Blockchain Revolutionizing Healthcare Industry: A Systematic Review of Blockchain Technology Benefits and Threats

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Abstract

Blockchain technology has been gaining significant traction in the healthcare industry in the past few years. The value proposition of using blockchain technology is to augment interoperability among healthcare organizations. However, the disruptive technology comes with costly drawbacks. The aim of this paper is to explore the benefits and threats of blockchain technology as a disruptive innovation in the healthcare sector. Current blockchain applications were reviewed through studies conducted to identify uses and potential challenges of blockchain technology based on its current implementations. This literature review highlights gaps in research and the need for further blockchain studies, particularly in the healthcare domain.

Key Words: Blockchain Technology, Disruptive Innovation, Healthcare Industry, Electronic Health Records (EHRs), Applications, Benefits, Threats.

Introduction

One of the challenges encountered by the healthcare industry is the inability to safely manage and retrieve personal health information (PHI) in a timely manner. Effective management and retrieval of patient data would enable healthcare providers to capture a holistic picture of a patient's health, improve patient-physician interaction, and achieve better use of healthcare-related data[1]. Interoperability has enormous potential to transform the health sector through the development of affordable cures and cutting-edge treatments for numerous diseases but depends upon smooth, effective data exchange, and distribution across all the well-known network participants and health professionals[2]. Privacy and security threats are common challenges faced by the healthcare industry. The rise in cybersecurity attacks and security breaches of healthcare records has stimulated the pressing need of healthcare organizations to invest in advancing security technologies[3]. As a disruptive innovation, blockchain technology is paving the way for new potential of solving serious data privacy, security, and integrity issues in healthcare and facilitating the paradigm shift of patient-centric interoperability, while enabling decentralization and transparency of stored information[4]. The global pandemic has revealed a lack of interoperability in the current healthcare system and the need for accurate clinical data that can be widely distributed to healthcare providers in an efficient and secure manner[5].

Blockchain is seen as a key breakthrough that will likely have a considerable influence on a myriad of different industries such as healthcare, supply chain management, and business. A peer-to-peer network called blockchain was initially proposed by Satoshi in 2008 and then commercialized in 2009 when Bitcoin emerged as its first use case [46]. Kassab et al reported that in 2016, "healthcoin" was developed by Diego Espinosa and Nick Gogerty as the first platform based on blockchain to manage and reward Type-2 diabetes prevention[39]. Users submit their biomarkers into the blockchain. If the biomarker is an improvement, the system rewards the patient with digital tokens: healthcoin that can be applied toward government tax breaks and/or discounts on multiple fitness brands[6]. Future technology may open the door to significant opportunities, ranging from research and economics to interactions between patients and physicians [7]. Blockchain technology conflates complexity, novelty, and diversity, which has posed challenges in gauging the value proposition of incorporating the technology[47]. Due to its complexity, blockchain may be used for managing business processes or as a workflow system[8].

Several research studies have been conducted on the benefits and challenges of blockchain technology in the healthcare industry. However, some of the potential applications have not yet deployed[9]. The objective of this literature review is to explore the research studies that have been conducted on applications of blockchain technology as a disruptive innovation in healthcare industry[10], addressing current and potential uses, benefits, and threats of the technology based on the historical research studies. Several researchers suggested studying the outcomes of leveraging blockchain technology in the context of improving security of health records, meeting social determinant of health needs, and improving health outcomes[11,12, 3, 4]. Based on this context, the previously available scholarship on blockchain were analyzed through a systematic review as an assessment tool. The findings convey key insights on the current state of research investigation on blockchain, including benefits and implications as a disruptive innovation in healthcare industry [13]. The study also highlights the gaps in research and the need for further blockchain research in healthcare domain.

This paper was framed to guide future researchers and decision-makers on the current knowledge of benefits, drawbacks, and gaps in blockchain research landscape. The findings were conveyed to proactively identify key challenges pertaining to blockchain adoption and application in the healthcare domain to support improvement opportunities and tackle challenges at their initial stages. This paper was framed to explore the theoretical lens of disruptive innovation theory and innovation diffusion theory. The study was organized to begin with a background of blockchain technology, then explore its key uses and potential benefits within a healthcare context based on the research studies and addressing possible threats discussed by literature from an organizational, social, and technological level. Finally, this review provides recommendations to guide future research, bridge the gaps identified in literature, and further examine the prototypes implemented in the healthcare sector.

Literature Review

Blockchain is considered a relatively recent invention that first appeared in 2008 and provided the technical foundation for the birth of the cryptocurrency known as "bitcoin." In general, blockchain may be thought of as a method of network organization that combines distributed ledgers and databases. In this design, records are updated or maintained by a certain authority but are dispersed over all computers connected to the network so that no one node has the power to change the data that is being stored. For the handling of sensitive data, such as health information or financial transactions, this specific component might be useful[14]. The healthcare industry, one of the biggest in the world, frequently must deal with a complicated network of interrelated stakeholders that are subject to a variety of rules and have their patient data dispersed across numerous databases. Blockchain technology can help healthcare professionals in this difficult situation address the present inefficiencies in the sector[15].

Healthcare data management systems encounter issues including data transparency, traceability, immutability, audit, data provenance, flexible access, trust, privacy, and security. By overcoming these obstacles and bringing about significant advances, blockchain technology can completely transform healthcare data administration, blockchain establishes confidence in health data by enabling the tracking of changes from their source to their present form. Current projects and recent case studies show how useful blockchain technology is for a range of healthcare applications. However, there are issues that need to be resolved for blockchain to be successfully adopted in the healthcare industry. Overcoming these difficulties and further investigating the possibilities of blockchain in healthcare data management should be the main goals of future research[8].

Several review articles on blockchain technology's use in industries including banking, the internet of things (IoT), the energy sector, government, and privacy and security are now available in the open literature. A broad thorough critical assessment of the most recent research on blockchain-based healthcare applications is not addressed, despite a few review papers discussing the uses of blockchain technology in healthcare. For instance, most of the studies give a brief overview of blockchain-based healthcare applications. Despite being the first to provide a high-level overview of new blockchain-based healthcare applications, the study largely focuses on the practical applications and advantages of this technology[16].

Blockchain technology can change the topology of a healthcare network such that data are added in a decentralized fashion. Blockchain improves data security, confidentiality, and interoperability while allowing patients to integrate themselves into an ecosystem[17]. Bibliometric analyses of blockchain technology in the healthcare sector are few. In this regard, there is a growing body of literature examining and debating the potential and current applications of blockchain in healthcare. To our knowledge, however, none of these studies examine the potential environmental and health effects of this industry's potential use of blockchain. This lack of attention should be addressed because, in theory, any technical improvements to the healthcare sector should be made in a way that does not hurt either the environment or people's health. This study addresses blockchain technology and healthcare studies to bridge the gap. It also discusses potential directions for future research with the right depth and breadth in pertinent areas.

Theory

Disruptive innovation theory has analyzed and addressed growth driven by innovation[18]. The theory was originally initiated by Clayton Christensen et al. in 1995 and has pervaded the clinical healthcare dialect over the past years. Increased adoption of blockchain technology in the healthcare domain will lead to a disruptive shift in the foundation of the healthcare system[13]. Despite the growing use of the concept in literature, there are gaps in comprehending disruptive innovations in a healthcare context as there is no objective definition in healthcare literature[19]. In addition, there is no published literature that compares perceived healthcare disruptive innovations. Therefore, key innovations in the sector remain in silos, which limits our ability to identify disruption.

Innovation diffusion theory states that characteristics of innovation affect how organizations gather knowledge, which consequently affects the decision to adopt or reject the innovation. These characteristics are: (1) relative advantage; (2) compatibility; (3) complexity; (4) trialability; and (5) observability[20]. Haleem and Hartley[3, 20] have noted that lack of blockchain understanding is a barrier to technology diffusion. Given the relatively early stage of blockchain development, most healthcare organizations often rely on consultants when adopting modern technology [2]. Additional barriers to diffusion success are switching costs and the network effect[10].

Methodology

Systematic reviews are an effective way of evaluating and interpreting research relevant to a particular research question, topic area, or phenomenon of interest based on previous research outcomes[21]. Systematic reviews are common in the medical field and healthcare domain. Nonetheless, there are many research studies addressing blockchain technology applications in healthcare[4, 13, 22, 23]. For example,[24] conducted a systematic review of the adoption of blockchain platforms in healthcare and how they improved the industry outcomes.

To compile data and insights on blockchain in healthcare research, meta-analysis was conducted and identified studies were included in the review using a list of relevant terms through the search of several electronic databases including PubMed, MEDLINE, Scopus, EBSCO, and IEEE Xplore, and other databases for research including ScienceDirect, and Google Scholar. By choosing the mentioned databases, the intention was to focus on peer-reviewed articles that have been published in healthcare journals. The database was searched to determine whether a publication contained at least one of the keywords or search terms in the title, abstract, or keywords. In total, 1,830 articles were identified. The Boolean operator was utilized with a combination of "AND/OR" of search terms. The following search string was used: blockchain AND (healthcare OR medical) AND (challenge, threat, OR benefit OR uses OR [1]application). Following this process, 37 articles were determined to be relevant to the study. Subsequently, a backward reference-list checking was conducted to identify other relevant literature[5]. As a result, 10 more articles were identified. In total, 47 articles were identified to be relevant to this literature review.

To narrow down the literature selection process to the relevant articles, all publications that are fully available in English language and published between 2016 and 2022 were included. Duplicate articles, book chapters, and papers that discussed blockchain from a technical and engineering perspective were excluded. Based on *figure 1*, 33 articles were identified in the final population for analysis as relevant literature. EndNote software was utilized for duplicate removal and final screening. To ensure reliability, the search process was comprehensively documented to identify studies, assess relevance, and synthesize the structure of the paper. The goal was to find research articles focused on blockchain applications, benefits, and threats in healthcare domain. This literature will answer the following research questions: How has blockchain been defined in literature? What are the potential blockchain applications in healthcare domain? What are the blockchain benefits in healthcare literature? What are the possible threats of blockchain technology in the healthcare industry? For the purposes of the review, blockchain research was categorized into three categories: 1) Applications in healthcare industry, 2) Benefits of blockchain, and 3) Threats of the technology.

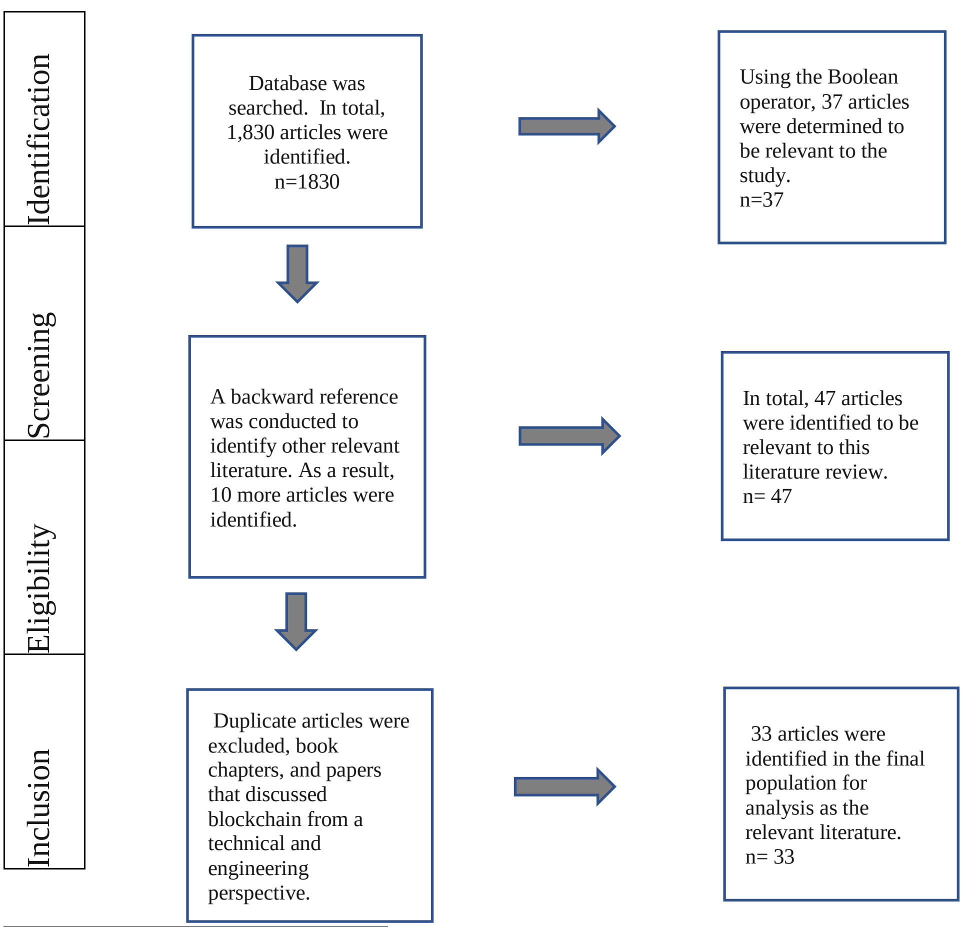

Fig.1. PRISMA for Identification and Inclusion Process of Systematic Review

Background

Most of the scholars describe blockchain using their properties[13, 48] defined blockchain as a decentralized transparent ledger with transaction records. Blockchain technology is characterized as “an open, distributed network that may record transactions between two individuals rapidly and in a verified and conspicuous way.” Blockchain is described by several authors as a digitized decentralized ledger to allow recordkeeping of all peer-to-peer transactions without the need for a centralized authority[19]. Blockchain was also described as “a distributed ledger system, which maintains all transactions synced across users”[25]. Researchers highlighted that information that has already been used in a transaction cannot be altered or deleted, and users can openly and transparently audit any transactions. The technology protects data from manipulation and alteration. The studies addressed that blockchain offers tremendous efficiency and affordable solutions in the healthcare industry. The essential technology characteristics include decentralization, traceability, immutability, and provenance[26].

Since 2016, the demand for blockchain technology has increased globally, and several large technology firms, such as IBM, Intel, and Microsoft, are heavily invested in blockchain technology development. The World Economic Forum estimates that, by 2025, 10 percent of the global gross domestic product will be stored on blockchain technology[27]. The marketplace for blockchain technology was estimated to be worth around $339.5 million globally in 2017, and it is expected to increase to $2.3 billion by 2021. By 2030, blockchain is anticipated to provide $3.1 trillion in economic value. According to International Data Corporation (IDC), worldwide spending on blockchain will increase from about $1.5-$2.9 billion in 2018- 2019 and rise?? to $11.7 billion in 2022[10]. For the anticipated period of 2017–2022, the anticipated annual compound growth rate is 73.2 percent[49]. The US healthcare industry is the world’s largest and absorbs more than $1.7 trillion per year[28]. Today, the average annual cost of healthcare per person in America is $10,739, which is more than residents of any other country[28]. Abdel-Basset[5], noted that blockchain technology can be used to manage pandemics by considering different data sources, which can be statistically analyzed to extract essential features and patterns for healthcare professionals and the government.

Although understanding blockchain technology might be challenging, the fundamental ideas behind it are rather straightforward. Blockchain is a database of a group of data that is electronically stored on a computer network[50]. In an examination of academic literature where blockchain applications have been applied to diverse topics, it can transform the traditional industry with its features, which include decentralization, anonymity, persistency, and auditability[29]. The studies reviewed have covered several instances of blockchain technology being used in healthcare, as well as the issues and potential fixes. The design decisions and compromises made by the researchers were addressed in the many situations where this innovative technology was used[11]. The Office of the National Coordinator for Health Information Technology (ONC) has described several features critical to the development of an interoperable health system, which are addressed by blockchain[9]. The research studies have covered a wide range of settings for using this technology, including blockchain-based applications across many different sectors[11]. Then the researchers describe some aspects of blockchain technology for medical record management, insurance claim process, biomedical research, and health data ledgers[30]. There is a consensus among researchers that, with blockchain technology, patient data will be truly owned and controlled by the right owner of the data, which is the patient[31]. The healthcare industry is a suitable candidate for the use of blockchain technology since it may address critical concerns including computerized claim verification and global health management[23]. With the assistance of this technology, patients may maintain their personal information and choose with whom it will be shared, overcoming the present problems with data ownership and exchange. Despite the general belief that the benefits of adopting blockchain-based technology may be exaggerated, a new study suggests that enterprises will still make significant investments in this area in the future[2].

It might be argued by researchers that this system has not yet lived up to expectations, a reality that may be explained by the widespread deployment of blockchain, particularly in relation to governmental restrictions and other difficulties[19]. Another key barrier to the widespread adoption of blockchain is that both general and specialized users such as patients or doctors are unaware of how it operates, its technological aspects, or its benefits for processing data[1]. The researchers proposed that it could take some time for this technology to build all anticipated and expected stages of transformational change in business, mostly due to implementation obstacles in the manner of organizational and social issues such as security concerns and governance[8,19,24]. This may also be made worse by widespread misunderstandings about how blockchain technology is used in government policies and regulations. By removing these obstacles, recent research aims to assist blockchain clear changes and expedite its spread[32].

The papers reviewed described many blockchain uses and potential issues often at the conceptual level. However, empirical studies are limited as blockchain research remains early-stage and immature, particularly in healthcare[5,11,27]. Blockchain technology is a prominent example of disruptive innovation. However, poor identification can lead to poor understanding of the technical features and potential of an innovation and the possible barriers to adoption and ways to overcome them[33].

Healthcare Industry Challenges

Some of the numerous concerns hospitals and other healthcare organizations deal with daily include patient data access, medication storage logs, and medical records. Patient care, information security, and privacy must all be balanced in the healthcare sector. Major challenges the healthcare sector faces include putting the patient first, privacy and access, accuracy of medical data, pricing, management of supply chains and prescription records. Even if the conventional technique of storing data through a centralized database can be damaging, as indicated in research, it can also be susceptible to hacking or even a single failure point[13].

The fact that all the servers temporarily go offline while the changes are being made to the databases used to store medical data is another problem with a traditional database. Given that healthcare is a 24/7 industry, this little gap might prove to be quite deadly[23]. Another concern with medical records is the cost associated with transferring records among different entities. The lack of availability of test results can be dangerous in terms of delayed treatment. Also, sending data via email is considered a security risk. A system integrating patient consent and access to authorized individuals would improve efficiency and save on financial costs[9]. Blockchain technology is being promoted as the "solution" to issues in a variety of healthcare issues[34]. By doing a thorough literature review and responding to the research questions posed in the research, this study attempts to discover blockchain technology capabilities in the healthcare sector. The potential of blockchain technology has extended to the healthcare sector, enabling a change in the way the present system and its utilization of technology currently operate.

The study seeks to emphasize the potential paths for blockchain research in healthcare, as well as to emphasize the possible uses of the platform. According to literature, blockchain technology is currently being researched in the field of healthcare, where it is mostly employed for network access, data exchange, and record management[23]. Additionally, it demonstrates that many studies lack implementation or prototype information. The authors of literature reviewed reached the conclusion that blockchain application-based research is expanding and growing at an exponential rate[5]. The research has also demonstrated that the exponential growth of blockchain technology initiatives in the healthcare industry are projected to have a major influence. A systematic study method was conducted, employing a well-planned monitoring strategy to look for pertinent papers. Several studies have put out various scenarios for the application of blockchain in healthcare systems. The assessment also identifies benefits as well as shortcomings and potential future research topics. To further comprehend, define, and assess the usefulness of blockchain in healthcare, additional study is still required[9].

Main Features of Blockchain Technology

The four key characteristics of blockchain were identified by research studies and serve as the foundation upon that it has expanded. Technology's four distinguishing characteristics are: decentralization, immutability, transparency, and provenance[8]. Healthcare systems have used centralized systems up to the advent of blockchain to fulfill data exchange requirements. A centralized institution is employed to hold all the information in a central network, and only that entity and the user may communicate with each other. Even though centralized systems have indeed been in use for a long time, there are certain restrictions associated with this kind of network. Since the data is kept in a single main place and by a single organization, this turns into a red flag for would-be cybercriminals or hackers and even represents a lone source of potential failure[36,37].

Blockchain offers a decentralized network as an alternative option to a centralized one, removing the necessity for a single centralized power to rule over the network[22,23], discussed the idea of immutability, which states that once data or information has been generated it should not be changed. When a blockchain record has been created, it cannot be changed once it has joined the network[9]. This is a crucial aspect of the blockchain that may be used to stop a lot of unethical or questionable behavior in any sector[41]. Blockchain transparency is a term that is frequently misunderstood. With the use of sophisticated encryption, a person's identity is concealed and just their upgradable is shown[8]. The provenance feature of the blockchain implies that any additions to the blockchain are visible to all the patient's network members[39].

Blockchain Applications in Healthcare

Blockchain is a relatively emerging and developing technology that offers creative uses in the healthcare industry. The development of affordable cures and cutting-edge treatments for numerous diseases depends on smooth, effective data exchange and distribution across all the well-known network participants and health professionals. In the upcoming years, this will hasten the expansion of the healthcare sector. The studies reviewed highlighted that Ethereum and Hyperledger fabric seem to be the most used platforms/frameworks in this domain[12]. The studies unveiled blockchain technology prospects in the supply chain highlighting the benefits for the healthcare business. This is among the primary areas that the digital revolution enhances and innovates since it immediately affects living quality. Blockchain technology is also growing in popularity in the healthcare industry. It presents several significant and spectacular opportunities, ranging from research and economics to interactions between patients and physicians[7]. The most significant research explored and organized according to several use cases in this domain, include electronic health records (EHRs), remote monitoring of patients, pharmaceutical distribution network, and healthcare insurance claims[8,10,24].

1.Electronic Health Records

The administration of health data, which might be enhanced by the capacity to integrate disparate systems and enhance the precision of EHRs, should be given priority in the effort to change healthcare. While the phrases electronic patient records (EPRs) and electronic health records (EHRs) are sometimes used interchangeably, they have different meanings. EMRs, or electronic medical records, are a more recent name for the paper charts kept by clinicians in their offices. The medical and treatment histories of patients in a single practice are recorded in an EMR. EHRs, on the other hand, put a greater emphasis on a patient's overall health, going beyond the usual clinical data gathered at the doctor's office and taking a more comprehensive approach to a patient's care.

According to the studies reviewed, blockchain helps manage EHRs. To handle authorization and data exchange across healthcare entities, Ekblaw et al. described MedRec, an EHR-related solution that suggests a decentralized method. The MedRec platform provides patients with information and understanding about who may access their medical records. FHIR Chain (Fast Health Interoperability Records and Blockchain) is another program that incorporates EHRs[36]. It is a medical record management-focused, blockchain-based platform for exchanging clinical data that is developed using bitcoin, and patients can get solutions from FHIR Chain. Nonetheless, Xia et al. introduced Medshare, an ethereum program for systems that experience a lack of communication for information sharing among cloud computing owing to the negative risks towards disclosing the content of personal data information. When exchanging medical data in cloud archives, Medshare offers data monitoring, and governance among large data organizations. MedBlock and BlockHIE are two further EMR apps built on the blockchain. MedBlock offers a method for searching records.

The suggested method keeps track of the addresses of health records blocks that are organized by health professionals. Each patient assessment has a link to the relevant blockchain record. Jiang et al. proposal for BlockHIE presents a blockchain-based healthcare system[34]. BlockHIE blends off-chain retention, in which data is kept in database systems of external institutions, with on-chain validation to continue taking advantage of current databases. Another blockchain-based healthcare platform addressed in the literature is called Ancile, which employs smart contracts to ensure data security, confidentiality, access management, and EMR compatibility[45].

2. Remote Patient Monitoring

Remote patient surveillance refers to the gathering of medical data using smart phones, wireless body sensor sensors devices, and Internet of Things (IoT) devices to be able to monitor various patients' conditions[30]. Blockchain technology is crucial for the storage, exchange, and retrieval of remotely gathered health data. It offers a solution in this setting where information is sent from mobile devices to a blockchain-based application on Hyperledger[2, 23]. By providing real-time patient monitoring applications, ethereum platform contracts may allow automated interventions in a safe setting[51,12]. Other literature suggested ways highlight the enormous potential of the IoT in various fields, particularly how it is being widely utilized in e-health. Io Health, a data-flow architecture that integrates the IoT with blockchain and may be used for accessing, storing, and managing e-health data, is a suggestion made in this area[36].

3. Pharmaceutical Supply Chain

The pharmaceutical sector is another recognized use case for blockchain as patients may suffer severe effects if they get fake or subpar medicine. According to a study by the World Health Organization (WHO), over 100,000 people die in Africa due to improper dosing from counterfeited drugs obtained from untrusted vendors[4] and research has determined that blockchain technology has the power to solve this issue. Drug counterfeit has also been tackled by the researchers, who suggest a safe, irreversible, and verifiable supply chain for pharmaceuticals built on blockchain-based technology to prevent it[19,34]. In relation to drug regulating issues, drug standardization difficulties were addressed. Researchers?? have drawn attention to the challenges in identifying fake medications and suggested a blockchain-based approach to do so. Even though the suggested approach is only implemented in a small number of articles, several intriguing studies have addressed problems with the pharmaceutical supply chain[4].

4. Health Insurance Claims

One area of healthcare that can profit from blockchain's absoluteness, openness, and traceability of stored data on it is healthcare insurance claims. Blockchain technology has promising solutions to handle health insurance claims. However, there are few prototypes and applications of these systems[9]. MIStore, a cryptocurrency health coverage system that offers the medical coverage data that is well-secured and maintained, was located[34,35].

Benefits of Blockchain in Healthcare Sector

The blockchain technology enables medical professionals to embrace the notion of a public database that can be used to develop shareable, customized healthcare plans for their patients. As a result, this may readily assist in the facilitation and creation of personalized health plans that classify the patients based on their shared genetic data, age, and gender. Researchers have identified and divided blockchain benefits into individual benefits, organization-related benefits, and government benefits. Since users may only establish their identities once in the blockchain network, and the recorded identification traits are encrypted and kept in every blockchain server, users will not need to re-register their identities for accessibility in the foreseeable future.

Additionally, several researchers have highlighted the benefits of blockchain technology and how they addressed existing challenges in healthcare applications[12,19,42]. For example, ChengYing et al., 2018, explored the benefits of blockchain to link patients' EHRs across different healthcare services.

Patient-level Benefits

The literature on blockchain technology offers proof that the technology can get around some of the problems with the current healthcare system. The advantages of blockchain technology allow for efficient maintenance and interchange of health records. The decentralization of patient information creates a single point of truth for connectivity and efficiency[2]. Data reconciliation among all parties engaged in the transaction is made unnecessary by leveraging blockchain, which improves cost effectiveness[10]. Only authorized people are granted access to sensitive and important patient data and protected health records, and a lifelong and continuous health status record may be created using blockchain technology[38].

Patient data in the current healthcare information systems is frequently corrupted, prone to data breaches, or at elevated risk of failing. Data security is hence the main advantage of blockchain technology. According to a survey on the present status of EHRs with a sample size of 8,774, almost 40 percent of physicians view connectivity and EHR design as the main causes of their dissatisfaction[32]. It is challenging to transfer, retrieve, and analyze data due to the restricted data exchange and absence of compatibility among healthcare storage solutions. Berryhill et al.[43] noted that better compatibility is made possible by blockchain technology.

Organization-level Benefits

In terms of organizational advantages, blockchains have the capacity to offer safe patient data sharing across healthcare organizations. The group of authorized healthcare organizations taking part in the private network would be able share and access the information stored in the blockchain in a safe and trustworthy fashion[3]. Other studies emphasized the need of using blockchains to streamline the management of clinical trials because the study involves extremely sensitive patient-related data[27].

Government Benefits

Blockchain technology has enabled the government to offer new public healthcare designs, assist in addressing fraud and waste, reduce the cost and sophistication of different health activities, and identify misuse and fraud activities[31]. It is thought that establishing a public blockchain will save costs, speed up learning, reduce risk, boost technology acceptance, and have an impact on regulations[28]. Another advantage of blockchain applications is successful care surveillance, especially for extremely ill patients since this technology can help physicians perform appropriate medical treatments. To do this, patients' wearable technology, including smart watches, cell phones, and smart glasses, must be linked to the public blockchain of the healthcare provider[4]. In this section of the literature, the blockchain benefits that are most explored and addressed by previous studies were highlighted.

1.Securing Patient Data

Protecting patient information is one of the most important aspects of the healthcare industry. Falsifying patient records might contribute to difficulty for hospitals and physicians to diagnose and treat their patient's illness or issue. According to research studies, more than 176 million medical data records were compromised between 2009 and 2017. The data was hacked by cybercriminals, who then exploited it unethically[35]. Health data may be gathered using blockchain without having to move it all to a single place or centralized database. In the current EHR system, healthcare professionals hold the records, while patients have the right to access their own health records. Improved security and data integrity are made possible by the dissemination of health records and the data integrity of the data[13]. Data integrity is essential to healthcare since the current healthcare system has problems providing patients with accurate or sufficient information. Blockchain reduces the likelihood that unauthorized users would be able to extract health information[29].

2. Medical Drugs Supply Chain Management

Medications or pharmaceuticals are created in laboratories and pharmaceutical firms all over the world. According to each country's needs, these medications are further distributed across the world. What happens if the medications are tampered with while being transported across the nation? As a result, the importers and exporters must have access to a transparent, tamper-proof healthcare supply chain. Blockchain minimizes this issue because of its transparency, decentralization, and tamper-proof properties[3]. Each carrying point for the medicine will be added to the blockchain after a distributed ledger has been established, making the whole transportation process visible[37].

3. Single Longitudinal Patient Records

Every medical chart will be added to the blockchain ledger since it is made up of a chain of blocks called a blockchain. Examining the pre-compiled records would allow healthcare providers to have a broader picture of patients' medical conditions. Additionally, it will assist in mastering patient indices, streamlining data meticulously, and avoiding expensive errors[29].

4. Supply chain optimization

Authenticating the origin of medical supplies to assure the legitimacy of medications is a problem facing the healthcare industry. Supplies may be tracked from manufacture to every step of the supply chain with the use of blockchain technology. This makes it possible to acquire items transparently and visibly. This may assist businesses in implementing artificial intelligence (AI) and improving demand forecasting and supply optimization, while also boosting consumer confidence[44].

5. Drug Traceability

The most trustworthy, dependable, and safe way to trace every medicine back to its source is via blockchain. There will be a hash value associated with every data block including drug-related information. By using this hash code, the data is protected against manipulation. All parties with permission to see the blockchain can see the events. By scanning the QR code and pulling up all the essential details, such as the manufacturer's information, the legitimacy of the acquired drugs will be seamlessly verified[44].

6. Updated medical supply chain management

Blockchain is ideally suited for organizing and tracking the flow of medicine supply because of its security, dependability, and decentralized storage. Technology improves patient safety through building a reliable supplier network. In a single unchangeable record that's also securely held, blockchain unifies all the operations including manufacturing, packaging, marketing, shipping, and warehousing information. Blockchains adopt GS1 (open global standard for tracking healthcare products)[27].

7. Improved electronic health record systems

Systems for keeping track of patient's health information digitally are known as electronic health records (EHRs). By connecting EHRs and distributing property of the records across all stakeholders, blockchain overcomes issues with availability, compatibility, and verification[19].

8. Improved recruitment for clinical trials and Research

A cryptocurrency blockchain that replicates the hiring process has been developed by researchers to safeguard study participants' anonymity while enabling access to study results for all academics[4]. Data integrity and provenance are critical characteristics in clinical trials. Blockchain network can transparently show the data from the origin to the final clinical report[27]. Technology allows researchers to access vast amounts of unprocessed data that might lead to important medical advancements without jeopardizing patient confidentiality[38].

Threats of Blockchain Technology in Healthcare

Blockchain technology has a myriad of benefits, however, there are also considerable risks associated with the technology. Risks in this research were divided into three categories: organizational; societal; and technological threats. Scaling problems, authorization and security problems, and excessive power and energy usage were all recognized by researchers as the common three technical dangers[32]. The most important technical risk to blockchain advanced technologies is scalability. Since there is no limitation on the number of people who join the network, the scaling issue has evolved into a major worry for blockchain-based applications. Additionally, issues occur when utilizing wearable technology to track blockchain networks since the amount of data provided by these sensors grows exponentially[40]. Researchers have claimed that private permissioned blockchain deployment brings the most benefits for health care applications, however, it is usually combined with security risks[30]. Private permissioned blockchains are most prone to a 51 percent attack[37]. Additionally, blockchain is vulnerable to cyber-attacks in which the attackers can seize control of the network. If the attackers disrupt or even reverse transactions that have been validated inside the network, a disaster may result. Additionally, this evaluation identified high energy use as a hazard since it pertains to the usage of public blockchains and is a mining method that causes a lot of energy consumption. This issue got worse when more people joined the public blockchain and more payments were being processed every second.

The absence of legal authority-issued blockchain technology rules was another major societal danger highlighted. Meanwhile, interoperability problems, shortage of technical expertise for integrating pharmacological suppliers, setup expenses, and transaction costs were the main sources of organizational risks. Interoperability was seen as one of the main obstacles to blockchain technology acceptance in the healthcare industry due to lack of trust among healthcare organizations and a shortage of information technology (IT) personnel qualified to use blockchain technology. Employing blockchain technology without the necessary technical knowledge and capacity might have fatal results[8]. The included research revealed eight challenges to blockchain technology, which were categorized as organizational, societal, or technical/technological concerns. Studies discovered two different forms of social dangers, three distinct types of organizational threats, and three distinct types of technological threats. The following section provides more information on the risks explored by researchers[5].

1. Technical or technological threats

The scalability problem with blockchain technology was due to the network's constrained processing capacity for transactions. Additionally, according to two studies, the exchange between trading volume and the amount of processing power needed to handle those transactions is the major limitation of scalability. Authorization and security were issues and constraints associated with blockchain technology. According to several studies, distributed ledger technology is vulnerable to assaults. Other research studies identified significant issues, particularly with blockchain networks, including high consumption of energy and sluggish processing speed brought by a significant increase in network users[31,39,40].

2. Social threats

According to research studies, the societal acceptability of blockchain technology was a key obstacle to implementation. Scholars revealed that it is challenging for the legal authorities to grant access due to the decentralization of medical data and the withdrawal of a trusted third-party emphasizing privacy as a valid concern. Literature reviews also emphasized the absence of governance norms and standards as a barrier to blockchain adoption in the healthcare industry[30].

3. Organizational threats

According to research studies, compatibility is one of the main problems with blockchain adoption in the healthcare sector from an organizational standpoint. Studies described interoperability issues as lack of confidence among parties and absence of transparent standards, which make it difficult for healthcare organizations to communicate full patient data. The upkeep of an interconnected supply chain for pharmaceuticals for the networks that lack the necessary technical knowledge to manage the system was another issue noted by research. In addition, the initial cost of installation is rather significant for blockchain, even though it can save costs in the long term[46].

Some solutions have been proposed to address the highlighted challenges. For example, as a countermeasure to the challenge of scalability, given the large volume of clinical data involved, the trend is to store the actual healthcare data on the cloud and store only the pointers of the data on blockchain, along with their fingerprints[22]. A considerable number of papers were found on the implementation of blockchain-based EMR applications in which different strategies were considered to tackle these challenges. Yet, some publications propose different workarounds to improve the security and privacy challenges of blockchain[11,23,42].

Blockchain as an Opportunity to Approach Medicine in a Novel Way

Blockchain is a potential solution for health data security because of its eternity, autonomy, and total openness[36]. Patients' identity and medical information will continue to be retained in confidence using blockchain if the system is secure. By eliminating inefficient instrumentation, this ground-breaking solution will simplify the challenging billing procedure[40]. Blockchain technology may usher in a new framework for the exchange of health data by improving the efficiency, dependability, and security of EHRs as a decentralized ledger that stores important transactional data[11]. By allowing the safe transfer of patient medical records, controlling the medication supply chain, and enabling the regular and accurate of patient records, ledger technology assists healthcare scientists in deciphering genetic code. Medical files protection, diverse genomes management, electronic information management, interoperability, digitized tracking, and issue outbreak are a few of the outstanding and technologically derived aspects used to create and implement blockchain technology[3].

