interviews) can help fine-tune mining algorithms leading to an improved fraud conversion rate.

3. There is also a significant gap in implementing the methods reviewed in this article in real-world use cases since fraudulent intent is difficult to prove, and without fraudulent intent, the actors cannot be prosecuted.

4. Complex algorithms are difficult for the downstream examiner's team to understand and use. In a healthcare fraud business workflow, it is very important that the methods used in each step along the way are transparent and easy to comprehend. Such logistical issues are hypothesized in impeding progress from algorithm design to implementation.

5. Most methods in the literature use publicly available data, which is a major limitation to implementation in a business setting. However, other methods that have used private data sources, such as those from electronic health records or private payer data, are limited due to data privacy and legal issues and are thus difficult to replicate to a real-world setting.

6. Drilling down from provider-level data-based leads (using advanced statistical methods) to specific claim-level leads is important for an investigator to make a case of fraud. This gap might be addressed by educating investigators on pursuing such data-based provider leads from an investigation standpoint in collaboration with the data team.

The ability of a method to tease out the metrics that best identify a fraudulent provider lead needs some fine-tuning as well. The literature included different modeling metrics to assess a model; however, from a practical implementation standpoint, research on the costs associated with a fraud investigation is not quantified. This is a significant gap that needs to be addressed so the statistical methods to identify fraud can be modified from an error-based to a cost-based solution.

In conclusion, this article reviewed healthcare fraud detection systems and methods found in the academic literature, discussed limitations and implementation gaps of such methods to real-world business setting, and concluded with an outline of potential solutions to address these gaps.

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Factors That Influence Clinician Experience with Electronic Health Records

By Vimal Mishra, MD, MMCi; David Liebovitz, MD; Michael Quinn, PhD; Le Kang, PhD; Thomas Yackel, MD MBA; and Robert Hoyt, MD, FACP, FAMIA

Abstract

Objectives: To report quantitative and qualitative analyses of features, functionalities, organizational, training, clinical specialties, and other factors that impact electronic health record (EHR) experience based on a survey by two large healthcare systems.

Materials and Methods: A total of 816 clinicians—352 (43 percent) physicians, 96 (12 percent) residents/fellows, 177 (22 percent) nurses, 96 (12 percent) advanced practice providers, and 95 (12 percent) allied health professionals—completed surveys on different EHRs. Responses were analyzed for quantitative and qualitative factors. The measured outcome was calculated as a net EHR experience.

Results: Net EHR experience represents overall satisfaction that clinicians report with the EHR and its usability. EHR experience for Virginia Commonwealth University Medical Center and University of Chicago Medicine was low**.** There were noticeable differences in physician and nursing experiences with EHRs at both universities. EHR personalization, years of practice, impact on efficiency, quality of care, and satisfaction with EHR training contributed significantly to the net EHR experience. Satisfaction of certain specialty practitioners such as endocrinology, family medicine, infectious disease, nephrology, neurology, and pulmonology was noted to be especially low. Ability to use a split-screen function to view labs, follow-up training from other providers rather than vendors, reduced documentation time burden, fewer click boxes, more customizable order sets, improved messaging, e-prescribing, and improved integration were the most common desired EHR improvements requested on qualitative analysis.

Discussion: EHR experience was low regardless of the system and may be improved by better EHR training, increased utilization of personalization tools, reduced documentation burden, and enhanced EHR design and functionality. There was a difference between provider and nursing experiences with the EHR.

Conclusion: Designing better EHR training, increasing utilization of personalization tools, enhancing functionality, and decreasing documentation burden may lead to a better EHR experience.

Introduction

Despite early optimism regarding the potential benefits of electronic health records (EHRs), reported outcomes with ubiquitous use are mixed, and EHRs are believed to contribute greatly to physician burnout.[1] Clinicians have expressed dissatisfaction with EHRs due to poor usability, time-consuming data entry, interference with face-to-face patient time, inefficiency, lack of interoperability, and degradation of documentation.[2] Moreover, studies indicate that EHRs create clerical and cognitive burden, as well as interruptions and distractions that negate any benefits.[3] EHRs place much greater demands on a clinician's time compared to paper-based charts.[4]

Most clinicians see value in EHRs, but they want substantial improvements. Experiences with EHRs can affect career plans as well as satisfaction. A 2017 study by Sinsky et al. reported approximately 20 percent of physicians surveyed planned to reduce clinical hours in the next 12 months, and 26 percent planned to leave practice in the next two years. Dissatisfaction with EHRs was an independent risk factor for those plans.[5] In another study by Robertson et al., survey data indicated that 53 percent of primary care clinicians reported they were "dissatisfied or very dissatisfied" with their work-life balance and that EHRs had a negative impact on work-life balance.[6]

Many healthcare organizations are evaluating current EHR practices to identify factors that impact and improve EHR experience. Even though a lot has been published regarding poor experience with EHRs and their impact on clinicians, not much is known regarding functionality, organizational, training, and other factors that impact EHR experience. This is the first article based on the KLAS Arch Collaborative survey to report qualitative and quantitative factors that influence the clinician's experience with the EHR as well as compare experiences of physicians, nursing, and clinical subspecialties from two large academic medical centers.[7] These factors identify areas of concern and focus on future EHR usability enhancements and implementation strategies that could lead to a better EHR experience and possibly decreased clinician burnout.

Methods

Settings

Virginia Commonwealth University Health System (VCU) is a large, urban academic medical center located in Richmond, Virginia. VCU staff includes more than 830 physicians, 750 residents and fellows, and 400 advanced practice providers representing 200 specialties. VCU has used Cerner EHR in outpatient and inpatient setting since 2006.[8]

University of Chicago Medicine (UCM) clinical facilities include the University of Chicago Medical Center, Ingalls Memorial (a community-based hospital and outpatient facility in Harvey, Illinois), and dozens of outpatient clinics around the Chicago area. Physician staff includes 848 attending physicians and 1,132 residents and fellows. Epic EHR modules have been in use since 1995 at the University of Chicago and ambulatory, and inpatient documentation were fully adopted in 2011. Ingalls Health System completed a merger with the University of Chicago Medicine in October 2016 and used Cerner Soarian Inpatient Clinicals. Medical staff members at Ingalls use an array of ambulatory EHR solutions.[9]

Survey Instrument

The EHR Experience Survey is web-based and offered free for KLAS Arch Collaborative members. A PDF report summary and spreadsheet were sent to the participating organizations shortly after survey completion.

The survey is organized into the following themes 1) General Background; 2) Training; 3) EHR Personalization; 4) Satisfaction with EHR features; 5) Satisfaction with Organization; and 6) Free Text Comments. The surveys used by VCU and UCM were not identical and were administered six months apart. At VCU, the survey results were frequently reported for "all clinicians" and "physicians" only; at UCM, reports were divided into “all clinicians,” “physicians and advanced practitioners,” “nurses,” and “allied health professionals.” Details of the survey are displayed in **Table 1**.

Subject Recruitment

At University of Chicago Medicine and Virginia Commonwealth University, emails linked to the KLAS survey were sent on two occasions two weeks apart to all attending physicians, non-physician care providers, nursing staff members, and other non-provider clinical staff members. The survey was open for VCU from September 2017 to December 2017. Initial and subsequent survey messages were sent to UCM in April and May of 2018.

Quantitative Analysis

Most survey question responses used a Likert scale “very dissatisfied,” “dissatisfied,” “satisfied,” and “very satisfied” and were reported as dummy codes 1-4, with 1 being equivalent to “very dissatisfied” and 4 “very satisfied.” Several questions also included “indifferent” in the answer choices, leading to a 1-5 scale. The outcome of interest was the “net EHR experience” score. It was calculated by subtracting all negative responses from all positive responses on a scale of negative 100 to positive 100.

Comparisons for the continuous variables among groups were conducted using the Wilcoxon rank-sum test, while the chi-square test was used for comparing proportions. Jamovi 1.2.5.0 (The jamovi project (2021), *jamovi* (Version 1.6), and R 3.6.0 (R Foundation for Statistical Computing, Vienna, Austria) were used to analyze the quantitative results of the survey.

Qualitative Analysis

Two comment sections were included in each survey and asked the following questions: “What was the most valuable EHR feature?” and “What are the desired improvements?” These qualitative data were analyzed using a modified template approach.[10,11] A 30 percent sample of the comments for each of the two open-ended questions was reviewed to identify common, recurrent themes. These identified themes served as an initial codebook. Coding was then conducted by a team of two informatics fellows, a computer science undergraduate student and an attending physician who initially coded responses independently. To ensure inter-rater reliability, coding professionals then met in pairs to review their respective codes, discuss to consensus, and modify the initial codebook by adding any newly identified recurrent themes. To serve as an index of relative salience among survey respondents, frequencies of individual coded occurrences within each theme were computed using the “countif” statistical function in Microsoft Excel. Themes that were observed to have relatively high coding frequencies were then independently reviewed for sub-themes by a practicing physician (DL) and a social scientist (MQ), who subsequently met to discuss to consensus.

Results

Clinician Characteristics

Table 2 lists clinician characteristics. Continuous data were rounded to the nearest whole number. Overall, the clinician characteristics of both institutions were similar, with the exception that UCM had a higher percentage of medical specialties compared to VCU and a higher percentage of EHR users from the ambulatory and inpatient locations.

VCU

The survey was sent to 2,120 clinicians using a health system listserv. Of the 429 clinicians who began the survey, 361 completed the survey, with an overall survey return rate of 17 percent. Clinical background included 150 physicians, 59 resident/fellows, 84 nursing staff members, 59 PA/NPs, and nine allied health clinicians (**Table 2**). Eleven percent of physicians have been practicing between zero and four years, 43 percent between five and 14 years, and 30 percent more than 25 years, representing an experienced group of physicians across 31 specialties.

UCM

The survey was sent to 4,800 clinicians. Of the 525 clinicians who began the survey, 455 (87 percent) completed the survey with an overall survey return rate of 9.5 percent. Ten percent of physicians had been practicing between zero to four years, 32 percent between five and 14 years, and 31 percent more than 25 years. Approximately half (48 percent) of physicians reported using the EHR in both inpatient and ambulatory settings. Seventy-four (40 percent) mainly used the EHR in ambulatory settings, and 23 (12 percent) used the EHR in inpatient settings. A majority (75 percent) of physicians had practiced on an EHR for more than five years. Two-hundred three (80 percent) used Epic and 22 (11 percent) used Cerner. One-hundred thirty-four (63 percent) were adult doctors, 43 (20 percent) represented both adult and peds, and 36 (17 percent) pediatrics.

Physician and Nursing Staff Satisfaction with EHR Features

VCU physicians consistently reported poor satisfaction with most EHR features as compared to their nursing peers (**Table 3**). The difference in satisfaction at VCU reached statistical significance for ratings on: easy to learn, analytics, and impact on efficiency, suggesting the EHR’s functional and design challenges impacted physician workflow.

At UCM, there was not a statistically significant different between physicians and nurses in terms of the net experience score. However, they were statistically different for satisfaction responses on reliability (83 percent versus 68 percent), indicating nursing perceived EHR use to be less reliable compared to physicians. UCM physicians’ satisfaction rating on analytics and efficiency was also noted to be statistically significant compared to nursing peers. Only 47 percent of physicians at both universities were satisfied with EHR-enabled quality of care, needed functionality (41 percent), expected external integration (21 percent), efficiency (19 percent), and analytics and reporting (16 percent) capabilities. Satisfaction with vendor EHR design quality (29 percent) and EHR implementation and support (37 percent) were also noted to be low.

Thirty-three percent of clinicians at VCU and 47 percent of clinicians at UCM were satisfied with the quality of EHR design. Subgroup analysis of vendor satisfaction showed that only 25 percent of physicians at VCU were satisfied compared to 42 percent at UCM. Thirty-three percent of UCM physicians were satisfied with their EHR implementation and support; at VCU, 39 percent physicians were satisfied. Satisfaction with the personal endeavor to learn the EHR was consistently reported to be high for nursing staff as compared to physicians at both institutions and was statistically significant.

Satisfaction with initial training was significantly lower for physicians compared to the nursing staff at both institutions.

Physicians at VCU reported completing 40 percent of charts during clinic hours as compared to 90 percent by nursing peers. At UCM, only 40 percent of physicians were satisfied with patient safety and EHR, and 32 percent were satisfied by patient-centeredness of EHR.

Satisfaction of physicians and practitioners at VCU in cardiology, endocrinology, family medicine, obstetrics and gynecology, infectious disease, neurology, pulmonology, and otolaryngology specialty areas was noted to be below 50 percent, whereas for UCM, more than 50 percent of specialty practitioners in emergency medicine, endocrinology, family medicine, infectious disease, neurology, nephrology, and orthopedics surgery reported being dissatisfied (**Table 4**).

EHR Personalization

The utilization of EHR personalization tools (e.g., order sets) was a significant predictor of EHR experience. At VCU, nine personalization questions were presented to all clinicians irrespective of their clinical background. At UCM, questions were presented only to staff physicians, NP/PAs, and residents/fellows. Personalization responses from non-providers at VCU were removed for this analysis. In addition, based on the number of personalization tools being utilized by providers, responses were further categorized: 1) very low/no personalization for providers using less than two tools; 2) low personalization for providers using between two and three tools; 3) moderate personalization for provider using three to four tools; and 4) high if using more than four personalization tools.

Forty-two percent of providers at VCU and 30 percent of providers at UCM reported very low/no personalization. The utilization of the data input personalization tool was higher than data review and navigation personalization tools. Clinical templates were the most frequently used data input personalization tool both at VCU and UCM. Fifty-eight percent of providers at VCU who utilized clinical templates found them very useful or useful; only 16 percent of the providers did not use clinical templates. At UCM, 62 percent of providers found templates useful or very useful; 14 percent of providers did not use them.

Interestingly, order sets, a tool that has a potential to decrease clinical variation, was not utilized by 47 percent of providers at both institutions. Only 32 percent of providers at VCU and 30 percent at UCM found them useful. More than 50 percent of providers at VCU did not use report views, shortcuts, filters, sorting orders, or layouts; while, at UCM, utilization of report views, shortcuts, sort orders, and layouts were in the range of 39-59 percent.

Net EHR Experience

The overall net EHR experience score for VCU was 6.2, or slightly positive, while the net EHR score for UCM was higher at 19.7. The net EHR experience for VCU physicians was negative 6.2, which was significantly worse compared to the nursing staff experience score at VCU of 14.92.

The UCM net EHR experience score for physicians and nursing was noted to be lower than the average UCM score at 10.36 and 10.19.

Qualitative Results

Most Valuable EHR Features

Five common themes characterized respondents’ comments regarding valuable EHR features: 1) communication, 2) e-prescribing, 3) training and support, 4) vendor responsiveness, and 5) efficiency. The communication functions of “electronic consults,” “updates of patient information,” and “discharge instructions” were cited as valuable features. “Ability to e-prescribe Schedule II drugs” and “having access to medication fill history” were reported as valuable e-prescribing features, while having “weekly updates” and “relevant tutorials” were reported as valuable vendor responsiveness functions. Within the efficiency theme, 10 sub-themes were identified (**Table 5**).

Desired Improvements

Across both UCM and VCU samples, six common themes characterized respondents’ comments regarding desired EHR improvements: 1) ability to view labs during a patient encounter, 2) follow-up training and support, 3) dictation function, 4) alarm fatigue/validity 5) improved communication function, and 6) improved functionality. Ability to use a split-screen function to view labs during a patient encounter and highlighted abnormal lab findings were reported as desired lab improvements. Follow-up training from other providers rather than vendors who don’t understand the workflow was also cited as a needed improvement. The frequency of unnecessary “pop-up” reminders and notes was reported as distracting and inefficient, as was the need to cut and paste from earlier notes.

Within the “improved functionality” theme, a large number of comments were noted in both the UCM and VCU samples (144 and 163, respectively). Subsequent review identified 15 sub-themes within the “efficiency” theme. The most frequently cited desired improvements in functionality sub-themes were reduced documentation time burden, fewer click boxes for patients, more customizable order sets, improved messaging, and e-prescribing, and improved internal integration (**Table 5** and **Table 6**).

Discussion

EHR experience scores were low at both institutions and worse among physicians than nurses. Physicians at both universities had lower satisfaction scores for most domains of EHR features, with significantly lower scores for ease of learning, analytics, and reporting and efficiency compared to nursing peers, suggesting EHR usability may be disproportionately worse for physicians as compared to other clinician groups. Moreover, only 47 of physicians at both universities were satisfied with EHR enabled quality of care, needed functionality (41), and expected external integration (21). Satisfaction of certain specialty practitioners such as endocrinology, family medicine, infectious disease, nephrology, neurology, and pulmonology is low, suggesting the need for better EHR design and training to meet the demand of specialty areas. Previous studies from Emani et al. and Shanafelt et al. have reported similar physician concerns and challenges with provider use of an EHR system.[12,13]

In our survey, a minority (25 VCU versus 42 UCM) of physicians reported satisfaction with EHR design quality, a finding consistent with a “not acceptable” EHR usability ranking. Usability challenges are related to several factors that include vendor non-adherence to EHR usability standards but also related to customization choices made by both the EHR vendors and healthcare providers during EHR implementation. According to two recent studies, the average System Usability Scores on EHR use by physicians was 46 and for nurses was 58, both failing grades.[14,15] This difference between physician and nurse usability and satisfaction scores might be partially explained by VCU data where nurses had a much higher chart completion rate during working hours. In addition, our survey noted low satisfaction with EHR implementation and support at both institutions (34 UCM versus 39 VCU). Low satisfaction with EHR usability, implementation, and support underscores the need for research and investment in the discovery, dissemination, and application of scientifically proven best practices for EHR implementation and governance.[16]

Utilization of EHR personalization tools is a major predictor of EHR experience. Data input personalization tools like clinical templates, order sets, macros, and order lists improve EHR efficiency by streamlining, organizing, and reducing the effort needed to input data into the EHR. Forty-two percent of providers at VCU and 30 percent of providers at UCM utilized very low/no personalization. More than 50 percent of providers at VCU did not use report views, shortcuts, filters, sorting orders, and layouts, while at UCM, utilization of report views, shortcuts, sort orders, and layouts were in the range of 39-59 percent, which suggests the need for a significant investment in training and EHR personalization. Improved personalization could lead to better EHR efficiency, better physician agreement that the EHR enables quality care, more provider trust that the EHR vendor has built a quality tool, and higher overall EHR satisfaction.