Chen et al. 2019[23]noted that blockchain-based digital structures would ensure that unauthorized changes to the logistical data are avoided. They foster confidence and inhibit those who are interested in obtaining drugs from handling information, funds, and medicine in an unauthorized manner. The use of technology can significantly enhance patients' conditions while keeping costs low. In multi-level authentication, it removes all hurdles and difficulties. Patients, physicians, and other healthcare professionals may all quickly and securely exchange the same information because of the technology's decentralized nature. Medical entities are constantly experimenting, researching, and learning about blockchain technology particularly for health records solutions. By adopting medications, enhancing payment alternatives, and decentralizing patient health history information, technology has established itself as an indispensable innovation in healthcare. The medical industry is heavily dependent on blockchain in addition to advanced technologies like machine learning and AI. There are several legitimate ways that blockchains are transforming the healthcare sector. A single blockchain system stores all the data, protecting it from loss and change. Leveraging this approach, physicians may simply get all the information required to make an accurate diagnosis and suggestions. A substantial organization with blockchain database that is encrypted may get protected from hazards and attacks from the outside world. Such rescue, assaults, and other issues, including computer malfunction or hardware breakdown, will have minimal impact on healthcare organizations appropriately deploying a blockchain network[10].

The research studies highlighted the technology's potential to fundamentally transform the current segmentation in which patients sign fresh consents for every consultation, clinical procedure, and medical test[23,43]. It has the potential to become a crucial component of healthcare consent management that promotes information sharing. A blockchain-based supply chain system ensures security, reliability, and promptness of pharmaceuticals delivery. The presence of this technology solves issues that cannot be addressed by current conventional methods[32]. Reliability, protection, and data interchange among many systems are necessary for great healthcare[42].

Discussion

The research has been describing blockchain technology as a disruptive innovation.
However, blockchain research is an emerging field in healthcare, which indicates that it is mostly used for data sharing, health records, and access control along with other areas such as supply chain

management or drug prescription management. Some scholars addressed other applications including the interchange of clinical testing dataset and the potential for uncovering advantages for test subjects. Technology has the potential to become a crucial component of healthcare consent management that promotes information sharing. However, much potential for blockchain is still unexploited.
A blockchain-based supply chain system ensures the security, reliability, and promptness of the delivery of pharmaceuticals. It enables the manufacturer to keep the correct formulation mixture in accordance with medical standards. Medical devices can charge for patient information, confirm that the designated patient is receiving the therapy, and communicate operational data with authorities in an anonymized manner[5].

Recent years have seen notable advancements in medical research and enhanced medical treatments. Reliability, protection, and data interchange among many systems are necessary for a great healthcare system. Research proposed to use blockchain for building a personal health record system to bridge the gap between patient and organization[34]. Blockchain has the potential to support health records and transfer the ownership of the medical records to the patients. The use of blockchain technology in the healthcare industry is exciting. It is recommended that challenges encountered in implementing blockchain solutions should be explored in these applications. Furthermore, none of the reviewed studies described how the blockchain application was compliant with healthcare regulations, which is another area that needs to be more explored on an extended level. Also, blockchain is prone to cyber-attacks along with interoperability issues and lack of technical skills for integrating systems. In addition, high energy consumption was highlighted in this review as a threat since it relates to public blockchain use, which consumes a great amount of energy.

Limitation and Future Direction

The studies in this review describe many blockchain potential uses, benefits, and issues, often at the conceptual level. Despite the growing use of the concept in literature, there are gaps in comprehending it on empirical and theoretical levels due to the limited number of studies. However, the current and proposed studies are growing exponentially. Disruptive innovation is a term that has diffused into the healthcare industry, but there is widespread ambiguity in the use of the term[19]. Data driven studies on outcomes of specific blockchain solutions in the healthcare industry are highly recommended to pave the way for future applications. Like any emerging technology, it will introduce innovation, benefits, and risks into society. Future research is suggested to include blockchain's instrumental role in population health management and how to mitigate risks associated with utilizing the technology. Expanding healthcare research from the administrative and strategic perspectives of blockchain adoption and its economic impact on healthcare organizations will fill some gaps in the research landscape.

There is currently extremely limited research on certain applications and prototypes of blockchain solutions that would open unlimited opportunities for future research to delve into. There is also further research needed to expand on the value of blockchain uses in healthcare through developing proof of concepts to deepen researchers' understanding of the technology in relation to healthcare system strategic needs. Future research is recommended around blockchain scalability and risk of specific blockchain cybersecurity attacks that can halt the entire system and jeopardize users' information. Frizzo-Baker[10] discussed the argument that only 20 percent of the barriers to blockchain adoption and success are technological, while the other 80 percent are related to organizational practices. Conducting research on organizational strategies and practices in the adoption and implementation of innovative technologies in healthcare was proposed.

Conclusion

The purpose of this systematic review was to examine the current state and research topics of blockchain technology in healthcare, along with the applications and key benefits and challenges associated with this technology. The findings show that in the past few years blockchain has gained traction to be implemented in the healthcare sector with a potential to improve the authenticity and transparency of healthcare data, while highlighting the major challenges uncovered in this review. Blockchain's decentralization, immutability, and transparency features have enabled better management of patient health records and supply chain management. However, many healthcare organizations remain hesitant to adopt blockchain technology due to threats such as security, interoperability issues, and lack of technical skills related to blockchain technology.

The studies reviewed suggest that we are still at the beginning of the road toward the full utilization of blockchain technology in the healthcare sector. It was proposed that research be conducted on each of digital platforms discussed in the literature to identify use cases of blockchain technology and to assess its feasibility. However, doubts remain regarding the value of blockchain technology in relation to the technical experiences of users. The goal is to empower patients with the ownership of their medical data accessing and sharing. The proper utilization of blockchain can increase interoperability while maintaining privacy and security of data. Increased interoperability would be beneficial for health outcomes. However, more research still needs to be conducted to better understand and evaluate the utility of blockchain technology in healthcare. Furthermore, this paper contributes to the research on blockchain technology by highlighting current studies and identifying potential research gaps that could positively impact the industry if properly addressed.

References

1. M. Mettler, "Blockchain technology in healthcare: The revolution starts here," *2016 IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom)*, pp. 1–3, Sep. 2016, doi: https://doi.org/10.1109/healthcom.2016.7749510.

2. M. Attaran, "Blockchain technology in healthcare: Challenges and opportunities," *International Journal of Healthcare Management*, vol. 15, no. 1, pp. 1–14, Nov. 2020, doi: https://doi.org/10.1080/20479700.2020.1843887.

3. A. Haleem, M. Javaid, R. P. Singh, R. Suman, and S. Rab, "Blockchain Technology Applications in Healthcare: An Overview," *International Journal of Intelligent Networks*, vol. 2, no. 2, pp. 130–139, 2021, doi: https://doi.org/10.1016/j.ijin.2021.09.005.

4. S. Khezr, M. Moniruzzaman, A. Yassine, and R. Benlamri, "Blockchain Technology in Healthcare: A Comprehensive Review and Directions for Future Research," *Applied Sciences*, vol. 9, no. 9, p. 1736, Apr. 2019, doi: https://doi.org/10.3390/app9091736.

5. M. Abdel-Basset, V. Chang, and N. A. Nabeeh, "An Intelligent Framework using Disruptive Technologies for COVID-19 analysis," *Technological Forecasting and Social Change*, vol. 163, p. 120431, Oct. 2020, doi: https://doi.org/10.1016/j.techfore.2020.120431.

6. M. Warkentin and C. Orgeron, "Using the security triad to assess blockchain technology in public sector applications," *International Journal of Information Management*, vol. 52, p. 102090, Feb. 2020, doi: https://doi.org/10.1016/j.ijinfomgt.2020.102090.

7. D. V. Dimitrov, “Blockchain Applications for Healthcare Data Management,” *Healthcare Informatics Research*, vol. 25, no. 1, p. 51, 2019, doi: https://doi.org/10.4258/hir.2019.25.1.51.

8. I. Yaqoob, K. Salah, R. Jayaraman, and Y. Al-Hammadi, “Blockchain for Healthcare Data management: opportunities, challenges, and Future Recommendations,” *Neural Computing and Applications*, vol. 34, pp. 1–16, Jan. 2021, doi: https://doi.org/10.1007/s00521-020-05519-w.
9. A. A. Vazirani, O. O’Donoghue, D. Brindley, and E. Meinert, “Implementing Blockchains for Efficient Health Care: Systematic Review,” *Journal of Medical Internet Research*, vol. 21, no. 2, p. e12439, Feb. 2019, doi: https://doi.org/10.2196/12439.

10. J. Frizzo-Barker, P. A. Chow-White, P. R. Adams, J. Mentanko, D. Ha, and S. Green, “Blockchain as a disruptive technology for business: A systematic review,” *International Journal of Information Management*, vol. 51, no. 102029, p. 102029, Nov. 2019, doi: https://doi.org/10.1016/j.ijinfomgt.2019.10.014.

11. M. Prokofieva and S. J. Miah, “Blockchain in healthcare,” *Australasian Journal of Information Systems*, vol. 23, Jul. 2019, doi: https://doi.org/10.3127/ajis.v23i0.2203.

12. Y. Lu, “The blockchain: State-of-the-art and research challenges,” *Journal of Industrial Information Integration*, vol. 15, pp. 80–90, Sep. 2019, doi: https://doi.org/10.1016/j.jii.2019.04.002.

13. B. Reddy, Madhushree, and P. S. Aithal, “Blockchain as a Disruptive Technology in Healthcare and Financial Services - a Review Based Analysis on Current Implementations,” *papers.ssrn.com*, May 27, 2020. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3611482

14. C. Schinckus, “A Nuanced perspective on blockchain technology and healthcare,” *Technology in Society*, vol. 71, p. 102082, Nov. 2022, doi: https://doi.org/10.1016/j.techsoc.2022.102082.

15. A. S. Rajawat, P. Bedi, S. B. Goyal, R. N. Shaw, A. Ghosh, and S. Aggarwal, “AI and Blockchain for Healthcare Data Security in Smart Cities,” *AI and IoT for Smart City Applications*, pp. 185–198, 2022, doi: https://doi.org/10.1007/978-981-16-7498-3_12.

16. S. Namasudra and G. Chandra Deka, *Applications of Blockchain in Healthcare*. Singapore: Springer Singapore, 2021. doi: https://doi.org/10.1007/978-981-15-9547-9.

17. H. M. Hussien, S. M. Yasin, N. I. Udzir, M. I. H. Ninggal, and S. Salman, “Blockchain technology in the healthcare industry: Trends and opportunities,” *Journal of Industrial Information Integration*, vol. 22, p. 100217, Jun. 2021, doi: https://doi.org/10.1016/j.jii.2021.100217.

18. C. Christensen, M. Raynor, and R. Mcdonald, “What is disruptive innovation? Twenty years after the introduction of the theory, we revisit what it does-and doesn’t-explain,” 2015. Available: https://www.innosight.com/wp-content/uploads/2018/01/Innosight_HBR_What-is-Disruptive-Innovation.pdf

19. V. Sounderajah *et al.*, “Are disruptive innovations recognized in the healthcare literature? A systematic review,” *BMJ Innovations*, vol. 7, no. 1, p. bmjinnov-2020-000424, Sep. 2020, doi: https://doi.org/10.1136/bmjinnov-2020-000424.

20. J. L. Hartley, W. Sawaya, and D. Dobrzykowski, “Exploring blockchain adoption intentions in the supply chain: perspectives from innovation diffusion and institutional theory,” *International Journal of*

Physical Distribution & Logistics Management, vol. ahead-of-print, no. ahead-of-print, Dec. 2021, doi: https://doi.org/10.1108/ijpdlm-05-2020-0163.

21. M. Turner, B. Kitchenham, P. Brereton, S. Charters, and D. Budgen, "Does the technology acceptance model predict actual use? A systematic literature review," *Information and Software Technology*, vol. 52, no. 5, pp. 463–479, May 2010, doi: https://doi.org/10.1016/j.infsof.2009.11.005.

22. C. Agbo, Q. Mahmoud, and J. Eklund, "Blockchain Technology in Healthcare: A Systematic Review," *Healthcare*, vol. 7, no. 2, p. 56, Apr. 2019, doi: https://doi.org/10.3390/healthcare7020056.

23. Y. Chen, S. Ding, Z. Xu, H. Zheng, and S. Yang, "Blockchain-Based Medical Records Secure Storage and Medical Service Framework," *Journal of Medical Systems*, vol. 43, no. 1, Nov. 2018, doi: https://doi.org/10.1007/s10916-018-1121-4.

24. T.-T. Kuo, H. Zavaleta Rojas, and L. Ohno-Machado, "Comparison of blockchain platforms: a systematic review and healthcare examples," *Journal of the American Medical Informatics Association*, vol. 26, no. 5, pp. 462–478, Mar. 2019, doi: https://doi.org/10.1093/jamia/ocy185.

25. Z. Zheng, S. Xie, H. N. Dai, X. Chen, and H. Wang, "Blockchain challenges and opportunities: a survey," *International Journal of Web and Grid Services*, vol. 14, no. 4, pp. 352–375, 2018, doi: https://doi.org/10.1504/ijwgs.2018.095647.

26. A. Siyal, A. Junejo, M. Zawish, K. Ahmed, A. Khalil, and G. Soursou, "Applications of Blockchain Technology in Medicine and Healthcare: Challenges and Future Perspectives," *Cryptography*, vol. 3, no. 1, p. 3, Jan. 2019, doi: https://doi.org/10.3390/cryptography3010003.

27. T. K. Mackey *et al.*, "'Fit-for-purpose?' – challenges and opportunities for applications of blockchain technology in the future of healthcare," *BMC Medicine*, vol. 17, no. 1, Mar. 2019, doi: https://doi.org/10.1186/s12916-019-1296-7.

28. R. Hillestad *et al.*, "Can Electronic Medical Record Systems Transform Health Care? Potential Health Benefits, Savings, And Costs," *Health Affairs*, vol. 24, no. 5, pp. 1103–1117, Sep. 2005, doi: https://doi.org/10.1377/hlthaff.24.5.1103.

29. H. A. Fatoum, S. Hanna, J. D. Halamka, D. C. Sicker, P. Spangenberg, and S. K. Hashmi, "Blockchains integrated with digital technology revolution: The future of healthcare ecosystems. (Preprint)," *Journal of Medical Internet Research*, May 2020, doi: https://doi.org/10.2196/19846.

30. I. Radanović and R. Likić, "Opportunities for Use of Blockchain Technology in Medicine," *Applied Health Economics and Health Policy*, vol. 16, no. 5, pp. 583–590, Jul. 2018, doi: https://doi.org/10.1007/s40258-018-0412-8.

31. A. A. Monrat, O. Schelen, and K. Andersson, "A Survey of Blockchain From the Perspectives of Applications, Challenges, and Opportunities," *IEEE Access*, vol. 7, pp. 117134–117151, 2019, doi: https://doi.org/10.1109/access.2019.2936094.

32. K. Yaeger, M. Martini, J. Rasouli, and A. Costa, "Emerging Blockchain Technology Solutions for Modern Healthcare Infrastructure," *Journal of Scientific Innovation in Medicine*, vol. 2, no. 1, 2019, doi: https://doi.org/10.29024/jsim.7.

33. J. Yli-Huumo, D. Ko, S. Choi, S. Park, and K. Smolander, “Where Is Current Research on Blockchain Technology?—A Systematic Review,” *PLOS ONE*, vol. 11, no. 10, p. e0163477, Oct. 2016, doi: https://doi.org/10.1371/journal.pone.0163477.

34. A. Hasselgren, K. Kralevska, D. Gligoroski, S. A. Pedersen, and A. Faxvaag, “Blockchain in healthcare and health sciences—A scoping review,” *International Journal of Medical Informatics*, vol. 134, p. 104040, Feb. 2020, doi: https://doi.org/10.1016/j.ijmedinf.2019.104040.

35. A. Shahnaz, U. Qamar, and A. Khalid, “Using Blockchain for Electronic Health Records,” *IEEE Access*, vol. 7, no. 1, pp. 147782–147795, 2019, doi: https://doi.org/10.1109/access.2019.2946373.

36. A. Ekblaw, A. Azaria, J. Halamka, A. Lippman, and T. Vieira, “A Case Study for Blockchain in Healthcare: ‘MedRec’ prototype for electronic health records and medical research data White Paper MedRec: Using Blockchain for Medical Data Access and Permission Management IEEE Original,” 2016. Available: http://www.truevaluemetrics.org/DBpdfs/Technology/Blockchain/5-onc_blockchainchallenge_mitwhitepaper_copyrightupdated.pdf

37. R. El-Gazzar and K. Stendal, “Blockchain in Health Care: Hope or Hype?,” *Journal of Medical Internet Research*, vol. 22, no. 7, p. e17199, Jul. 2020, doi: https://doi.org/10.2196/17199.

38. S. Ølnes, J. Ubacht, and M. Janssen, “Blockchain in government: Benefits and implications of distributed ledger technology for information sharing,” *Government Information Quarterly*, vol. 34, no. 3, pp. 355–364, Sep. 2017, doi: https://doi.org/10.1016/j.giq.2017.09.007.

39. M. H. Kassab, J. DeFranco, T. Malas, P. Laplante, Giuseppe Destefanis, and V. V. Graciano Neto, “Exploring Research in Blockchain for Healthcare and a Roadmap for the Future,” *IEEE Transactions on Emerging Topics in Computing*, pp. 1–1, 2019, doi: https://doi.org/10.1109/TETC.2019.2936881.

40. T. McGhin, K.-K. R. Choo, C. Z. Liu, and D. He, “Blockchain in healthcare applications: Research challenges and opportunities,” *Journal of Network and Computer Applications*, vol. 135, pp. 62–75, Jun. 2019, doi: https://doi.org/10.1016/j.jnca.2019.02.027.

41. M. Hölbl, M. Kompara, A. Kamišalić, and L. Nemec Zlatolas, “A Systematic Review of the Use of Blockchain in Healthcare,” *Symmetry*, vol. 10, no. 10, p. 470, Oct. 2018, doi: https://doi.org/10.3390/sym10100470.

42. R. Ben Fekih and M. Lahami, “Application of Blockchain Technology in Healthcare: A Comprehensive Study,” *Lecture Notes in Computer Science*, pp. 268–276, 2020, doi: https://doi.org/10.1007/978-3-030-51517-1_23.

43. J. Berryhill, T. Bourgery, and A. Hanson, “Blockchains Unchained: Blockchain Technology and its Use in the Public Sector,” *www.oecd-ilibrary.org*, Jun. 2018, doi: https://doi.org/10.1787/3c32c429-en.

44. M. A. Engelhardt, “Hitching Healthcare to the Chain: An Introduction to Blockchain Technology in the Healthcare Sector,” *Technology Innovation Management Review*, vol. 7, no. 10, pp. 22–34, Oct. 2017, doi: https://doi.org/10.22215/timreview/1111.

45. A. Rot and B. Blackie, “Blockchain’s Future Role in Cybersecurity. Analysis of Defensive and Offensive Potential Leveraging Blockchain-Based Platforms,” *ieeexplore.ieee.org*, 2019. https://ieeexplore.ieee.org/abstract/document/8779855/ (accessed Oct. 30, 2023).

46. I. Leila, H. Materwala, and S. Zeadally. "Lightweight blockchain for healthcare." *IEEE Access* 7 (2019): 149935-149951.

47. Z. Aneesh, A. Grilo, and T. Nodehi. "The value proposition of blockchain technologies and its impact on Digital Platforms." Computers & industrial engineering 155 (2021): 107187.

48. S. Melanie. *Blockchain: Blueprint for a new economy*. " O'Reilly Media, Inc.", 2015.

49. D. Aguiar, E. Júlio, Bruno S. F. B. Krishnamachari, and J. Ueyama. "A survey of blockchain-based strategies for healthcare." *ACM Computing Surveys (CSUR)* 53, no. 2 (2020): 1-27.

50. T. Sudeep, Q. Bhatia, P. Patel, A. Kumari, P. k.Singh, and W. Hong. "Machine learning adoption in blockchain-based smart applications: The challenges, and a way forward." *IEEE Access* 8 (2019): 474-488.

51. G. Kristen N., O. Ossipova, C. P. Kohlios, A. Baccarini, E. Howson, and T. Hayajneh. "Healthcare blockchain system using smart contracts for secure automated remote patient monitoring." *Journal of medical systems* 42 (2018): 1-7.

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Current Challenges in Sepsis Documentation and Coding: A Review of the Literature

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Abstract
Sepsis has continued to climb the charts as one of the most frequent principal diagnoses for hospitalizations in the US and one of the most expensive conditions to treat in the nation's hospitals. It is unsurprising that it warrants additional scrutiny by payers and also remains one of the most frequently denied diagnoses. Challenges arise in sepsis billing due to the variety of definitions of the condition and changing clinical indicators impacting documentation and coding. This article reviews the literature related to the diagnosis, documentation, coding, and billing of sepsis since the more widespread implementation of the Sepsis-3 definition in 2017 to outline the challenges and recommendations discussed by industry leaders. Addressing accurate sepsis diagnosis and reimbursement relies on clear organizational policies, accurate and helpful tools, education and training, and consistent denial management.

Keywords: sepsis, septicemia, coding, denials, CDI

Introduction

Sepsis has been recognized as a leading cause of death and significant financial burden with incidence increasing annually, with some claiming that it may still be underrecognized and underreported.[1] This may be due, in part, to the lack of a universal clinical definition, challenges in coding sepsis, and regular denials of sepsis on claims.[2] The clinical criteria remain complicated and ambiguous, without clear biological, imaging, or laboratory features to uniquely identify a septic patient.[3] Septicemia or severe sepsis with a major complication, Medicare Severity Diagnosis Related Group (MS-DRG) 871, was the most frequently billed MS-DRG in FY 2019, leading many payers to scrutinize sepsis-related claims, reviewing them both prepayment and post-payment.[4] There are increasing clinical validation denials due to misaligned sepsis criteria between providers and payers, a lack of clinical indicators and/or documentation, and the additional focus on these types of claims. Denials are expensive and resource-intensive, and inaccurate coding of sepsis in claims data may negatively impact funding and accurate epidemiological representation.[5]

A Rising Problem

It is clear that the challenge of diagnosing, treating, and billing sepsis are not going away, as the number of sepsis-related admissions and claims continue to rise. Table 1 shows the number of discharges and associated average charges and payments from Medicare inpatient hospitals in 2020, both nationally and within the highest and lowest states. This highlights the increasing number of discharges and the wide range in average submitted charge.

The Healthcare Cost and Utilization Project (HCUP) has further highlighted the burden of sepsis-related admissions and claims amongst all payers. Septicemia was the most frequent principal diagnosis for hospitalizations in the United States in 2018 with 2,218,800 stays representing eight percent of nonmaternal, nonneonatal inpatient stays.[6] This number more than doubled in seven years, with just over one million discharges indicated in 2011.[7] Sepsis also remained the most expensive condition treated in U.S. hospitals, costing $41.5 billion in aggregate and averaging $18,700 per stay.[8] This was up from $38.2 billion (8.8 percent of national costs) in 2017, $23.6 billion (6.2 percent) in 2013, and $20.3 billion (5.2 percent) in 2011.[9,10,11] Cost was highest in the West and lower in the Midwest and South.[12]

Part of this cost may be associated with the high use of the intensive care unit (ICU) for patients diagnosed with sepsis. In 2011, HCUP indicated that MS-DRG 871 was among the most common conditions with the highest proportion of ICU utilization in 29 states at 59 percent. Those without a major complication or comorbidity, MS-DRG 872, were at 27.5 percent.[13] A 2012 statistical brief from HCUP that highlighted super-utilizers, those individuals who consume a large share of health care resources, indicated that septicemia was amongst the 10 most common principal diagnoses for these patients across all payers.[14] It was also among the top 10 conditions with discharges to post acute care (PAC) in 2013, with MS-DRGs 870-872 accounting for 441,400 discharges to PAC (39.4 percent) with the most going to skilled nursing facilities (53.5 percent).[15] Septicemia also accounts for a large portion of readmissions. In 2014, septicemia ranked among the top 20 diagnoses with the highest 7-day (6.7 percent) and 30-day (18.5 percent) readmission rates.[16] This was confirmed again in 2018 when hospital stays for septicemia had the highest number of 30-day all-cause readmissions at 314,600 (accounting for 8.3 percent of all readmissions).[17]

In addition to high cost, septicemia is of particular concern for certain vulnerable populations. According to the 2018 HCUP data, rural areas had the highest rate of stays for septicemia but decreased mean length of stay and cost per stay.[18] A 2014 study showed that septicemia was more than 10 times higher among those aged 75+ years than those aged 18 to 44 years, making it the most common diagnosis among that age group (7.6 percent).[19] It was also found that among patients readmitted within 30 days of an index stay for septicemia, uninsured patients were more likely than patients with insurance to return within 7 days.[20] In 2018, average readmission costs were highest amongst the self-pay/no charge patients and those with Medicaid accounting for 8.6 percent and 9.6 percent of the aggregate, respectively.[21,22] As this data shows, sepsis continues to be a prevalent and problematic condition with high costs. It is no surprise that it has warranted increased scrutiny by payers and thus, higher denial rates. It is important that facilities address the diagnosis, documentation, and coding of sepsis to ensure quality patient care and accurate reimbursement.

Scope and Objectives

The scope of this article is twofold: to provide a comprehensive review of the current challenges related to sepsis documentation, coding, and billing and to provide recommendations on how to address these challenges. A search was conducted of peer-reviewed articles published since 2017 related to the diagnosis and billing of sepsis using EBSCOhost database and Google Scholar.

The search was limited to this time period to highlight the challenges since the Sepsis-3 definitions were announced and had begun adoption amongst providers and payers. Search terms were used to identify sources that addressed sepsis definitions, coding sepsis, clinical documentation integrity (CDI) guidelines concerning sepsis, sepsis query recommendations, and sepsis-related claims denial management. Of the more than 200 articles reviewed, the content of nearly 100 specifically referenced the diagnostic and billing challenges of sepsis and associated recommendations. The research team recognizes that much of the expertise in this area is not evident in peer-reviewed journals. Thus, the search was expanded to professional journals and publications, as well as associated blogs and Q&A forums moderated by coding and CDI experts. This included the *Journal of AHIMA*, *ICD-10 Monitor*, *Coding Clinic*, Centers for Medicare & Medicaid Services (CMS) data tables, and Association of Clinical Documentation Integrity Specialists (ACDIS) publications and forums, among others. After screening the sources that met the criteria of the search, 95 sources were thoroughly evaluated for inclusion in this article. In total, 51 were used to synthesize the challenges of coding and billing for sepsis and recommendations to reduce sepsis-related claims denials.

The Challenges

Definitions and Clinical Indicators

According to the *Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3)*, sepsis is "life-threatening organ dysfunction caused by a dysregulated host response to infection."[23] This organ dysfunction and dysregulated host response is what differentiates sepsis from other infections.[24] However, this definition still raises some confusion and controversy.[25] This may be due to the changing definitions of sepsis since 1992 when the *Definitions for Sepsis and Organ Failure and Guidelines for the Use of Innovative Therapies in Sepsis* first identified what is now referred to as Sepsis-1, based primarily around systemic inflammatory response syndrome (SIRS) with infection. This committee also introduced the concept of a continuum of severity, establishing a model of sepsis, severe sepsis, and septic shock. Septic shock is defined as "a subset of sepsis in which underlying circulatory and cellular metabolism abnormalities are profound enough to substantially increase mortality."[26] The definition was again revised in 2003, expanding the list of findings that may be seen in septic patients and defining sepsis "as the presence of infection and a wide list of general, inflammatory, perfusion, and hemodynamic parameters."[27] These changing definitions shifted the diagnosis of sepsis from being based on SIRS with defined vital signs and laboratory values suggestive of infection to being based on organ dysfunction.[28]

The Sepsis-3 definition relies on the measures of organ dysfunction, which can be based on a Sequential Organ Failure Assessment (SOFA) score of two points or more. The SOFA score is a mortality prediction score to grade the severity of organ dysfunction in the presence of infection. It is assumed a normal, healthy patient has a baseline SOFA score of zero.[29] This scoring model was developed and validated in an ICU setting; when used outside of the ICU it may underestimate organ dysfunction and sepsis.[30] Duke et al. found that "the SOFA score had high specificity but poor sensitivity for clinical sepsis," stating that "clinical reliance on the SOFA score may delay recognition and treatment of patients during early stages of sepsis."[31] One challenge is that there are variable thresholds for defining organ dysfunction. As Rhee et al. states, "For example, there are multiple definitions for acute kidney injury, which differ from thresholds used in the SOFA score and other ICU-based organ dysfunction scores."[32]

Furthermore, this definition relies on some knowledge of baseline functioning that may not be known.[33] Patients may also be evaluated using the quick SOFA (qSOFA) score, but it has also been studied with mixed results. Arberry et al. found that qSOFA led to an overestimate of sepsis, recommending the use of both qSOFA and SOFA to clearly identify organ dysfunction.[34] In a study by Anand et al., of the 271,500 patients who had a positive qSOFA score on admission, only one in six had sepsis pointing to low sensitivity for identifying sepsis.[35] Salomao et al. found that the qSOFA lacked sensitivity when compared to the previous SIRS criteria and Evans et al., (2021) recommends "against using qSOFA compared with SIRS, NEWS, or MEWS as a single screening tool for sepsis or septic shock."[36,37] Singer et al. clarifies that "neither qSOFA nor SOFA is intended to be a stand-alone definition of sepsis."[38] Similarly, SIRS is meant as a screening test.[39] The qSOFA should be used as the screening protocol within the first hour and then SOFA criteria becomes more credible with findings of organ dysfunction as the patient stay progresses.[40]

In addition to the challenges related to defining and measuring organ dysfunction, the adoption of different sepsis definitions by various entities has added to the confusion. Some professional groups have declined to endorse the new Sepsis-3 standards, including The American College of Emergency Physicians, Infectious Diseases Society of America, and Latin American Sepsis Institute. CMS has shown preference for Sepsis-2 definitions for review and payment and Sepsis-1 measurement criteria over Sepsis-3.[41] However, many other third-party payers have adopted Sepsis-3 criteria and recovery audit contractors (RACs) have begun moving towards Sepsis-3. In a member survey conducted by ACDIS (2020), 65 percent indicated that their facility uses Sepsis-2 criteria and only 15 percent use Sepsis-3 criteria. Physicians are not bound to a particular sepsis definition or set of criteria, and many hospitals are either still using Sepsis-2 criteria or unsure which one to use. This can lead to conflicting evaluations of claims and ultimately result in denials.[42]

Regardless of the definition or clinical criteria, a sepsis diagnosis is dependent upon the patient story and physician judgment, and can be subjective.[43,44] Patients present with ailments that may or may not be infectious and organ dysfunction that may or may not be due to infection, and a septic patient may or may not have a positive blood culture and bacteremia may or may not cause sepsis.[45,46] The uncertainties in the diagnosis, scoring models, and clinical presentation can lead to unclear documentation that may negatively impact coding and ultimately lead to a denial. The physician's documentation must make a clear connection between the abnormal clinical findings that support organ dysfunction and the diagnosis of sepsis.[47]

Coding and CDI

Coding sepsis can often be as challenging as diagnosing it, with CMS guidelines keeping the "SIRS plus infection plus organ dysfunction" definition that does not clearly align with the new clinical definition of sepsis.[48] The *AHA Coding Clinic Fourth Quarter 2017* states "a code is assigned when the provider documents sepsis and an associated acute organ dysfunction," but this not always explicitly clear in physician documentation practice.[49] The listed conditions that are identified as representing acute organ dysfunction is not exhaustive and if the documentation is unclear it warrants a query.[50] When sepsis is coded, it is most commonly (72 percent of the time) code A41.9, Unspecific Sepsis.[51]

Additional challenges can arise when coding viral sepsis as ICD-10-CM does not provide a specific viral sepsis code, but rather directs A41.89, Other specified sepsis, as the best option.[52] According to a random sample of 2021 fee-for-service claims through the Comprehensive Error Rate Testing (CERT) dataset, incorrect coding was indicated for 9.8 percent of MS-DRG 870 claims, 5.9 percent of MS-DRG 871 claims, and 8.5 percent of MS-DRG 872 claims.[53] Additional claim errors were noted for no documentation. This leads to an increased number of queries and possible underreporting. In a study done by Arberry et al., it was found that although 59 percent of the charts audited had evidence of sepsis at admission and 52 percent had sepsis documented somewhere in the notes, sepsis was much less likely to be documented on the discharge summaries (10 percent) or coded (17 percent).[54] Another study, by Wilhelms et al., concluded "that 55 percent of critically ill patients with severe sepsis were discharged from hospital without ICD codes that are widely used to identify sepsis."[55] Similar studies have shown how poorly sepsis is coded in administrative data.[56]

Sepsis raises challenges for CDI professionals as well. According to a 2019 survey by ACDIS, sepsis was the top queried diagnosis for clinical validation.[57] Clinical validation is a process by which documentation is evaluated to ensure that the medical record demonstrates enough clinical support for all documented diagnoses as mandated by the False Claims Act.[58] A clinical validation query request should be sent whenever there is a lack of clinical support for sepsis within the documentation. Options for specifying sepsis as "ruled in" or "ruled out" should be included in the query choices, in addition to the clinical indicators which support the diagnosis of sepsis during the current encounter.