A significant predictor of net EHR experience score at VCU was initial training. Deliberate and comprehensive end-user training is essential for implementation, actualization, and end-user satisfaction. Given the variety of roles and specialized workflows performed by medical staff, physicians comprise a unique group of end users for whom distinct recommendations are essential. However, there are few guidelines in the literature addressing the development and implementation of an EHR training program for physicians. At UCM, the net EHR experience score was highly correlated with several areas, including initial training, clinical practice, specialty, follow-up training, and personalization. Because two-thirds of UCM respondents used Epic, it is possible that differences in the UCM and VCU survey responses may relate both to vendor differences and to rollout, design, and training philosophy differences. While vendor differences may affect the extent of personalization possible, the correlation between higher net experience scores and personalization at UCM suggests that enabling personalization is a tactic that may improve user experience. Our findings regarding the importance of training and personalization were mirrored in a 2019 study by several Arch Collaborative members but add to the literature by providing differences between physician and nursing experiences and qualitative data analysis.[17]

Additional significant predictors of net EHR experience include satisfaction with EHR impact on clinical efficiency, quality of care, ease of learning, available analytics capabilities, and internal and external integration, highlighting areas of focus for future EHR enhancements.

The qualitative analysis revealed several additional themes. In the most valuable improvements comment section, the greatest number of responses reflected efficiency gains. This was true at both VCU and UCM and suggests system changes that result in improved efficiency gains are those deemed most valuable by users. Other categories included improvements in communication, training, prescribing, and vendor responsiveness. In the desired improvements comment section, responses related to functionality greatly exceeded other categories. Further, when sub-themes for functionality were explored, reducing the documentation time burden was the largest category at both VCU and UCM.

Several limitations of this study should be noted. In addition to a low survey response rate, the majority of responses from UCM reflected the use of a single EHR (Epic); but approximately 30 percent of responses were from users at Ingalls Memorial who used Cerner Soarian and a variety of other ambulatory EHR systems. The inter-institutional comparison reported did not account for this intra-institutional variation. In addition, the surveys administered to the two academic medical centers were not identical, making exact comparisons difficult. The survey was not validated and did not utilize an instrument to evaluate EHR usability or burnout. The workflow of physicians, nursing, and allied health professionals is very different. This survey is not specific enough to capture all aspects of the usability of all functional groups.

Conclusion

Despite near-universal adoption of outpatient and inpatient electronic health records, substantial EHR experience challenges persist. In this paper, we report the quantitative and qualitative analyses of feature, functionalities, organizational, training, and other factors that affect EHR experience while highlighting differences in experiences of physicians, nursing, and clinical specialties based on a survey by two large healthcare systems. Experience with EHRs and their usability is low regardless of the system. It may be improved by designing better EHR training by the providers who understand the EHR system, clinical content, and workflow; decreasing documentation burden; increasing utilization of personalization tools; enhancing external and internal integration and functionality features; having fewer click boxes and more customizable order sets; improving messaging, e-prescribing, and factors that impact efficiency and clinical care. A substantial percentage of clinicians received no follow-on EHR training, an area for future improvement.

In the post-meaningful use era, we anticipate attention to usability by EHR vendors and reduced documentation requirements by government and private insurers. Further research and investment are needed to determine best practices.

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Evaluation of Physicians' Electronic Health Records Experience Using Actual and Perceived Measures

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Abstract

Background: Inadequate electronic health record (EHR) interface design hinders the physician-EHR experience, which may lead to increase physician frustration and fatigue levels.

Objectives: The objective of this study was to examine the physician EHR experience by evaluating the congruency between actual and perceived measures among physicians with different EHR expertise and utilization levels.

Methods: We conducted a cross-sectional EHR usability study of intensive care unit (ICU) physicians at a major Southeastern medical center. We used eye-tracking glasses to measure provider EHR-related fatigue and three surveys to measure the perceived EHR experience.

Results: Of the 25 ICU physicians, 11 were residents, nine were fellows, and five were attending physicians. No significant differences were found between actual fatigue levels and their perceived EHR usability (p=0.159), workload (p=0.753), and satisfaction (p=0.773).

Conclusion: We found that there was low congruency between physicians' EHR-related fatigue and the perceived ratings for usability, satisfaction, and workload, which suggests using actual and perceived measures for a comprehensive assessment of the user experience. EHR-related fatigue may not be instantly felt by some physicians, hence the similar rating of perceived EHR experience among physicians.

Keywords: EHR, fatigue, usability, workload, satisfaction

Introduction

Using electronic health records (EHR) contribute to physician fatigue.[1,2] The reported effect of EHR use on physician fatigue and burnout dramatically increased from 46 percent to 70 percent within a short time frame.[3,4] Stringent documentation policies, prolonged time and effort fetching for information, and work out of work hours are the main contributors to EHR-related fatigue.[5-7] Additionally, inadequate EHR interface design hinders the physician-EHR experience that leads to exhaustion.[8]

Evaluations of the physician EHR experience have heavily relied on objective and subjective responses.[9-11] User experience is defined as the perceptions and responses that result from using a product or tool.[12] User responses to EHR use can be measured using physiologic data such as blinking rates, pupillometry, and heart rate.[13,14] User perceptions to EHR use can be measured through subjective measures including surveys and interviews.[15]

Popular survey instruments used to assess EHR-related fatigue include the NASA Task Load Index (TLX),[16] and System Usability Scale (SUS),[17] and Questionnaire for User Interface Satisfaction (QUIS). NASA TLX measures the perceived workload of using a given system using six factors.[18] Recently, clinical researchers have adopted the SUS to measure the perceived usability of EHR systems by assessing 10 usability criterion.[19] The QUIS is used to assess the user satisfaction with a given information system by assessing 27 satisfaction items.[20] Although not designed for healthcare systems, researchers have used the QUIS to assess provider and patient satisfaction with regards to health information systems such as EHRs.[21,22] It is unclear whether survey-based assessments are accurate measurements of the relationship between EHR usability and physician fatigue.

Only recently, the effect of EHR use on physicians' fatigue levels was objectively quantified using physiologic measures, namely pupillometry.[23,24] By measuring changes in pupil size, researchers reported it takes approximately 20 minutes of continuous EHR use for 80 percent of physicians to experience fatigue at least once. The use of eye-tracking methods can precisely measure the impact of EHR use on physicians' cognition, which provides new context that subjective methods cannot provide. To our knowledge, no study has examined the accuracy of both subjective and objective measures as an indicator of EHR-related fatigue levels.

The limited knowledge around the consistency of subjective and objective measurements in assessing physician fatigue levels drove our research question of: Is there congruency between perceived and actual EHR experiences for physicians? We hypothesized that the EHR perceived experiences will not be congruent with the actual experiences for physicians. Our goal was to understand which types of measurement are more appropriate to evaluate EHR experiences such as usability, workload, and satisfaction. Therefore, the objective of this study was to examine the physician EHR experience by evaluating the congruency between actual and perceived EHR experience measurements among physicians with different EHR expertise and utilization levels.

Methods

We conducted a cross-sectional EHR usability study of a 30-bed medical intensive care unit (MICU) physicians at a major Southeastern medical center. The MICU used Epic as the institutional EHR system. We created a usability framework for this study that included four ICU patient cases, administration of three EHR surveys, and the use of eye-tracking device.[25] We recruited a random sample of 25 MICU physicians including residents, fellows, and attendings through departmental emails and flyers. For each physician, we collected information regarding their years of Epic experiences and the estimated average number of hours spent using Epic per week.

A summary of the four simulation patients and tasks is provided below:[26]

Case 1: A 44-year-old female patient with multisystem organ failure. Participants were asked to manage medication orders and determine input from consulting clinical teams. Case 2: A 60-year-old female patient with acute hypoxic respiratory failure. Participants were asked to review clinical documentation and flowsheets, to evaluate changes related to the patient's condition and mechanical ventilation, and to analyze microbiology data. Case 3: A 25-year-old male patient with severe sepsis infection. Participants were asked to assess the clinical flowsheet, assess laboratory data, evaluate antibiotics and intravenous fluid management, and manage laboratory studies. Case 4: A 56-year-old male trauma patient with postoperative heart failure and volume overload. Participants were asked to identify trends in the patient's weight during previous clinical encounters and to manage orders for IV fluids and other medications.

We defined *actual* EHR experience as the fatigue level assessed by eye-tracking glasses using pupil size as measurement. We defined the *perceived* EHR experience as the level of workload, usability, and satisfaction measured by three different surveys NASA-TLX, SUS, and QUIS, respectively.

For Epic experiences, we defined three experience groups. Novice experience was defined as one to three years of Epic experience, intermediate was defined as three to five years of experience, and expert was defied a over five years of Epic experience.