Quality documentation ensures that anyone reading the medical record after discharge should come to the same conclusion as the providers in regards to the diagnosis of sepsis. Some speculate that the diagnosis of sepsis may be overused by the providers because the result of not treating a case of potential sepsis could be fatal for the patient. "Therefore, anyone who submits a clinical validation query for sepsis should consider the option of prophylactic or empiric treatment as a valid choice for those cases with little to no clinical support in the medical record."[59] A note from the ACDIS editor in 2019 also indicated that sepsis remained a top search term for the organization's website, highlighting the challenges and uncertainty that come with its documentation.[60]

Denials and Payment Reviews

Despite these findings of potential underreporting, MS-DRGs 871 and 872 remain increasingly frequently billed DRGs leading to enhanced scrutiny by payers and challenges in compliance and reimbursement.[61] These uncertainties make sepsis a regularly and controversially denied diagnosis.[62] In a September 2022 Q&A forum, ACDIS indicated that nearly 70 percent of respondents to interviews of CDI professionals reported that sepsis was one of their top denied diagnoses.[63] Most denials are due to a lack of documentation or clear clinical indicators; even when coded based on a definite physician diagnosis, missing clinical indicators can lead to a denial.[64,65] This may be due, in part, to payers capitalizing on the gaps between Sepsis-2 and Sepsis-3 clinical criteria.[66]

It is important that those involved in the revenue cycle check insurance contracts for clear definitions and requirements. The record may not show evidence of impaired homeostasis as evidenced by altered mental status from baseline, hyperglycemia, hypotension, oliguria, coagulopathy, thrombocytopenia, ileus, acute hepatic failure, elevated lactate and capillary mottling, or acute respiratory distress syndrome, among others.[67] The payer may indicate "there is no evidence that the patient's symptoms were due to any localized infection" or may acknowledge the condition as documented, but not "think this was a valid diagnosis."[68] The record may lack laboratory findings that support SOFA indicators or clinical evidence of SOFA criteria. Denials have included reasonings such as "no mention of toxic in appearance" or "no positive blood culture." The treatment plan is also considered and may result in a denial if it does not reflect the greater levels of monitoring and intervention required to treat sepsis.[69] Continued issues in the documentation and coding of sepsis will only lead to increased denials and audits.[70]

Recommendations

In order to accurately diagnosis and bill for sepsis, facilities must identify their sepsis issues and their impact on the facility. This includes identifying the prevalence of sepsis and sepsis-related issues (such as denials) in their patient population by considering community demographics, their payer mix, claims and quality reporting data, and benchmarks. Costs can be identified through various reports and payer contracts, and current medical definitions should be clarified. Once the problem has been clarified, there are strategies to improve sepsis diagnosis, documentation, coding, and billing. A consistent, system-wide approach should be used utilizing a sepsis team that may include medicine and nursing, laboratory and pharmacy, billing and admitting, coding, CDI, and quality assurance.[71]

Policies and Tools

Facilities need to clarify which sepsis definitions and criteria are being used to ensure consistency between providers.[72] Even if it is decided to use different criteria than the payer, having clear definitions and documentation guidelines can support an argument for denial by highlighting standardized internal criteria.[73,74] Institutional definitions provide consistency and clarity for providers, coders, and CDI staff in documentation, education, clinical validation, and the query process.[75] Including a works cited with facility definitions helps verify that the criteria is from the industry, not just an individual facility.[76]

A consensus statement should define sepsis and severe sepsis, and provide guidance regarding documentation of "early sepsis" or "meets sepsis criteria."[77] Facilities should review and update sepsis screening policies, intake forms, and treatment protocols utilizing a multidisciplinary group of medical professionals to ensure they meet the designated definitions.[78] Working together to clarify and update the definitions, policies, and tools encourages conversation across multiple departments and helps the facility establish common standards and consistency.[79]

Diagnostic criteria should be established for the organization and communicated to clinical staff for accurate recognition and reporting of sepsis based on infection and organ dysfunction.[80] Facility-defined clinical indicators including sepsis screening criteria, definitions, and SOFA criteria should be clearly communicated and readily available to clinical staff .[81] This could be incorporated into a template, such as a discharge summary template, to provide clinicians with an aide and encourage thorough documentation. This can then be used by the coders as a clear indication of sepsis.[82] Arberry et al. found that implementing such a template improved sepsis documentation by 28 percent.[83] Organizations such as ACDIS provide forms and tools such as query templates. Some electronic health record vendors, such as Epic, provide dropdown menus that guide more specific documentation and/or scoring tools such as a SOFA score calculator.[84] Facilities may also consider creating a care process model like the one created by a workgroup at Intermountain Healthcare that provides algorithms for diagnosing and treating sepsis and septic shocks, outlines important definitions and clinical characteristics, and includes an adult sepsis bundle worksheet and tidal volume conversion tables.[85] Such algorithms can clearly show the clinical indicators that led to the diagnosis of sepsis. Once facility-wide definitions and criteria are decided upon, a process should be put in place to regularly re-assess and update the criteria to ensure compliance with the latest clinical guidance and coding guidelines.[86]

Policies and procedures related to the coding and billing of sepsis should also be reviewed. It should be clear when coding and CDI queries are needed to establish sepsis. Coding and CDI staff should work together to ensure clinical indicators clearly support a diagnosis of sepsis, and query when the evidence is insufficient.[87] For example, the ICD-10-CM official guidelines recommend querying about a negative or inconclusive blood culture, documentation of "urosepsis," and any indication of acute organ dysfunction if it is not clear that it is related to sepsis. Competing etiologies can weaken the validity of sepsis and should be outlined in a query to ensure the provider has all key pieces of information.[88] Query templates may be helpful to ensure they include the relevant clinical indicators to support the diagnosis of sepsis.[89] Organizations may want to implement pre-bill reviews for sepsis stays.[90] The facility should establish clear escalation policies and the need for a second-level review for sepsis claims and denials. Rebutting a denial should be supported by a comprehensive appeal letter. A standard appeal template may be helpful, particularly for repeated denials related to a disagreement between sepsis definitions and clinical criteria.[91]

Payer contracts should specify which definition of sepsis and diagnostic criteria the payer is using. As changes are made to payment policies and contracts with payers, these changes need to be communicated to providers and revenue cycle staff. Such contracts should outline the desired clinical information, facts, and context needed to support a diagnosis of sepsis.[92] For example, if an organization decides to use the SIRS criteria, this should be reflected in the contract so if denials arise due to a conflict between the SIRS criteria and Sepsis-3 criteria, the facility to can refer back to the contract in their appeal letter.[93] Compare payer denial activity to contract terms and identify issues. If sepsis claims are continuing to be denied even when agreed upon criteria are being used, there could be an error occurring such as a disconnect with a third-party reviewer. Track contact requirements to ensure they are being met and follow up as needed.[94]

Education and Training

Clinical staff may need updated training on documentation requirements. They should be encouraged to document a clear clinical picture including signs and symptoms to indicate both the infection and organ dysfunction, tying together observations, indicators, and logic.[95,96] An infection without organ failure may sometimes be described as "septic", but does not actually meet the definition of "sepsis."[97] Documentation needs to identify "sepsis," "severe sepsis," or "septic shock," be clear and consistent, identify the source of infection, and clarify that the sepsis is related to the source infection. Clarifying the relationships can be evident with words like "causing" or "caused by," "associated with" or "related to," "from," "due to," or "with."[98]

The documentation must include a statement like "dysregulated host response to infection" and the association organ dysfunction, such as hypotension, renal failure, encephalopathy, etc.[99] General phrases such as "multiple system organ failure" should be avoided.[100] Clarifying a clear relationship is important. Rather than stating "elevated creatinine in the setting of sepsis, hypotension," a statement such as "acute kidney injury, likely due to sepsis with hypotension" shows a stronger link between the conditions. Documentation should also clarify if the infection was or may have been related to a recent surgery or device and if it was present on admission.[101]

Regardless if the sepsis resolves during an inpatient stay, discharge summary documentation should highlight that sepsis was a condition on admission through consistent documentation by all providers.[102,103] If using the Sepsis-3 definition, clinical staff should be encouraged to include the SOFA and/or qSOFA score on every chart where sepsis is a diagnostic consideration.

In addition to clarifying what providers need to include in sepsis documentation, training may also need to be provided on what to avoid or use caution with when documenting. Providers should avoid sepsis-adjacent phrases, such as "urosepsis," "sepsis-like," "meets sepsis criteria," or "sepsis syndrome."[104] The term "urosepsis" is vague and nonspecific; if the patient has sepsis due to a urinary tract infection, that must be clarified in the documentation.[105] Even terms such as "septicemia," "SIRS," and "septic, toxic" can be problematic because they may describe infection but do not definitively clarify sepsis with organ dysfunction. Documenting a "history of sepsis" does not indicate the condition on the current stay, even if it resolved following admission.[106] Although R78.81 Bacteremia will still group to MS-DRGS 870-872, documenting "bacteremia" alone can also be problematic. Providers may use these terms interchangeably, but by the coding definition bacteremia does not usually meet medical necessity for an inpatient admission as it implies the patient is asymptomatic.[107] If sepsis is present, documentation should indicate it with statements like "sepsis due to e-colic bacteremia" or "sepsis with positive blood cultures."[108,109]

In addition to education and training for clinical staff, a targeted effort should be made to ensure all coding and CDI staff are adequately trained on the new definitions and clinical criteria. Documentation of SIRS with an infection is no longer enough to code sepsis; coders needs to look for sepsis and organ dysfunction.[110] Arberry et al. found that additional training for coders improved their ability to capture a sepsis code by 21 percent.[111] CDI staff need to look for the progression of infectious symptoms throughout the patient stay and for contradictory notes between the emergency department and attending physician.[112] Does the treatment provided support the diagnosis of sepsis? According to DeFilippis, "the best practice for CDI is to know each of the 3 standards and try to ensure that *all* clinical indicators present under *each* definition are documented."[113] Using the facility-wide definitions and clinical criteria as decided on to frame queries shows cohesion across the organization and may help with future appeals.[114]

Examples of circumstances that may indicate a need for CDI assessment and a possible query include, but are not limited to:

- Less defined diagnostic language, such as "septicemia" or "urosepsis"
- Unspecified type of sepsis
- Conflicting diagnoses throughout the chart
- Lack of language clarifying the relationship between the source infection and sepsis

- Lack of language clarifying the relationship between organ damage and severe sepsis or septic shock
- Lack of identified source infection
- Lack of positive blood cultures
- Lack of SIRS/SOFA indicators
- Documentation of sepsis in only one chart document
- An indication that the sepsis protocol/bundle was provided without documented sepsis
- Lack of clinical indicators[115]

The CDI team can help to escalate documentation issues and engage the physician champion to work with physicians who struggle with providing the appropriate criteria.[116] It is important that providers know the CDI and coding staff are on their side and that accurate documentation and code assignment are vital to quality patient care.[117]

With so many involved in the revenue cycle, it is important to encourage and support collaboration between contract teams, physicians, coders, CDI professionals, and quality assurance professionals. When concerns are communicated to the contracting team, the payer representative can work to address them with the payer.[118] Training should then be provided to clarify any updated changes in the contract. CDI professionals should take time to review any potential sepsis records holistically to address any insufficiencies with the provider, using it as an opportunity to educate rather than simply query. Taking time to improve documentation at the source will create a sustainable change in capturing accurate sepsis diagnosis.[119] CDI should also work with quality assurance to ensure consistent and high-quality claims data that supports quality indicators.[120]

Denial Management

Despite best efforts, denials will still occur. The majority of denials come from multiple sets of criteria for the diagnosis of sepsis, physician documentation, and change in definition of sepsis. "The majority of sepsis denials are clinical denials. Clinical denial audits are where the payer is questioning whether or not the physician's diagnosis of sepsis is clinically supported."[121]

Facilities should address denials by reviewing the medical record to identify significant findings the auditor may have missed, being prepared to defend the claim. Those working on denials must rely on official coding guidelines and medical literature and should support physicians when fighting a challenging denial.[122] They should collaborate with coders, CDI staff, and physicians to ensure that the documentation clearly describes the condition of sepsis. In addition, denial management should never depend on the denial letters to list all the clinical indicators; rather, they should always review the record to be sure that there are no other clinical findings to help support the diagnosis that was reported. Appeal letters should acknowledge the differences of opinion and must include all supporting documentation and references that help support the diagnosis of sepsis.[123]

This literature review was predominantly limited to the primary publications from organizations that represent health information management and clinical documentation integrity. The study may not have captured all relevant articles based on search terms and databases used. Future studies should focus on empirical research methods to analyze sepsis-related documentation, coding practices, and claims data. Furthermore, the recommendations in this literature review are based on the practices of a variety of professionals. Facilities are encouraged to internally monitor improvements based on any changes made to continue to make modifications and verify which improvements are impacting sepsis-related patient outcomes and denial rates.

Conclusion

Sepsis will continue to be one of the most frequent and expensive conditions billed for making it ever more important to be diagnosed, billed and reimbursed accurately.

However, until there is a consensus on sepsis definitions, an adoption of new clinical criteria, or new set of sepsis codes, challenges and discrepancies will remain. Differing definitions and interpretations of clinical indicators leads to inconsistencies in documentation, impacting coding and ultimately the claim. The increasing number and steadily progressing costs of treating the condition have payers scrutinizing sepsis-related claims.

Facilities need to clarify institutional definitions to ensure consistency throughout the organization and alignment with what is outlined in payer contracts. Clinicians may need updated training and education on sepsis definitions and clinical indicators, and how to document them in a way that accurately reflects the patient condition. Facilities may also consider updating systems, templates, and algorithms to guide clinicians in quality documentation. Coding and CDI staff should also be involved in these training efforts to ensure alignment between documentation and coding.

Ultimately, having a clearly defined model within a facility can prevent denials and help support appeals. Most importantly, although much of the literature reviewed focused on accurate coding and billing of sepsis, the accurate diagnosis and treatment of sepsis is essential to improving the care and outcomes of patients (Remer, 2019).[124]

Tables and Figures

Table 1: 2020 Medicare Inpatient Hospitals – National Figures with Range by State[125]

MS-DRG	Discharges		Average Submitted Charge		Average Medicare Payment Amount	
MS-DRG 870[*]	National	42,625	National	$249,413.56	National	$49,689.83
	California	5,187	Nevada	$458,644.99	Alaska	$70,513.65
	Vermont	16	Maryland	$84,231.85	Arkansas	$35,897.21
MS-DRG 871[**]	National	587,611	National	$69,793.85	National	$13,357.43
	California	65,337	Nevada	$128,860.04	Maryland	$20,876.51
	Wyoming	612	Maryland	$24,468.77	Vermont	$10,077.82
MS-DRG 872[***]	National	128,651	National	$38,568.70	National	$6,931.09
	California	14,105	New Jersey	$64,627.85	Alaska	$10,585.30
	Wyoming	194	Maryland	$12,965.16	Vermont	$5,186.86

*MS-DRG 870 Septicemia or Severe Sepsis with MV >96 hours **MS-DRG 871 Septicemia or Severe Sepsis w/o MV >96 hours w/ MCC ***MS-DRG 872 Septicemia or Severe Sepsis w/o MV >96 hours w/o MCC

References

American Hospital Association (AHA). "Severe sepsis and acute organ dysfunction/failure." *Coding Clinic,* Fourth Quarter (2017).

AHA. "Sepsis coding issues." *Coding Clinic,* Third Quarter (2016).

Association of Clinical Documentation Integrity Specialists (ACDIS). "2022 CDI week bonus Q&A: Denial trends and CDI involvement." *CDI Strategies* 16, no. 40 (2022).

ACDIS. "Q&A: Clinical validation of sepsis." *CDI Blog* 11, no. 3 (2018).

ACDIS. "Q&A: Sepsis appeals." *CDI Strategies* 15, no. 18 (2021).

ACDIS. "Setting guideposts: Organizationwide clinical definitions." *CDI Journal* 13, no. 5 (2019).

ACDIS. "What criteria does your facility use for sepsis diagnoses?" (February 17, 2020). https://acdis.org/poll/what-criteria-does-your-facility-use-sepsis-diagnoses-0

Anand, Vijay, Zilu Zhang, Sameer S. Kadri, Michael Klompas, Chanu Rhee, and CDC Prevention Epicenters Program. "Epidemiology of quick sequential organ failure assessment criteria in undifferentiated patients and association with suspected infection and sepsis." *Chest* 156, no. 2 (2019): 289-297.

Arberry, Jamie, Zanya Henry, and Tumena Corrah. "A simple measure to improve sepsis documentation and coding." *Clinical Medicine* 21, no. 3 (2021): 222.

Archibald, Linnea. "Note from the ACDIS editor: Resources for everyone's favorite topic." *CDI Strategies* 13, no. 46 (2019).

Barrett, Marguerite L., Mark W. Smith, Anne Elixhauser, Leah S. Honigman, and Jesse M. Pines. "Utilization of intensive care services, 2011: Statistical Brief #185." *Agency for Healthcare Research and Quality* (2014).

Boy, Kim. "Reasons for denials and prevention: Sepsis series." *Health Information Associates* (November 22, 2019). https://hiacode.com/blog/education/reasons-for-denials-and-prevention-for-sepsis

Centers for Medicare & Medicaid Services (CMS). "Medicare fee-for-service comprehensive error rate testing." Data.CMS.gov (2021).

CMS. "Medicare inpatient hospitals – by geography and service." Data.CMS.gov (2020).

DeFilippis, Margaret. “Achieving and protecting sepsis reimbursement.” *Managed Resources* (May 30, 2019).

Duke, Graeme J., Maria Bishara, Steve Hirth, Lyn-Li Lim, and Leon J. Worth. "Performance of hospital administrative data for detection of sepsis in Australia: The sepsis coding and documentation (SECOND) study." *Health Information Management Journal* (2022): 18333583221107713.

Engoren, Milo, Troy Seelhammer, Robert E. Freundlich, Michael D. Maile, Matthew JG Sigakis, and Thomas A. Schwann. "A Comparison of Sepsis-2 (Systemic Inflammatory Response Syndrome Based) to Sepsis-3 (Sequential Organ Failure Assessment Based) Definitions–A Multicenter Retrospective Study." *Critical Care Medicine* 48, no. 9 (2020): 1258.

Evans, Laura, Andrew Rhodes, Waleed Alhazzani, Massimo Antonelli, Craig M. Coopersmith, Craig French, Flávia R. Machado et al. "Surviving sepsis campaign: international guidelines for management of sepsis and septic shock 2021." *Intensive Care Medicine* 47, no. 11 (2021): 1181-1247.

Fingar, Kathryn R., Marguerite L. Barrett, and H. Joanna Jiang. “A comparison of all-cause 7-day and 30-day readmissions, 2014: Statistical Brief #230.” *Agency for Healthcare Research and Quality* (2017).

Fleischmann-Struzek, Carolin, Daniel O. Thomas-Rüddel, Anna Schettler, Daniel Schwarzkopf, Angelika Stacke, Christopher W. Seymour, Christoph Haas, Ulf Dennler, and Konrad Reinhart. "Comparing the validity of different ICD coding abstraction strategies for sepsis case identification in German claims data." *PloS one* 13, no. 7 (2018): e0198847.

Frady, Allen. “Note from the instructor: Sepsis – stop looking at it as just one set of criteria.” *CDI Strategies* 12, no. 21 (2018).

Frady, Allen. “Q&A: Conflicting documentation of sepsis and bacteremia.” *CDI Blog* 11, no. 171 (2018).

Hasaballa, Hesham. “Avoiding sepsis denials.” *Sound Physicians* (November 29, 2017). https://soundphysicians.com/blog/avoiding-sepsis-denials/

Health Care Compliance Association (HCCA). “Payer denials hit sepsis amid conflicting clinical protocols; diagnosis is doubted.” *Report on Medicare Compliance* 26, no. 18 (2017).

Intermountain Healthcare. “Recognition and Management of severe sepsis and septic shock.” *Care Process Model* (August 2020).

Jiang, H. Joanna, Audrey J. Weiss, Marguerite L. Barrett, and Minya Sheng. “Characteristics of hospital stays for super-utilizers by payer, 2012: Statistical Brief #190.” *Agency for Healthcare Research and Quality* (2015).

Klompas, Michael, and Chanu Rhee. "Current sepsis mandates are overly prescriptive, and some aspects may be harmful." *Critical Care Medicine* 48, no. 6 (2020): 890-893.

Krauss, Glenn. “Tread lightly with sepsis MS-DRGs.” *ICD10monitor* (May 11, 2021). https://icd10monitor.medlearn.com/tread-lightly-with-sepsis-ms-drgs/

Kuqi, Alba. “Successfully appealing clinical validation and coding issues in sepsis.” *Journal of AHIMA* (October 26, 2021).

Liang, Lan, Brian Moore, and Anita Soni. “National inpatient hospital costs: The most expensive conditions by payer, 2017: Statistical Brief #261.” *Agency for Healthcare Research and Quality* (2020).

Maigur, Andrew. “Surviving the Sepsis-3 condundrum.” *Premier Pulse* (September 26, 2019). https://www.premierhealth.com/your-health/articles/premier-pulse/surviving-the-sepsis-3-conundrum

McBrayer, Shelly, and Cesar M. Limjoco. “Q&A: Facility-specific sepsis criteria.” *CDI Blog* 11, no. 200 (2018).

McDermott, Kimberly W., Anne Elixhauser, and Ruirui Sun. “Trends in hospital inpatient stays in the United States, 2005-2014: Statistical Brief #225.” *Agency for Healthcare Research and Quality* (2017).

McDermott, Kimberly W., and Marc Roemer. “Most frequent principal diagnoses for inpatient stays in U.S. hospitals, 2018: Statistical Brief #227.” *Agency for Healthcare Research and Quality* (2021).

National Association of Healthcare Revenue Integrity (NAHRI). “Refreshing denial management: Targeting trends with data and collaboration.” *NAHRI Journal* 6, no. 1 (2022).

Nehring, Sarah. “Coding corner: 10 things every coder wishes providers knew about sepsis documentation and coding.” *CDI Journal* 13, no. 3 (2019).

Parker, Shirlivia M. “How CDI professionals can lead the clinical validation denials process.” *Journal of AHIMA* (March 14, 2022).

Penn State Health Milton S. Hershey Medical Center. “Facility defined clinical indicators for adult sepsis.”

Remer, Erica E. “Payers and clinicians should use clinically accepted criteria when diagnosis sepsis.” *ICD10monitor* (January 28, 2019). https://icd10monitor.medlearn.com/payers-and-clinicians-should-use-clinically-accepted-criteria-when-diagnosing-sepsis/

Rhee, Chanu, Maximilian S. Jentzsch, Sameer S. Kadri, Christopher W. Seymour, Derek C. Angus, David J. Murphy, Greg S. Martin et al. "Variation in identifying sepsis and organ dysfunction using administrative versus electronic clinical data and impact on hospital outcome comparisons." *Critical Care Medicine* 47, no. 4 (2019): 493.

Riel, Carolyn. “Fight until the very end: Sepsis and malnutrition denials.” *CDI Journal* 14, no. 6 (2020).

Rodenberg, Howard, and the ACDIS Regulatory Committee. “Sepsis’ clinical evolution: Understand essential challenges to developing effective queries.” *Association of Clinical Documentation Improvement Specialists* (2019).

Salomão, R., B. L. Ferreira, M. C. Salomão, S. S. Santos, L. C. P. Azevedo, and M. K. C. Brunialti. "Sepsis: evolving concepts and challenges." *Brazilian Journal of Medical and Biological Research* 52 (2019).

Singer, Mervyn, Clifford S. Deutschman, Christopher Warren Seymour, Manu Shankar-Hari, Djillali Annane, Michael Bauer, Rinaldo Bellomo et al. "The third international consensus definitions for sepsis and septic shock (Sepsis-3)." *Jama* 315, no. 8 (2016): 801-810.

Tian, Wen. "An all-payer view of hospital discharge to postacute care, 2013: Statistical Brief #205." *Agency for Healthcare Research and Quality* (2016).

Torio, Celeste M., and Roxanne M. Andrews. "National inpatient hospital costs: The most expensive conditions by payer, 2011: Statistical Brief #160." *Agency for Healthcare Research and Quality* (2013).

Torio, Celeste M., and Brian J. Moore. "National inpatient hospital costs: The most expensive conditions by payer, 2013: Statistical Brief #204." *Agency for Healthcare Research and Quality* (2016).

Valdez, Dawn. "Note from the instructor: Sepsis clinical indicators, competing etiologies – a critical thinking exercise." *CDI Blog* 14, no. 29 (2021).

Valdez, Dawn. "Q&A: Clinical validation of sepsis and clinical criteria." *CDI Strategies* 16, no. 50 (2022).

Weiss, Audrey J., and H. Joanna Jiang. "Overview of clinical conditions with frequent and costly hospital readmissions by payer, 2018: Statistical Brief #278." *Agency for Healthcare Research and Quality* (2021).

Wilhelms, S. B., S. M. Walther, Fredrik Huss, and Folke Sjöberg. "Severe sepsis in the ICU is often missing in hospital discharge codes." *Acta Anaesthesiologica Scandinavica* 61, no. 2 (2017): 186-193.

1. Arberry, Jamie, et al. "A simple measure to improve sepsis documentation and coding." *Clinical Medicine* 21, no. 3 (2021): 222.
2. Duke, Graeme J., et al. "Performance of hospital administrative data for detection of sepsis in Australia: The sepsis coding and documentation (SECOND) study." *Health Information Management Journal* (2022).
3. Singer, Mervyn, et al. "The third international consensus definitions for sepsis and septic shock (Sepsis-3)." *Jama* 315, no. 8 (2016): 801-810.
4. Krauss, Glenn. "Tread lightly with sepsis MS-DRGs." *ICD10monitor* (May 11, 2021).
5. Arberry et al.
6. McDermott, Kimberly W., and Marc Roemer. "Most frequent principal diagnoses for inpatient stays in U.S. hospitals, 2018: Statistical Brief #227." *Agency for Healthcare Research and Quality* (2021).

7. Torio, Celeste M., and Roxanne M. Andrews. “National inpatient hospital costs: The most expensive conditions by payer, 2011: Statistical Brief #160.” *Agency for Healthcare Research and Quality* (2013).
8. McDermott et al. (2021).
9. Liang, Lan, et al. “National inpatient hospital costs: The most expensive conditions by payer, 2017: Statistical Brief #261.” *Agency for Healthcare Research and Quality* (2020).
10. Torio et al. (2013).
11. Torio, Celeste M., and Brian J. Moore. “National inpatient hospital costs: The most expensive conditions by payer, 2013: Statistical Brief #204.” *Agency for Healthcare Research and Quality* (2016).
12. McDermott et al. (2021).
13. Barrett, Marguerite L., et al. “Utilization of intensive care services, 2011: Statistical Brief #185.” *Agency for Healthcare Research and Quality* (2014).
14. Jiang, H. Joanna, et al. “Characteristics of hospital stays for super-utilizers by payer, 2012: Statistical Brief #190.” *Agency for Healthcare Research and Quality* (2015).
15. Tian, Wen. “An all-payer view of hospital discharge to postacute care, 2013: Statistical Brief #205.” *Agency for Healthcare Research and Quality* (2016).
16. Fingar, Kathryn R., et al. “A comparison of all-cause 7-day and 30-day readmissions, 2014: Statistical Brief #230.” *Agency for Healthcare Research and Quality* (2017).
17. Weiss, Audrey J., and H. Joanna Jiang. “Overview of clinical conditions with frequent and costly hospital readmissions by payer, 2018: Statistical Brief #278.” *Agency for Healthcare Research and Quality* (2021).
18. McDermott et al. (2021).
19. McDermott, Kimberly W., et al. “Trends in hospital inpatient stays in the United States, 2005-2014: Statistical Brief #225.” *Agency for Healthcare Research and Quality* (2017).
20. Fingar et al.
21. Ibid.
22. Weiss and Jiang.
23. Singer et al., 805.
24. Ibid.
25. Duke et al.
26. Singer et al., 805.
27. Rodenberg, Howard, and the ACDIS Regulatory Committee. “Sepsis’ clinical evolution: Understand essential challenges to developing effective queries.” *Association of Clinical Documentation Improvement Specialists* (2019): 2.
28. Engoren, Milo, et al. "A Comparison of Sepsis-2 (Systemic Inflammatory Response Syndrome Based) to Sepsis-3 (Sequential Organ Failure Assessment Based) Definitions–A Multicenter Retrospective Study." *Critical Care Medicine* 48, no. 9 (2020): 1258.
29. Singer et al.
30. Duke et al.
31. Ibid.

32. Rhee, Chanu, et al. "Variation in identifying sepsis and organ dysfunction using administrative versus electronic clinical data and impact on hospital outcome comparisons." *Critical Care Medicine* 47, no. 4 (2019): 497.
33. Frady, Allen. “Note from the instructor: Sepsis – stop looking at it as just one set of criteria.” *CDI Strategies* 12, no. 21 (2018).
34. Arberry et al.
35. Anand, Vijay, et al. "Epidemiology of quick sequential organ failure assessment criteria in undifferentiated patients and association with suspected infection and sepsis." *Chest* 156, no. 2 (2019): 289-297.
36. Salomão, R., et al. "Sepsis: evolving concepts and challenges." *Brazilian Journal of Medical and Biological Research* 52 (2019).
37. Evans, Laura, et al. "Surviving sepsis campaign: international guidelines for management of sepsis and septic shock 2021." *Intensive Care Medicine* 47, no. 11 (2021): 1064.
38. Singer et al., 807.
39. Frady.
40. McBrayer, Shelly, and Cesar M. Limjoco. “Q&A: Facility-specific sepsis criteria.” *CDI Blog* 11, no. 200 (2018).
41. Rodenberg and the ACDIS Regulatory Committee.
42. Riel, Carolyn. “Fight until the very end: Sepsis and malnutrition denials.” *CDI Journal* 14, no. 6 (2020).
43. Klompas, Michael, and Chanu Rhee. "Current sepsis mandates are overly prescriptive, and some aspects may be harmful." *Critical Care Medicine* 48, no. 6 (2020): 890-893.
44. Krauss.
45. Arberry et al.
46. Klompas and Rhee.
47. Kuqi, Alba. “Successfully appealing clinical validation and coding issues in sepsis.” *Journal of AHIMA* (October 26, 2021).
48. Hasaballa, Hesham. “Avoiding sepsis denials.” *Sound Physicians* (November 29, 2017).
49. American Hospital Association (AHA). “Severe sepsis and acute organ dysfunction/failure.” *Coding Clinic*, Fourth Quarter (2017).
50. Ibid.
51. DeFilippis, Margaret. “Achieving and protecting sepsis reimbursement.” *Managed Resources* (May 30, 2019).
52. AHA. “Sepsis coding issues.” *Coding Clinic*, Third Quarter (2016).
53. CMS. “Medicare fee-for-service comprehensive error rate testing.” Data.CMS.gov (2021).
54. Arberry et al.
55. Wilhelms, S. B. et al. "Severe sepsis in the ICU is often missing in hospital discharge codes." *Acta Anaesthesiologica Scandinavica* 61, no. 2 (2017): 189.
56. Arberry et al.
57. Archibald, Linnea. “Note from the ACDIS editor: Resources for everyone’s favorite topic.” *CDI Strategies* 13, no. 46 (2019).
58. Valdez, Dawn. “Q&A: Clinical validation of sepsis and clinical criteria.” *CDI Strategies* 16, no. 50 (2022).

59. Ibid.
60. Archibald.
61. Krauss.
62. Parker, Shirlivia M. “How CDI professionals can lead the clinical validation denials process.” *Journal of AHIMA* (March 14, 2022).
63. ACDIS. “2022 CDI week bonus Q&A: Denial trends and CDI involvement.” *CDI Strategies* 16, no. 40 (2022).
64. Boy, Kim. “Reasons for denials and prevention: Sepsis series.” *Health Information Associates* (November 22, 2019).
65. DeFilippis.
66. HCCA. “Payer denials hit sepsis amid conflicting clinical protocols; diagnosis is doubted.” *Report on Medicare Compliance* 26, no. 18 (2017).
67. Boy.
68. DeFilippis, 38.
69. Boy.
70. Krauss.
71. DeFilippis.
72. Riel, Carolyn. “Fight until the very end: Sepsis and malnutrition denials.” *CDI Journal* 14, no. 6 (2020).
73. Frady.
74. McBrayer and Limjoco.
75. Rodenberg and the ACDIS Regulatory Committee.
76. ACDIS. “Setting guideposts: Organizationwide clinical definitions.” *CDI Journal* 13, no. 5 (2019).
77. ACDIS. “Q&A: Clinical validation of sepsis.” *CDI Blog* 11, no. 3 (2018).
78. Riel.
79. ACDIS (2019).
80. Arberry et al.
81. Penn State Health Milton S. Hershey Medical Center. “Facility defined clinical indicators for adult sepsis.”
82. Arberry et al.
83. Ibid.
84. Maigur, Andrew. “Surviving the Sepsis-3 condundrum.” *Premier Pulse* (September 26, 2019).
85. Intermountain Healthcare. “Recognition and Management of severe sepsis and septic shock.” *Care Process Model* (August 2020).
86. ACDIS (2019).
87. HCCA.
88. Valdez, Dawn. “Note from the instructor: Sepsis clinical indicators, competing etiologies – a critical thinking exercise.” *CDI Blog* 14, no. 29 (2021).
89. Riel.
90. HCCA.
91. ACDIS. “Q&A: Sepsis appeals.” *CDI Strategies* 15, no. 18 (2021).

92. Krauss.
93. Riel.
94. National Association of Healthcare Revenue Integrity (NAHRI). “Refreshing denial management: Targeting trends with data and collaboration.” *NAHRI Journal* 6, no. 1 (2022).
95. HCCA.
96. Krauss.
97. Hasaballa.
98. DeFilippis.
99. Hasaballa.
100. Maigur.
101. Nehring, Sarah. “Coding corner: 10 things every coder wishes providers knew about sepsis documentation and coding.” *CDI Journal* 13, no. 3 (2019).
102. Maigur.
103. Nehring.
104. Maigur.
105. Nehring.
106. DeFilippis.
107. Frady.
108. Ibid.
109. Nehring.
110. Ibid.
111. Arberry et al.
112. Riel.
113. DeFilippis, 33.
114. ACDIS (2019).
115. DeFilippis.
116. Riel.
117. Nehring.
118. Parker, Shirlivia M. “How CDI professionals can lead the clinical validation denials process.” *Journal of AHIMA* (March 14, 2022).
119. Krauss.
120. DeFilippis.
121. Boy.
122. Riel.
123. Boy.
124. Remer, Erica E. “Payers and clinicians should use clinically accepted criteria when diagnosing sepsis.” *ICD10monitor* (January 28, 2019).
125. CMS. “Medicare inpatient hospitals – by geography and service.” Data.CMS.gov (2020).

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Evaluating Telemedicine Perception and Readiness among Healthcare Workers in Malaysia

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Evaluating Telemedicine Perception and Readiness among Healthcare Workers in Malaysia

Introduction:
Increased access to healthcare is a priority for public healthcare services. Our study investigated healthcare workers' (HCWs) perceptions and readiness to use telemedicine services.

Methodology: A self-administered online questionnaire was designed, validated, and disseminated among public HCWs in a single tertiary healthcare facility from a Malaysian northwestern state. Sections include sociodemographics, perception, and readiness domains. Descriptive and univariate statistics were used to determine correlation between selected parameters.

Results: A total of 288 HCWs participated: 66.3 percent agreed that new technology can be used alongside current practice. On core readiness, 29.1 percent would not consider telemedicine without prior physical interaction with patients. For clinical readiness, 56.6 percent would consider telemedicine services for clinical practice. All perception domains (except disadvantage) had significant positive correlations with readiness domains (r=0.12-0.57, p<0.05).

Conclusion: The perceptions and readiness of telemedicine among our public HCWs were suboptimal. Our findings denote potential limitation on cybersecurity and clinical practice gaps.

Keywords: telemedicine, health personnel, perception, technology, computer-assisted instruction

Introduction

Increased access to healthcare services to achieve the best health outcomes is essential for healthcare providers and patients. Apart from walk-in and appointment-based ambulatory care, the Ministry of Health Malaysia (MOHM) also provides alternatives to improve access to healthcare services, such as domiciliary care services and home medication review.[1]

According to the World Health Organisation (WHO), telemedicine is defined as a tool that can improve patient outcomes by improving access to care and medical information through information and communications technology (ICT).[2] Telemedicine is also a clinical service that leverages ICT, video imaging and telecommunication linkages to enable healthcare workers to provide healthcare services at a distance.[3] This enables patients from rural areas or with mobility problems to access clinicians virtually through telemedicine.

Background

Telemedicine can be conducted in several ways. For example, healthcare workers (HCWs) can perform the most basic service: a simple telephone or video call. Portable telemedicine kits such as electrocardiograms (ECGs) or vital signs monitors currently include a computer, laptop, or tablet. Detailed medical images captured by high-resolution digital cameras can be sent to specialists. Lastly, there is robust telemedicine software capable of storing clinical data and facilitating real-time video conferences. Based on a study conducted in the United States (US), telephone calls and electronic health records (EHR) can facilitate screening or treating a

patient without needing in-person visits and improve the decision-making process among healthcare teams in ambulatory and emergency care.[4]

Telemedicine has been applied to almost all countries around the world. Although New Mexico has the sixth lowest population density in the US, a large percentage of the population still could not effectively access healthcare services.[5] Even though telemedicine may be successfully implemented in certain regions of the world, unexpected barriers to adoption may still occur.[5] This is reflected by a telemedicine readiness study in Uganda's public health facilities that concluded 70 percent of healthcare professionals were aware of telemedicine, but only 41 percent had used telemedicine services due to a lack of facilities.[6]

In a more local setting, the determinants of telemedicine acceptance in public hospitals in Malaysia were said to be: having computer self-efficiency; perception of usefulness; top management support; and government policies.[7] A recent study among people in Sabah showed a high level of acceptance towards telemedicine.[8]

Through SWOT (strengths, weaknesses, opportunities, and threats) analysis[9], some healthcare professionals identified that the coronavirus disease 2019 (COVID-19) pandemic had greater strength and opened more opportunities for more innovative healthcare delivery, although the infection carried a heavy threat to the healthcare system. Based on a systematic review of the roles of telemedicine during the COVID-19 pandemic[10], most studies stated that telemedicine is most beneficial in risk reduction in the transmission of SARS-CoV-2 by preventing direct physical contact between clinicians and patients, in turn reducing the presence of public from high-risk areas such as hospitals. Limited mobility due to the initial lockdown enforced by the Movement Control Order (MCO) made access to healthcare services slightly inconvenient, and numerous outpatient appointments had to be deferred.[11] The MCO marked the nationwide movement restriction order imposed by the Malaysian government on March 18, 2020, as a means of breaking the chain of COVID-19 infection.[12] The Malaysian Medical Council (MMC) also recognized telemedicine by releasing an advisory notice on telemedicine practice during the COVID-19 pandemic.[13] Furthermore, since the pre-COVID-19 pandemic in May 2019, five public health clinics have pioneered virtual clinics in implementing telemedicine.

Clinicians' perceptions of telemedicine are primarily connected to their willingness to adopt the technology into clinical practice. Readiness on telemedicine conveys the organization's leadership in understanding and changing management plans to adapt. Furthermore, the equipment must be located where it is convenient to be used. In addition, clinical decision-making, functioning, and telemedicine processes require administrative policies and procedures. These include standardized, well-defined, easy-to-use mechanisms for the referral and transfer of patients, record keeping, and prerogative to use telemedicine at receiving and referring sites.[14]

In Malaysia, local studies on telemedicine among healthcare professionals are scarce, and earlier data showed that only a minority accepted the reduction in physical communication through telemedicine.[15] This lack of acceptance may be due to how vital direct interaction with patients is,[16] technological limitations, Internet challenges, lack of trust, feelings that the tools are impersonal or prone to error, and other reasons. There is, otherwise, no published study looking at both perception and readiness for telemedicine among clinicians and how far have they experienced and implemented telemedicine. Hence, this study aimed to investigate public HCWs' perceptions and readiness to use telemedicine services in a single tertiary healthcare facility in a northwestern state of Malaysia.

Methods

Design

This was a cross-sectional study involving the development, validation, and distribution of an English language self-administered online questionnaire conducted from August to September 2021.

Selection of sites and participants

Sites included three groups of government healthcare facilities located within the vicinity of the small state of Perlis. This included the state hospital, health clinics under the district health office, and the state health department. The questionnaire was distributed among "telemedicine aware" public healthcare workers in the state of Perlis, Malaysia. "Telemedicine aware" are those who are aware of telemedicine's existence but have not used it. "Telemedicine naïve" individuals were excluded to answer the objective of this study. Our study further included health professionals who had basic information technology (IT) usage and who were directly involved in patient care: medical doctors, nurses, pharmacists, therapists, psychologists, counselors, and dieticians. The stated inclusion criteria were included in the consent section, and only those fulfilling all criteria were allowed to answer the questionnaire.

Procedures

The questionnaire was content validated by a selected panel of experts consisting of IT savvy medical doctors, pharmacists, and ICT officers working in Perlis State Health Department, Kangar District Health Office, and Hospital Tuanku Fauziah, Perlis, to provide input on the content suitability with the Malaysian healthcare system. Sentences were reworded to make them more comprehensible. The questionnaire was then pilot tested among 10 public healthcare workers working in the neighbouring state of Kedah. It took 15–20 minutes to complete the questionnaire, which was distributed through instant messaging and official workplace email. An implied consent section was incorporated in the first section of the online form.

Measurement

Perception and readiness of telemedicine was measured using a self-administered, web-based questionnaire. The questionnaire consisted of three sections:

- Sociodemographics
- Perception domains: advantages (7 items), disadvantages (8 items), necessity (6 items), ease of use (6 items), security (6 items)
- Readiness domains: core (10 items), e-learning (3 items], clinical (3 items), overall (1-item)

Perception toward telemedicine was evaluated based on the advantages and disadvantages of telemedicine application, the necessity of using telemedicine, ease of use of the information and communication technologies in clinical practice, and telemedicine technology security. Core readiness refers to the extent of full readiness to switch to telemedicine as a solution to displeasing current healthcare service provision.[17] Core readiness consists of 10 questions: Q1-4 on the integration of telemedicine, Q5-7 on comfort with telemedicine, and Q8-10 on process workflow. Negative (reverse) items included core readiness items 8-10, in which ”Strongly Disagree” or ”Disagree” responses were taken as positive attitudes, and the corresponding data were transformed. Readiness for e-learning refers to an individual's readiness to adopt a digital mode of learning via electronic devices,[18] and clinical readiness is readiness to provide clinical services via telemedicine.[19]

The perception domains were adapted from Ayatollahi et al. (2015),[20] while readiness domains were adapted from Kiberu et al. (2019).[21] Perception and readiness remained on a five-point Likert scale. The total score was the mean sum of all the items in the domain. The cut-off point for positive perception and readiness was any score greater than the mean score.

Sample Size calculation
Sample size estimation was calculated using the population proportion formula.[22] Preliminary data indicate that the prevalence of the "telemedicine aware" group was 0.286.[21] Therefore, in a local population size of healthcare workers provided by the Human Resource Unit, Perlis State Health Department, of approximately 3,000 individuals, with a pre-set type I error probability and precision at 0.05, a minimum sample size of 285 was required.

Statistical Analysis
The data analysis was performed using IBM SPSS Statistics for Windows (Version 20.0). Descriptive statistics were employed for all variables. Domains of perception and readiness were analyzed by Spearman's correlation.

Ethical Consideration
This study was registered with the National Medical Research Register (NMRR-21-134-58360) and approved by the Medical Research and Ethics Committee (MREC), Ministry of Health Malaysia.

Results
A total of 288 healthcare workers in the state of Perlis, Malaysia completed the survey (Table 1) who were "telemedicine aware". The respondents had a mean age of 36 and work experience of 11 years. Most respondents were female (78.1 percent), Bumiputera, i.e., Malaysian of indigenous Malay origin (87.5 percent), diploma holders (50.3 percent), allied health professionals and nurses (50 percent) working in the district health office or health clinics (55.6 percent).

Across the domains of perception toward telemedicine (Table 2), "disadvantages" subdomain scored the lowest (Mean score: 25±6.1 out of 40 points). Only a small number of HCWs agreed that telemedicine technology causes psychological harm to the patients (Mean score: 3±1.0), reduces the efficiency of patient care (Mean score: 3±1.0), and breaches patient privacy (Mean score: 3±1.0). Respondents had the most positive perception on the security aspect of telemedicine (Total score percentage: 80 percent). Most respondents agreed that telemedicine technology requires a secured network for access to medical information (Mean score: 4±0.9) and to avoid data breaches (Mean score: 4±0.9). In addition, a majority agreed (Mean score: 4±0.9) that telemedicine technology needs legal clarity such as patient consent. A sizable number of respondents agreed (31.6 percent) and strongly agreed (4.5 percent) that telemedicine technology reduces the efficiency of patient care. Similarly, 36.4 percent perceived telemedicine could lead to greater malpractice among clinicians as a certain degree of professional skills or learning could not be achieved thoroughly. On the perception of the necessity of telemedicine technology, 55.2 percent perceived telemedicine technology as a requirement for patient care. Most respondents agreed (66.3 percent) that new telemedicine technology can be used alongside current clinical practice. This result also aligned with the perception that telemedicine can provide doctors instant access to patient information (62.9 percent). The majority believed that software's user-friendliness (55.2 percent) matters more than the system's quality (50.7 percent) in encouraging usage. Some 64.9 percent of our respondents acknowledged that telemedicine would change the referral process. Similarly, most agreed that telemedicine improves productivity (54.8 percent), but less than half agreed it reduced clinicians' errors (43.4 percent).

The mean score of core readiness was the lowest at 64 percent compared to other readiness domains (Table 3). On integrating telemedicine, 29.1 percent would not consider using telemedicine without prior physical interaction with the patient. However, most respondents were still comfortable with telemedicine, with 62.1 percent agreeing it is worth investing.

The overall readiness to use telemedicine was moderately correlated (Table 4) with the advantages that telemedicine has to offer (r=0.523, p<0.01) but correlated with telemedicine security at a low level (r=0.225, p<0.01).

Discussion

This was a cross-sectional study to determine the perception and readiness toward telemedicine among HCWs in a single tertiary healthcare facility in a suburban state of northwestern Malaysia. The domains of perception illustrating the highest and lowest total mean scores meant that these were the main issues of focus as they may either facilitate or hinder the implementation of telemedicine in this population. Our study determined that our HCWs were generally ambivalent on the concept of telemedicine as part of clinical patient care, partly due to security concerns. Though overall readiness was high, the core readiness domain scored the lowest, indicating insufficient quantitative evidence that the population was fully ready for telemedicine use in the clinical setting.

A sizable number of respondents (31.6 percent agreed and 4.5 percent strongly agreed) that telemedicine technology reduces the efficiency of patient care. Indeed, certain diseases and disorders do require a face-to-face physical examination and cannot be diagnosed virtually via telemedicine. In the worst-case scenario, improper medical consultation may even result in injury, damage, or even loss of life, according to a study by Kiberu et al. (2019) that affirmed telemedicine was associated with technological flaws.[21] A doctor may potentially deliver wrong referrals of specific medical services to patients as telemedicine might limit the primary medical examination, resulting in improper diagnosis. According to an investigation lead by the Consolidated Risk Insurance Company (CRICO), a leading medical professional liability insurance provider in the United States, 66 percent of telemedicine-related claims received between 2014 and 2018 were diagnosis-related.[23]

Generally, human-related factors such as users' perception and readiness toward telemedicine technology greatly influence the use of information technology in healthcare organizations. Therefore, many strategies must be considered to implement this technology substantially including human-related factors, infrastructures, accessibility, and security. A similar study by Judi et al. (2009) inveterate that a secure telemedicine network in keeping patient information and documentation confidential is crucial to public and providers' acceptance of the technology.[24] A recent systematic analysis suggested that certain security techniques, such as watermarking, cryptography, and steganography, are important methods of medical image security.[25] The findings of studies looking into the security aspects of telemedicine is therefore important to specifically address the issue of cybersecurity in the local setting. Regions of the same country may have technological advancement of varied levels, and this will further determine the type of security needed in their local clinical setting. For the population that were assessed in this study, there is no available centralized EHR system.

On the benefits of telemedicine technology, 70.8 percent of respondents perceived that telemedicine minimizes needless travel expenditures for patients. In this sense, the impression of utility has a favourable influence on telemedicine adoption. A study by Bagayoko et al. (2013) showed that telemedicine technology could improve healthcare professionals' recruitment, satisfaction, and retention of patients in rural areas.[26] However, infrastructure development should be seriously considered to allow limitless accessibility to technology, particularly in geographically deprived regions.

For clinical readiness, 56.6 percent of our respondents would consider using telemedicine services for clinical practice. Numerous studies have shown how system attributes determine the system usage. For instance, Saig-Rubió et al. (2014) discovered that the factor influencing telemedicine usage was ICT's perceived ease of usability.[27] According to Chang et al. (2009), telemedicine can increase its effectiveness if it is simple to use.[28] Overall readiness domain in our study scored a mean of 4 out of 5, with more than half (51.4 percent) of respondents agreeing that HCWs are ready to integrate telemedicine into routine clinical practice. Furthermore, 53.1 percent of our respondents agreed that telemedicine could bridge the clinical skills gap as telemedicine helps provide better long-term care to patients. Hence, one conclusion is that telemedicine is necessary for healthcare providers.

Regarding e-learning readiness, 73.6 percent agreed telemedicine enhances e-learning. A study has further demonstrated that people generally acknowledged the benefits of telemedicine in e-learning and were prepared to use it.[21] These findings are also in line with the literature, which supports that e-learning is crucial in training and maintaining the skills of the HCWs.[29]

When evaluating the core readiness toward telemedicine, the results showed that HCWs were mostly concerned about how telemedicine would affect workflow, work practice, and referral processes. In terms of workflow and work practice, adjustments must be made to incorporate new technology in the work process. Before this may happen, a lot of user training must be done. With reference to the result of this study, the HCWs did not optimally perceive telemedicine as easy to use (Percentage score: 70 percent). Another concern was that telemedicine would change the referral process. Some changes in law would be required for referrals to private health care facilities.

With regards to correlation between perception and readiness toward telemedicine usage among HCWs, all perception domain except "disadvantage" subdomain had significant positive correlations with readiness domain. Positive perceptions (except on disadvantage elements) increased readiness among healthcare workers. However, despite the perceived disadvantages of telemedicine, they do not significantly affect the readiness of HCWs toward telemedicine. The overall readiness to use telemedicine had significant positive correlation with telemedicine security, but at a low level (r=0.225, p<0.01). This result may indicate that security is a concern among the HCWs we surveyed. The security of medical information handling should be inspected prior to implementation of telemedicine in this population.

Limitation

Our study was limited in its methodological approach. The questionnaire was distributed via email and text messaging. Despite its easy accessibility and ease of use, it may also limit participation as workplace emails were typically accessed during working hours, which may not be convenient. A concern that was discussed was the possibility of incorrect diagnosis. However, this study did not examine different classes of treatment, which makes it a study limitation. Future studies should be conducted to bridge this knowledge gap.

Conclusion

The perceptions and readiness among our HCWs in Perlis toward telemedicine were suboptimal. Despite the potential of telemedicine as a beneficial tool for many medical and surgical consultations, psychological counselling, medical reports generation and storage, laboratory updates, medication refills and communication with other facilities, it does not replace HCWs' hands-on expertise. The limitation in cybersecurity and clinical practice gaps requires further improvement and modification to sustain its use.

Resources

1. MOHM, "Annex 30 Otorhinolaryngology (ORL) Service Guidelines During COVID-19 Pandemic," 2021.

2. World Health Organization, "Telemedicine: Opportunities and Developments in Member States - Report on the Second Global Survey on eHealth," 2010.

3. Ronald S Weinstein et al., "Telemedicine, Telehealth, and Mobile Health Applications That Work: Opportunities and Barriers," American Journal of Medicine, 2014, https://doi.org/10.1016/j.amjmed.2013.09.032.

4. Elham Monaghesh and Alireza Hajizadeh, "The Role of Telehealth during COVID-19 Outbreak: A Systematic Review Based on Current Evidence," BMC Public Health (BioMed Central, August 2020), https://doi.org/10.1186/s12889-020-09301-4.

5. Deborah Helitzer et al., "Assessing or Predicting Adoption of Telehealth Using the Diffusion of Innovations Theory: A Practical Example from a Rural Program in New Mexico," Telemedicine Journal and E-Health 9, no. 2 (July 2003): 179–87, https://liebertpub.com/doi/10.1089/153056203766437516.

6. Vincent Micheal Kiberu, Richard E. Scott, and Maurice Mars, "Assessing Core, e-Learning, Clinical and Technology Readiness to Integrate Telemedicine at Public Health Facilities in Uganda: A Health Facility - Based Survey," BMC Health Services Research (BioMed Central Ltd., April 2019), https://doi.org/10.1186/s12913-019-4057-6.

7. Suhaiza Zailani et al., "Determinants of Telemedicine Acceptance in Selected Public Hospitals in Malaysia: Clinical Perspective," Journal of Medical Systems 38, no. 9 (2014), https://doi.org/10.1007/s10916-014-0111-4.

8. Maneesha Manzoor et al., "Attitudes towards and the Confidence in Acceptance of Telemedicine among the People in Sabah, Malaysia," International Journal of Health Sciences, no. April (2022): 2376–86, https://doi.org/10.53730/ijhs.v6ns3.6040.

9. Mohammad Mamunur Rashid, "Strength, Weakness, Opportunity, and Threats (SWOT) Analysis of Telemedicine in Healthcare: Bangladesh Perspective," Journal of Scientific and Technological Research 3, no. 1 (2020): 63–69.

10. Monaghesh and Hajizadeh, "The Role of Telehealth during COVID-19 Outbreak: A Systematic Review Based on Current Evidence."

11. Vincent Khor et al., "Experience from Malaysia During the COVID-19 Movement Control Order," Urology 141, no. January (2020): 179–80, https://doi.org/10.1016/j.urology.2020.04.070.

12. Kuok Ho Daniel Tang, "Movement Control as an Effective Measure against COVID-19 Spread in Malaysia: An Overview," Journal of Public Health (Germany), 2020, https://doi.org/10.1007/s10389-020-01316-w.

13. Malaysian Medical Council Advisory et al., "Malaysian Medical Council Advisory on Virtual Consultation (during the COVID-19 Pandemic)" 1971, no. Amended (2020).

14. Penny Jennett et al., "Organizational Readiness for Telemedicine: Implications for Success and Failure.," Journal of Telemedicine and Telecare 9 Suppl 2 (2003), https://doi.org/10.1258/135763303322596183.

15. Mohamed Izham Mohamed Ibrahim, C. W. Phing, and S. Palaian, "Evaluation of Knowledge and Perception of Malaysian Health Professionals about Telemedicine," Journal of Clinical and Diagnostic Research 4, no. 1 (2010): 2052–56.

16. Ibrahim, Mohamed Izham Mohamed, C. W. Phing, and S. Palaian. "Evaluation of Knowledge and Perception of Malaysian Health Professionals about Telemedicine." Journal of Clinical and Diagnostic Research 4, no. 1 (2010): 2052-56.

17. Kabelo Leonard Mauco, Richard E. Scott, and Maurice Mars, "Critical Analysis of E-Health Readiness Assessment Frameworks: Suitability for Application in Developing Countries," Journal of Telemedicine and Telecare 24, no. 2 (2018): 110–17, https://doi.org/10.1177/1357633X16686548.

18. A. H.Hetty Rohayani, Kurniabudi, and Sharipuddin, "A Literature Review: Readiness Factors to Measuring e-Learning Readiness in Higher Education," Procedia Computer Science 59, no. Iccsci (2015): 230–34, https://doi.org/10.1016/j.procs.2015.07.564.

19. Ontario Telemedicine Network, "Clinical Site Readiness Assessment Tool," Online source (2011), https://telemedecine-360.com/wp-content/uploads/2019/03/2011-OTN-clinical_site_readiness_assessment_tool.pdf.

20. Haleh Ayatollahi, Fatemeh Zahra Pourfard Sarabi, and Mostafa Langarizadeh, "Clinicians' Knowledge and Perception of Telemedicine Technology," Perspectives in Health Information Management 12, no. Fall (2015).

21. Kiberu, Scott, and Mars, "Assessing Core, e-Learning, Clinical and Technology Readiness to Integrate Telemedicine at Public Health Facilities in Uganda: A Health Facility - Based Survey." *BMC Health Services Research*19 (2019): 1-11.

22. Stanley Lemeshow et al., “Lemeshow Adequacy of Sample Size in Health Studies,” 1990, 13.

23. David E. Newman-Toker et al., “Serious Misdiagnosis-Related Harms in Malpractice Claims: The ‘Big Three’-Vascular Events, Infections, and Cancers,” Diagnosis 6, no. 3 (August 2019): 227–40, https://doi.org/10.1515/dx-2019-0019.

24. H. M. Judi et al., “Feasibility and Critical Success Factors in Implementing Telemedicine,” Information Technology Journal 8, no. 3 (2009): 326–32, https://doi.org/10.3923/itj.2009.326.332.

25. Mahmoud Magdy et al., Security of Medical Images for Telemedicine: A Systematic Review, Multimedia Tools and Applications, vol. 81 (Multimedia Tools and Applications, 2022), https://doi.org/10.1007/s11042-022-11956-7.

26. Cheikh Oumar Bagayoko et al., “Continuing Distance Education: A Capacity-Building Tool for the de-Isolation of Care Professionals and Researchers,” Journal of General Internal Medicine 28, no. SUPPL.3 (September 2013): 666–70, https://doi.org/10.1007/s11606-013-2522-1.

27. Francesc Saigí-Rubió, Joan Torrent-Sellens, and Ana Jiménez-Zarco, “Drivers of Telemedicine Use: Comparative Evidence from Samples of Spanish, Colombian and Bolivian Physicians,” Implementation Science 9, no. 1 (October 2014), https://doi.org/10.1186/s13012-014-0128-6.

28. Jun Yih Chang, Liang Kung Chen, and Chia Ching Chang, “Perspectives and Expectations for Telemedicine Opportunities from Families of Nursing Home Residents and Caregivers in Nursing Homes,” International Journal of Medical Informatics 78, no. 7 (July 2009): 494–502, https://doi.org/10.1016/j.ijmedinf.2009.02.009.

29. Jennifer Chipps, Petra Brysiewicz, and Maurice Mars, “A Systematic Review of the Effectiveness of Videoconference-Based Tele-Education for Medical and Nursing Education,” Worldviews on Evidence-Based Nursing (John Wiley & Sons, Ltd, April 2012), https://sigmapubs.onlinelibrary.wiley.com/doi/10.1111/j.1741-6787.2012.00241.x.

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Tables

Table 1. Sociodemographic characteristics of respondents (*n*=288)

Characteristics	***n***	**%**
Age (years old)	36±8.1[a]	
Gender		
Male	63	21.9
Female	225	78.1
Ethnicity		
Bumiputera	252	87.5
Non-Bumiputera	36	12.5
Highest education level		
Diploma	145	50.3
Degree	121	42.0
Master	20	6.9
PhD	2	0.7
Occupation		
Specialist/Consultant	10	3.5
Medical officer	35	12.2
Houseman officer	9	3.1
Dental officer	44	15.3
Pharmacist	36	12.5
Nurse	71	24.7
Medical assistant	10	3.5
Allied health professionals	73	25.3
Working place		
District health office/health clinics	160	55.6
Hospital	112	38.9
State health department	16	5.6
Working area		
Clinical	253	87.8
Non-clinical	35	12.2
Working Experience (in years)	11±8.2[a]	

Note: [a] Presented as mean±standard deviation.

Table 2. Perception of telemedicine technology among respondents (*n*=288)

No.	Items	*n* (%)					Score	
		Very Little	Little	No effect	Large	Very Large	Mean ±SD	%
Advantages (Maximum score: 35)							26±4.8	74.3
1.	To what extent are you familiar with the benefits of telemedicine?	18 (6.3)	27 (9.4)	121 (42.0)	94 (32.6)	28 (9.7)		
2.	To what extent is telemedicine effective in reducing unnecessary patients' transportation costs?	5 (1.7)	1 (0.3)	78 (27.1)	134 (46.5)	70 (24.3)		
3.	To what extent is telemedicine effective in reducing the costs of patient care in hospitals?	5 (1.7)	4 (1.4)	100 (34.7)	124 (43.1)	55 (19.1)		
4.	To what extent will telemedicine influence users' satisfaction?	7 (2.4)	13 (4.5)	132 (45.8)	101 (35.1)	35 (12.2)		
5.	To what extent will telemedicine technology save clinicians' time?	6 (2.1)	12 (4.2)	83 (28.8)	129 (44.8)	58 (20.1)		
6.	To what extent will telemedicine technology provide faster and better medical care?	6 (2.1)	15 (5.2)	99 (34.4)	110 (38.2)	58 (20.1)		
7.	In your opinion, how effective will telemedicine technology improve patient care?	7 (2.4)	15 (5.2)	96 (33.3)	125 (43.4)	45 (15.6)		
Disadvantages (Maximum score: 40)							25±6.1	62.5
1.	To what extent may telemedicine technology disrupt a doctor-patient relationship?	18 (6.3)	35 (12.2)	122 (42.4)	93 (32.3)	20 (6.9)	3±0.9	
2.	To what extent will telemedicine reduce the effectiveness of patient care?	20 (6.9)	40 (13.9)	124 (43.1)	91 (31.6)	13 (4.5)	3±0.9	
3.	In your opinion, could telemedicine technology cause	34 (11.8)	56 (19.4)	126 (43.8)	62 (21.5)	10 (3.5)	3±1.0	

	psychological harm to the patient?							
4.	To what extent will telemedicine technology breach patient privacy?	25 (8.7)	51 (17.7)	116 (40.3)	85 (29.5)	11 (3.8)	3±1.0	
5.	To what extent will telemedicine technology reduce the efficiency of patient care?	25 (8.7)	47 (16.3)	128 (44.4)	76 (26.4)	12 (4.2)	3±1.0	
6.	To what extent may telemedicine technology result in unauthorized access to patient medical information?	17 (5.9)	43 (14.9)	113 (39.2)	93 (32.3)	22 (7.6)	3±1.0	
7.	To what extent may telemedicine technology increase the expenses of a hospital?	26 (9.0)	48 (16.7)	120 (41.7)	80 (27.8)	14 (4.9)	3±1.0	
8.	To what extent may telemedicine technology increase malpractice in healthcare?	20 (6.9)	36 (12.5)	127 (44.1)	85 (29.5)	20 (6.9)	3±1.0	
Necessity (Maximum score: 30)							22±4.1	73.3
1.	To what extent is telemedicine technology necessary for patient care?	3 (1.0)	15 (5.2)	111 (38.5)	121 (42.0)	38 (13.2)		
2.	To what extent can telemedicine provide timely healthcare service to patients?	3 (1.0)	17 (5.9)	104 (36.1)	122 (42.4)	42 (14.6)		
3.	To what extent should new technology be used along with the current practice?	3 (1.0)	9 (3.1)	85 (29.5)	127 (44.1)	64 (22.2)		
4.	To what extent will telemedicine be able to provide services to the underprivileged and those in remote areas?	12 (4.2)	24 (8.3)	113 (39.2)	87 (30.2)	52 (18.1)		
5.	To what extent can telemedicine technology provide doctors with instant	3 (1.0)	9 (3.1)	95 (33.0)	127 (44.1)	54 (18.8)		

	access to patient information?							
6.	To what extent are national standards essential for telemedicine technology implementation?	7 (2.4)	21 (7.3)	115 (39.9)	105 (36.5)	40 (13.9)		
Ease of use (Maximum score: 30)							21±4.2	70.0
1.	To what extent does the ease of use of telemedicine technology make it practical for the clinical staff?	5 (1.7)	21 (7.3)	116 (40.3)	113 (39.2)	33 (11.5)		
2.	To what extent does user friendly software ease the clinicians to apply telemedicine technology?	5 (1.7)	18 (6.3)	106 (36.8)	118 (41.0)	41 (14.2)		
3.	To what extent does easy-to-use telemedicine technology increase the efficiency of clinical users?	4 (1.4)	15 (5.2)	111 (38.5)	115 (39.9)	43 (14.9)		
4.	To what extent does ease of use of telemedicine technology reduce clinicians' errors?	9 (3.1)	24 (8.3)	130 (45.1)	99 (34.4)	26 (9.0)		
5.	To what extent does ease of use of telemedicine technology facilitate its learning?	3 (1.0)	10 (3.5)	128 (44.4)	110 (38.2)	37 (12.8)		
6.	To what extent does ease of use of telemedicine increase clinicians' skills?	7 (2.4)	36 (12.5)	148 (51.4)	77 (26.7)	20 (6.9)		
Security (Total score: 30)							24±4.7	80.0
1.	To what extent is authorised access necessary for the use of telemedicine?	3 (1.0)	8 (2.8)	105 (36.5)	100 (34.7)	72 (25.0)	4±0.9	
2.	To what extent are security policies and guidelines necessary for the use of	5 (1.7)	8 (2.8)	88 (30.6)	105 (36.5)	82 (28.5)	4±0.9	

	telemedicine technology?						
3.	To what extent does telemedicine need to be supported by all healthcare community?	3 (1.0)	5 (1.7)	92 (31.9)	110 (38.2)	78 (27.1)	4±0.9
4	To what extent does telemedicine technology require a secured network for access to medical information?	3 (1.0)	2 (0.7)	85 (29.5)	83 (28.8)	115 (39.9)	4±0.9
5.	To what extent does telemedicine technology require legal clarification (e.g., consent) for patients?	4 (1.4)	3 (1.0)	87 (30.2)	92 (31.9)	102 (35.4)	4±0.9
6.	To what extent should a secured network be created to prevent breaching of data confidentiality when using telemedicine?	3 (1.0)	6 (2.1)	90 (31.3)	84 (29.2)	105 (36.5)	4±0.9

Table 3. Readiness to adapt telemedicine among respondents (*n*=288)

No.	Items	*n* (%)					Score	
		Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean ±SD	%
Core (Maximum score: 50)							32±4.7	64.0
1.	In your opinion, telemedicine will help reduce patients' hospital/clinic visits	2 (0.7)	6 (2.1)	57 (19.8)	119 (41.3)	104 (36.1)	4±0.8	
2.	Would you prefer to use telemedicine over traditional mode of care?	4 (1.4)	23 (8.0)	107 (37.2)	101 (35.1)	53 (18.4)	4±0.9	
3.	Would you consider using telemedicine even without prior physical interaction with the patient?	26 (9.0)	58 (20.1)	93 (32.3)	75 (26.0)	36 (12.5)	3±1.1	
4.	In your opinion, telemedicine would solve healthcare workers' shortage	23 (8.0)	24 (8.3)	104 (36.1)	90 (31.3)	47 (16.3)	3±1.1	
5.	In your opinion, telemedicine is more cost-effective as compared to traditional mode of care	4 (1.4)	25 (8.7)	115 (39.9)	98 (34.0)	46 (16.0)	4±0.9	
6.	In your opinion, it is worth investing in telemedicine infrastructure	2 (0.7)	6 (2.1)	101 (35.1)	115 (39.9)	64 (22.2)	4±0.8	
7.	In your opinion, telemedicine is an effective service for emergency cases	20 (6.9)	35 (12.2)	99 (34.4)	78 (27.1)	56 (19.4)	3±1.1	
8.	In your opinion, telemedicine affects normal process workflow*	8 (2.8)	21 (7.3)	126 (43.8)	97 (33.7)	36 (12.5)	3±0.9	

9.	In your opinion, telemedicine will change work practices*	7 (2.4)	9 (3.1)	88 (30.6)	123 (42.7)	61 (21.2)	2±0.9	
10.	In your opinion, telemedicine will change referral process*	4 (1.4)	9 (3.1)	88 (30.6)	125 (43.4)	62 (21.5)	2±0.9	
e-Learning (Maximum score: 15)							11±2.2	73.3
1.	In your opinion, telemedicine enhances e-learning (e.g., CME)	2 (0.7)	4 (1.4)	70 (24.3)	114 (39.6)	98 (34.0)		
2.	In your opinion, healthcare workers are ready to adopt e-learning	2 (0.7)	15 (5.2)	94 (32.6)	102 (35.4)	75 (26.0)		
3.	In your opinion, telemedicine can bridge clinical skills gap	4 (1.4)	19 (6.6)	112 (38.9)	100 (34.7)	53 (18.4)		
Clinical (Maximum score: 15)							11±2.4	73.3
1.	Would you consider the use of telemedicine service for clinical practice?	6 (2.1)	20 (6.9)	99 (34.4)	110 (38.2)	53 (18.4)		
2.	Are you confident on patients' outcomes as a result of e-prescription or e-consultation?	7 (2.4)	24 (8.3)	118 (41.0)	103 (35.8)	36 (12.5)		
3.	In your opinion, telemedicine will improve patients' clinical outcome	6 (2.1)	12 (4.2)	142 (49.3)	93 (32.3)	35 (12.2)		
Overall (Maximum score: 5)							4±0.9	80.0
1.	In your opinion, healthcare workers are ready to integrate telemedicine in routine clinical practice	6 (2.1)	22 (7.6)	112 (38.9)	104 (36.1)	44 (15.3)	4±0.9	

Note: *”Strongly Disagree” or ”Disagree” responses were taken as positive attitude toward item.

Table 4. Correlation coefficients (*r*) of perception and readiness domains

Readiness / Perception	*r*			
	Core	e-Learning	Clinical	Overall
Advantages	0.546**	0.564**	0.570**	0.523**
Disadvantages	-0.090	-0.063	-0.072	-0.096
Necessity	0.397**	0.464**	0.479**	0.435**
Ease of use	0.407**	0.514**	0.488**	0.479**
Security	0.124*	0.445**	0.255**	0.225**

Note: **,* Correlation is significant at $p<0.01$ and $p<0.05$, respectively.

Incorporating Digital Health Competencies into The Health Information Curriculum: A Case Study

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Abstract

This case study aims to provide insight into establishing a health information curriculum that includes knowledge, skills, and abilities on digital competencies (DigCom) and provides instructional suggestions for developing a digital health pedagogy for instructors of the health information discipline. The context for incorporating digital health competencies into the health information curriculum recognizes the underlying challenges of health inequity, health literacy, and digital health literacy, along with the social determinants of health.

Keywords: digital health, health equity, digital literacy, social determinants of health, technology

Introduction

The scope of digital health in the United States and globally has grown exponentially, from computing platforms and software to mobile devices and mobile medical applications, digital therapeutics, telehealth, and other digital tools such as smartphones and wearable devices and sensors.[1] Grand View Research, Inc., predicts the digital health market is expected to reach 1.5 trillion dollars by 2030.[2] Digital health provides enormous opportunities in healthcare for both the provider and consumer of care. The adoption of digital health offers increased access to care, cost reduction, efficiencies, patient satisfaction, and quality care.[3] Although it has been referred to as the digital transformation of healthcare, mHealth (mobile health) has been around for over 20 years and during the past decade, digital health has become the main topic of this transformation.[4,5] However, the recent pandemic has rapidly advanced the use of digital tools, devices, and health technology in today's mainstream healthcare. With digital tools and advanced health technology, digital health has been shown to improve patient outcomes for many, yet still there remain challenges. The demand for the use of digital health technology adds pressure on an already burdened healthcare workforce to increase its technical skills and capabilities.

In addition to the advancements in healthcare technology, educators are facing a generation of students who are digital natives, and who may find their expectations for the use of technology beyond what professors can provide.[5] The need to include digital health competencies in health information (HI) profession educational programs lacks exploration. The program curriculum is a blueprint for student learning and experiences in the classroom. Currently, there is an absence of digital health competencies included as an intentional component of the curriculum. All health information programs vary in their curriculum construct and instructional design. Regardless of their content variations, programs must meet the American Health Information Management Association (AHIMA) Curricula Competencies© to be accredited by the Commission on Accreditation of Health Informatics and Information Management Education (CAHIIM).

The Digital Competence (DigCom 2.0) Framework developed by the European Commission Joint Research Centre describes 21 learning outcomes in 5 areas: 1) information and data literacy, including management of content (information and information literacy); 2) communication and collaboration, and participation in society (communication and collaboration); 3) digital content creation, including ethical principles (digital content creation); 4) safety (security); and 5) problem solving.[6]

This case study aimed to identify what digital health competencies and skills are currently needed, identify where they can be addressed in the AHIMA competencies and provide instructional suggestions for implementing a digital health pedagogy.

Methods

A review of the 2018 AHIMA Health Information Management Curricula Competencies© and incorporates digital health into the curriculum. The analysis of this case study forms the basis of incorporating digital health competencies into the following AHIMA 2018 Curriculum Competencies©, digital health data structure, and content.

From December 2022 to January 2023, three reviewers, experts in the content and familiar with AHIMA's Health Information Management (HIM) Baccalaureate Curriculum Competencies©, Curriculum Guidance, and the DigComp Conceptual Reference Model, conducted an evaluation. Their assessment centered on content applications of the AHIMA HIM Baccalaureate Curricula Competencies© and the integration of digital competencies within both the Curriculum Competencies and Curriculum Guidance.