For Epic user types, we created three groups as well. First, low use is defined as zero to 20 hours of Epic use per week; intermediate use is defined as 20-40 hours of Epic use per week; and high use is defined as over 40 hours of Epic use per week.

Physicians reviewed four ICU patient records, and after reviewing each case, a research assistant (RA) asked a series of clinical questions to assess the level of comprehension. After completing all four cases, physicians completed three validated surveys—NASA-TLX, SUS, and QUIS—to assess the perceived workload, usability, and satisfaction of the EHR. The study was conducted in a private office space to avoid disruption to the MICU environment. Institutional Review Board approval was obtained prior to conducting the study.

Study Materials

After the study, we collected and analyzed pupillometry data for each physician from the eye-tracking device. Pupillometry data calculates the pupil size for the right and left eye for each millisecond of the study. EHR-related fatigued was defined as the instance when the average pupil size of both eyes is smaller than the baseline average pupil size of both eyes. We previously reported that all 25 physicians experienced fatigue while using the EHR.[23] Physicians experienced different number of fatigue instances during the study ranging from 1-4. Physicians who experience a single fatigue instance were defined as "low fatigue," two or three fatigue instances were defined as "medium fatigue," and four fatigue instances were defined as "high fatigue."

For each physician, we calculated perceived workload, usability, and satisfaction scores. For NASA-TLX, we calculated the a total workload score using raw TLX scores from 0 to 100, without applying weights.[27] For TLX, a score above 55 represents an overload, while a score under 55 is considered normal workload.

For SUS, we computed a total usability score based on the standard methods. For odd items, we subtracted one from the user response; for even-numbered items, we subtracted the user responses from 5. Then, we added the converted responses for each physician and multiplied that total by 2.5. This converts the range of possible values from zero to 100. SUS score between 0-50 is defined as unacceptable, 51-80 is acceptable, and 81-100 is excellent usability.[28,29]

For QUIS, we calculated a total satisfaction score by averaging the score of the five "overall" items. Each item is rated based on 10-point scale; therefore, QUIS scores ranged 0-10. Scores between 1-5 were defined as low satisfaction, 6-7 is medium satisfaction, and 8-10 is high satisfaction (**Table 1**).

Outcomes

Primary endpoints of this study were actual experience measured by eye-tracking fatigue scores and perceived experiences measured by workload (NASA-TLX), SUS (usability), and satisfaction (QUIS). Secondary endpoints were physician EHR expertise (number of years using the EHR system) and physician EHR utilization (self-reported number of hours using the EHR per week).

Statistical Analysis

We aggregated all eye-tracking and survey data into a single file for data analysis using SPSS® and MS Excel®. We used descriptive analysis to quantify differences between objective fatigue scores, and subjective usability, workload, and satisfaction scores. We also conducted Pearson Correlation test to examine the association between objective and subjective measures to understand if there is a relationship between both measurement types.

Results

Of the 25 ICU physicians, 11 were residents, nine were fellows, and five were attending physicians. Twelve (48 percent) were male; the mean age was 33 years (range: 28-55 years) and rhe mean weekly number of hours of current Epic use was 31.1 hours (IQR: 7.95-52.1 hours). Mean prior experience with Epic was four years (IQR: 2.0-5.5 years).

Among all 25 participants, the average total time to complete the four patient cases was 31:04 minutes. Residents spent the most time (40:44 minutes); fellows were the quickest (17:58 minutes), and then attendings (26:45 minutes). The average time to chart review was 4:42 minutes. Attending spent most time reviewing the records (5:25 minutes) followed by residents (5:05 minutes) and fellows (3:27 minutes). The average time to answer questions and complete tasks was 11:32 minutes. Residents spent the most time answering questions (20:21 minutes), followed by attendings (3:59 minutes) and fellows (3:13 minutes).

Actual and Perceived EHR Experience

All physicians experienced at least one fatigue instance such that four (16 percent) physicians experienced high fatigue levels, 11 (44 percent) experienced medium fatigue, and 10 (40 percent) experienced low fatigue levels. The overall rating for EHR satisfaction was “Medium” with a score of 6 out of 10. The overall rating for EHR usability was “Acceptable” with a score of 61 out of 100. The overall EHR workload level was “Normal” with score of 44 out of 100.

Using the QUIS, one (4 percent) physician rated their overall EHR satisfaction as “high,” 17 (68 percent) reported “medium” EHR satisfaction, and seven (28 percent) reported “low” EHR satisfaction levels. Using the SUS, one (4 percent) physician reported “excellent” EHR usability, 19 (76 percent) reported “acceptable” EHR usability, and five (20 percent) reported “unacceptable” EHR usability. For the NASA TLX, 21 (84 percent) physicians indicated “normal” EHR workload, and four (16 percent) reported “high” EHR workload.

No significant differences in EHR satisfaction were found between physicians experiencing low, medium, and high fatigue levels (**Figure 1**). The median (IQR) EHR satisfaction rating for physicians who experienced low fatigue was 5.7 (5.1-6.3), medium fatigue was 5.7 (5.5-6.1), and high fatigue was 5.4 (5.2-5.8). One-way ANOVA test showed that the distribution of EHR satisfaction is the same across the three fatigue categories (p=0.773).

Similarly, no significant differences in the perceived EHR usability ratings were found between physicians' experiences varying levels of fatigue (**Figure 2**). The median (IQR) EHR usability rating for physicians who experienced low fatigue was 55 (45.6-64.4), medium fatigue was 67.5 (62.5-71.3), and high fatigue was 63.8 (57.5-68.1). One-way ANOVA test showed that the distribution of EHR usability is the same across the three fatigue categories (p=0.159).

There were no significant differences in the perceived EHR workload found between physicians' experiences varying levels of fatigue (**Figure 3**). The median (IQR) EHR workload rating for physicians who experienced low fatigue was 44.6 (38.1-51), medium fatigue was 45.8 (34-51.3), and high fatigue was 52.1 (44.8-54.2). One-way ANOVA test showed that the distribution of EHR usability is the same across the three fatigue categories (p=0. 753).

Effect of EHR Expertise and Use

Based on self-reported years of EHR experience, there were four (16 percent) "novice" EHR users, 14 (56 percent) "intermediate" EHR users, and seven (28 percent) "expert" EHR users. EHR expertise was significantly associated with EHR satisfaction such that an increase in the number of years of EHR expertise was correlated with a higher EHR satisfaction ratings (p<0.05) (**Table 2**). No significant correlation was found between perceived usability or workload. Additionally, actual fatigue was not significantly associated with EHR expertise.

Based on self-reported hours spent in the EHR per week, there were seven (28 percent) physicians of "basic" EHR use, eight (32 percent) physicians of "intermediate" EHR use, and 10 (40 percent) physicians of "advanced" EHR use. EHR usability was significantly associated with the level of EHR use such that an increase in the number of hours spent using the EHR was correlated with higher EHR usability rating (p<0.05) (**Table 2**). Additionally, the level of EHR use was marginally correlated with both perceived EHR workload and satisfaction. EHR use was negatively correlated with perceived EHR workload such that an increase in EHR use was associated with lower EHR workload (p<0.1). Also, EHR use was positively correlated with EHR satisfaction such that an increase in the number of hours spent in the EHR was associated with higher satisfaction rating (p<0.1). No significant relationship was found between actual fatigue and EHR expertise (p=0.3) or EHR use (p=0.5).

Discussion

We conducted a cross-sectional study to investigate the differences between actual and perceived EHR experience of 25 ICU physicians with different EHR expertise and utilization levels while using a prominent EHR system. Our findings show that there were no significant associations between the actual and perceived EHR experiences, which may suggest that the varying levels of EHR-related fatigue experienced by physicians are not reflected in their subjective evaluation of EHR usability, workload, and satisfaction. We found that physicians who experienced low, medium, or high fatigue levels had relatively similar ratings of their perceived usability, workload, and satisfaction. This suggests that actual fatigue levels measured by physiologic data collected from eye-tracking devices may be more accurate to assess EHR-related fatigue levels.

EHR-related fatigue was not significantly associated with EHR expertise or EHR use. Physicians, despite their number of years using an EHR or their number of hours spent in the EHR, experienced similar fatigue levels. This may suggest that the problem of EHR-related fatigue may be less of a user issue and more of a design issue. For instance, if a physician with 10 years using the EHR experiences the same fatigue levels as a physician with one year experience, this suggests that the problem may be in interface design. Common interface design flaws that we observed during the study included information overload in some EHR screens such as the Flowsheet, heavy emphasis on memorization rather than recall, and challenges finding the latest and most accurate information.

All physicians experienced varying degrees of EHR-related fatigue, which validates the theory that EHRs contribute to physician fatigue.[30-33] Although, we expected that fatigued physicians would report low ratings for EHR usability, workload, and satisfaction. However, physicians, in general, reported “acceptable” EHR usability, “normal” EHR workload, and “medium” EHR satisfaction. This suggests that EHR-related fatigue is not instantly felt by some physicians and, therefore, two physicians who experience different actual fatigue levels may rate their EHR experience similarly, which may not reflect the actual EHR experience. Future studies should examine the long-term effect of EHR-related fatigue on physician burnout.[34,35]

Limitations

This study had limitations. This was a single site and a single EHR study. Although we examined only one EHR, this EHR is the most prominent EHR system in the US. The study focused only on ICU physicians, and the generalizability of the study findings may not be applicable to other specialties. We collected continuous pupil size data throughout the experiment for each physician and only one perceived survey data at the end of the experiment. We did not administer the surveys after each patient case to avoid disruption of the continuous EHR use, which would jeopardize the reliability of the eye-tracking data.