Terminology Definitions

In this study, key terminologies are clearly defined and elaborated upon:

Computer Literacy: A foundational understanding of computer operations and interactions, emphasizing the essential skills needed to operate and troubleshoot a computer. While computer literacy does not equate to mastery over advanced software or programming, it prioritizes understanding the computer's core functions and components. This encompasses skills like starting the computer, interacting with its main features, and addressing common issues. Essentially, computer literacy sets the foundation for advanced technological exploration and expertise. [7]

Digital Health: Digital health is the use of information and communication technologies in medicine and other health professions to manage illnesses and health risks and to promote wellness.[8]

Digital Literacy: Digital literacy is the ability to use information and communication technologies to find, evaluate, create, and communicate information, requiring both cognitive and technical skills.[9]

Health Equity: Health equity is the attainment of the highest level of health for all people. Achieving this means removing economic, social, and other barriers that might prevent individuals from accessing the care and resources they need.[10]

Health Literacy (Personal): Health literacy (personal) is the degree to which individuals can find, understand, and use information and services to inform health-related decisions and actions for themselves and others.[11]

Health Literacy (Organizational): Health literacy (organizational) is the degree to which organizations equitably enable individuals to find, understand, and use information and services to inform health-related decisions and actions for themselves and others.[11]

Social Determinants of Health: Social determinants of health (SDOH) are the conditions in the environments where people are born, live, learn, work, play, worship, and age that affect a wide range of health, functioning, and quality-of-life outcomes and risks.[12]

AHIMA Competencies

The 2018 Health Information Management (HIM) Curricula Competencies© consist of six common domains representing the academic framework for the areas of mastery vital for all health information professionals regardless of academic level. With the 2018 HIM Curricula Competencies©, previous subdomains were removed, and the competencies were revised in a broader context which allows for more flexibility permitting educators and academic programs to adjust to changes in educational demands. Specific curriculum competencies are addressed in the following six common domains.[13]

Domain I. Data Structure, Content, and Information Governance
Domain II. Information Protection: Access, Use, Disclosure, Privacy, and Security
Domain III. Informatics, Analytics, and Data Uses
Domain VI. Revenue Cycle Management
Domain V. Health Law and Compliance
Domain VI. Organizational Management and Leadership

The first three domains within the 2018 AHIMA Health Information Management Curricula Competencies© were explored for incorporation of digital (health) competencies into the curriculum.

Results

As a result of reviewing the literature on digital health competencies and the 2018 AHIMA Health Information Management Curricula Competencies©, curriculum design considerations were addressed. From this review, assessment examples for the competencies are provided, challenges and issues related to the domain content areas are discussed, and tips for curriculum design are included. The key content areas covered in this section include Domain I.: Data structure, content, and information governance; Domain II.: Information protection access, use, disclosure, privacy, and security; Domain III.: Informatics, analytics, and data use of the 2018 AHIMA Health Information Management Curricula Competencies©.

Health Information Curriculum Design

Digital health tools have the potential to transform healthcare, and so the healthcare industry is responding to the challenges associated with digital health. For example, chief information officers (CIOs) are looking to add strategies that support patient engagement. [14.] Patients must engage and use the digital health tool to experience the benefits, yet patients may not have digital health literacy, health literacy, or access to technology to use digital health tools. Some states have issued public awareness campaigns for health and digital literacy and advances in developing intuitive technology to support digital health tools. For example, the healthcare industry has recognized that digital health tools are making significant care advancements, but patients must engage with the technology to take advantage of these advancements.

In 2019, Google managed 1 million health-related searches per day, accounting for 7% of Google searches or 70,000 per minute.[15] People search for health information; however, health literacy remains a problem. The CDC prominently displays health literacy activities by state, with many states offering health literacy campaigns.[16]

There are many underlying challenges that the industry is addressing to transform healthcare with health technology. Still, the question remains unanswered: Can these digital health tools and digital competencies be effectively incorporated into the health information curriculum to support the transformation of healthcare? Is the absence of digital health competencies noted in the health information curriculum? Many medical schools have implemented digital health competencies into their educational programs[17], are health information educators addressing digital health tools in their programs?

Domain I.: Digital Health Curriculum Consideration

Using the existing AHIMA competencies©, health information programs can easily incorporate digital health competencies into Domain I. For example, the study of data structure, content, and information governance provides foundational competencies needed for digital health. In addition, students learn about the stakeholders in the healthcare industry and the relationship between entities and stakeholders in the healthcare industry. Healthcare consumers are key stakeholders in healthcare and have a vested interest in using digital health tools. It is the consumers' limitation in health literacy, and digital literacy that can be addressed in the HI curriculum. These gaps, as noted in the curriculum, limit the HIM professional's advocacy work to support the consumer. Integrating both education and promotion of health literacy and digital literacy skills into the foundation of the HIM curriculum domain would help digital health competencies.

Secondly, Domain I supports the structure and capture of data. Understanding the life cycle of data from the generating, capturing, processing, storing, and using data are fundamental elements of data integrity. Health information professionals are data professionals who understand that the data cycle begins with the generation of data (structure) – knowing stakeholders' needs, such as when to get the right data at the right time with integrity, is paramount to supporting health transformation.

Thirdly, Domain I supports healthcare external forces such as accreditation, regulation, and licensure. Curriculum considerations should include the following:

- What are the legal considerations for healthcare settings with the use of digital health technology?
- What are the legal concerns for digital health related to fraud and abuse, HIPAA, False Claims Act, and other laws?
- What about accrediting body requirements for digital health technology such as artificial intelligence (AI)?
- Are there biases and risks associated with the use of digital health technology?
- What impact does digital health technology have on health disparities?

To summarize Domain I, many curriculum considerations can be incorporated into this domain, such as the evaluation of policies and strategies to achieve data integrity; digital health and tools disruption in healthcare and the use of digital tools for data capture; foundational knowledge of digital health and health literacy. Finally, Domain I could easily capture the role of the external forces surrounding digital health tools.

Challenges

Although digital health tools are widely used among healthcare professionals, the HIM professional may encounter several challenges relating to data structure, content, and information governance. These challenges include the speed at which these tools are entering the market and the academic program's ability to use these tools similarly to industry. The healthcare industry is faced with the challenge that digital tools are rapidly entering the market, and not all health professionals are prepared to use digital health tools.[18,19] The lack of preparedness and confidence with the digital tools among healthcare providers has a downstream effect on those individuals, such as the health information professionals implementing the tools. Many health information professionals work closely with the providers on implementing and integrating digital tools within a healthcare system. Therefore, the health information professional should be prepared to work with providers and patients with digital health competencies, such as include digital literacy, eHealth literacy, psychological and emotional acceptance of digital health, and digital technology.[20]

Design Tips

Domain I.: Data Structure, Content, and Information Governance is a broad category that incorporates such content as healthcare stakeholders, external and internal forces, strategies for policies, governance and organizational, and health record requirements, and types of data structures, among other content. Missing from Domain 1 is the focus on engaging stakeholders in the use, education, and training of digital health tools. An increase in the use of digital tools beyond the electronic health record and the collection and use of data beyond the traditional healthcare settings could be incorporated into Domain I. The health data ecosystem in healthcare should contain not only electronic health records but all devices generating data from digital tools. Didactic coursework, laboratory exercises, and capstone projects (digital health projects) could be built into the curriculum. [21] This coursework should consist of the health data ecosystem with personal health, genetic data, devices generating data, and the electronic health record.

Domain II.: Information protection access, use, disclosure, privacy, and security competency

Historically, the health information management professional's role in privacy and security of health information was documented in the AHIMA Code of Ethics as "protecting information; promoting confidentiality and teaching others of the importance of this principle; preserving and securing health information".[22] Although privacy and security have evolved today, it remains a prominent focus for the health information professional. As a result, privacy and security are embedded into the health information management curriculum through Domain II.

Privacy and security concerns should prompt academic programs to consider the technological aspects of digital health—for example, the use of privacy-enhancing technologies or privacy-preserving technologies. Privacy and security strategies for digital health can encompass digital literacy, similar to Domain I, because a lack of digital literacy compounds one's understanding of privacy and security, along with concerns for vulnerable populations needs.

The DigCom 2.0 digital health model identifies safety as an important digital health competency. Safety is a broad category that encompasses protecting an individual's health data by understanding the digital environment.[23] Students need to develop the knowledge, skills, and attitudes to safeguard the devices that house the data. Domain II could explicitly include the knowledge, skills, and abilities for privacy and security by addressing the digital environment as they relate to safety.

Challenges

Privacy and security remain a challenge for digital health technologies. The use of digital health tools has increased data and compounded the concern for privacy among individuals and healthcare providers. Privacy challenges include the following but are not limited to those: individuals are unaware of how their data is used, the length of time data is retained (immortality of data), and the value of data.[24] Keeping in mind the persistence of privacy and security in healthcare data, education is needed on the evolving trends as digital health tools continue to disrupt healthcare.

The curriculum should be updated with the latest methods of deidentification and reidentification — the anonymization of health data using data masking techniques can be incorporated into the curriculum. In addition, the health information management curriculum should include global policy and regulation as digital health expands globally. The pace and adoption of privacy regulations are accelerating.[25] As the aforementioned curriculum updates are needed, the focus is on digital tools that capture the collection of data and how that data is used. For example, students should be exposed to sound management practices that provide the foundation for data-sharing practices and policies.

Design Tips

Many design tips can be used, including many assessments such as case studies, risk assessments, policy writing, and projects. For example, projects may include the student selecting a digital application whereby the student can recommend privacy strategies used or used for the desired application. Then, the student can evaluate the application for strategy and create a privacy awareness infographic handout explaining the privacy strategies. For example, infographics may include the following: Is the privacy policy accessible to the public? Or is the privacy policy written in plain language? Does it inform the patient about the technology?

Finally, curriculum consideration for Domain II can include identifying the legal, ethical, and regulatory considerations for digital health. For example, is there a need to address privacy regulations such as GDRP or state privacy regulations? How does privacy policy impact digital health? Students can compare US state laws for privacy and security. Do any of these laws address digital health apps? For example, does HIPAA need to be updated to reflect digital health? Students should also be introduced to the FTC's and FDA's roles in digital health apps and devices.

Domain III.: Informatics, analytics, and data use

Health informatics involves the interaction between humans and information through information processing and digital health technologies. There is ample opportunity to examine health informatics concepts and evaluate data, information, and digital content as part of incorporating digital competencies such as solving technical problems or suggesting technological solutions. Data analytics in healthcare is widespread and serves multiple purposes. Data analysts serve the purposes of administrative (used in operations management), financial, and clinical (accelerates research in prevention and disease and population management). The use of data analytics from research studies to create dashboards and reports can be utilized to examine healthcare findings with data visualization techniques. The effective use of data and the displays are crucial to healthcare and strong consideration for a digital health curriculum. Digital competencies include effective presentations, interactive videos, QR code and infographics.

Challenges

As digital health tools are introduced and huge amounts of data become readily available, data analytics and data use become challenging. In addition, the understanding of bias in data is a concern and should be addressed with the creation of digital content. Consideration of the ethical implications of algorithms is essential, along with the concern and knowledge for health equity and vulnerable populations.

Design Tips

Design tips for curriculum considerations include applying a fundamental understanding of the ethical and legal issues related to accessing and using information technologies, accounting for the social determinants of health, and incorporating analytic tools, data visualization techniques, and research methodologies. Assessment that creates questions and methods to collect data for social determinants of health in electronic health records and other digital health tools can be developed. Data analytic assignments offer students the opportunity to develop skills filtering and analyzing data and creating useful information. Students should be introduced to data analytic tools and open-sourced data lakes to practice and hone their analytic skills. It is also important that students develop data visualization and presentation skills through explanations of how data was used and most importantly the outcomes of the analysis keeping with the digital competencies of digital communication and collaboration, developing digital content and digital problem solving. [26]

Discussion/Conclusion

As evident from this case study, there are various ways an educator can introduce digital health into their curriculum. Whether one is developing an entire course on digital health or simply providing a lecture and assignment within a module of a course, it is important that students are made aware of the need to continue learning about digital health and health technology advances and their impact on the management of health information. Students should also be aware of digital health disparities and the importance of equity in healthcare with the use of digital health tools and health technology. Consider including social determinants of health and discuss their effects on health equity, the lack of digital literacy, and health disparities relating to digital health tools and health technology. Digital health is expanding and will continue to serve a valuable role in the future of healthcare. Therefore, it is incumbent upon educators to ensure their students receive an education that makes them more marketable in the workforce and seen as highly valued employees by including digital competencies (DigCom) within their health information curriculum.

References:

1. Aungst, Timothy Dy, and Ravi Patel. "Integrating digital health into the curriculum—considerations on the current landscape and future developments." *Journal of medical education and curricular development* 7 (2020): 2382120519901275.
2. Bloomberg Press Digital Health Market to Hit $1.5 Trillion by 2030: Grand View Research, Inc. October 14, 2022 https://www.bloomberg.com/press-releases/2022-10-14/digital-health-market-to-hit-1-5-trillion-by-2030-grand-view-research-inc
3. Food & Drug Administration. What is Digital Health? https://www.fda.gov/medical-devices/digital-health-center-excellence/what-digital-health

4. Meskó B, Drobni Z, Bényei É, Gergely B, Győrffy Z. Digital health is a cultural transformation of traditional healthcare. Mhealth. 2017 Sep 14;3:38. Doi: 10.21037/mhealth.2017.08.07. PMID: 29184890; PMCID: PMC5682364.
5. Aungst, Timothy Dy, and Ravi Patel. "Integrating digital health into the curriculum—considerations on the current landscape and future developments." *Journal of medical education and curricular development* 7 (2020): 2382120519901275..
6. Kluzer S., Pujol Priego L. (2018). DigComp into Action – Get inspired, make it happen. S. Carretero, Y. Punie, R. Vuorikari, M. Cabrera, and O'Keefe, W. (Eds.). JRC Science for Policy Report, EUR 29115 EN, Publications Office of the European Union, Luxembourg, 2018. ISBN 978-92-79-79901-3, doi:10.2760/112945.
7. Institute of Electrical and Electronics Engineers (IEEE). https://ctu.ieee.org/what-is-the-difference-between-computer-literacy-and-digital-literacy/
8. Ronquillo Y, Meyers A, Korvek SJ. Digital Health. 2023 May 1. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2023 Jan–. PMID: 29262125
9. Policy (OITP), Office of Information Technology, and Digital Literacy Task Force. 2011. "What Is Digital Literacy?" Alair.ala.org. https://alair.ala.org/handle/11213/1626
10. American Health Information Management. AHIMA Public Policy Statement: Health Equity. https://www.ahima.org/media/c12azcqf/ahima-health-equity-public-policy-statement.pdf
11. Centers for Disease Control and Prevention. https://www.cdc.gov/healthliteracy/learn/index.html
12. Healthy People 2030. https://health.gov/healthypeople/priority-areas/social-determinants-health
13. AHIMA 2018 Health Information Management Degree Curriculum©, AHIMA. "Academic Curricula Competencies." 2020. Available at: http://www.ahima.org/education/academic-affairs/academic-Curriculum
14. Runyon,B., Hakkennes,S. Predicts 2023: Changing How Healthcare Provider Services and Operations Are Delivered. Gartner. December 5.
15. Drees, J. (2019). Google receives more than 1 billion health questions every day. Becker's Health IT. https://www.beckershospitalreview.com/healthcare-information-technology/google-receives-more-than-1-billion-health-questions-every-day.html
16. Centers for Disease Control and Prevention. *Activities by State*. Retrieved January 31, 2023 from https://www.cdc.gov/healthliteracy/statedata/index.html
17. Utukuri M, D'souza F, Deighton A, Le EP, Osei-Boadu B, Gadi N, Axiaq A, Aung YY, Agboola B, Chand CP, Dibblin C, Patel CR, Abedi M, Hirniak J, Ta NH, Rudd JH, Sethi R. Digital health: a neglected part of health curricula? Future Healthc J. 2022 Mar;9(1):18-20. doi: 10.7861/fhj.2021-0102. PMID: 35372764; PMCID: PMC8966807.
18. Kutney-Lee, A., Sloane, D.M., Bowles, K.H., Burns, L.R., Aiken, L.H., 2019. Electronic Health Record Adoption and Nurse Reports of Usability and Quality of Care: The Role of Work Environment. Applied Clinical Informatics 10 (1), 129–139. https://doi.org/10.1055/s-0039-1678551.
19. Kleib, Manal PhD, RN; Nagle, Lynn M. PhD, RN, FAAN, FCAN; Furlong, Karen E. PhD, RN; Paul, Pauline PhD, RN; Duarte Wisnesky, Uira PhD, RN; Ali, Shamsa MN.

Are Future Nurses Ready for Digital Health?: Informatics Competency Baseline Assessment. Nurse Educator 47(5):p E98-E104, September/October 2022. | DOI: 10.1097/NNE.0000000000001199

20. Longhini, J., Rossettini, G., & Palese, A. (2022). Digital Health Competencies Among Health Care Professionals: Systematic Review. *Journal of medical Internet research*, *24*(8), e36414. https://doi.org/10.2196/36414
21. Aungst, Timothy Dy, and Ravi Patel. "Integrating digital health into the curriculum—considerations on the current landscape and future developments." *Journal of medical education and curricular development* 7 (2020): 2382120519901275.
22. Flite, Cathy; Harman, Laurinda B.. "Code of Ethics: Principles for Ethical Leadership" *Perspectives in Health Information Management* (Winter, January 2013).
23. Kluzer S., Pujol Priego L. (2018). DigComp into Action - Get inspired, make it happen. S. Carretero, Y. Punie, R. Vuorikari, M. Cabrera, and O'Keefe, W. (Eds.). JRC Science for Policy Report, EUR 29115 EN, Publications Office of the European Union, Luxembourg, 2018. ISBN 978-92-79-79901-3, doi:10.2760/112945
24. Grande, David, Xochitl Luna Marti, Rachel Feuerstein-Simon, Raina M. Merchant, David A. Asch, Ashley Lewson, and Carolyn C. Cannuscio. "Health policy and privacy challenges associated with digital technology." *JAMA network open* 3, no. 7 (2020): e208285-e208285.
25. Henein, Nader, Willemsen, Bart. "The State of Privacy and Personal Data Protection, 2020-2022. Gartner, August (2020)
26. Kluzer S., Pujol Priego L. (2018). DigComp into Action - Get inspired, make it happen. S. Carretero, Y. Punie, R. Vuorikari, M. Cabrera, and O'Keefe, W. (Eds.). JRC Science for Policy Report, EUR 29115 EN, Publications Office of the European Union, Luxembourg, 2018. ISBN 978-92-79-79901-3, doi:10.2760/112945.

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The Perceptions towards the Effectiveness of mHealth Applications during the COVID-19 Pandemic among Saudi Healthcare Providers

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Abstract

In Saudi Arabia, the use of mobile health (mHealth) applications is one of the modern approaches that had been implemented to enhance the provision of healthcare services in response to the COVID-19 pandemic. This study aimed to explore the perception towards mHealth applications among healthcare professionals. This cross-sectional study recruited 300 health providers using a stratified random sampling technique in a tertiary hospital. A self-administered questionnaire measured demographics, the rate of utilization of applications, and the perception towards its effectiveness for monitoring COVID-19 patients. The results indicate that 84 percent of respondents strongly believed in the role of mHealth apps during the pandemic and 82 percent used them. There was a significantly high perception across male, young, and high- income providers ($p < 0.05$). Many providers agreed that these apps were useful to improve coordination among professionals (52 percent) and reduce travel needs (63.4 percent). Finally, most providers found mHealth apps effective to enhance the quality of patient-centered care.

Key words: COVID-19, Healthcare providers, Mobile health apps, mHealth, Utilization

Introduction

The 2030 vision of Saudi Arabia (Saudi Vision 2030) which provides a roadmap for national economic growth, global engagement, and enhanced quality of life , is encouraging the use of mobile health (mHealth) applications in the healthcare industry to improve healthcare activities. The implementation of new technology in the healthcare system is a significant way to improve healthcare services and outcomes through accessible healthcare.[1] mHealth is the practice of using remote communication mobile devices to support electronic healthcare delivery.[2] mHealth is now the basis for many effective applications in numerous healthcare fields including disease expectation, prevention, management, diagnostics, treatments plan, and patient education.[3]

A 2020 study explained that the application allows healthcare consumers to access healthcare from anywhere; it provides the means for virtual consultation with healthcare professionals.Moreover, the mHealth application could be used by patients to book appointments, view lab test results, request medication refills, and print medical reports.[4] A study released in the same year highlighted that the quality of healthcare services and overall satisfaction levels can be improved by using mHealth applications. It Also referred to the easy and fast medical care received by the users. mHealth utilization is still low in the kingdom of Saudi Arabia (KSA), due to factors including lack of exposure, awareness, and suitable skills to use the latest cellphones and its continuous updated software systems.[5]

COVID-19, was first identified in December 2019 in Wuhan.[6] In February 2023, the cumulative number of newly diagnosed cases was 828,294, and 69,198,422 vaccination doses so far were taken all over the kingdom. [7]

To control the spread of the COVID-19 virus at the beginning of the crisis, the Saudi government adopted emergency actions nationwide, including the closure of schools, universities, workplaces, and quarantine to protect the community.[8] The Saudi government has worked to provide smart applications on mobile phones that are designed to provide protection as well as healthcare services for citizens and residents. The ministry of Health approved and implemented multiple mHealth apps as an immediate response to the novel coronavirus in KSA, including: Tawakkalna (indicates the infectious status of the users by colored codes, detects violation of the control procedures and books for vaccination), Tabaud (tackles the spread of COVID infection; helps users to know if they contacted positive people and ensures social and physical distancing), Rest Assured (Tataman) (provides healthcare and assurance for citizens and residents during home isolation or quarantine; preserves their wellbeing and supports their recovery measures), Mawid (helps patients to reserve appointments in primary healthcare facilities in coordination with the concerned specialty), Sehhaty (allows users to access medical information and health e-services including PCR-testing and vaccination which are supplied by various health facilities in the Kingdom), and Seha (provides patients with virtual medical consultation from professionally licensed Ministry of Health (MoH) physicians of different specialties). [9]

The importance of mHealth adoption has become more valuable with the spread of the COVID-19 pandemic. At the present time, it is expected that 89 percent of the population uses the internet, and most of the population in Saudi Arabia has access to different types of smart devices such as smartphones, laptop computers, and desktop computers.[10] Furthermore, the 2030 vision considered mHealth as a crucial transformational step to reach a high-quality and patient-centric care approach. The MoH's Sehhaty mobile health app is one example that clarifies how the adoption of mHealth could provide justifiable solutions to improve access and satisfaction with healthcare services. The app provides a complete personal health record and educates patients. The uses of mHealth in Saudi Arabia were efficient in decreasing the cost, time, and amount of effort required to provide care for patients. [11]

The use of the mHealth apps by health professionals could enhance the utilization and adoption by patients. These applications could increase care accessibility, improve health outcomes, and satisfaction with the provided services. Therefore, this study aimed to explore the utilization rate and perceptions regarding the effectiveness of mHealth applications among Saudi healthcare providers in response to the COVID-19 pandemic.

Methods

Study design and settings

This descriptive, cross-sectional study was conducted from April to June 2021, at a governmental tertiary healthcare facility in Jeddah, Saudi Arabia. It provides secondary and tertiary healthcare services for more than 76,000 patients throughout the past 6 months and works 24/7 with 43,675 bed capacity.[12]

Sampling and target population

The target population were healthcare providers actively enrolled in work at the concerned health facility, during the study period. A power analysis using the G*Power calculator was used to verify the required sample size. In G*Power, a multiple regression omnibus (R2 deviation from zero) test was utilized for prior power designs to test whether the eight predictors can be used to explain the healthcare providers' perceptions towards mHealth applications. The alpha was set at an acceptable level of 0.05, power was set at the level of 80 percent, and the medium effect size was set for this analysis. The test indicates a sample size of 108 was needed.

The study subjects were recruited through a stratified multistage random sampling technique. The hospital included 14 clinical departments, each was including a definite number of health providers (physicians, nurses, and technicians). In the first stage, we randomly chose nine departments to reach the computed sample size. Then we randomly selected a sample from every category of health providers working in the chosen departments considering the inclusion criteria. The sample size has been increased to 300 to represent most of the healthcare professionals in the hospital.

The inclusion criteria included enrollment of active Saudi and non-Saudi healthcare professionals who directly contact patients. The exclusion criteria comprised non-active healthcare professionals (those on vacation), physicians and nursing staff who were in internship year or training scholars, as well as healthcare workers who were in direct contact with patients.

The research received institutional ethical approval from the Research Ethics Committee at Batterjee Medical Colleges (BMC) Jeddah branch, Saudi Arabia with approval reference code number (Res 2021-0003). The survey was conducted in full agreement with the Declaration of Helsinki (2000). Informed consent was highlighted on the front page of the questionnaire. Confidentiality was assured for all participants.

Procedures

The concerned data was collected through an anonymous self-administered questionnaire, which was structured based on a review of similar literature.[13,14] The questionnaire consisted of two parts, the first included sociodemographic information, the rate of mHealth applications' use in medical practice, and the history of COVID-19 infection. The second part measured the degree of perception towards the effectiveness of mHealth applications for monitoring COVID-19 patients through 13 questions followed the Likert scale; responses ranged from 0 (strongly disagree) to 5 (strongly agree). Therefore, the minimum score was 0 and the maximum was 65. The questionnaire took around 4 to 5 minutes to complete. It was structured in the English language and tested for its validity by three experts whose feedback was taken into consideration, and reliability was good (Cronbach Apla was 0.89). Data was collected through interviews with the investigators who used Google Form to gather data from the sampled study subjects.

The investigators were allocated to the previously randomly chosen departments and contacted the selected study subjects who were provided with a QR code for the survey link or received the link via their professional emails. The selected providers filled in the questionnaire anonymously. Once they submitted the form, their responses were saved automatically in the Google Excel spreadsheet ready for data management.

Statistical analysis

The recruited data was exported from the Excel spreadsheets, then tabulated, organized, and analyzed by using the (SPSS) software program version 26. All scores were summed up for each participant and then divided into three categories of self-perception regarding the use of mHealth apps: mHealth believers: ≥44; mHealth opened: 22-44; and mHealth skeptics: ≤ 21. Descriptive statistics were presented by frequency and percentage for qualitative variables, while mean and SD presented the quantitative variables. Demographics were the explanatory variables, and the outcome variables were the levels of perception towards the effectiveness of mHealth apps, as well as the degree of its utilization. The Chi-squared test was used as the inferential test of significance between substantial groups for selected demographic variables. While the Montecarlo Exact test was used when 25 percent of cells with the observed and expected observation were less than 5. The level of significance was adopted at $P < 0.05$.

Results

This study enrolled 300 healthcare providers. Table (1) showed that 52 percent were females, more than half aged between 26 and 35 years old (58 percent), and of Saudi nationality (54 percent). The greatest proportion of the recruited participants had a master's degree and were physicians (62.7 percent, and 45.3 percent respectively). Most of the providers had negative medical morbidity (65 percent) while (10 percent) of them reported having hypertension and asthma.

Table 1 also indicated the utilization of the mHealth applications; all the study subjects used governmentally implemented apps including Sehhaty and Tawakkalana, while half of them had Tataman and Mawaid. Few providers sometimes used other applications such as BMJ Best Practice, and Epicorrate in clinical field practice. It was noticed that 8 percent used those apps when they got infected with COVID-19. Regarding the history of COVID-19 infection, the majority of participating providers reported a negative history of infection (92 percent), and only (8 percent) were infected. Whereas smokers represented 20 percent of the overall participants

Table 2 shows that the providers promptly supported the different benefits of mHealth apps, where 48 percent, 52 percent, and 63.4 percent strongly agreed about the efficiency of apps in appointing for the COVID-19 vaccine, overcoming the distance barrier against accessibility to healthcare, and facilitating the coordination between health professionals, respectively .

Table 3 indicates that more male providers strongly believed in mHealth uses (93.6 percent) than females (73.6 percent) (p=0.004). mHealth believers were more significant among younger age groups and single providers; where mHealth believers presented 94 percent of age interval (20 - 25) years and 97.2 percent of single providers. Compared to 25 percent among those aged more than 45 years and 78.7 percent of the married providers were mHealth believers.

Discussion

This cross-sectional study analyzed the data of 300 healthcare providers in a tertiary healthcare facility related to the MoH to examine the factors that impacted the utilization of mHealth applications by health professionals in response to the COVID-19 pandemic. The demographic results showed that more than half of the respondents were between 26 to 35 years old (58 percent). Age groups were similar in a study of 2020 who found that younger subjects are more likely to use the mobile application by themselves than older patients. [15]

For the utilization of mHealth applications**,** the result of the question ("Do you have at least one of these applications on your mobile phone?") revealed that Sehhaty and Tawakkalana apps powered by MoH are the most popular among the participants. That is definitely because Tawakkalana became mandatory by the Saudi government in response to the pandemic, it targets all citizens and residents. The Sehhaty app provides access to medical records that might be used in medical practice. Therefore, the healthcare provider's responses were based on their personal experiences. The second tier of commonly used apps included Tatamman, Mawid, and Tabaud. Participants also reported frequently using other medical applications such as BMJ Best Practice and EpiCorates to support clinical decisions. In general, the results showed that most of the participants (71.3 percent) used at least one of these applications during early the COVID-19 pandemic between January to March 2021 for monitoring and following up on patients, and 28.7 percent of the participants mentioned they never used those mHealth apps.

On the other hand, a recent cross-sectional study in 2021 assessed the utilization of mHealth applications among patients and found that the use of the Sehhaty application made up only 13.1 percent of the recruited patients, which is less than our detected utilization rate.[16] That difference could be attributed to the purposeful and oriented use of medical apps between health providers. Meanwhile, our study findings were consistent with a national survey that measured the general population's use of MoH health applications and revealed a higher utilization rate, which was 47 percent .[17.]

The present study found no major difference in the perception of mHealth between various professions of healthcare providers. The same observation was detected by a 2019 study, which explained that these technologies have become more commonplace. However, a study reported a difference between different clinical job ranks, where registrars were the highest users of mHealth technology (54 percent) compared to residents (36 percent) and consultants (9.7 percent) .[18]

Our analiyisis indicated a signficant association between believing in mHealth and younger age category , this is could be explained by the authors that the younger generation is more likely to adopt technology than the older ones.

In the literature on understanding gender differences in mHealth adoption, it is stated that males had a higher level of mHealth adoption intention compared with females.[19] To make inferences on gender and age, further research is needed as few studies examined the gender effect on using mHealth during the COVID-19 era. The current study revealed that mHealth believers predominantly were male (93.6 percent).This finding contradicts a previous study that reported the utilization of smart device technologies during medical care settings was more frequent among females than males.[18] in addition, a 2016 study reported that female physicians more strongly agreed that personal digital devices enhanced their clinical performance.[20.]

Considering marital status, single health providers accounted for a larger percentage of mHealth believers than married ones, who might have more time and faster rate of work performance. That is in alignment with the above-mentioned observation that younger age is significantly associated with a strong agreement regarding mHealth apps' usefulness. Likewise, having more than enough income was a significant contributor to being mHealth believers since the high income allows the acquisition of advanced technology and a higher-quality network.[18] Moreover, the providers in that group might themselves be users of personal wellness/health applications.

The self-perception of the healthcare providers regarding using mHealth apps revealed a high utilization and acceptance rate; (44 percent) of healthcare providers agreed that they would use video conferencing consultation, and half of participants would prefer to use distance consultations for minor health problems, and to monitor treatment of COVID - 19 patients.

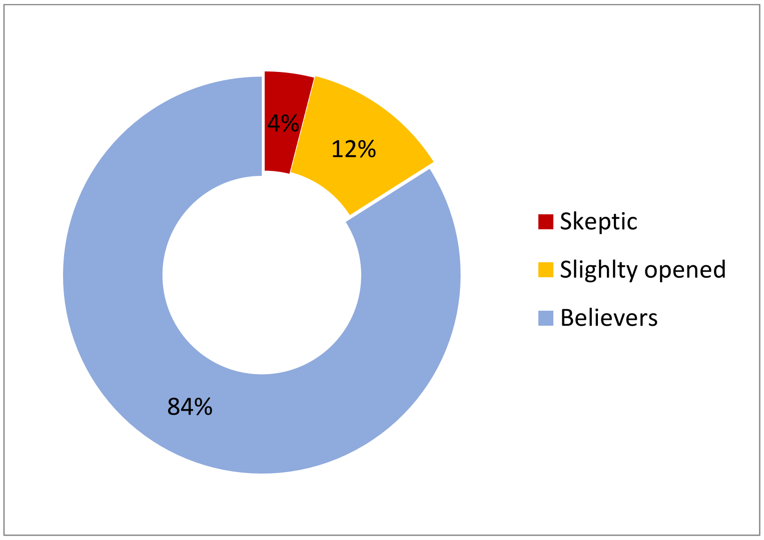

Fig2. Perception of studied healthcare providers regarding the utilization of mHealth apps in monitoring patients during the COVID-19 Pandemic

As shown in Fig. 2, mHealth believers represented 84 percent of all providers, a much higher rate than a related prior report, which declared that 43.3 percent of recruited physicians were strongly confident in eHealth during managing their HIV/AIDS patients.[21] This enormous discrepancy could be explained by the fast breakthrough of digital health technology and its prominent deployment during the COVID-19 crisis and its consequences.

Furthermore, the finding of this study detected a significant association between believing in the role of mHealth apps and negative COVID-19 infection history. In alignment with the findings, the number of users who have used mHealth apps is higher than that of those who have not used them. The not infected group with COVID-19 represented 82 percent (n=246) of the total sample, 85.3 percent (n=210) of this group were found to be mHealth believers. That could reflect an indirect relationship between increased utilization of mHealth apps and reduced infection rate of COVID-19 cases in Saudi Arabia during the late phases of the pandemic. For instance, during the COVID-19 pandemic, mHealth apps have been used for tracing and monitoring contagious cases and their contacts.[22] Consistently, three apps (Tawakkalna, Tatamman, Tabaud) were quickly developed and made available within three months of the pandemic emergence. All the different apps served different needs and they were modified to provide sound information about COVID-19 to raise people's awareness.[23] Of note, neither educational qualification level nor nationality of the studied providers influenced the perception level regarding mHealth apps' usefulness.

Moreover, our results showed that most of the healthcare providers believed that the development of mHealth applications can provide some advantages including improving coordination among different health professionals (52 percent strongly agreed, 38 percent agreed), reducing travel needs (63.4 percent strongly agreed, 18 percent agreed) , and serving medically deprived areas (36 strongly agreed, 50 percent agreed). A prior study supported similar results, where a big proportion of the recruited physicians agreed that due to the provision of digital health, the clinical decision is facilitated, patient safety is improved, and contact between providers is enhanced. Also, it favored the dissemination of medical skills and experiences between professionals. [21]

In line with our findings, a related study highlighted that telemedicine services and patient mHealth applications are valuable tools and viable options for delivering high-quality of care to patients, with less travel and waiting times and lower risk of hospital-acquired infection.[22] Another study reported that adopting such applications could address some of the basic issues in the health system, such as limited resources, long waiting times, and general dissatisfaction with health services.[16]

A 2021 study aimed to explore the effect of using a mHealth application in a telemedicine setting in Abu Dhabi and found that the majority of the mHealth “Remote Care” application users recommended others to use the mobile application for getting healthcare services (79.88 percent). Similarly, 33 percent and 53 percent of the participants in our study strongly agreed and agreed to recommend using current popular mHealth apps to stay updated and informed about the symptoms of COVID-19 disease. [24]

Several health applications for managing COVID-19 have been launched and used in Saudi Arabia and globally. Issues such as privacy, safety, security, and data protection remain the major concerns for users.[15,25] Current findings show that 36.6 percent strongly agreed and 28.6 percent of providers agreed about the possibility of breaching the privacy and confidentiality of patients’ information while using mHealth apps. That replicates a 2020 study that investigated the attitudes of physicians who treat HIV patients regarding the eHealth. Results found that 80 out of 219 physicians (36.5 percent) strongly opposed the eHealth technology, since it challenges the confidentiality of clinical data and thought out that is a threat for medical information security.[21]

The present study demonstrated that around half of health providers strongly agreed (45.3 percent) or agreed (50 percent) that mHealth applications are of worthwhile benefit in tracking patients' health data. That was consistent with a related study in the US that assessed healthcare providers' perception regarding specific apps for tracking health status.[13] Former literature mentioned that patient-generated health data would facilitate the communication between patients and health professionals, help to define the goals, and identify the patient’s preferences and expectations. Furthermore, when patients receive sufficient information, better health outcomes would be achieved.[26,27]

This could be contributed to the providers’ beliefs that patient-generated data are more trustworthy and reliable than the patient's self-report, that sometimes mispresents his/her medical status, and to avoid the recall bias of the patient's medical history.

In addition, our research has demonstrated that 50 percent of healthcare providers prefer to use distance consultation to monitor the compliance to treatment between the COVID-19 patients. Consistently, it was reported that mHealth applications is one of the significant methods to assure adherence to medications uptake.[28,29]

Likewise, the current study demonstrated that 48 percent of providers strongly agreed with using the apps to make appointments for vaccinations against COVID-19 infection, to facilitate high administration of the vaccines.

Previous studies have concluded that mHealth applications were useful to enhance appointment procedures among patients of various clinical issues. For instance, it facilitated healthcare provision for HIV–positive pregnant females, reminding women for routine postnatal care, fostering childhood immunization coverage, and ensuring adherence to the periodic follow up for patients with non-communicable diseases.[29-32]

Overall, the study findings reflected an advent of mHealth applications between the studied providers due to the transformative effect of this technology on healthcare delivery, particularly for health monitoring and management, where 24 percent strongly agreed and 44 percent agreed that mHealth technology will speed progress toward more individualized diagnosis and treatment. Similar literature pointed out its significant role in this regard. [33,34]

Conclusion

Findings revealed a high rate of mHealth believers among the studied providers who showed significant variations across their age, gender, social status, and level of income in terms of self-perception regarding effectiveness of mHealth. Many professionals perceived that mHealth apps were useful for providing remote counseling. Most providers recommended utilization of health information technology for checking and monitoring on COVID–19 patients. That would positively imply medical practice. Further research should be conducted to study this area in focus and on a wider scale, as mHealth and eHealth are rapidly growing sectors of health transformation in the kingdom.

Study Limitations

There are several limitations. First, the cross-sectional design of the study didn't allow for casual relationship analysis. Second, the data was collected through a questionnaire which was structured by the authors according to the prevailing pandemic circumstances. We didn't deploy one of the standard technologies adopting models due to their simplicity and narrow spectrum which focuses on general individual's perceptions towards usage of technology. That rendered those models inappropriate to our study's aim and target population. Third, the data regarding the adoption and utilization of mHealth were self-reported and might be overestimated.

References

1. Ren J.,Liu C., Gao Q., Yang L., Huang X., Guo Q. Use of appropriate healthcare technologies: A cross-sectional study in rural Zhejiang of China. BMC Health Serv Res. (2015); 15:295.

2. Iyengar S.R. Fundamentals of Telemedicine and Telehealth.eds: Gogia SH Mobile health (mHealth). Academic Press. (2020); Ch12: 277-294. ISBN 978-0-12-814309-4. https://doi.org/10.1016/B978-0-12-814309-4.00012-4, https://www.sciencedirect.com/science/article/pii/B9780128143094000124.

3. Alanzi T. A Review of Mobile Applications Available in the App and Google Play Stores Used During the COVID-19 Outbreak. J Multidiscip Healthc. (2021); 12 (no.14):45-57. DOI: 10.2147/JMDH.S285014. PMID: 33469298; PMCID: PMC7812813.

4. Agarwal N. and Biswas B. Doctor consultation through mobile applications in India: An overview, challenges and the way forward. Healthc Inform Res (2020); 26:153-8.

5. Jadi Amr. Mobile Health Services in Saudi Arabia-Challenges and Opportunities. International Journal of Advanced Computer Science and Applications. (2020); 11. DOI: 10.14569/IJACSA.2020.0110422.

6. Center for Disease Control and Prevention (CDC). Basics of COVID -19.. Access on June 2023.

7. Saudi Ministry of Health (MOH)a. Prevalence of problem at the national level. Available at: https://covid19.moh.gov.sa/ Accessed on February 8, 2023.

8. mHealth application used in KSA, available at: https://www.moh.gov.sa/en/Support/Pages/MobileApp.aspx. Accessed February 5, 2021.

9. Saudi Ministry of Health (MOH). Available at: https://covid19.moh.gov.sa/. https://covid19awareness.sa/en/apps-for-your-health-2 . Accessed on April 4, 2021.

10. Otaibi M.N. Internet of Things (IoT) Saudi Arabia Healthcare Systems: State-Of-The-Art, Future Opportunities and Open Challenges. Journal of Health Informatics in Developing Countries. (2019).
11. Hassounah M., Raheel H., Alhefzi M. Digital Response During the COVID-19 Pandemic in Saudi Arabia. J Med Internet Res. (2020);22(no.9): e19338. DOI: 10.2196/19338.
12. Ministry of Health (MOH). King Abdullah Medical Complex-Jeddah: 76+ Thousand Patients Served in 6 Months, March 2018 access on 23 Jan (2021). available at: https://www.moh.gov.sa/en/Ministry/MediaCenter/News/Pages/news-2018-03-06-005.aspx
13. Holtz B., Vasold K., Cotten S., Mackert M., Zhang M. Health Care Provider Perceptions of Consumer-Grade Devices and Apps for Tracking Health: A Pilot Study. JMIR Mhealth Uhealth. (2019);7(no.1): e9929. DOI: 10.2196/mhealth.9929. PMID: 30668515; PMCID: PMC6362391.
14. Kong T., Scott M.M., Li Y., Wichelman C. Physician attitudes towards-and adoption of-mobile health. Digit Health. (2020); 6:2055207620907187. Published 2020. doi:10.1177/205520762090718.
15. Istepanian R.S., and AlAnzi T.U., Chapter Twenty Two - Mobile health (m-health): Evidence-based progress or scientific retrogression, In Biomedical Engineering, Biomedical Information Technology (Second Edition), (2020), Pages 717-733, ISBN 9780128160343, https://doi.org/10.1016/B978-0-12-816034-3.00022-5.
16. Alharbi R., Qadri A., Mahnashi M., Hakami A., Darraj B., Shnaimer J., Gosadi I. Utilization of Health Applications Among Patients Diagnosed with Chronic Diseases in Jazan, Saudi Arabia During the COVID-19 Pandemic. Patient Prefer Adherence. (2021); 15:2063-2070. https://doi.org/10.2147/PPA.S329891.
17. Alharbi A., Alzuwaed J., and Qasem H. Evaluation of e-health (Seha) application: a cross-sectional study in Saudi Arabia. BMC Med Inform Decis Mak. (2021); 21: 103. https://doi.org/10.1186/s12911-021-01437-6.
18. Abu-Elenin M.M. Uses of Smart Device Technology in Medical Field among Clinical Physicians: Is It Important? The Egyptian Journal of Community Medicine. (2020);38(no.3):58-66.
19. Zhang X.I., Guo X.I., Lai K.H., Guo F.E., Chenlei L.I. Telemedicine and e-Health. (2014):39-46. http://doi.org/10.1089/tmj.2013.0092.

20. Jamal A.M., Temsah M.H., Khan S.K., Al-Eyadhy A.Y., Koppel C.R., Chiang M.F. Mobile Phone Use Among Medical Residents: A Cross-Sectional Multicenter Survey in Saudi Arabia. JMIR Mhealth Uhealth (2016);4 (2) e61:1-7.
21. Jacomet C., Ologeanu-Taddei R., Prouteau J.et al. Adoption and Attitudes of eHealth Among People Living with HIV and Their Physicians: Online Multicenter Questionnaire Study. JMIR Mhealth Uhealth. (2020);8(no.4): e16140. Published 2020 Apr 15. doi:10.2196/16140.
22. Salathé M., Althaus C.L., Neher R., Stringhini S., Hodcroft E., Fellay J. et al. COVID-19 epidemic in Switzerland: on the importance of testing, contact tracing, and isolation. Swiss Medical Weekly. (2020); 150, w20225. https://doi.org/10.4414/smw.2020.20225.
23. Alassaf N., Bah S., Almulhim F., AlDossary N. and Alqahtani M. Evaluation of Official Healthcare Informatics Applications in Saudi Arabia and their Role in Addressing COVID-19 Pandemic. Healthcare informatics research. (2021); 27(no.3), 255–263. https://doi.org/10.4258/hir.2021.27.3.255
24. Taha A.R., Shehadeh M., Alshehhi A., Altamimi T. Housser E., Simsekler M.C. et al. The integration of mHealth technologies in telemedicine during the COVID-19 era: A cross-sectional study. PLoS ONE. (2021);17(no.2): e0264436. https://doi.org/10.1371/journal.pone.0264436
25. Sharma T. and Bashir M. Use of apps in the COVID-19 response and the loss of privacy protection. Nat Med. (2020);26(no.8):1165–1167. doi:10.1038/s41591-020-0928-y - DOI – PubMed.
26. Nundy S., Lu C.E., Hogan P., Mishra A. and Peek M.E. Using Patient-Generated Health Data From Mobile Technologies for Diabetes Self-Management Support: Provider Perspectives From an Academic Medical Center. J Diabetes Sci Technol. (2014) 1;8(no.1):74–82. DOI: 10.1177/1932296813511727. [PMC free article] [PubMed] [CrossRef] [Google Scholar]
27. Menachemi N., Powers T.L., Brooks R.G. The role of information technology usage in physician practice satisfaction. Health Care Manage Rev. (2009);34(no.4):364-71. DOI: 10.1097/HMR.0b013e3181a90d53. PMID: 19858921.
28.Babirye D., Shete P.B., Farr K, Nalugwa T., Ojok C., Nantale M. et al.Feasibility of a short message service (SMS) intervention to deliver tuberculosis testing results in peri-urban and rural Uganda. J. Clin. Tuberculos. Other Mycobacter. Dis., (2019);16: 100110.

29. Unger J.A., Drake A.L, Perrier T., Akinyi P., Akinyi P., Osborn L. SMS messaging to improve ART adherence: perspectives of pregnant HIV-infected women in Kenya on HIV-related message content. AIDS Care. 2018; 30: 500-505.
30. Mbuthia F., Reid M., Fichardt A. mHealth communication to strengthen postnatal care in rural areas: a systematic review. BMC Pregnancy Childbirth. (2019); 19: 406.
31. Eze P., Agu S.A., Agu U.J., Acharya Y. Acceptability of mobile-phone reminders for routine childhood vaccination appointments in Nigeria - a systematic review and meta-analysis. BMC Health Serv Res. (2021)26;21(1):1276. doi: 10.1186/s12913-021-07296-1. PMID: 34836531; PMCID: PMC8627092.
32. Al Najjar S., Al Shaer T. Factors affecting adherence to an appointment system in the clinic for non-communicable diseases in UNRWA's Khan Younis Health Centre and the role of mobile phone text messages to improve adherence: a descriptive cross-sectional study.The Lancet. (2018); 391: S42.
33. Kaunda Khangamwa B.N., Steinhardt L.C., Rowe A.K., Gumbo A., Moyo D., Nsona H. et al.The effect of mobile phone text message reminders on health workers' adherence to case management guidelines for malaria and other diseases in Malawi: lessons from qualitative data from a cluster-randomized trial Malar. J., 17 (1) (2018), p. 481
34. Osei E.R., Mashamba-Thompson T. P. Mobile health applications for disease screening and treatment support in low-and middle-income countries: A narrative review. Heliyon. (2021);7(3):e06639. ISSN 2405-8440. https://doi.org/10.1016/j.heliyon.2021.e06639

Tables

Table1: Demographics and Utilization of mHealth Apps of Studied Health Providers

Demographic and descriptive characteristics:	**n=300**	**%**
Gender		
Male	156	52%
Female	144	48%
Age		
20-25	66	22%
26-35	174	58%
36-45	36	12%
≥45	24	8%
Nationality		
Saudi	162	54 %
Non – Saudi	138	46%
Education attainment		
Bachelor	34	11.3%
Master	188	62.7%
PhD	78	26%
Social Status		
Single	138	46%
Married	150	50%
Divorced/Widow	12	4%
Your job/occupation		
Physicians	136	45.3%
Nurse	50	16.7%
Therapist (Physiotherapist, Radiotherapy, Nutritionist)	114	38%
Level of income		
Not enough	12	4%
Enough with no saving	158	53.1%
Enough and saving	130	42.9%
Do you have at least one of these applications on your mobile phone?		
Tabaud app		
Tawakkalna app	72	24%
Sehhaty app	300	100%
Tataman app	300	100%
Mawid app	48	16%
BMJ best practice /Epicorates	110	36.3%
Other	96	32%
	12	4%
Do you use at least one of these applications during the COVID-19 pandemic in the last 3 months for monitoring and follow-up of patients?		

Yes No	214 86	71.3% 28.7%
When you got infected with COVID-19, did you use any of these applications? Yes No I didn't get infected with COVID-19 and used mHealth apps.	 24 30 246	 8% 10% 82%

Table 2: Perception of the Studied Health Providers Regarding the Usefulness of mHealth Apps

Variable	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
Do you favor video conferencing consultation?	90 (30%)	132(44%)	66(22%)	6(2%)	6(2%)
Do you prefer to use distance consultation to give a new prescription for treatment?	108(36%)	114(38%)	48(16%)	18(6%)	12(4%)
Do you prefer to use distance consultations for minor health problems (sore throat, cold, etc.)?	108(36%)	162(54%)	12(4%)	18(6%)	0(0%)
Do you prefer to use distance consultation to monitor the treatment of COVID-19 patients?	90(30%)	150(50%)	54(18%)	6(2%)	0(0%)
Do you agree that personal data may be misused on mobile health applications?	42(14%)	138(46%)	48(16%)	60(20%)	12(4%)
Do you agree that mHealth technology will speed progress toward more individualized diagnosis and treatment?	72(24%)	132(44%)	66(22%)	30(10%)	0(0%)
Do you think the development of mHealth would be efficient for improving coordination among different health professionals?	156(52%)	114(38%)	18(6%)	12(4%)	0(0%)
Do you think the development of mobile health would be efficient for reducing travel?	190(63.4%)	54(18%)	36(12%)	14(4.6%)	6(2%)
Do you think the development of mHealth would be efficient	108(36%)	150(50%)	36(12%)	6(2%)	0(0%)

for servicing medically deprived areas?					
Do you recommend utilizing mobile software applications for checking on COVID-19?	96(32%)	120(40%)	42(14%)	30(10%)	12(4%)
Do you recommend using current popular mobile apps to stay updated and informed about the symptoms of COVID-19?	98(33%)	158(53%)	16(5%)	18(6%)	10(3%)
Are you satisfied using the apps to make appointments for vaccinations?	144(48%)	138(46%)	18(6%)	0(0%)	0(0%)
Do you think that development of mHealth applications is a worthwhile benefit to tracking patients' health data?	134(45.3 %)	150(50%)	6(2%)	10(3.3%)	0(0%)
Do you think that the use of mHealth applications is liable to breaching of patients' data privacy and confidentiality?	109(36.6%)	86(28.6%)	74(24.6%)	26(8.6%)	5(1.6%)

Table 3: The Association Between Perception Regarding the Usefulness of mHealth Apps and Demographic Characteristics of the Studied Health Providers

Demographic variable	**Perception regarding the usefulness of mHealth apps**				
	mHealth skeptic	mHealth slightly opened	mHealth strong believers	χ^2	*p*
Gender					
- *Male*	4(2.5%)	6(3.9%)	146(93.6%)	10.9	0.004*
- *Female*	8(5.5%)	30(20.9%)	106(73.6%)		
Age					
- 20-25	0(0%)	4(6%)	62(94%)	MCET*	<0.0001**
- 26-35	2(1.1%)	10(5.7%)	162(93.2%)	41.4	
- 36-45	2(5.5%)	12(33.3%)	22(61.2%)		
- ≥45	8(33.3%)	10(41.7%)	6(25%)		
Nationality					
- Saudi	6(3.6%)	14(8.6%)	142(87.8%)	1.97	0.3
- Non – Saudi	6(4.3%)	22(15.9)	110(79.8%)		
Education attainment					
- Bachelor	0(0%)	6(17.6%)	28(82.4%)	6.45	0.16
- Master	4(2.1%)	24(12.8%)	160(85.1%)		
- PhD	8(10.2%)	6(7.6%)	64(82.2%)		
Marital status					
- Single	2(1.4%)	2(1.4%)	134(97.2%)	32.557	<0.0001**

- Married	8(5.3%)	24(16%)	118(78.7%)		
- Widow/divorced	2(16.6%)	10(83.4%)	0(0%)		
Health provider category					
- Physicians	4(3%)	12(8.8%)	120(88.2%)	3.41	0.4
- Nurse	2(4%)	10(20%)	38(76%)		
- **Therapist (**Physiotherapist, Radiotherapy, Nutritionist)	6(5.4%)	14(12.2%)	94(82.4%)		
Level of income					
- Not enough	2(16.7%)	6(50%)	4(33.3%)	11.9	0.01*
- Enough with no saving	6(3.8%)	16(10.1%)	136(86.1%)		
- Enough and saving	4(3.1%)	14(10.7%)	112(86.2%)		
COVID-19 infection history					
- Infected	2(3.7%)	10(18.5%)	42(77.8%)	MCET	0.0006*
- Not infected	10(4.1%)	26(10.5%)	210(85.4%)	14.7	

MCET,* *p*-value <0.05, ***p*-value <0.0001

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Predicting Hospital Readmission in Medicaid Patients with Heart Failure Using Administrative and Claims Data

By Jaehyeon Yun, Vishal Ahuja, Daniel F. Heitjan

Objective: To develop a model that predicts the risk of 30-day, all-cause readmission in Medicaid patients hospitalized for heart failure.

Design: Retrospective study of a population cohort to create a predictive model.

Setting and Participants: We analyzed 2016–2019 Medicaid claims data from seven US states. We defined a heart failure admission as one in which either the admission diagnosis or the first or second clinical (discharge) diagnosis bore an ICD-10 code for heart failure. A readmission was an admission for any condition (not necessarily heart failure) that occurred within 30 days of a heart failure discharge.

Methods: We estimated a mixed-effects logistic model to predict 30-day readmission from patient demographic data, comorbidities, past healthcare utilization, and characteristics of the index hospitalization. We evaluated model fit graphically and measured predictive accuracy by the area under the receiver operating characteristics curve (AUC).

Results: 6,859 patients contributed 9,336 heart failure hospitalizations; 2,667 (28.6 percent) were 30-day readmissions. The final model included age, number of admissions and emergency room visits in the preceding year, length of stay, discharge status, index admission type, US state of admission, and past diagnoses. The observed vs. predicted plot showed good fit, and the estimated AUC of 0.745 was robust in sensitivity analyses.

Conclusions and Implications: Our model robustly and with moderate precision identifies Medicaid patients hospitalized for heart failure who are at a high risk of readmission. One can use the model to guide the development of post-discharge management interventions for reducing readmissions and for rigorously adjusting comparisons of 30-day readmission rates between sites/providers or over time.

Keywords: Burden of heart failure; claims database analysis; hospital admissions; Medicaid; prediction model.

Introduction

Roughly 2.1 percent of Americans had heart failure between 2015 and 2018, giving rise to an estimated annual cost of $30.7 billion.[1] Heart failure is the second-leading cause of hospitalization in the United States and the leading cause of hospitalization among adults over 65.[2] Patients with heart failure have elevated rates of all-cause mortality, and they are at higher risk of 30-day readmission when hospitalized for other conditions.[3]

The medical community has long sought to identify heart failure patients who are at elevated risk for readmission and to craft interventions for improving post-discharge management, with many authors having devised models for predicting 30-day readmission in this population. Although there are now several such models aimed at Medicare patients with heart failure,[4 5 6 7 8 9 10 11] to the best of our knowledge only one such model has been derived from Medicaid patients specifically. [12]

The Medicaid program, jointly funded by federal and state governments, provides medical insurance to low-income US individuals.[13] The single largest source of health insurance in the US, it covers nearly 86 million Americans including children, pregnant women, low-income adults, and individuals with disabilities.[14 15] Given the scope of Medicaid and the distinctive characteristics of the covered population,[16] there is a need for readmission models that are designed for this set of patients.[17 18] We address this gap by using a large Medicaid claims database to develop a novel model for predicting the risk of 30-day readmission among Medicaid patients hospitalized for heart failure.

Methods

Data: We retrieved Medicaid claims through a system operated by Digital Health Cooperative Research Centre (DHCRC), an Australian healthcare research organization, and HMS, Inc. (now part of Gainwell Technologies), a US healthcare analytics company that coordinates Medicaid benefits in several states. We extracted data from the *claims*, *eligibility*, and *provider* databases. The *claims* database consists of four files comprising institutional, medical, pharmacy, and dental data for each patient encounter. The institutional file includes information on the hospitals and other facilities where the encounters took place; encounter-specific provider data; and patient data such as presenting diagnoses and conditions (represented by International Classification of Disease [ICD] 10 codes). The *eligibility* database contains patient demographics, eligibility criteria, and dates of eligibility. The *provider* database includes information on medical service providers.

Study cohort: We had access to Medicaid claims from seven US states served by HMS: fee-for-service claims from Florida; Medicaid Managed Care claims from Georgia, Indiana, Kentucky, and Ohio; and claims of both types from Colorado and Nevada. The claims were dated from January 1, 2016, to June 21, 2019, in Florida; to July 1, 2019, in Ohio; to July 26, 2019, in Nevada; and to August 1, 2019, in the other states.

We used ICD-10 codes to identify heart failure patients from two sources: admission codes in hospitalization claims, and clinical diagnosis codes in physician and hospitalization claims. In the physician and hospitalization claims, we defined a patient as having heart failure if any diagnosis field contained an ICD-10 code starting with I50. Through this approach, our cohort included all patients who had a claim indicating diagnosis of heart failure.

Hospital admissions: A heart failure admission was any claim satisfying all the following criteria:

- It was institutional (not professional, pharmacy, or dental);
- It represented an inpatient hospitalization (excluding long-term care, outpatient, rehabilitation, etc.);
- It was designated as a final "admit thru discharge" claim; and
- Heart failure appeared as either the admission diagnosis or the first or second clinical (discharge) diagnosis.

Index hospitalization: We used index admissions from January 1, 2017, or later, allowing us at least one year of patient history prior to each hospitalization. We then excluded as index admissions any admission whose discharge code indicated in-hospital death or transfer to a short-term general hospital, another type of institution not defined in the Medicaid code list, a Critical Access Hospital, or hospice care. We then identified admissions (for any condition) that occurred within 30 days after discharge from a previous admission; we designated these as *readmissions*. A readmission for heart failure could serve as the index hospitalization for a subsequent readmission if it also met the criteria for an index admission. Figure S1 presents a schematic of the extraction of the data set.

Potential predictors: Our list of potential predictors of readmission appears in Table 1. We used ICD-10 categories to group *past, admission,* and *main* diagnoses into a coarser list of variables. A *past* diagnosis is an ICD-10 code in a diagnosis field from a prior (to the index) hospitalization or physician visit. An *admission* diagnosis is an ICD-10 code reported in the admission diagnosis field of the index admission — the proximal reason for the hospitalization. A *main* diagnosis is an ICD-10 code reported in the main diagnosis field of the index hospitalization — the discharge diagnosis for the hospitalization.[19]

Outcome: The outcome variable was occurrence of a readmission within 30 days of the discharge from the index hospitalization.

Censoring events: Our database does not include information on mortality except for hospitalized individuals who received a discharge code indicative of death. But because it includes eligibility dates, a subject who died at home could nevertheless be censored for follow-up of a preceding index hospitalization. Also, an index admission could be censored if the number of days of eligibility following an index discharge was less than 30. We did not treat admissions with censored follow-up as index admissions, but we did count them as readmissions when they occurred within 30 days of a prior index admission.

Prediction model: We predicted 30-day readmission using a logistic generalized linear mixed model (GLMM) including patient and provider random effects. This model accounts for potential correlation of outcomes within patients or providers; failure to model this correlation could invalidate confidence intervals and statistical tests.[20]

Handling of count and continuous predictors: Table 1 includes two count variables (number of hospitalizations and emergency room visits in the 12 months preceding the index hospitalization) that we treated as continuous predictors. We modeled length of stay (LoS) with linear splines to account for the possibility of a complex, non-monotone effect of LoS on readmission risk.[21]

Model development:. We identified the best set of predictors using LASSO variable selection in the R package glmnet.[22] This procedure seeks to balance model fit with model complexity, including only variables that contribute substantially to predictive value. With the large number of records in the database, it was impractical to apply the LASSO with the logistic GLMM; therefore, in the model selection step, we used logistic regression without patient and provider random effects. Having identified the best set of predictors, we re-estimated the coefficients of the selected model including the patient and provider random effects. We evaluated the model's predictive accuracy by computing the area under the receiver operating characteristic curve (AUC). We applied a five-fold cross-validation technique to avoid overfitting bias.[23] We assessed significance of predictors in the final GLMM using Wald tests and 95% confidence intervals for regression coefficients. To evaluate calibration, we created a plot of observed versus predicted probability of 30-day readmission.

Missing values: Most variables had few missing values. Among demographic factors, age and sex were complete for all patients, but marital status was available only in Nevada, and race/ethnicity was available only in Florida, Colorado, and Nevada. We therefore excluded marital status and race/ethnicity from our predictive models. We also omitted a small fraction of index admissions whose discharges were recorded with codes "reserved for national assignment" in the data dictionary. Finally, we removed a small fraction (< 0.01%) of index admissions that lacked a national provider identifier.

Sensitivity analysis*:* We assessed robustness by re-estimating the model under a range of conditions:

- Including and excluding the provider random effects.
- Using a more specific case identification method that defined heart failure patients as those who had either i) ≥2 outpatient diagnoses of heart failure or ii) ≥1 hospitalization for heart failure. We re-estimated the predictions using this smaller cohort.
- Excluding index admissions longer than 28 days.
- Including only index admissions where enrollment was continuous for one year before admission and 30 days after discharge.
- Excluding elective admissions.

We executed all computations in Spark (Apache Software Foundation; Wakefield, MA) and R (The R Foundation; Vienna, Austria).

The authors' Institutional Review Board reviewed the study proposal and determined that it does not meet the criteria of human-subjects research. The authors had full access to the data; we take responsibility for its integrity and the data analysis.

Results

The final study cohort of 6,859 patients accounted for 9,336 hospitalizations, of which 2,667 (28.6 percent) were 30-day readmissions. The median age was 55 years at the time of the earliest claim, and 45.2 percent of the patients were female (Table 2).

Among diagnosis variables associated with the index admission, the LASSO procedure eliminated the heart failure type and the admission and main diagnosis, retaining several prior diagnosis indicators. Table 3 presents the coefficients in the selected prediction model. A plot of observed *versus* expected deciles of 30-day readmission probabilities (Figure S2) demonstrates that the predicted and observed readmission rates closely match. Figure 1 presents the ROC curve for the final model, whose AUC is 0.745. Figure S3 presents estimated readmission rate as functions of LoS of the index admission, showing higher readmission rates for very short stays.

Sensitivity analysis: We excluded the provider random effect from the logistic GLMM and re-ran our model including only the patient random effects. This model gave an AUC of 0.733, similar to the AUC obtained from the model that included provider random effects.

We re-estimated the model using the cohort identified by a more specific heart failure case definition that excluded a small fraction (1.7 percent) of patients. This model selected all predictors and past diagnoses in Table 3, giving an AUC of 0.745 — the same as the model using the full data set.

We were concerned that a small fraction (2.0 percent) of index hospitalizations that exceeded 28 days would unduly influence predictions. Re-running the logistic GLMM excluding these observations resulted in an AUC of 0.745, the same as from the model based on the full data set.

We re-ran the model excluding 2,401 subjects (35.0 percent) whose 3,138 hospitalization claims had non-continuous enrollment for a year before or 30 days after admission, yielding an estimated AUC of 0.774. This suggests that having more complete information on previous claims leads to superior prediction.

Patients hospitalized electively were not likely admitted for decompensated heart failure.[24] Excluding 886 (9.5 percent) index admissions that were designated as elective, we obtained an AUC of 0.762.

Discussion

We used Medicaid claims data to develop and validate a model predicting 30-day readmissions in patients hospitalized for heart failure. Unlike existing heart failure readmission models, which often use electronic health record fields and include a heterogeneous mix of payers, we built our model with only claims data from a Medicaid population. Our model performed at least as well as others that use more granular clinical and pharmacy claim data. Given the higher readmission rates among Medicaid patients hospitalized for heart failure compared to those insured by other payers, [12] our model may be useful for identifying patients at elevated risk for readmission and targeting post-discharge management interventions to reduce readmissions and contain costs.

Among Medicaid patients with heart failure hospitalized in 7 states between 2016 and 2019, 28.6 percent of admissions resulted in readmission within 30 days of discharge. This is similar to overall 30-day readmission rates observed in studies including mixed insurance coverage but larger than the rate in a previous Medicaid cohort.[12] We observed wide variation in readmission rates across the seven states in our analysis (11.9 percent to 33.7 percent; Table 2), a pattern similar to that observed with overall 30-day Medicaid readmissions across states.[17] This variation likely reflects heterogeneity in eligibility, coverage, management, and readmission reduction efforts at the state level. Our study is consistent with previous work that has examined readmissions in patients with heart failure and found that age, number of prior admissions and ER visits, length of stay, and post-discharge care environment are independent predictors of readmission. The predictors differ somewhat from those observed in a previous study that included 1,198 Medicaid and 3,350 commercially insured patients. [12]

In contrast to some previous studies that have described a positive association between increasing length of stay and readmission risk in patients with heart failure, our analysis using a spline regression model suggests that the relationship between LoS and readmission risk is non-monotone, with an early peak in readmissions at two days and declining thereafter. Others have described a similar non-monotone relationship between LoS and readmission risk in heart failure readmissions.[24] Our model selection procedure omitted male sex, which typically predicts a higher readmission rate.

The predictive accuracy of our claims-only 30-day readmission risk model for Medicaid patients with heart failure is moderate and comparable to those noted in recent papers. A 2011 review article[25] identified six models for predicting readmission in heart failure — three from retrospective administrative data [6 26] and three from real-time administrative data and retrospective primary data collection.[5 27 28] Of those analyses that evaluated predictive accuracy by AUC, none exceeded 0.72.[5] Among several readmission models created since 2011,[6 29 8 9 10 11 12] only one,[9] applying a naïve Bayes classifier to electronic health record data, gave an AUC (0.78) comparable to ours. The only model that specifically uses claims data — taken from Medicaid and commercial insurance — found an AUC of 0.64. [12] By contrast, models for prediction of mortality in heart failure cohorts have generally achieved high accuracy; the model of Amarasingham, for example, gives an AUC of 0.86. [518]

Our model has several novel elements: First, we use splines to flexibly model non-monotone trends. Second, we include state as a predictor to account for the heterogeneity of Medicaid coverage, programs, and readmission initiatives. Finally, we include multiple index admissions for each subject and each provider by estimating a GLMM rather than a logistic model that includes only a single observation per patient, as is common in healthcare prediction models.

Although at least one previous heart failure prediction model explicitly included Medicaid claims, [12] ours is the first to focus exclusively on the Medicaid population, which has higher rates of heart failure complications and readmissions than Medicare and commercially insured populations.[16] Payer type is an important predictor in readmission models in the US and reflects the underlying patient populations covered. Medicaid payer status is an independent risk factor for readmission,[26] as covered patients are poorer, have higher rates of chronic conditions, and possess socioeconomic disadvantages that are difficult to quantify.[16 30] We found the post-discharge environment to be a significant predictor of readmission, possibly reflecting the level of social support available.

Our model may be useful in programs to prevent readmission. At the hospital level, one could implement the prediction calculation as a clinical decision support (CDS) tool in the electronic health record system, [31 32] enabling deployment of tailored care-transition services to patients at highest risk.[33] Because the prediction equation involves some factors that only become known at discharge — discharge diagnosis and code and length of stay — one might implement a provisional calculation, for example calculating the readmission probability should the patient be discharged to an institution at the current date. Patients whose predicted probabilities of readmission are high would be retained and re-evaluated for discharge at a later time. At the health system level, one could reallocate resources to hospitals that have larger numbers of high-risk patients, or to institutions (such as rehabilitation hospitals) that commonly admit high-risk heart failure patients who are discharged from hospitals.

The discharge code (home or institution) and the length of stay are the only factors in our model on which intervention is possible. But because we have estimated a *predictive* model rather than a *causal* model, the odds ratios associated with these factors may not reflect the effects we would observe by intervening on them. A readmission prevention plan based on our model (or any predictive model) should be evaluated in a randomized trial.

To evaluate the potential cost saving from reducing readmissions in heart failure, consider that there are (in rough terms) 1 million heart failure hospitalizations per year, with 10 percent covered by Medicare, at an average cost of $11,000. [34] Our data suggest that about 20 percent of these cases, or 20,000 total, are readmissions. Then a program that would reduce readmissions by only 10 percent would prevent 2,000 readmissions for a savings of $22,000,000 annually in Medicaid alone. This is a conservative figure, as evaluations of AI-supported prevention systems have found that one can reduce the number of readmissions by 14 percent or more. [31 32]

A strength of our study is its sole focus on Medicaid patients with heart failure — a large but understudied population that is at high risk for readmission. The pooling of Medicaid claims data from seven states enhances the generalizability of our model and provides a larger sample size than many previous studies of heart failure readmissions.

Our study has several limitations: Although our data set is derived from several states in the South, Midwest, and West, it does not constitute a probability sample of all Medicaid claims, and therefore estimates of readmission rates and the effects of risk factors may not be generalizable to the entire US population. A second potential source of bias is the exclusion of patients who were not continuously enrolled in Medicaid, which could lead to missed index hospitalizations and readmissions. A third is the unavailability of factors that are likely to affect readmission risk such as race, marital status, patient satisfaction, and quality of patient-provider communication; their absence could bias the effects of other factors that appear in the model. Finally, because our claims data are de-identified, we cannot link them to the National Death Index, and therefore we likely failed to capture all deaths.

A recent article from our group estimated a statistical model for 30-day readmission in Medicaid patients diagnosed with diabetes.[35] Using similar methods, the final model included age, sex, age-sex interaction, past diagnoses, US state of admission, number of admissions in the preceding year, index admission type, index admission diagnosis, discharge status, LoS, and the LoS-sex interaction. As with our heart failure analysis, the diabetes model fit well, and the estimated AUC of 0.761 was robust in sensitivity analyses and superior to AUCs found in other studies, even those using more granular data sets.

Conclusions and Implications

In this study, we derived and validated a claims-only statistical model to predict 30-day readmissions for hospitalized Medicaid patients with heart failure. Our model shows moderate accuracy similar to other models that are based on more detailed clinical and demographic data. It may be of use to health plans, policy makers, and health systems as they seek to risk-stratify populations and refine, develop, and target interventions to help contain readmission-related costs in Medicaid programs. Future work, including external validation of the risk model within Medicaid programs at the state or payer level, can facilitate the design of readmission-reduction initiatives to reduce morbidity and healthcare costs.

References:

1. Virani SS, Alonso A, Aparicio HJ, et al. Heart disease and stroke statistics—2021 update: A report from the American Heart Association. *Circulation*. 2021;143(8):e254-e743. doi: 10.1161/CIR.0000000000000950.

2. McDermott KW, Roemer M. Most frequent principal diagnoses for inpatient stays in US hospitals, 2018. *Healthcare Cost and Utilization Project*. 2021. doi: 10.4135/9.

3. Soh JGS, Wong WP, Mukhopadhyay A, Quek SC, Tai BC. Predictors of 30-day unplanned hospital readmission among adult patients with diabetes mellitus: A systematic review with meta-analysis. *BMJ Open Diabetes Research & Care*. 2020;8(1). doi: 10.1136/bmjdrc-2020-001227.

4. Keenan PS, Normand ST, Lin Z, et al. An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure. *Circulation: Cardiovascular Quality and Outcomes*. 2008;1(1):29-37. doi: 10.1161/CIRCOUTCOMES.108.802686.

5. Amarasingham R, Moore BJ, Tabak YP, et al. An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data. *Medical Care*. 2010;48(11):981-988. doi: 10.1097/MLR.0b013e3181ef60d9.

6. Hammill BG, Curtis LH, Fonarow GC, et al. Incremental value of clinical data beyond claims data in predicting 30-day outcomes after heart failure hospitalization. *Circulation: Cardiovascular Quality and Outcomes*. 2011;4(1):60-67. doi: 10.1161/CIRCOUTCOMES.110.954693.