Conclusion

We investigated the physician-EHR experience by evaluating the degree of congruency between actual EHR-related fatigue levels with the perceived EHR usability, workload, and satisfaction. We found that there was no relationship between changes in EHR-related fatigue and the perceived ratings, which suggests using actual and perceived measures for a comprehensive assessment of the user experience. It is possible that subjective data provides a baseline to EHR perceptions; however, this study demonstrated that the use of physiologic data (i.e., pupil size) provide a more in-depth evaluation of the actual impact of EHR on physician fatigue and well-being.

Declarations

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Availability of data and material: Data is available upon request.

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Consent to participate: All participants were consented prior to the study.

Consent for publication: The authors consent for the publication of this work.

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Barriers and Facilitators to Automated Self-Scheduling: Consensus from a Delphi Panel of Key Stakeholders

By Elizabeth Woodcock, DrPH, MBA, FACMPE, CPC

Abstract

Introduction: Automated self-scheduling may benefit healthcare organizations, yet uptake has been slow. The aim of this study was to develop a consensus statement regarding the organizational-level determinants of implementation success based on the collective knowledge of experts. A three-stage modified Delphi method was used to reach consensus on the top determinants of implementation of self-scheduling solutions by healthcare organizations. A panel of 53 experts representing 41 academic health systems identified barriers and facilitators involving the organization's inner and outing settings, as well as the characteristics of the intervention and the individuals engaged in the solution. Offering convenience for patients is the leading enabler for organizations to implement the technology. The consensus may aid healthcare organizations and suppliers engaged in adopting and developing self-scheduling technology to improve implementation success. Further research is recommended to diagnose and examine each barrier and facilitator and how these factors interact.

Objective: The aim of this study was to develop a consensus statement regarding the determinants of implementation success based on the collective knowledge of experts working in the field.

Methods: A Delphi panel was constructed based on selected participants employed by academic health systems and experienced with self-scheduling implementation. Panelists were recruited based on participation in an educational event that featured the topic. Purposive and snowball sampling were used. Panelists participated in surveys collected over three rounds. An 80 percent agreement among panelists and interquartile range (IQR) ≤ 1 determined the barriers and facilitators. The top-10 determinants were presented in rank order.

Results: Between January 6, 2021, and May 26, 2021, 53 panelists representing 41 academic health systems participated in three rounds of surveys to reach consensus on the barriers and facilitators to implementation of self-scheduling by healthcare organizations in the United States. In round one, panelists documented 530 determinants. In round two, the determinants were grouped into 72 barriers and 85 facilitators, each of which participants rated on a five-point Likert scale. Fifteen determinants met the 80 percent threshold and 1.0 IQR. The final round concluded with a top-10, rank-ordered listing of determinants (seven facilitators and three barriers) that also incorporated a median rating score using five-point Likert scale.

Conclusion: A three-stage modified Delphi method was used to reach consensus on the top determinants of implementation of self-scheduling solutions by academic health systems. The consensus may aid healthcare organizations and suppliers engaged in adopting and developing self-scheduling technology to improve implementation success. Further research is recommended to diagnose and examine each barrier and facilitator and how these factors interact.

Keywords: Delphi panel, automated self-scheduling, barriers and facilitators, implementation

Introduction

Appointment management in the ambulatory setting is important for healthcare organizations as waits and delays lead to poor management outcomes: dissatisfied patients, scheduling disruptions, and wasted appointment slots. For example, according to the Patient Access Collaborative,[1] the median new patient lag time for a scheduled ambulatory appointment in the United States is 16.35 days, while the median utilization rate of appointment slots is only 73.6 percent.

Automated self-scheduling may benefit healthcare organizations in their efforts to manage staffing costs,[2-7] patient satisfaction,[8-10] appointment attendance,[11-15] patient accountability,[16] and information transparency.[17,18] Self-scheduling may offer the convenience patients seek.[19-20] Automated, self-service reservation systems have helped other industries striving for improvements in customer loyalty,[21] operations,[22,23] profitability,[24] and customer wait times.[25]

Despite evidence to support the value of the technology to healthcare organizations, the uptake of self-scheduling in healthcare has been minimal to date.

Providers have expressed reluctance about self-scheduling based on cost, flexibility, safety, and integrity.[26] As the technology emerged in the early 2000s, physician and software developer Dr. Jonathan Teich elucidated a critical challenge related to complexity: “Before you can successfully implement self-scheduling, you have to implement ‘Mabel.’ Mabel is the generic scheduling administrator who has been working for Dr. Smith for 35 years, and knows a thousand nuances and idiosyncrasies and preferences that have been silently established over the years … Unfortunately for the computer world, it’s extremely difficult to find out what Mabel really knows, let alone try and put it into an algorithm.”[27] In addition to the Mabel factor, physicians have conveyed a fear of losing control.[28-30]

Researchers have also documented patients’ hesitancy about self-scheduling based on concerns about accuracy, security, and a lack of empathy as compared to a human interaction.[31] Further, patients’ prior experience with technology, as well as communication preferences, have been recognized as barriers.[32]

What remains unknown is the potential influence of the current diffusion of self-service technology, the changes in patients’ access to virtual delivery platforms, and the heightened expectations for convenience that have resulted from the COVID-19 pandemic as it relates to healthcare organizations’ uptake of self-scheduling. By identifying barriers and facilitators to automated self-scheduling, the research will assist healthcare organizations seeking solutions to the management of the ambulatory enterprise, ultimately benefiting patients through improved service, reduced disruptions, and enhanced utilization of providers’ time.

Background

Despite the acknowledged benefits of administrative technology in healthcare, adoption has been slow, with implementation barriers cited as evidence of the limited diffusion.[33]

The goal of the study was to derive a consensus statement regarding the organizational-level barriers and facilitators to implementation of automated patient self-scheduling by healthcare organizations in the United States. The primary research question posed was: “What is the consensus regarding the barriers and facilitators as identified by professionals employed by academic health systems engaged in the implementation of patient self-scheduling?” The research aimed to inform healthcare organizations considering the implementation of self-scheduling. More broadly, the study may enlighten suppliers in the creation and maintenance of the technology for healthcare organizations.

Methods

Design

The consensus process was conducted using a three-stage modified Delphi technique to solicit, identify, and synthesize determinants of the implementation of self-scheduling technology by healthcare organizations. The modified Delphi technique is a structured, participatory qualitative research method.[34] Named for the Oracle at Delphi in Ancient Greece, the Delphi technique, which was originally developed by the RAND Corporation in 1948,[35,36] involves an iterative process until consensus is obtained. Due to the anonymity of the process, the risk of domination by one individual or coalition is avoided.[37] The Delphi method has become a popular technique in health sciences research[38] and technology foresight.[39] The research method was selected, as the literature lacked evidence of the determinants of implementation of the technology under study.[40] As self-scheduling represents an emerging technology for healthcare organizations, the opinions of stakeholders engaged as practitioners of the intervention are important.[41,42]

The Delphi method can account for key informants who are geographically and professionally diverse.[43,44] Given the workload of the panelists during the COVID-19 pandemic, the Delphi technique was selected, as it does not require a specific meeting time, thereby allowing a thoughtful response at a convenient time for participants.[45] This research was conducted electronically and was considered to yield the same results as a traditional paper-based survey.[46,47]

Participants

Participants were identified based on attendance at an educational event held in September 2020 that featured the implementation of automated self-scheduling solutions by academic health systems. Snowball sampling was subsequently applied to identify additional key informants with knowledge of the research subject. Panelists with direct expertise in the implementation of the technology were sought to ensure validity of the consensus statement.[48] The author sent communication to 74 potential participants between December 16, 2020, and January 6, 2021, inviting them to participate in the study. The goal was participation from 40 to 60 participants based on other research studies that developed consensus about a complex subject involving different stakeholders.[49] Fifty-three agreed to participate; 41 academic health systems were represented. Panelists were from all US Census Bureau-designated regions. (**Table 1** presents the count of Delphi panelists by region.) The outpatient enterprises of the academic health systems represented by the panelists ranged from 500,000 to more than 4 million patient encounters per annum.

Delphi Technique

The first Delphi survey was distributed between January 6, 2021 and February 21, 2021, via an online survey tool (SurveyMonkey®) to participants’ email addresses. In the initial round, data on participant demographics were collected to include role, training, and geography. The first round featured an open-ended response to avoid introducing bias in the study.[50,51] Participants were asked: "Describe six factors that negatively shape the implementation of self-scheduling at your organization" and "Describe six factors that positively shape the implementation of self-scheduling at your organization." The responses were documented as barriers or facilitators and mapped in alignment with the Consolidated Framework for Implementation Research (CFIR).[52] CFIR enabled the research to be presented in a standard, evidence-based framework, thereby facilitating the opportunity for industry adoption of the research findings.[53,54] The CFIR Domains and Constructs are presented in **Figure 1**.