7. Au AG, McAlister FA, Bakal JA, Ezekowitz J, Kaul P, van Walraven C. Predicting the risk of unplanned readmission or death within 30 days of discharge after a heart failure hospitalization. *American Heart Journal*. 2012;164(3):365-372. doi: 10.1016/j.ahj.2012.06.010.

8. Frizzell JD, Liang L, Schulte PJ, et al. Prediction of 30-day all-cause readmissions in patients hospitalized for heart failure: Comparison of machine learning and other statistical approaches. *JAMA Cardiology*. 2017;2(2):204-209. doi: 10.1001/jamacardio.2016.3956.

9. Shameer K, Johnson KW, Yahi A, et al. Predictive modeling of hospital readmission rates using electronic medical record-wide machine learning: A case-study using Mount Sinai heart failure cohort. *Pacific Symposium on Biocomputing*. 2017;22:276-287.

10. Golas SB, Shibahara T, Agboola S, et al. A machine learning model to predict the risk of 30-day readmissions in patients with heart failure: A retrospective analysis of electronic medical records data. *BMC Med Inform Decis Mak*. 2018;18(1). doi: 10.1186/s12911-018-0620-z.

11. Awan SE, Bennamoun M, Sohel F, Sanfilippo FM, Dwivedi G. Machine learning-based prediction of heart failure readmission or death: Implications of choosing the right model and the right metrics. *ESC Heart Failure*. 2019;6(2):428-435. doi: 10.1002/ehf2.12419.

12. Allen LA, Smoyer Tomic KE, Smith DM, Wilson KL, Agodoa I. Rates and predictors of 30-day readmission among commercially insured and Medicaid-enrolled patients hospitalized with systolic heart failure. *Circulation: Heart Failure*. 2012;5(6):672-679. doi: 10.1161/CIRCHEARTFAILURE.112.967356.

13. Centers for Medicare & Medicaid Services. Medicaid and CHIP beneficiary profile: Characteristics, health status, access, utilization, expenditures, and experience. *Center for Medicaid and CHIP Services*. 2020.

14. Medicaid.gov. Medicaid eligibility. Medicaid.gov web site. https://www.medicaid.gov/medicaid/eligibility/index.html Accessed 12-23-2021.

15. Medicaid.gov. June 2023 Medicaid & CHIP enrollment data highlights. Medicaid.gov web site. https://www.medicaid.gov/medicaid/program-information/medicaid-and-chip-enrollment-data/report-highlights/index.html. Accessed 10-19-2023.

16. Regenstein M, Andres E. Reducing hospital readmissions among Medicaid patients: A review of the literature. *Quality Management in Health Care*. 2014;23(4):203-225. doi: 10.1097/QMH.0000000000000043.

17. Trudnak T, Kelley D, Zerzan J, Griffith K, Jiang HJ, Fairbrother GL. Medicaid admissions and readmissions: Understanding the prevalence, payment, and most common diagnoses. *Health Affairs*. 2014;33(8):1337-1344. doi: 10.1377/hlthaff.2013.0632.

18. Billings J, Dixon J, Mijanovich T, Wennberg D. Case finding for patients at risk of readmission to hospital: Development of algorithm to identify high risk patients. *BMJ*. 2006;333:327-330. doi: 10.1136/bmj.38870.657917.AE.

19. Center for Medicare and Medicaid Services. CMS guidance: Diagnosis, procedure codes. https://www.medicaid.gov/medicaid/data-and-systems/macbis/tmsis/tmsis-blog/entry/51965 Web site. Updated 2020. Accessed 08-01-2021.

20. Stroup WW. *Generalized linear mixed models: Modern concepts, methods, and applications.* CRC Press; 2012.

21. Durrleman S, Simon R. Flexible regression models with cubic splines. *Statistics in Medicine*. 1989;8(5):551-561. doi: 10.1002/sim.4780080504.

22. Hastie T, Qian J, Tay K. An introduction to glmnet. http://glmnet.stanford.edu/articles/glmnet.html. Updated 2023. Accessed 07-17-2023.

23. Harrell FE, Lee KL. Regression modeling strategies for improved prognostic prediction. *Statistics in Medicine*. 1984;3:143-152.

24. Sud M, Yu B, Wijeysundera HC, et al. Associations between short or long length of stay and 30-day readmission and mortality in hospitalized patients with heart failure. *JACC. Heart failure*. 2017;5(8):578-588. doi: 10.1016/j.jchf.2017.03.012.

25. Kansagara D, Englander H, Salanitro A, et al. Risk prediction models for hospital readmission: A systematic review. *JAMA*. 2011;306(15):1688-1698. doi: 10.1001/jama.2011.1515.

26. Philbin EF, Disalvo TG. Prediction of hospital readmission for heart failure: Development of a simple risk score based on administrative data. *Journal of the American College of Cardiology*. 1999;33(6):1560-1566. doi: 10.1016/s0735-1097(99)00059-5.

27. Billings J, Mijanovich T. Improving the management of care for high-cost Medicaid patients. *Health Affairs*. 2007;26(6):1643-1654. doi: 10.1377/hlthaff.26.6.1643.

28. Krumholz HM, Chen Y, Wang Y, Vaccarino V, Radford MJ, Horwitz RL. Predictors of readmission among elderly survivors of admission with heart failure. *American Heart Journal*. 2000;139:72-77.

29. Ash AS, Ellis RP, Pope GC, et al. Using diagnoses to describe populations and predict costs. *Health Care Financing Review*. 2000;21:7-28.

30. Ku L, Ferguson C. Medicaid works: A review of how public insurance protects the health and finances of children and other vulnerable populations. *George Washington University Department of Health Policy, and First Focus*. 2011.

31. Romero-Brufau S, Wyatt KD, Boyum P, Mickelson M, Moore M, Cognetta-Rieke C. Implementation of artificial intelligence-based clinical decision support to reduce hospital readmissions at a regional hospital. *Appl Clin Inform*. 2020;11(04):570-577. doi: 10.1055/s-0040-1715827.

32. Wu CX, Suresh E, Phng FWL, et al. Effect of a real-time risk score on 30-day readmission reduction in Singapore. *Appl Clin Inform*. 2021;12(02):372-382. doi: 10.1055/s-0041-1726422.

33. Kripalani S, Theobald CN, Anctil B, Vasilevskis EE. Reducing hospital readmission rates: Current strategies and future directions. *Annual Review of Medicine*. 2014;65(1):471-485. doi: 10.1146/annurev-med-022613-090415.

34. Jackson SL, Tong X, King RJ, Loustalot F, Hong Y, Ritchey MD. National burden of heart failure events in the United States, 2006 to 2014. *Circulation: Heart Failure*. 2018;11(12):e004873. doi: 10.1161/CIRCHEARTFAILURE.117.004873.

35. Yun J, Filardo G, Ahuja V, Bowen ME, Heitjan DF. Predicting hospital readmission in Medicaid patients with diabetes using administrative and claims data. *American Journal of Managed Care*. 2023;29(8). doi: 10.37765/ajmc.2023.89409.

Table 1. Candidate predictors of readmission.

Type of variable	**Variable**
Demographics	Age Sex US state
Previous claims	Past diagnoses (comorbidity) Number of admissions in previous 12 months Number of emergency room visits in previous 12 months
Index hospitalization	Admission type (emergency or non-emergency) Heart failure type Length of stay Discharge code
Admission diagnoses	Admission diagnosis group Main diagnosis group

Table 2. Summary of Medicaid data on patients with heart failure from seven US states.

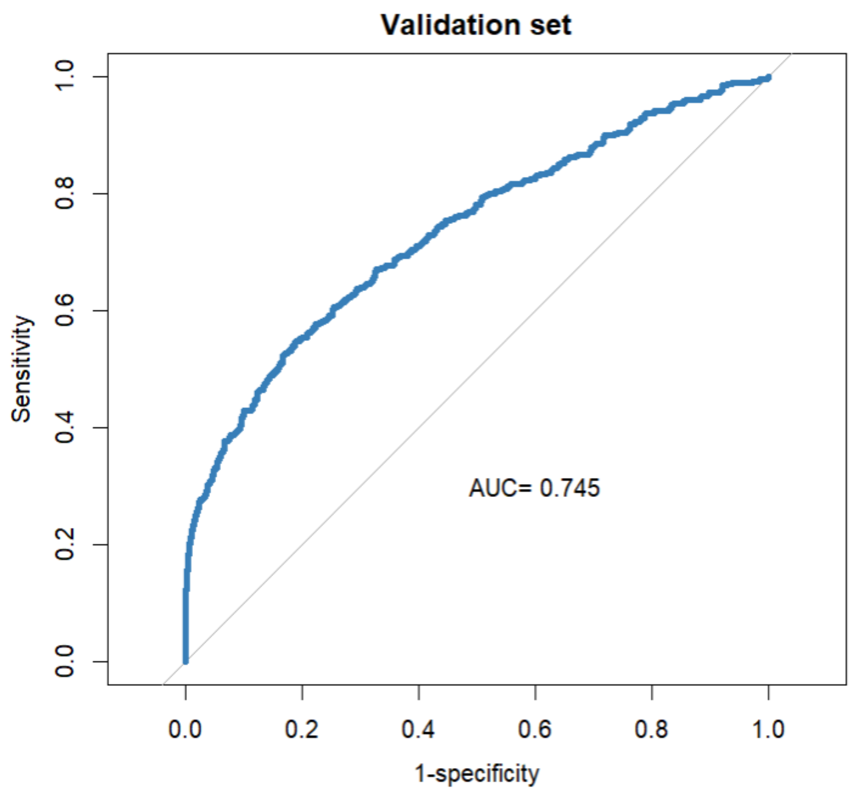
State	CO	FL	GA	IN	KY	NV	OH	Total
Patients	1,921	461	148	149	788	1,925	1,467	6,859
Claims	2,707	493	197	168	1,101	2,777	1,893	9,336
Age[a]	56 (47–62)	53 (43–60)	41 (35–48)	53 (42–59)	56 (49–63)	55 (47–60)	56 (49–61)	55 (47–61)
Female (%)	41.6	31.7	87.8	42.3	53.3	38.8	54.1	45.2
Readmit (%)	32.4	18.5	17.8	11.9	27.2	33.7	21.6	28.6
LoS[b]	5.6	6.8	5.0	6.1	5.8	6.2	6.0	6.0
Previous admissions[c]	7.5	1.4	1.5	0.8	2.5	3.3	3.1	4.2
Previous ER visits[d]	8.1	2.7	4.7	1.8	4.5	5.3	6.7	6.1
Discharged to an institution (%)	7.4	19.7	0.5	8.9	10.9	11.2	9.7	9.9
Emergent or urgent type admissions	92.0	95.3	93.9	86.9	86.5	88.4	90.3	90.1

[a]Median (1st quartile – 3rd quartile)
[b]Average length of stay.
[c]Average number of admissions in 12 months preceding the index claim.
[d]Average number of emergency room visits in 12 months preceding the index claim.

Table 3. Final prediction model.

Type of variable	Variable	Odds ratio (95% CI)
Demographic	Age	0.98 (0.98,0.99)
Previous claims	# admits last 12 months	1.15 (1.13,1.17)
	# emergency room visits last 12 months	1.00 (0.99,1.01)
Length of stay	LoS spline	See Figure S3
Discharge code (reference is discharged home)	Discharged to an institution	1.68 (1.39,2.02)
Admission type (reference is emergency)	Non-emergency	0.78 (0.63,0.95)
US state of claim (reference is Colorado)	Florida	0.80 (0.58,1.10)
	Georgia	0.89 (0.56,1.40)
	Indiana	0.50 (0.27,0.92)
	Kentucky	1.27 (1.02,1.58)
	Nevada	1.41 (1.19,1.68)
	Ohio	0.80 (0.66,0.97)
Past diagnosis (reference is absence of the condition)	Blood disorders	1.21 (1.03,1.42)
	Cardiac arrhythmia	1.05 (0.92,1.20)
	Chronic lower respiratory diseases	1.13 (0.99,1.28)
	Health services for specific procedures	1.07 (0.94,1.22)
	Hemolytic anemia	1.18 (1.03,1.34)
	Ischemic heart disease	1.06 (0.93,1.21)
	Obesity	0.89 (0.79,1.01)
	Renal failure	1.30 (1.13,1.49)
	Sepsis	1.09 (0.96,1.25)

Figure 1. The ROC curve for the final prediction model.



SUPPLEMENTAL MATERIAL

Predicting readmission in Medicaid patients hospitalized for heart failure using administrative and claims data

Supplemental Figure Legends

Supplemental Figure 1. Schematic of extraction of the data set.
Supplemental Figure 2. Observed versus expected plot showing deciles of 30-day readmission predicted probability.
Supplemental Figure 3. Linear splines for length of stay in the prediction model.

Figure S1. Schematic of extraction of the data set.

- Identify heart failure patients with

1. admission ICD-10 codes
2. clinical diagnosis ICD-10 codes

- Collect admissions from heart failure patients from CO, FL, GA, IN, KY, NV, OH (2017-2019) (n=142,530)

↓

- Choose index admissions whose billing type indicates institutional inpatient hospitalization with admission and discharge date (n = 133,443)

↓

- Delete index admissions whose discharge code indicates in-hospital death or transfer to a short-term general hospital, another type of institution not defined in the Medicaid code list, a Critical Access Hospital, or hospice care (n = 79,931)

↓

- Delete index admissions with post-discharge eligibility less than 30 days (n = 72,461)

↓

- Retain index admissions of type emergency, elective, urgent, trauma, etc. (n = 72,438)

↓

- Retain index admissions whose heart failure diagnosis appear as either the admission diagnosis or the first or second clinical (discharge) diagnosis. (n = 9,336)

Figure S2. Observed versus expected plot showing deciles of 30-day readmission predicted probability. The diagonal line indicates where the points would lie in a perfectly calibrated model.

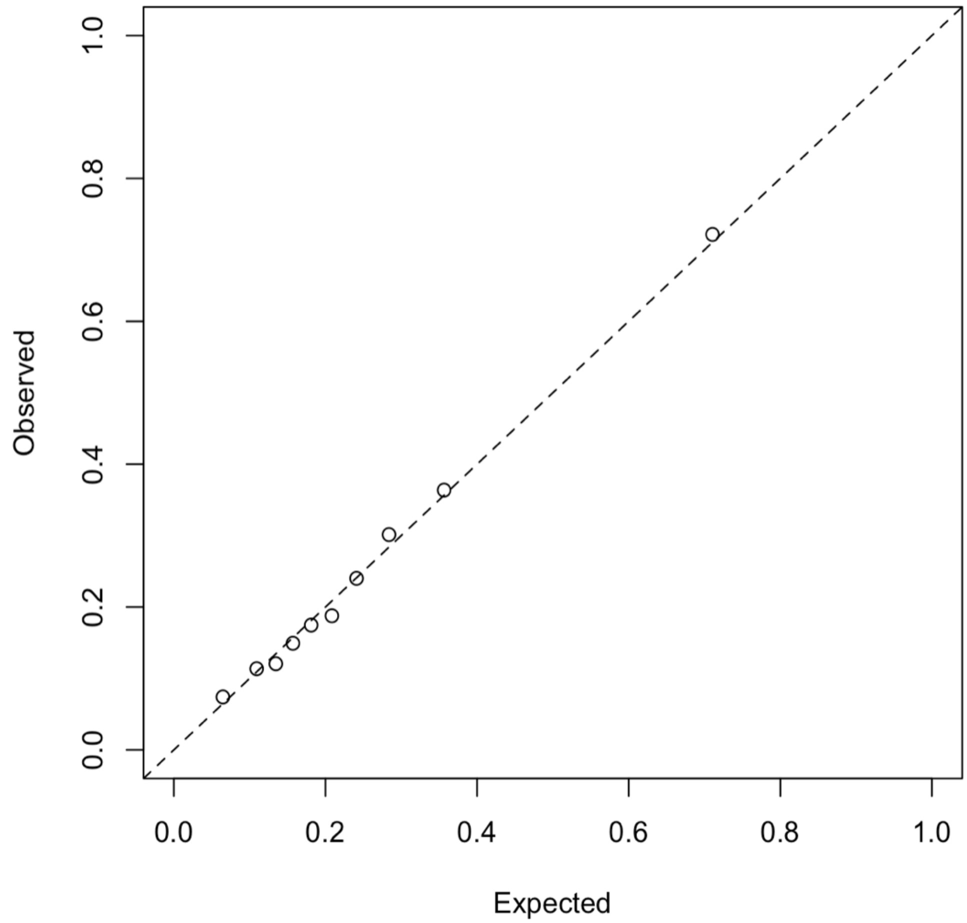
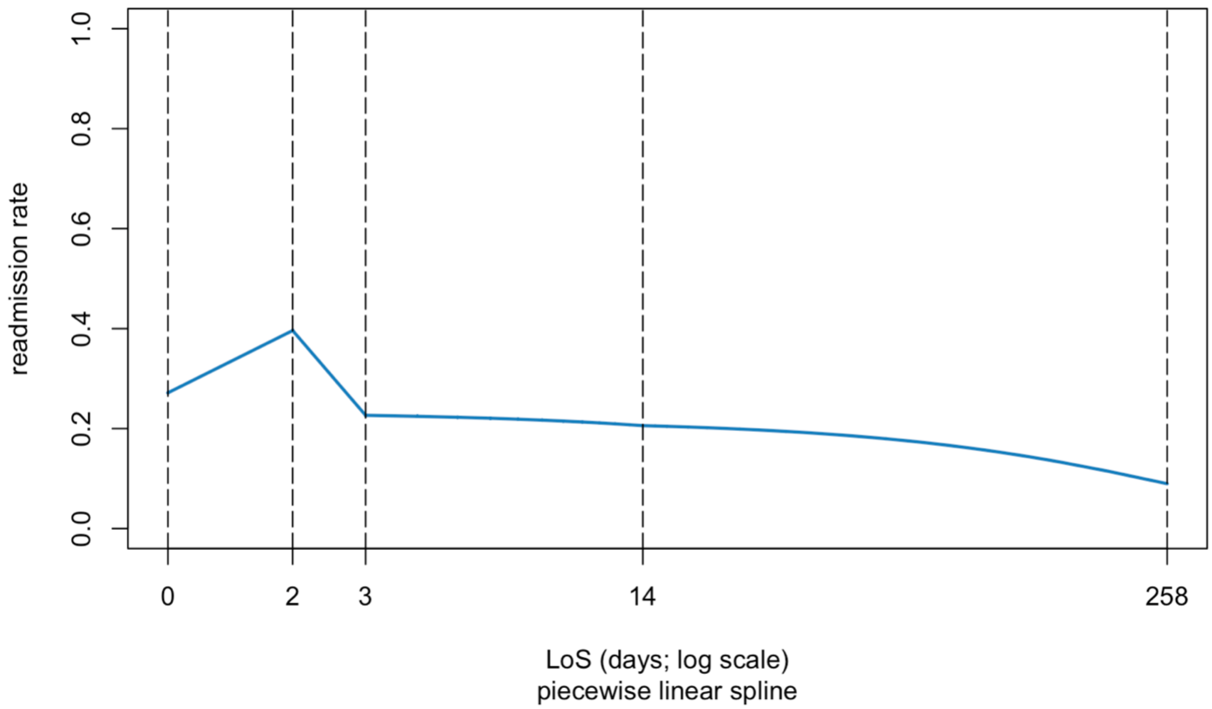


Figure S3. Linear splines for length of stay in the prediction model.



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Prediction of Electronic Health Record Documentation Compliance Using Machine Learning

By Alaa Fathi Al Habib and Hana Mohammed Alharthi, PhD

Abstract

A critical aspect of a high-quality continuum of patient care is health record documentation. Prediction of poor documentation of electronic health records (EHRs) will help identify physicians who may need early communication to ensure their compliance. Machine learning (ML), a subfield of artificial intelligence, can be used to predict which physicians are non-compliant with health record documentation in an effort to provide high- quality healthcare in the continuum of care and treatment.

Objectives: To employ artificial intelligence tools based on ML classifiers to predict which physicians are likely to be non-compliant with completion of health record documentation in the EHR system. Also, to identify factors affecting the completeness of EHR documentation.

Methods: The information from 90,007 discharged health records was obtained from the EHR system between January 2015 and August 2021, which included physician age, gender, department, and nationality; year of discharge; and patient insurance type. Several ML classifiers in Orange software were used to predict health record documentation completion. Random forest, K-nearest neighbor (KNN), support-vector machines (SVM), neural network, naïve Bayes, logistic regression and AdaBoost are the seven machine learning tools that were employed to test the data's prediction performance. These classifiers were used to create the best-fit model to predict documentation completeness.

Results: The best-fit model was the random-forest classifier, with AUC = 0.891 and F1 and Recall score = 0.831. Attributes found to be contributing to EHR documentation compliance are year of patient discharge, physicians age group and the department, respectively.

Conclusion: We demonstrate that the random-forest classifier helps hospital management identify physicians who might not complete EHR documentation. This knowledge can be applied to early-intervention methods to ensure that physicians at risk of not completing EHRs become compliant in an effort to enhance documentation adherence for overall improved patient-care quality and continuum of healthcare.

Key words: Documentation, Electronic health record, Machine learning, Quality of patient care.

Introduction

Worldwide, electronic health records (EHRs) and the use of electronic documentation are preferred because they decrease errors. The aim of EHRs is to enhance the healthcare providers' clinical documentation and decrease the possibility of poor documentation, thereby enhancing the quality and safety of patient care[1]. Inconsistency and discrepancy in inpatient health records affect the treatment provided to the patient[2]. Therefore, a critical aspect of a high-quality continuum of patient care is health record documentation.

Incomplete documentation of discharge notes affects the transfer of older patients from hospital to home care[3]. Moreover, effective communication of discharge documentation between healthcare providers improves patient outcomes and enhances healthcare provider satisfaction[4]. High rates of hospital readmissions are associated with incomplete discharge summaries[5]. Incomplete clinical documentation and delays in writing discharge summaries are associated with unplanned hospital readmissions[6].

Machine learning (ML) is a part of artificial intelligence whereby computers use a large set of data to identify the relationships between variables by computing algorithms[7,8]. It is an automated method to analyze data in which algorithms are used to develop models to predict an output variable based on input variables.

ML models have been applied to a variety of medical problems to discover new patterns in existing data[9]. It has been used to predict radiation pneumonitis in lung cancer patients[10], the hospital length of stay at the time of admission[11] and surgical site infection after neurosurgical operations[12]. Moreover, ML has been used to predict readmissions for heart failure patients[13] and the amputation rate for patients with diabetic foot ulcers[14].

The development of accurate prediction models depends greatly on the presence of complete documentation in patients' EHR[15]. ML models were used to identify opioid misuse and heroin use (OM) patients from paramedic trip notes[16]. They have also been used to detect the keywords "naloxone," "heroin," and both combined to identify the true cases of OM. It was also used to predict the documentation of serious illness based on physician notes within 48 hours of intensive care unit admissions for seriously ill patients[17].

Currently, the use of ML to assess predictive results in relation to health record documentation completion is rare: few researchers have evaluated ML and health record documentation in relation to specific variables[18].

Some physicians are not compliant in completing health record documentation, and hospitals may or may not have policies in place to ensure completion of such records. In this study, we employed ML to help hospital decision makers improve documentation compliance to enable physicians to comply with system health record documentation. We focused on creating a prediction model using ML classifiers to predict which physicians will not complete EHR documentation in the system.

In the hospital understudy, when a patient is admitted to the hospital, the hospital staff completes admission documentation, which includes administrative and clinical information. A physician determines whether the patient is ready for discharge and if so, will complete the admission and discharge documentation in the EHR system. The current problem is in completing the final diagnosis in admission and discharge documentation (Figure 1). This is considered one of the main pieces of documentation that the physician needs to complete. Incomplete documentation impacts continued health support of patients and might affect their safety. Also, it impacts hospitals' accreditation status because it is one of the accreditation standards.

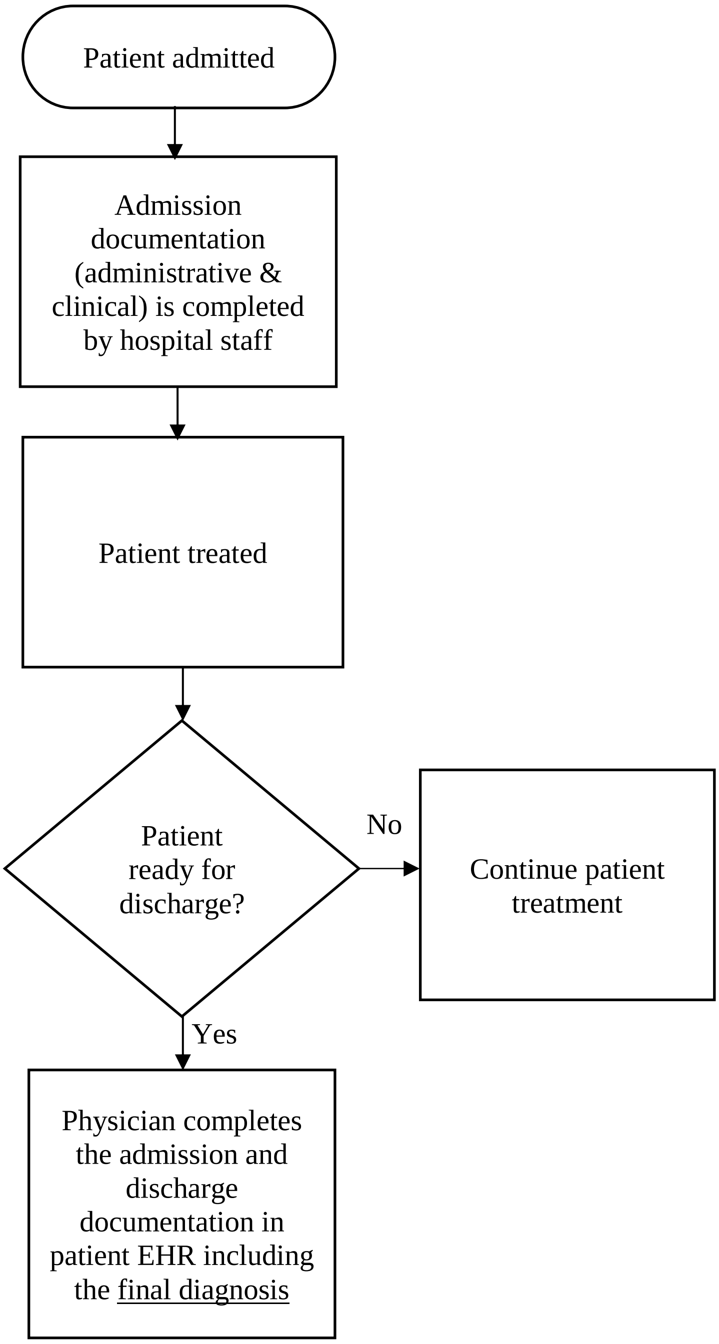


Figure 1. Workflow model for documentation process (current problem).

Material and Methods

Study location and parameters

This study is an experimental study that was conducted at a government hospital in Dammam City, Saudi Arabia. The data included one target variable, the completion of the electronic health record documentation, with two values (1,0) as well as six additional variables: clinical department; the physician's gender, age, and nationality; the year of discharge; and the patient's insurance type (Table 1).

Table 1. Health record documentation completion variables extracted to build the models.

Feature	Value	Data Type	Number of Category
Health record documentation completion	1= Complete 0= Incomplete	Categorical	2
Department	Department name	Categorical	33
Age	Age group of the physicians (30-39, 40-49, 50-59, >60)	Categorical	4
Gender	Male, female	Categorical	2
Nationality	Saudi, Syrian, Egypt, French, Greece, Indian, Jordan, Other Asian, Pakistan, Sudanese.	Categorical	10
Year of Discharge	2015, 2016,2017, 2018, 2019, 2020, 2021.	Categorical	7
Patient insurance type	Governmental, private	Categorical	2

Ethical statement

Human subject research was conducted with approval from the governmental hospital's Institutional Review Board, approval number H- 05- D- 107. The Institutional Review Board at Imam Abdulrahman bin Faisal University also approved the study on November 10, 2021, approval number IRB-PGS-2021-03-422. No consent was required because we aimed to develop a prediction model based only on physicians' variables.

Analysis
The software used in this data analysis was Orange, which is component-based visual-programming software for data visualization, ML, data mining and data analysis. The first step was retrieving the data for all patients who were discharged during the last seven years, from 2015 to 2021, and extracting it to an Excel sheet.

Rank feature in Orange software was used to demonstrate the most contributing factors to the clinical documentation completion.

The project methodology included several steps: data pre-processing, model development and model evaluation.

Data pre-processing
The data for all discharged patients was extracted from the hospital's health information system database to an Excel sheet. Patients discharged from January 2015 to August 2021 were included in the study. The data included 106,246 samples, which included 16,239 duplicate values. The duplicates were eventually removed using the "remove duplicates" tool in Excel, so the final data analyzed included 90,007 samples. The data included one target variable, the completion of the EHR documentation, with two values (1, 0) as well as six additional variables: clinical department; the physician's gender, age, and nationality; the year of discharge and the patient's insurance type (Table 1).

Developing the learning models
Orange version V3.31.1 was used to build the prediction model. Descriptive statistics for the study features were analyzed using IBM SPSS software version 28.0.1.1 (14). To develop the predictive models, seven classifiers in Orange software were used: random forest, KNN, AdaBoost, neural network, naïve Bayes, logistic regression and SVM.

The random-forest classifier produces a set of decision trees. Every tree is created from a small sample from the training data. When the classifier makes an individual tree, a random subset of attributes is drawn, and then the best attribute is selected[19]. KNN uses an algorithm to discover the closest training examples in features and uses the average to form the prediction[20]. AdaBoost is an algorithm that combines weak learners randomly selected from the dataset to make a strong learner[19]. Neural network is an ML model derived from the human brain. A typical neural network has an input layer, hidden layers and an output layer with different weights between layers and nodes[21]. Naïve Bayes is based on the Bayes theorem, in which the variables are assumed to be independent. It is a probabilistic classifier that calculates each variable independently against the target class[20]. Logistic regression is a regression analysis that can be used when the target variable is binary[19]. SVM is a kernel-based supervised learning algorithm that classifies the data into two or more classes. It is particularly designed for binary classification[22]. Table 2 presents a brief description of the various classifiers used in this study with their advantages and disadvantages.

Table 2. Classifiers brief description and their advantages and disadvantages.

#	Classifiers	Brief description	Advantages	Disadvantages
1	**Random Forest**	Random Forest classifier produces a set of decision trees. Every tree is created from a small sample from the training data. When the classifier makes an individual tree, a random subset of attributes is drawn then the best attribute is selected.	1. Used to solve both classification as well as regression problems 2. Less training time with high accuracy 3. Efficient in handling non-linear parameters	1. Complex 2. Change greatly with small change in data
2	**Neural Network**	Neural Network is a machine learning model derived from the human brain. A typical neural network has an input layer, hidden layers, and an output layer with different weights between layers and nodes.	1. Strong in representing complex data 2. Good presenting nonlinear relationships between input and output features	1. Complex 2. Data dependant
3	**AdaBoost**	AdaBoost is an algorithm that combines weak learners randomly from the dataset to make a strong learner.	1. Simple to implement 2. Handle both text and numeric data 3. Reduces bias and variance	1. Sensitive to missing values and outliers 2. Exposed to noisy data When weak classifier underperforms, the whole model may fail
4	**KNN**	KNN K- Nearest Neighbour uses an algorithm to discover the closest training examples in features and uses the average to form the prediction.	1. No training period 2. Very easy to implement 3. New data can be added seamlessly which will not impact the accuracy of the algorithm	1. Does not work well with large dataset 2. Sensitive to missing values and outliers

5	**SVM**	SVM support-vector machine is a kernel-based supervised learning algorithm that classifies the data into two or more classes. SVM is particularly designed for binary classification.	1. Handles non-linear data efficiently 2. Used to solve both classification as well as regression problems	1. Long training time 2. Difficult to interpret
6	**Logistic Regression**	Logistic Regression is a regression analysis that can be used when the target variable is binary.	1. Easy to use 2. Simple to implement 3. Perfect fitting on linearly separable datasets 4. Overfitting can be reduced by regularization	1. Effected by outliers 2. Boundaries are linear 3. Assumes the data is independent
7	**Naïve Bayes**	Naïve Bayes is based on Bayes Theorem, where the variables are assumed to be independent. It is a probabilistic classifier that calculates each variable independently against the target class.	1. Used small amount of training data 2. Training time is less 3. Easy to implement 4. Mainly targets the text	1. Does not take into account the number of occurrences of each data. 2. Assumes that all predictors are independent

Model Evaluation

Model evaluation is an important phase in model development. It explains how well a given classifier is performing. In our data, the target variable was slightly imbalanced, with 60.76 percent for complete documentation and 39.23 percent for incomplete documentation.

Stratified five-folds was used in cross-validation because it is the default parameter shown in Orange. The confusion matrix allows for the identification of misclassified cases or those that are truly classified. With the test and score feature in Orange, the classifiers were evaluated for prediction performance through cross-validation and the area under curve (AUC) score because the accuracy was compared across all classifiers. Performance metrics included AUC as a measurement of the classifier's ability to distinguish between classes. Higher AUC scores indicate better classifier ability to distinguish between true positives and true negatives. Classification accuracy (CA) is the number of correctly predicted values divided by the number of predictions made: Accuracy = (TN+TP) / (TP+FP+TN+FN). Recall returns the proportion of positive values correctly predicted, which is used to calculate the true positive rate: Recall= TP / (TP + FN). On the other hand, the false-positive rate = FP / (TN + FP). Specificity returns the proportion of negative values correctly predicted: Specificity = TN / (TN + FP). In addition, precision returns the true positives among all the values predicted to be positive: Precision = TP / (TP + FP). Finally, the F1 score is the harmonic mean of precision and recall. It is often used to compare classifiers. F1 score = (2 × Precision × Recall) / (Precision + Recall).

Results

The dataset of 90,007 discharged health records showed 60.8 percent of the final diagnoses in form A were completed and 39.2 percent were not. Male physicians discharged 83.7 percent of the discharged health records, 73.2 percent of the physicians were Saudis, and 59.7 percent were between the ages of 50 and 59. The internal-medicine department had the most discharges, with 22.0 percent. Also, the most discharges occurred in 2019, with 16.2 percent. Most of the discharged patients, 90.1 percent, were on government insurance (Table 3).

Table 3. Result of the descriptive statistics of the study variables.