The second survey was distributed between March 2, 2021, and April 4, 2021. Participants scored agreement or disagreement with statements on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree): "To what extent do you agree with this statement." The survey was self-administered, thus allowing participants to respond without risk of influencing one another's answers.[55] To describe the relative importance of each item, the median and interquartile range were calculated.[56] A consensus point of 80 percent was determined to prioritize the determinants.[57-59] During the second round of the online survey, four barriers and 11 facilitators received equal or greater than 80 percent of participants' votes. The 15 factors were compiled for the next round of the survey.

The third and final step of the Delphi was initiated with the panel on April 27, 2021. Responses were collected through May 26, 2021. Three survey rounds were employed to reach consensus.[60] The third and final survey included the 15 factors that received greater than 80 percent of participants' agreement during the second round. From these, participants were asked to rate each determinant using a Likert scale of 1 to 5 ranging from 1 (strongly disagree) to 5 (strongly agree): "To what extent do you agree with this statement." The median and interquartile range were calculated.[61] Participants were also asked to place in rank order the most important determinants of self-scheduling by healthcare organizations. The percent of the expert panel ranking the factor in the top 10 was also calculated to support the informants' consensus.[62] This iterative process permitted participants to reassess their views considering the aggregated results.[63] (See **Figure 2**.)

The Johns Hopkins Bloomberg School of Public Health's Institutional Review Board (IRB) determined that this research study does not qualify as human subjects research as defined by DHHS regulations 45 CFR 46.102, and therefore does not require IRB oversight. All participants provided informed consent to take part at the beginning of the process as part of the online survey.

Results

Of the 74 informants identified to participate, 53 agreed to contribute. Of the 53 who agreed to participate, 52 responded to the first round, 53 in the second round, and 52 in the third round. Up to four reminders were sent to encourage participation for each round beginning on the survey due date. The 53 participants represented 41 academic health systems and all regions of the United States. The participants were recruited from three categories: technology professionals (n=9), management professionals (n=41), and other stakeholders in self-scheduling (n=4) (e.g., clinicians who were engaged in the implementation). Management professionals included roles such as executive director of ambulatory operations, chief access officer, and vice president of ambulatory services. Participants could select more than one role. Eight participants were clinicians by training; 44 were not; one was unknown. All participants were individuals employed by healthcare organizations and experienced with a past, current, or future implementation of automated self-scheduling.

In the first round, a total of 530 factors that contributed to the implementation of self-scheduling by healthcare organizations were identified. Fifty-two participants cited a total of 277 factors that negatively shape the implementation of self-scheduling at their organization (barriers), and 253 positively shape the implementation of self-scheduling at their organization (facilitators). Participants submitted an average of 10.2 barriers and facilitators.

Fifty-three key informants responded to the second survey. The author categorized responses from Round 1 into 72 barriers and 85 facilitators based on CFIR. (See **Table 2**.) The key informants were asked to rate the 157 determinants using a five-point Likert scale. Fifteen factors were identified based on a consensus of 80 percent and higher than 1.0 interquartile range.

The 15 factors were presented to the expert panel in the third and final round. Fifty-two participants rank ordered the 15 factors between 1 (most important) and 15 (least important). The participants were also asked to rate each factor using a five-point Likert scale. The consensus of the panel is presented in **Table 3**. Three barriers and seven facilitators were identified.

Panel members gave the highest ranking to the enabler that reflected the patients' needs: "Convenience for patients to schedule appointments via our self-scheduling solution." The determinant also had the highest consensus, median, and percentage of experts who agreed or strongly agreed. Two other facilitators topped the list: the organizations' culture to support access and the relative advantage of self-scheduling as compared to the call center. Other facilitators were identified as peer pressure from competitors, the engagement of the academic health systems' executives, and the buy-in of leaders. Complexity was the primary barrier, as well as providers' resistance based on specialization and the variability of scheduling protocols.

In total, seven facilitators and three barriers were identified by the expert panelists. Four of the five domains of the CFIR were incorporated in the 10 determinants considered most important to panelists, providing evidence of the broad array of components that influence the implementation of automated self-scheduling. The CFIR domain of "process" was the only one not included in the consensus of key factors. The results of the Delphi panel confirmed myriad determinants of an effective implementation of technology by healthcare organizations.[64]

Discussion

With this study, stakeholders rated the determinants of implementation for automated self-scheduling by academic health systems. The use of the modified Delphi technique successfully yielded a consensus of the top determinants of implementation to automated self-scheduling as offered by academic health systems. Development of an evidence-based consensus of implementation determinants can be used to further the diffusion of the technology. To the best of the author's knowledge, this was the first study of its kind for this technology. The discussion of the determinants is presented in the framework of the eight CFIR constructs represented in the panelists' top-10 list.

Patient Needs and Resources

The most-cited determinant by the Delphi panel was an enabler based on the users' needs: "Convenience for patients to schedule appointments via our self-scheduling solution." Recognition of the need for innovation is the initial stage of Rogers Diffusion of Innovation Theory.[65] Awareness of the users' interest was also evident in another top-10 determinant cited by the expert panel: ease of use for patients. Implementation may have been hindered historically by a lack of attention to patient needs. A perceived benefit for patients has led to implementation success by healthcare organizations.[66,67] Proactive, clear communication about the benefits of the technology for patients facilitates implementation.[68]

Culture

Panelists documented and prioritized an organizational culture to promote access to care. There is evidence that culture impacts the success of technology implementation.[69-71] The determinant tracks closely with the awareness of the need for the technology to facilitate access for patients, yet it establishes the panel's perceived priority of the organization's culture to achieve it.

Relative Advantage

Automated self-scheduling can effectively replace the same transaction over the telephone. The ranking of the relative advantage may reflect the panelists' belief that automated self-scheduling offers a reduction of personnel costs, access outside of normal operating hours,[72,73] improved staff utilization,[74-80] and patient time savings.[81-83] Regardless of the source of the advantage, the perception that such exists is an essential condition for successful technology implementation.[84]

Complexity

Acknowledging and analyzing complexity to avoid inadvertent consequences is crucial to the effectiveness of an implementation.[85] The ranking of this determinant as the highest barrier may reflect the panel's perception that the complexity may not be diagnosed or addressed by current solutions. There is an adverse association between the perception of complexity and the success of an intervention.[86,87] Automated self-scheduling is a technology purchased, built, and deployed by a healthcare organization. Unlike other well-studied technology solutions like electronic health record systems, however, the primary user is the patient, not the organization, provider, or employee. The implementation of a patient-facing solution adds to the complexity and may increase the challenges of implementation.[88]

Knowledge and Beliefs about the Intervention

Providers' resistance has been demonstrated in other studies about novel healthcare technology.[89] Factors include fear and dissatisfaction with roles and responsibilities,[90] a lack of trust,[91] resistance to change,[92] and uncertainty.[93] Studies regarding physician receptivity, however, have centered on the implementation of electronic health record systems or their components. Similar barriers may exist for an administrative technology. The rationale regarding specialization may reveal the source of resistance, one that tracks closely with the previous barrier related to complexity.

Peer Pressure

The need to be competitive was revealed as the sixth facilitator to self-scheduling implementation. Panelists may consider self-scheduling to be a requirement rather than a luxury. This may reflect a mimetic response by healthcare organizations as it relates to competitors, considered to be highly influential for adoption of technology.[94] The competitive environment for healthcare organizations is significant, with mergers and acquisitions predicted to increase in the future based on various policy changes and financial positions.[95] Reacting to peers has been demonstrated to be particularly influential for organizations that are late adopters.[96]

Readiness for Implementation – Leadership Engagement

The expert panel concluded the involvement of leaders as important facilitators. Engagement of leaders has been determined to be of significance in all facets of technology implementation in healthcare.[97-99] The inclusion of two determinants related to the involvement of leaders in the top-10 list promotes its import as a facilitator of implementation. The ranking of executive leadership engagement may reveal that direct management support is not sufficient for implementation success. As self-scheduling involves stakeholders both internal and external to the organization, executive leaders may be a crucial facilitator for automated self-scheduling.

Adaptability

The final top-10 determinant, "variability about scheduling protocols across providers or specialties within a department," reflects an intervention characteristic. Adaptability is recognized as a critical factor as an intervention is disseminated more broadly within an organization.[100] Ease of modification is positively correlated with an effective implementation.[101-103]

The Delphi panel's key barriers and facilitators for self-scheduling offered insight into experts' perceptions of determinants of implementation success. The factors that are absent from the list may be of equal import. "Process" was the only CFIR domain that was not represented in the consensus of determinants. According to CFIR,[104] the domain, which incorporates engaging, executing, planning, and reflecting and evaluating, is the "single most difficult domain to define, measure, or evaluate in implementation research." The lack of the domain being considered as a barrier or facilitator may confirm the placement of automated self-scheduling at the beginning of the technology's life cycle.

The absence of cost (a construct within the "intervention characteristics" domain) and available resources (a construct within "inner setting") may indicate that financial outlay for the technological solution is not a barrier. Time, effort, and resources, however, may be needed for healthcare organizations to address barriers to patients' technology acceptance, a journey that has been determined to be present, complex, and nonlinear.[105,106] The presence of a digital divide has been well documented for other technologies,[107,108] and its absence as a barrier may also reflect the stage of the technology's life cycle. As the technology is diffused, additional research regarding the digital divide is warranted.

Opportunities for Research

Further research is warranted to identify actions that may address the barriers and facilitators to implementation of self-scheduling technology. The research ascertained the determinants. Healthcare organizations may now proactively tackle the barriers and seek facilitators to increase diffusion of the technology. For example, organizations may survey patients regarding their expectations for a digital access experience, using reports that feature the voice of the customer to draw the organizations' attention to the most important facilitator, the delivery of convenience. An inventory of competitors' capabilities may be shared with leadership to address peer pressure. Known barriers such as providers' resistance may be addressed proactively by open dialogue with providers about the technology, a step that may have otherwise been overlooked in the belief that the technological solution was solely administrative. **Table 4** lists actions for healthcare organizations to consider to remove barriers and promote facilitators based on the determinants identified by the expert panelists. Further research is warranted to identify effective actions to address each determinant.

Limitations

The Delphi technique has been criticized for the potential for bias in participant selection and engagement.[109] This study strived to overcome the bias through the variety of participants as it relates to geography, professional roles, and training.[110] The value of the Delphi technique is determined by the quality and stability of the panel of participating experts and the time between rounds, which were proactively managed by the author.[111] Participants represented various roles in academic health systems; however, they may not have represented persons from all areas of responsibility for implementation. The panel did not contain the opinions of suppliers (persons creating the technology) or patients (persons using the technology). As the research study aimed to develop a consensus for the implementation of the technology by healthcare organizations, these stakeholders were purposely excluded. This may have introduced bias in the results. The panels of experts represented healthcare organizations that were academic health systems; the ambulatory clinics associated with these healthcare organizations are large and complex. Gathering consensus from experts who represented academic health systems may limit generalizability of the results.

Conclusion

The purpose of this study was to provide consensus from a panel of experts engaged in automated self-scheduling about the barriers and facilitators to this novel technology. The Delphi method was effective in identifying 10, rank-ordered determinants of implementation success. The research may inform stakeholders about current priorities to consider the deployment and dissemination of this technology within healthcare organizations, thus contributing to the adoption of evidence-based practices to promote improvement efforts in managing service, access, and utilization of the ambulatory enterprise.

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Building Best Practices for Telehealth Record Documentation in the COVID-19 Pandemic

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Abstract

Telehealth services for patient visits have substantially surged during the COVID-19 pandemic. Thus, there is increased importance and demand for high-quality telehealth clinical documentation. However, little is known about how clinical data documentation is collected and the quality of data items included. This study aimed to identify the current state of and gaps in documentation and develop a best practice strategy for telehealth record documentation. Data were collected from January to February 2021 via a self-designed questionnaire for administrators and managers from physicians' offices and mental health facilities, resulting in 76 valid responses. Survey items included health organization demographic information, use of telehealth policies and procedures, and clinical documentation for telehealth patient visits. Findings from this study can be used to assist government, policymakers, and healthcare organizations in developing best practices in telehealth usage and clinical documentation improvement strategies.

Keywords: clinic data documentation, telehealth, quality improvement, best practice

Introduction

Healthcare documentation is the basis for communication between clinical practitioners and for reimbursement for care received. In-person care with well-established documentation practices has been the main focus for most physician practices rather than telehealth services. However, this changed as the demand for telehealth services use surged due to the COVID-19 pandemic. This increase in telehealth services has become a major driver of the US healthcare delivery system's work to expand telehealth rules and regulations.[1] As a result, there is an urgent need to build best practices for telehealth documentation.

The consensus among healthcare leaders is for the recognition of telehealth as a viable service for the health and welfare of patients everywhere. In addition, remote and telehealth services should be regulated, reimbursed, and treated with parity to that of services provided to patients in person.[2-4] Many healthcare leaders advocate for the same standards of documentation, maintenance, and transmission of patient information as traditional face-to-face patient encounters.[5-7] There continues to be backing for consistent telehealth coverage and payment across the board for all health care payers,[8-10] and further support of telehealth specific consents regarding the use of telehealth technologies, delivery models, and treatment methods or limitations.[11-13]

The American Medical Association (AMA) and Centers for Medicare & Medicaid Services (CMS) collaborated to reduce the burden of documentation for providers and eliminated the documentation requirement of medical necessity related to furnishing a visit in the home as opposed to in the office. Physicians can now choose whether their documentation is based on the total time spent or medical decision-making to support their evaluation and management (E/M) code selection.[14,15] This has not changed the documentation for telehealth services, which requires additional information to be captured, including 1) consent from the patient or patient representative (verbal or written) for visit; 2) the category for an office visit—real-time audio with video or audio/telephone only; 3) the date the patient was last seen or was billed for correspondence to avoid date overlap with other billable services; 4) the location of the patient for a visit; 5) provider location for a visit; 6) the names and roles of all participants; and 7) the start time and end time for telehealth encounter (length of time billing provider spent on the day of the visit and how time was spent if billing by time or a time-based code).[16,17] Documentation of the locations of both the patient and the physician is vital for payment purposes. Payment for telehealth services depends on the distant site or location of the provider as well as the originating site of the patient receiving care. Under the Social Security Act Section 1834(m), the use of a home as an office for a provider is not allowed as well as that for a patient unless the patient is receiving end-stage renal disease (ESRD) treatments.[18] However, CMS expanded telehealth coverage included the use of a home for all Medicare and Medicaid patients during the COVID-19 pandemic.[19,20]

As CMS continues to explore the possibilities for the expansion of telehealth services beyond the COVID-19 pandemic, the Office of Inspector General (OIG) will begin the process of auditing Medicare Part B telehealth services.[21] The OIG will focus on the assessment of whether telehealth services meet Medicare requirements. These audits will include documentation of distant and originating site locations, use of telehealth technology, and virtual check-in services.[22] Medical practices must now develop policies, procedures, and best practices for telehealth documentation in order to be prepared for such audits.

Currently, best practice recommendations for telehealth documentation includes supporting telehealth billing requirements and implementing documentation guidelines for telehealth services in the curriculum for medical students.[23,24] Reviewing consent forms to confirm they are relevant to virtual care visits, recording whether visits are audio-only or audio with video, and calculating visit time correctly for the provider (not including staff time) are all areas that should be especially considered.[25,26] To accommodate telehealth documentation requirements, note templates in the electronic health record should be modified along with clinician training and the development of procedures and forms to make documentation as streamlined as possible.[27,28]

Continuous monitoring of the guidelines on telehealth documentation from national and discipline-specific organizations such as the US Department of Health and Human Services (HHS), the Association of American Medical Colleges (AAMC), the American Academy of Family Physicians (AAFP), and the American Hospital Association (AHA) should be a priority for every practice.[29-32] Furthermore, policies and procedures must be updated to include telehealth chart audits as part of the practice compliance plan.[33]

It is also necessary to ensure documentation procedures address the need to adequately describe the physical findings that may and may not be acquired through distant care, detail the patient’s surroundings, and integrate this into the clinical assessment, and use patient-generated data within the overall scope of the treatment plan.[34] This can be a challenge since the recent pandemic has accelerated the need for more virtual care delivery and many states and third-party payers including CMS have changed their rules and/or requirements.[35,36] The authors of this paper have attempted to provide insights for healthcare managers to understand how physician offices and other healthcare facilities are adapting processes to meet these new expectations as well as to offer best practices for successful navigation and documentation of telehealth visits.

The objective of this study is threefold: to assess the clinical data documentation status by types of healthcare facilities and by telehealth start dates; to explore policy and procedures used for telehealth data documentation; and to develop a strategy for the best practice in telehealth data documentation during and post the COVID-19 pandemic era.

Methods

Research Tool

A self-designed survey was developed and served as a data collection tool. This survey was designed based on the purpose of the study and from information gathered in the literature review. The survey questions used for this study included three main categories: demographic characteristics (such as healthcare facility types); data documentation collected (included 15 documentation items (**Table 1** and **Table 2**)), and telehealth usage (such as telehealth start date, policies and procedures used). All questions were tested and validated for logic flow, accuracy, and clarity.

Sample Selection

Two network email distribution lists were identified as the survey deliverables: one is Mid-Atlantic Telehealth Resources Center (MATRC), and another is Missouri Medical Group Management Association (Missouri MGMA). These two distribution lists covered states such as Pennsylvania, West Virginia, Kentucky, Virginia, North Carolina, New Jersey, Delaware, Maryland, Washington DC, and Missouri. The online survey links were sent to the contact persons from each network, and they were asked to distribute the survey link to their network mailing list. The total potential respondents are unknown due to the self-selection network survey distribution nature. The target participants included office managers and administrators from healthcare facilities who have used or are currently using telehealth services for patient care. Individuals who received the survey link could consent to and complete the survey or could forward the survey link to other eligible people in the same healthcare facility. Only one respondent per healthcare facility was inquired to complete the survey.

Survey Administration

Before the final survey was distributed, a pilot test was conducted on the survey logistics, validity and clarity of the questions. We selected 11 managers from physicians’ offices to perform the pilot testing of the survey. The survey was revised and modified based on the responses and comments received from the pilot testing. The estimated time to complete the survey was 10 minutes.

The survey was distributed and administered through the Qualtrics online survey platform. In addition, two follow-up reminders were sent to each network after the initial survey distribution.

Analysis

For this study, we included survey items related to demographic information, such as healthcare facility types; date of initial telehealth use; types of telehealth services provided; data documentation status, such as data item collection; and policies and procedures used for data documentation. Other survey data collected from the study were reported elsewhere.

The question related to data documentation was a five-point Likert scale question, which included Never, Rarely, Sometimes, Often, and Always for the collection of listed data items. In this analysis, we combined scales of Sometimes, Often, and Always as a “Yes” group, while Never and Rarely as a “No” group to the responses of data collection items.

Qualtrics software was used for quantitative data analysis and included descriptive frequency distributions. For the free-text items, such as responses under the “others,” we coded and grouped them based on thematic and qualitative analysis approach.

Results

Demographic Information

There were 76 total responses to the survey. Manager and administrator made up the largest group of respondents (75 percent) when asked for their job title. The remainder of respondents self-described their role as coordinator (11 percent), healthcare provider (10 percent), or other (4 percent). Half (50 percent) of respondents worked in a physician practice, followed by behavioral/mental health (22 percent) and hospital (1 percent). The remaining 27 percent of “other” respondents worked at a variety of healthcare facilities in addition to the ones listed above. Other categories of healthcare facilities include PACE Center, Free Clinic, Nurse Practitioner Clinic, Rehabilitation Outpatient, and Inpatient/Outpatient multi-facilities. The majority of the respondents were located in North Carolina (54 percent), Missouri (20 percent), and West Virginia (12 percent), with responses received from 11 different states in total.

Data Documentation

Respondents were asked if their organizations collected the 15 documentation elements detailed in Tables 1 and 2. For this study, “always,” “often,” and “sometimes” were grouped as “yes” responses; while “rarely” or “never” were grouped as “no” responses to the documentation collection items. A total of 54 respondents answered this question. The responses were analyzed by the type of healthcare facility (**Table 1**), and how long they had been offering telehealth services (**Table 2**).

Respondents were asked to identify their type of healthcare facility. The type of healthcare facility was classified as physician office, hospital, mental health, and others. The other category included free clinics, community health centers, nurse practice clinics, inpatient/outpatient facilities, academic centers, or unspecified facilities. Respondents also were asked how long their organization had been offering telehealth services. The groups were less than one year, one to four years, and five years or more.

Totals for the documentation elements collected by type of facility/setting are displayed in Table 1. The totals are also displayed by the length of time offering telehealth in Table 2. There was only one respondent from a hospital setting, and all documentation elements were reported as collected (100 percent). The most frequently collected documentation items for physician offices and mental health were the communication method, date of service, diagnosis and impression, and recommendations (100 percent for all). The other settings category had similar findings, with the top three most collected documentation items being the date of service (94 percent), patient informed consent (94 percent), and diagnosis and impression (94 percent). Again, for all settings, the date of service, and diagnosis and impression were in the top three documentation elements collected.

The least collected documentation elements for physician offices were consulting physician (56 percent), referring physician (63 percent), and criteria used to evaluate whether the case was appropriate for telehealth (69 percent). The three least collected items in the mental health settings were consulting physician (67 percent), referring physician (67 percent), and patient identification number (67 percent). In the other setting category, the items reported to be least frequently collected were referring physician (63 percent), start and stop time (67 percent), consulting physician (75 percent), and patient location (75 percent). For all settings the consulting physician and referring physician were among the least reported documentation elements collected.

Respondents were asked how long their organization had been offering telehealth services. The results are displayed in Table 2, grouped into less than one year, one to four years, and five years or more. Of those offering telehealth less than one year, communication method (97 percent), date of service (97 percent), and diagnosis and impression (91 percent) had the most responses as being collected. The lowest reported numbers in this group were for criteria used to evaluate if telehealth was appropriate for the case (42 percent, compared to 100 percent and 91 percent in the other groups), consulting physician (56 percent), and the reason for using telehealth (57 percent).

In the one-to-four years group, eight of the 15 documentation elements were reported as collected by 100 percent of respondents. Start and stop time (70 percent), consulting physician (80 percent), and referring physician (80 percent) had the lowest number of responses. Those offering telehealth for five years or more had five documentation elements reported as collected by 100 percent of respondents. This group had the lowest percentage of documentation collection in referring physician (56 percent), start and stop time (67 percent), and documenting other care providers involved or individuals present (67 percent).

Policies and Procedures Used

Respondents were asked what type of policies they used in guiding their delivery of telehealth services. Options included in-house written guidelines, federal/state governmental guidelines, third-party payer guidelines, professional association guidelines, or no guidelines. Forty-nine respondents answered the question and could have selected as many options as applied to their organization.

Only one hospital outpatient setting was reported utilizing federal/state government, third-party payer, and professional association guidelines. Additional care settings reported and displayed in **Table 3** included physician office, mental/behavioral health, and other settings. Most respondents used in-house designed guidelines and federal/state designed guidelines in physician's offices and other settings; for mental/behavioral health, in-house designed and professional association guidelines were the most reported.

The length of time a facility had been offering telehealth services by the types of policies used was also collected. **Table 4** displays the categories of less than one year, one to four years, and five or more years offering telehealth. For all three groups, the top three options for telehealth policies reported were 1) in-house designed guidelines, 2) federal/state government designed, and 3) professional association guidelines.

Discussion/Conclusion

This study provides a closer look at specific data items that should be collected for telehealth patient visits. Policies and procedures used in telehealth by healthcare facilities that guided decision-making and data collection were also examined. The results from this study add to the body of knowledge regarding telehealth documentation and also point to areas in which improvements could be made.

The results from this study found that current practices in telehealth documentation are progressing toward but not yet completely meeting best practice goals. The rapid adaptation of telehealth within the last 18 months and the uncertainties in related documentation standards have left many without clear guidelines. Between 85 percent and 100 percent of respondents are collecting consent forms, type of visit, and length of visit information. Respondents were noted to have high rates of complete documentation in these areas.

The majority of respondents were collecting most of the documentation items. However, the elements that were lacking in the collection were consulting physician, referring physician, and criteria for determining whether the case was appropriate for telehealth. These findings point to the need for training of physician office staff to include the referring and consulting physicians in telehealth documentation. In addition, there should be criteria developed to document the appropriateness of the telehealth visit.

Documentation standards were reduced to facilitate timely care during the pandemic. This reduction in documentation requirements will be discontinued at some point following the acute phase of the pandemic. Facilities will need to tighten their policies and procedures as we move forward out of the pandemic.

Telehealth guidelines and related literature identified additional clinical documentation items needed for best practices in telehealth documentation. It is important to capture all required documentation for telehealth visits, as this is essential for the reimbursement of such services. These include but are not limited to:

- Appropriate consent forms
- Documentation of types of visit (audio/audio and video)
- Length of telehealth visits (time)
- Location of the patients and physicians (home vs. office)
- Identification of all participants in telehealth visits

In addition, the use of note templates specific to telehealth visits is recommended to ensure appropriate documentation is captured. Telehealth training should be provided to both practitioners and office staff. Office administrators should develop practice specific policies, procedures, and forms to address telehealth services, including documentation requirements and reimbursement guidelines. Checklists, including all essential information, are recommended for the clinical staff to use as a data collection tool.

Finally, telehealth documentation should address any limitations, such as low-quality images or an inability to see patient characteristics via video clearly. Templates should meet payer requirements, and practitioners should document with audits in mind. Facilities should be constantly monitoring the updated guidelines on telehealth documentation. Policies and procedures must be updated accordingly.

The study findings are somewhat limited by the geographic and specialty areas of the respondents to the study. While the respondents represented 11 states, both urban and rural settings, large and small practices, and a variety of types of providers, the respondents were all members of the Mid-Atlantic Telehealth Resources Center and the Missouri MGMA. The majority of the respondents were from physicians' offices. A larger, nationwide study would provide additional information about the use of telehealth throughout the country and in a wider variety of specialty settings. As the use of telehealth grows, further study will also be needed to fine-tune the challenges and barriers. There are a variety of telehealth-related issues that will require further study and insight, including implementation of new telehealth guidelines, privacy and security issues, and patient access issues. Further study in these areas could aid in the development of best practices in telehealth provision.

The COVID-19 pandemic spurred the quick adaptation to the use of telehealth services and, in turn, required additional telehealth data documentation. During their quick pivot to provide healthcare services in this alternative format to as many patients as possible, providers were less concerned with documentation. As telehealth services become more common, it is important that providers and organizations review and re-evaluate their policies and procedures related to telehealth documentation standards. All healthcare facilities require complete, timely, and high-quality data documentation to achieve the goals for best practices in the current high-demand data-driven environment.

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