	Variable	Frequency	Percent (%)
Health record documentation completion	0	35316	39.2
	1	54691	**60.8**
Gender	Female	14710	16.3
	Male	75297	**83.7**
Nationality	Egypt	8043	8.9
	French	1049	1.2
	Greece	1028	1.1
	Indian	1012	1.1
	Jordan	2511	2.8
	Other Asian	32	.0
	Pakistan	1219	1.4
	Saudi	65865	**73.2**
	Sudanese	285	.3
	Syrian	8963	10.0
Age Group	30-39	6436	7.2
	40-49	27064	30.1
	50-59	53703	**59.7**
	> 60	2804	3.1
Department	Anesthesiology	477	.5
	Bariatric Surgery	229	.3
	Chest Surgery	747	.8
	Dental – Advanced Restorative	1	.0
	Dental – Maxillofacial Surgery	896	1.0
	Dental- Pedodontics	1864	2.1
	Dentist General	160	.2
	Dermatology	572	.6
	Cardiac	75	.1
	Endocrinology	2867	3.2
	ENT Surgery	4797	5.3
	Gastroenterology	4464	5.0
	General Surgery	17273	19.2
	Hematology	696	.8
	Infectious Diseases	2396	2.7
	Internal Medicine	19835	**22.0**
	Nephrology	3039	3.4
	Neurosurgery	4125	4.6

	Neurology	3167	3.5
	Ophthalmology – General	1624	1.8
	Ophthalmology - Glaucoma	134	.1
	Ophthalmology - Pediatric	883	1.0
	Ophthalmology - Retina	653	.7
	Orthopedic surgery	8777	9.8
	Pediatric	219	.2
	Physical Therapy	1	.0
	Plastic Surgery	2257	2.5
	Psychiatry	78	.1
	Pulmonary	1036	1.2
	Rheumatology	1431	1.6
	Trauma Surgery	278	.3
	Urology	4365	4.8
	Vascular	591	.7
Year of discharge	2015	12138	13.5
	2016	13116	14.6
	2017	12446	13.8
	2018	12990	14.4
	2019	14544	**16.2**
	2020	13308	14.8
	2021	11465	12.7
Patient Insurance	Governmental	81054	**90.1**
	Private	8953	9.9

We used various ML classifiers to predict the clinical-documentation completion. The workflow was executed in Orange (Figure 2). Random forest, KNN, SVM, neural network, naïve Bayes, logistic regression and AdaBoost were the seven ML tools we employed to test the data's prediction performance. We evaluated each classifier's performance using the following metrics: the AUC, accuracy, F1 score, precision and recall. In terms of AUC, the result showed that random forest had the highest performance result, with an AUC of 0.891, followed by AdaBoost and neural network models, both with a score of 0.890, but neural network took longer to run than AdaBoost. Table 4 summarizes the metrics used to compare the classifiers' performance.

When we evaluated AUC metrics, an AUC close to 1 indicated the classifier is the best fit for prediction. The AUC curve (Figure 3) demonstrated the model's reliability, where true positive was the majority when the value of AUC was near 1. The confusion matrix for the random-forest classifier (Table 5) is another indicator of this algorithm's usefulness. The true-positive rate was 86.2% (47,149 / 47,149 + 7,542) = (47,149 / 54,691) and the false positive rate was 21.5% (7,580 / 27,736 +7,580) = (7,580 / 35,316). Therefore, the random-forest classifier was the best-fit model to predict EHR documentation incompleteness. Furthermore, the year of patient discharge was the most contributing attribute to the clinical documentation completion followed by the physicians age group and the department as shown in Figure 4.

Figure 1. Orange Workflow.

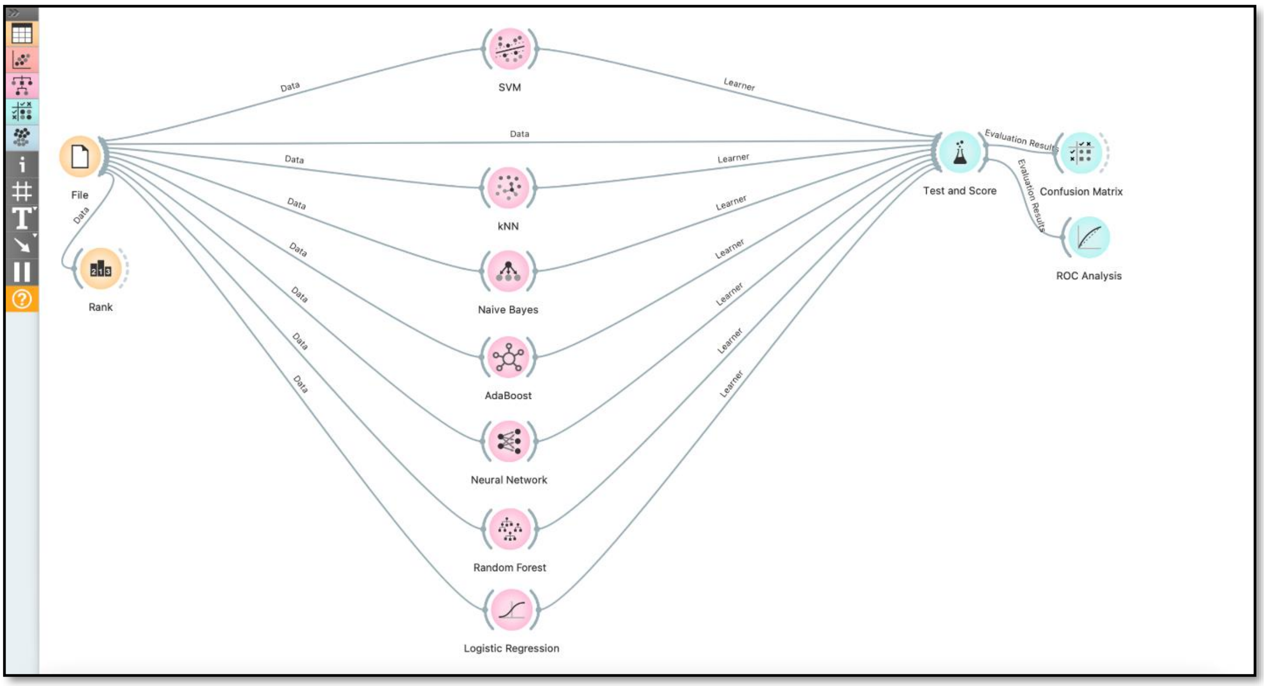


Figure 3. Result of the AUC curve for random forest model using 5-fold cross validation.

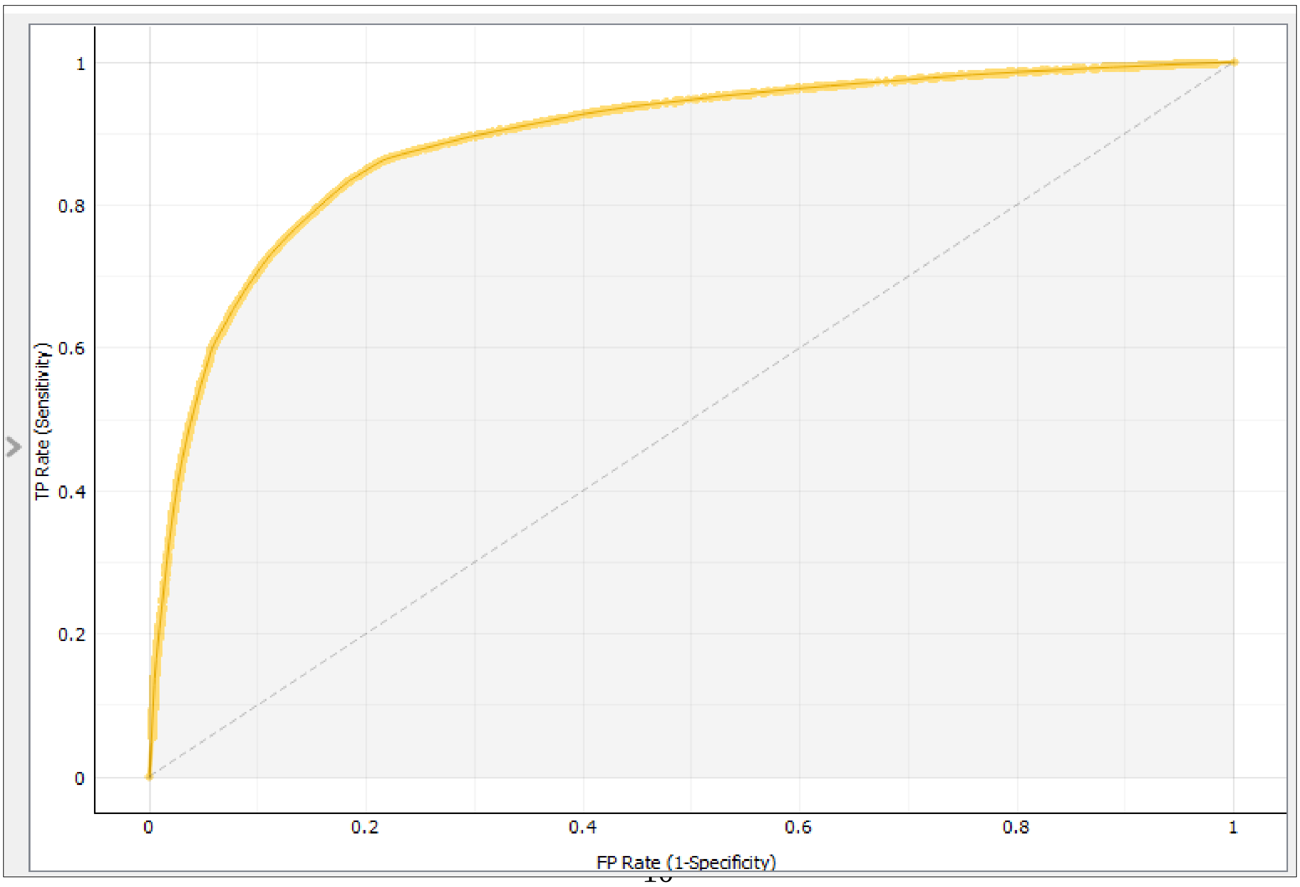
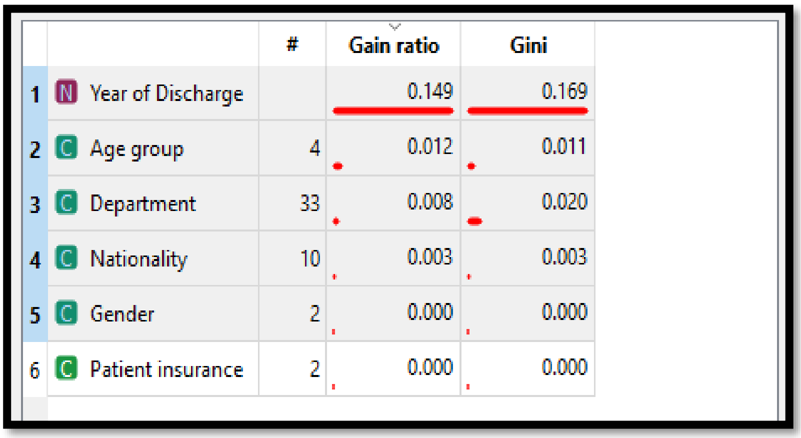


Figure 2. Result of the attributes Ranking.



		#	Gain ratio	Gini
1	N Year of Discharge		0.149	0.169
2	C Age group	4	0.012	0.011
3	C Department	33	0.008	0.020
4	C Nationality	10	0.003	0.003
5	C Gender	2	0.000	0.000
6	C Patient insurance	2	0.000	0.000

Table 4. Summary Results of all Classifiers showing that random forest is the best fit classifier.

Sampling type: Stratified 5- fold Cross validation					
Classifier	**AUC**	**CA**	**F1 score**	**Precision**	**Recall = sensitivity**
KNN	0.853	0.817	0.817	0.817	0.817
SVM	0.495	0.474	0.457	0.549	0.474
Random Forest	0.891	0.831	0.831	0.831	0.831
Neural Network	0.890	0.830	0.830	0.830	0.830
Naïve Bayes	0.842	0.749	0.750	0.751	0.749
Logistic Regression	0.621	0.634	0.579	0.622	0.634
AdaBoost	0.890	0.831	0.831	0.831	0.831

Table 5. Result of the confusion matrix for random forest classifier.

		Predicted		
		0	1	**Sum**
Actual	0	27736 TN (78.5%)	7580 FP (21.5%)	35316
	1	7542 FN (13.8%)	47149 TP (86.2%)	54691
	Sum	35278	54729	**90007**

Discussion

We used ML classifiers to predict which physicians are unlikely to complete EHR documentation. In this study, the AUC showed the random-forest model was the best model to predict completion of EHRs. Researchers have used AUC measurement in ML in multiple studies in the healthcare domain to evaluate various classifiers to predict certain health outcomes[6,9,11-14,23-26]. In various studies using ML, researchers have used clinical documentation in prediction, producing various results. One study showed that random forest was the best-fit model to predict documentation of behavioral change among hypertension patients[9]. However, other studies have shown other classifiers outperformed random forest in prediction. The completion of discharge documentation in pediatrics helped predict the 30-day readmission rate using a Radiant boosted tree classifier[6]. Logistic regression showed the best performance to show paramedic documentation to identify opioid and heroin misuse[16].

The study's ranking outcome facilitated the comprehension of how various factors influence clinical documentation completion. This insight can be used by hospital management to formulate new policies and procedures to enhance documentation adherence and address this problem. Additionally, the prediction module will provide precise determinations about which physicians may have incomplete documentation, enabling the identification of specific issues on an individual basis through alerts or notifications within the EHR system.

Upon utilizing the ranking feature within the Orange software, it became evident that the year of patient discharge held the most significant influence on documentation completion, although it’s worth noting that this may be influenced by the hospital’s accreditation cycle occurring during that year. Subsequently, the age group of physicians and their respective departments were also influential factors. Notably, physicians between the ages of 50-59 accounted for the highest number of major discharges and displayed the highest level of non-compliance. Examining departments, the internal medicine department stood out with the highest number of discharges, yet regrettably, they also exhibited the highest rate of non-compliant documentation. This underscores the importance of additional training and educational sessions to improve their documentation practices. Health record documentation can be improved through policy creation and implementation[27,28]. A study showed significant improvement when changes in health record documentation are measured after documentation policy enforcement[27]. Our findings can help hospital management modify their current policies and procedures related to electronic health documentation to enhance physicians' documentation adherence.

Current policy in the hospital under study states that physicians who are not compliant in completing their clinical documentation within 30 days of patient discharge are subjected to vacation suspension. The process of handling incomplete health record documentation starts two weeks after the patient's discharge. Afterward, a notification is sent by email to the head of department and then to the medical administration. But there is still a problem because a physician may not take vacation for few months; as a result, his/her clinical documentation will still not be completed. All these activities happen after the patient has been discharged.

As a result, our model can impede clinical workflow by sending an alert to the health information management department from the onset of patient admission that this treating physician has a high probability of not completing his/her clinical documentation.

Accordingly, a note is sent to that physician and to the head of department and medical administration at the time of patient admission rather than after patient discharge. This policy modification might help treating physicians adhere to policy and complete their documentation on time. We hope over time, more physicians will become more compliant and the norm will be to complete patients' documentation. This policy modification might lead to better quality control of patients' clinical documentation and improve healthcare outcomes.

Limitations and Future Work

Our study is the first to use ML approaches to predict health record documentation completion in Saudi Arabia. As such, our findings highlight this approach and methodology's relevance as a significant tool in the health information management field to improve the physician's documentation completion through an alert sent to treating physicians who are likely not to complete their EHR documentation at the onset of patient admission. Our study had a few limitations, which could be improved in future studies. Although we studied seven variables, future researchers can expand the number of variables that could increase the prediction accuracy, such as the physician's shift, degree, and years of experience as well as data from private and government hospitals. Although we used seven attributes in this research, our findings showed promising results in the prediction performance regarding documentation completion.

Conclusion

In this study, the main objective was to develop a ML tool to predict which physicians are not likely to complete health record documentation in the EHR system. The results showed that the random-forest classifier achieved high prediction accuracy over the other classifiers with (AUC = 0.891; F1 and recall score = 0.831). Health record documentation is critical to a patient's continuous treatment because it is considered a crucial element of patient care. Our results can help hospital management modify their current policies to enhance physicians' documentation adherence.

References

1. B. McCarthy *et al.*, "Electronic nursing documentation interventions to promote or improve patient safety and quality care: A systematic review," Journal *of Nursing Management*, vol. 27, no. 3, pp. 491–501, 2019, doi: 10.1111/jonm.12727.

2. A. Jacob, R. Raj, S. Alagusundaramoorthy, J. Wei, J. Wu, and M. Eng, "Impact of Patient Load on the Quality of Electronic Medical Record Documentation," *Journal of Medical Education and Curricular Development*, vol. 8, p. 2382120520988597, Jan. 2021, doi: 10.1177/2382120520988597.

3. R. M. Olsen, O. Hellzén, L. H. Skotnes, and I. Enmarker, "Content of nursing discharge notes: Associations with patient and transfer characteristics," vol. 2012, Sep. 2012, doi: 10.4236/ojn.2012.23042.

4. D. T. Coghlin *et al.*, "Pediatric Discharge Content: A Multisite Assessment of Physician Preferences and Experiences," *Hospital Pediatrics*, vol. 4, no. 1, pp. 9–15, Jan. 2014, doi: 10.1542/hpeds.2013-0022.

5. E. H. Hoyer, C. A. Odonkor, S. N. Bhatia, C. Leung, A. Deutschendorf, and D. J. Brotman, "Association between days to complete inpatient discharge summaries with all-payer hospital readmissions in Maryland," *Journal of Hospital Medicine*, vol. 11, no. 6, pp. 393–400, 2016, doi: 10.1002/jhm.2556.

6. H. Zhou *et al.*, "Using machine learning to predict paediatric 30-day unplanned hospital readmissions: a case-control retrospective analysis of medical records, including written discharge documentation," *Aust. Health Review*, vol. 45, no. 3, pp. 328–337, Apr. 2021, doi: 10.1071/AH20062.

7. T. L. Wiemken and R. R. Kelley, "Machine Learning in Epidemiology and Health Outcomes Research," *Annu Rev Public Health*, vol. 41, pp. 21–36, Apr. 2020, doi: 10.1146/annurev-publhealth-040119-094437.

8. N. Noorbakhsh-Sabet, R. Zand, Y. Zhang, and V. Abedi, "Artificial Intelligence Transforms the Future of Health Care," *The American Journal of Medicine*, vol. 132, no. 7, pp. 795–801, Jul. 2019, doi: 10.1016/j.amjmed.2019.01.017.

9. K. Shoenbill, Y. Song, M. Craven, H. Johnson, M. Smith, and E. A. Mendonca, "Identifying Patterns and Predictors of Lifestyle Modification in Electronic Health Record Documentation Using Statistical and Machine Learning Methods," *Prev Med*, vol. 136, p. 106061, Jul. 2020, doi: 10.1016/j.ypmed.2020.106061.

10. J. M. Luna *et al.*, "Predicting radiation pneumonitis in locally advanced stage II–III non-small cell lung cancer using machine learning," *Radiotherapy and Oncology*, vol. 133, pp. 106–112, Apr. 2019, doi: 10.1016/j.radonc.2019.01.003.

11. L. Turgeman, J. H. May, and R. Sciulli, “Insights from a machine learning model for predicting the hospital Length of Stay (LOS) at the time of admission,” *Expert Systems with Applications*, vol. 78, pp. 376–385, Jul. 2017, doi: 10.1016/j.eswa.2017.02.023.

12. T. Tunthanathip, S. Sae-heng, T. Oearsakul, I. Sakarunchai, A. Kaewborisutsakul, and C. Taweesomboonyat, “Machine learning applications for the prediction of surgical site infection in neurological operations,” *Neurosurgical Focus*, vol. 47, no. 2, p. E7, Aug. 2019, doi: 10.3171/2019.5.FOCUS19241.

13. S. B. Golas *et al.*, “A machine learning model to predict the risk of 30-day readmissions in patients with heart failure: a retrospective analysis of electronic medical records data,” *BMC Medical Informatics and Decision Making*, vol. 18, no. 1, p. 44, Jun. 2018, doi: 10.1186/s12911-018-0620-z.

14. P. Xie *et al.*, “An explainable machine learning model for predicting in-hospital amputation rate of patients with diabetic foot ulcer,” *International Wound Journal*, vol. 19, no. 4, pp. 910–918, 2022, doi: 10.1111/iwj.13691.

15. J. P. Ridgway, A. Lee, S. Devlin, J. Kerman, and A. Mayampurath, “Machine Learning and Clinical Informatics for Improving HIV Care Continuum Outcomes,” *Curr HIV/AIDS Rep*, vol. 18, no. 3, pp. 229–236, Jun. 2021, doi: 10.1007/s11904-021-00552-3.

16. J. T. Prieto *et al.*, “The Detection of Opioid Misuse and Heroin Use From Paramedic Response Documentation: Machine Learning for Improved Surveillance,” *J Med Internet Res*, vol. 22, no. 1, p. e15645, Jan. 2020, doi: 10.2196/15645.

17. A. Chan *et al.*, “Deep learning algorithms to identify documentation of serious illness conversations during intensive care unit admissions,” *Palliat Med*, vol. 33, no. 2, pp. 187–196, Feb. 2019, doi: 10.1177/0269216318810421.

18. S. M. Slattery, D. C. Knight, D. E. Weese-Mayer, W. A. Grobman, D. C. Downey, and K. Murthy, “Machine learning mortality classification in clinical documentation with increased accuracy in visual-based analyses,” *Acta Paediatrica*, vol. 109, no. 7, pp. 1346–1353, 2020, doi: 10.1111/apa.15109.

19. G. Shanmugasundar, M. Vanitha, R. Čep, V. Kumar, K. Kalita, and M. Ramachandran, “A Comparative Study of Linear, Random Forest and AdaBoost Regressions for Modeling Non-Traditional Machining,” *Processes*, vol. 9, no. 11, Art. no. 11, Nov. 2021, doi: 10.3390/pr9112015.

20. I. H. Witten, E. Frank, M. A. Hall, and C. Pal, *Data Mining: Practical Machine Learning Tools and Techniques*. San Francisco, UNITED STATES: Elsevier Science & Technology, 2016. Accessed: Jul. 15, 2022. [Online]. Available: http://ebookcentral.proquest.com/lib/uodammam-ebooks/detail.action?docID=4708912

21. X. Qi, G. Chen, Y. Li, X. Cheng, and C. Li, “Applying Neural-Network-Based Machine Learning to Additive Manufacturing: Current Applications, Challenges, and Future Perspectives,” *Engineering*, vol. 5, no. 4, pp. 721–729, Aug. 2019, doi: 10.1016/j.eng.2019.04.012.

22. R. Palaniappan, K. Sundaraj, and S. Sundaraj, “A comparative study of the svm and k-nn machine learning algorithms for the diagnosis of respiratory pathologies using pulmonary acoustic signals,” *BMC Bioinformatics*, vol. 15, p. 223, 2014, doi: 10.1186/1471-2105-15-223.

23. F. Tezza, G. Lorenzoni, D. Azzolina, S. Barbar, L. A. C. Leone, and D. Gregori, “Predicting in-Hospital Mortality of Patients with COVID-19 Using Machine Learning Techniques,” *Journal of Personalized Medicine*, vol. 11, no. 5, Art. no. 5, May 2021, doi: 10.3390/jpm11050343.

24. G. Kong, this link will open in a new window Link to external site, K. Lin, and Y. Hu, “Using machine learning methods to predict in-hospital mortality of sepsis patients in the ICU,” *BMC Medical Informatics and Decision Making*, vol. 20, pp. 1–10, 2020, doi: 10.1186/s12911-020-01271-2.

25. R. Marcinkevics, P. R. Wolfertstetter, S. Wellmann, C. Knorr, and J. E. Vogt, “Using Machine Learning to Predict the Diagnosis, Management and Severity of Pediatric Appendicitis,” *Frontiers in Pediatrics*, vol. 9, Apr. 2021, doi: 10.3389/fped.2021.662183.

26. Y.-T. Lo, J. C. Liao, M.-H. Chen, C.-M. Chang, and C.-T. Li, “Predictive modeling for 14-day unplanned hospital readmission risk by using machine learning algorithms,” *BMC Medical Informatics and Decision Making*, vol. 21, no. 1, pp. 1–11, Oct. 2021, doi: 10.1186/s12911-021-01639-y.

27. A. Thoroddsen and M. Ehnfors, “Putting policy into practice: pre- and posttests of implementing standardized languages for nursing documentation,” *Journal of Clinical Nursing*, vol. 16, no. 10, pp. 1826–1838, 2007, doi: 10.1111/j.1365-2702.2007.01836.x.

28. E. M. Lewiecki *et al.*, “Healthcare Policy Changes in Osteoporosis Can Improve Outcomes and Reduce Costs in the United States,” *JBMR Plus*, vol. 3, no. 9, Sep. 2019, Accessed: Mar. 29, 2022. [Online]. Available: https://www.proquest.com/docview/2307752133/abstract/2EC97084EC42481FPQ/1

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Understanding the Effects of a Modified Theory of Planned Behavior That Includes Privacy and Security on Continuance Intention of Telehealth Services

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Abstract

Most studies in telehealth focus on telehealth availability or use by healthcare systems or providers. Only a few behavioral studies explore determinants of individuals' continuance intention for telehealth.

This study seeks to identify factors that encourage individuals to continue the intention of using telehealth. We extended the Theory of Planned Behavior (TPB) by examining constructs that could identify reasons individuals plan to continue using telehealth including security and privacy.

A cross-sectional survey evaluated the determinants that predicted the continuance intention of telehealth. Responses from 194 individuals were analyzed with Partial Least Squares (PLS) Structural Equation Modeling. Perceived usefulness, security, attitudes, privacy, and subjective norms were important predictors of the continuance intention of telehealth. Conversely, perceived behavioral control did not influence the continuance intention of telehealth.

The extended TPB model predicted an individual's continuance intention of telehealth. Healthcare professionals can use these results to address individuals' telehealth privacy and security concerns and improve their perceptions of the usefulness of telehealth. Privacy and security concerns create barriers to telehealth use that must be reduced to facilitate repeated telehealth usage in future healthcare settings.

Keywords: Telehealth; Theory of Planned Behavior (TPB); privacy; security, usefulness

Introduction

Initially, telehealth use was primarily limited to facilitating medical care in rural and underserved areas. Pre-COVID-19, telehealth use expanded with the shift to patient and quality outcomes as well as cutting costs.[1] During the COVID-19 pandemic, telehealth visits were often the choice for most routine physician visits. Bestsennyy, Gilbert, Harris and Rost [2] indicated that telehealth use increased from 19 percent pre-COVID-19 to 46 percent during the pandemic. Kaiser Family Foundation [3] predicts that telehealth usage in the United States (US) will continue in the post-COVID-19 era.

According to Medicaid.Gov [4] telehealth provides a low-cost, convenient alternative to face-to-face office visits. Telehealth use increases provider access, reduces travel costs and wait times, and improves continuity of care.[5] Other researchers projected a potential $200 billion reduction in the cost of healthcare from the use of telehealth to manage chronic disease via remote monitoring of medical devices.[6]

However, many barriers to telehealth adoption exist including those related to users' concerns about their healthcare data privacy and security,[7] and the usefulness of telehealth.[8] Most research studies on telehealth have concentrated on availability, telehealth use by healthcare systems, or telehealth use by healthcare providers. Few behavioral studies explore determinants of the individual's intention to use or continuance intention of telehealth. The purpose of this study was to explore factors that can encourage individuals to use telehealth by identifying individuals' telehealth concerns and improving their perceptions of the usefulness of telehealth.

Background

Theory of Planned Behavior

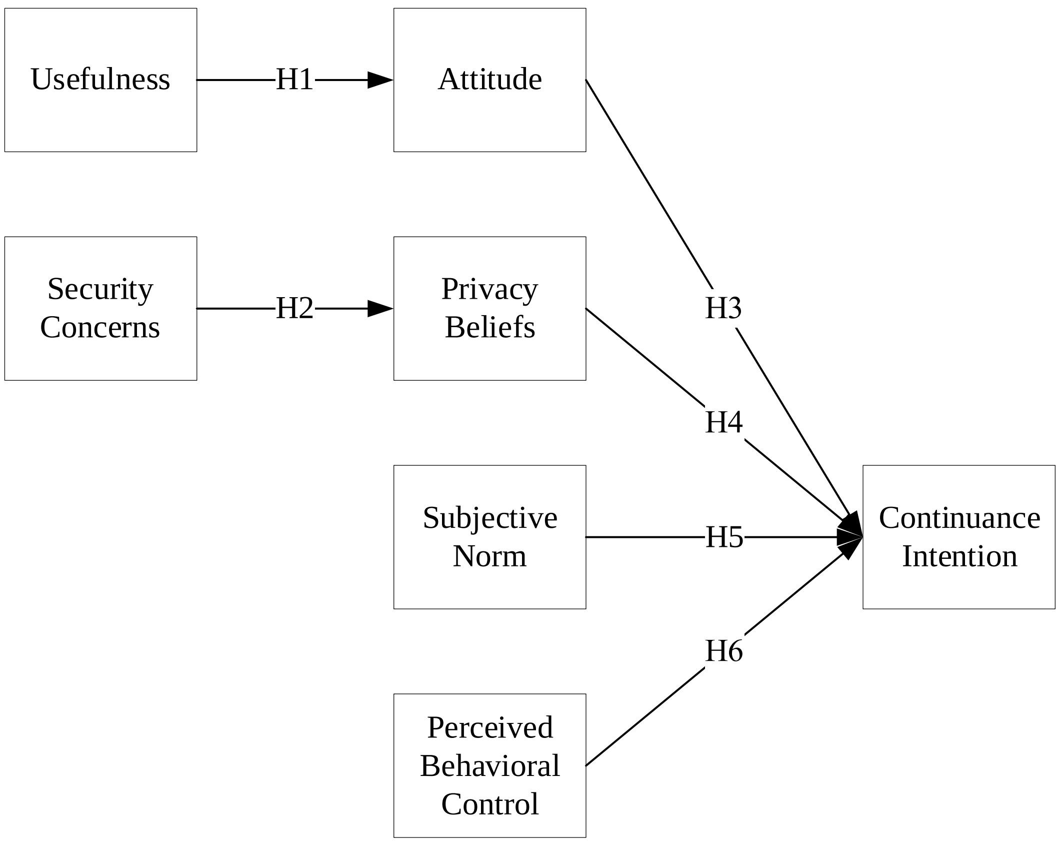
TPB is based on the social cognitive Theory of Reasoned Action (TRA). Ajzen and Fishbein [9] introduced the TRA to assess what motivates an individual to behave in a certain manner based on their intention, attitudes, and subjective norms. According to TRA, an individual's actions are influenced by their intention to act. The individual's intentions are determined by their attitude, which is their belief that the outcome will be favorable or beneficial, and by the level of "social pressure" (subjective norm) compelling them to complete the task.

Ajzen [10] added perceived behavioral control to the TRA resulting in the TPB. The TPB has been used to explore the pathways among attitude, perceived behavior control, subjective norms, and the intention to use various healthcare systems. Bell [11] predicted the intention to use a web-based medical appointment scheduling system at a primary care medical clinic with the TPB. During the COVID-19 pandemic, Ramírez-Correa, Ramírez-Rivas, Alfaro-Pérez and Melo-Mariano [12] used the TPB to predict the intention to use telemedicine. TPB is suitable for this study because one purpose of the study is to explore the determinants of an individual's continuance intention of telehealth. While individuals may adopt technology, their continuance intention is a better measure as it determines their decision to sustain that use of the technology rather than just using it once or only when required.[13] For example, Wang, Wang, Liang, Nuo, Wen, Wei, Han and Lei [13] identified antecedents to the continuance intention of mHealth in their metanalysis/systematic review. We believe it is important to ensure that individuals are going to continue to use the tool (continuance intention) rather than a one- or two-time use as required by an event such as the COVID-19 pandemic.

Hypothesis Development

In a novel approach, we extended the TPB model by incorporating usefulness, privacy beliefs, and security concerns into the model to determine how these constructs impact the causal pathways shown in Figure 1. Few studies have included these constructs in theoretical models for the continuance intention of telehealth.

Figure 1. Model for Continuance Intention of Telehealth



Chau and Hu [8] found that usefulness positively affected attitudes when exploring the adoption of telehealth by healthcare professionals. Hsieh et. al [14] concluded that usefulness had a positive effect on attitudes toward the adoption of adoption electronic health record exchanges. Thus, we add the hypothesis:

H1: Usefulness positively influences an individual's attitude toward using telehealth services.

Security concerns are the unease that one feels about whether their protected health information is vulnerable to risks that could disclose the information and whether protective actions are taken to guard against these threats. [15] Privacy is defined as an individual's belief that their protected health information will only be accessed by those with a "need to know." [16,17] Several prior researchers determined that security directly impacted an individual's intent to adopt m-payment systems. [18] Both Kisekka et al. [19] and Moqbel, Hewitt, Nah and McLean [15] determined that security concerns negatively impacted an individual's intention to use an e-health portal. Other researchers noted that security impacted privacy when exploring physicians' willingness to adopt telehealth.[20] For example, Elkefi and Layeb [7] investigated the benefits and challenges of telemedicine adoption for patients and caregivers after the COVID-19 pandemic and determined that security and privacy were important when studying the usability of telehealth tools. Smith, Smith, Kennett and Vinod [21] found technology barriers, including security concerns, when evaluating the telehealth use of cancer patients. Houser, Flite and Foster [22] recognized security as a challenge using telehealth. This study measured security as a risk that would be perceived as having a negative influence on an individual's continuance intention of telehealth.[15]

Thus, we propose the following hypothesis:

H2: Perceived security concerns negatively influence an individual's privacy concerns about telehealth.

Attitude is present in the original TPB. Attitude refers to whether an individual feels that the outcome will favor them. Ramírez-Correa, Ramírez-Rivas, Alfaro-Pérez and Melo-Mariano [12] established that the TPB significantly predicted behavioral intention to use telehealth, with attitude having the strongest influence on behavioral intentions. Using the TPB, Kisekka, Goel and

Williams [19] determined that the strongest predictor of intent to use an e-health portal was attitude. Thus, we posit the following hypothesis:

H3: Attitude positively influences an individual's continuance intention of telehealth services.

Privacy concerns negatively impact an individual's intention to use an e-health portal.[19] Pool, Akhlaghpour, Fatehi and Gray [23] determined that elderly patients were less likely to adopt and use telehealth due to privacy concerns. Hirani, Rixon, Beynon, Cartwright, Cleanthous, Selva, Sanders and Newman [24] found that expressed privacy concerns affected whether individuals with chronic conditions used telemedicine. Zhang, Guo, Guo and Lai [25] found that privacy concerns positively impacted usefulness. While these studies explore how privacy impacts one's use of telehealth, we believe that privacy beliefs will directly impact whether an individual will continue to use telehealth and will test the following hypothesis.

H4: Privacy beliefs positively influence an individual's continuance intention of telehealth.

Subjective norms are the social pressures that induce individuals to take actions that meet with the approval of their peers or the approval of society. Thus, if an individual believes that society approves of their intended actions, they are more likely to perform those actions. Kisekka, Goel and Williams [19] used the TPB and determined that subjective norms strongly predicted the intention to use telehealth. Ramirez-Rivas, Alfaro-Perez, Ramirez-Correa and Mariano-Melo [26] determined that subjective norms strongly influenced the intention to use telemedicine. Thus, we add this hypothesis:

H5: Subjective norm positively influences an individual's continuance intention of telehealth services.

Ajzen [10,]Ajzen [27] suggested that perceived behavioral control impacted the intent to perform different behaviors. Self-efficacy represents “beliefs in one’s capabilities to organize and execute the courses of action required to produce a given attainment.” [28] Often used in the TPB, perceived behavioral control is defined as “a person’s perception of the ease or difficulty of performing the behavior of interest.” [9] Researchers have determined that self-efficacy influences perceived usefulness when examining the intention to use internet banking [30] or mobile payment systems. We posit that perceived behavior control influences perceived usefulness. [30-32] Accordingly, we propose the following hypothesis:

H6: Perceived behavioral control positively influences an individual’s perceived usefulness of telehealth.

Methods

This cross-sectional survey study explores the factors influencing individuals' continuance intention of telehealth.

Measures

The measures for usefulness were modified from Davis [33] Privacy and security constructs were altered from studies by Dinev and Hart [34] and the remaining constructs were adapted from prior TPB studies including those by Ajzen [10]

Data collection

After receiving approval from the Internal Review Board, Qualtrics Survey Service provided a panel of individuals who completed the survey utilizing our requirements. The data was collected by Qualtrics in mid-2022. Specifically, we requested survey respondents from a general population of US residents over the age of 18. We requested respondents from only one country (i.e., the US) because residents of other countries may have different perceptions of privacy. Using our specifications, Qualtrics distributed email links to a random sample of their pool who were over age 18 from the US. Qualtrics literature indicates they take steps to prevent selection bias by following up with non-responsive participants. No identifiable information was collected from the participants. The anticipated demographics were a random sample of US residents. We obtained informed consent by using a click online button within the Qualtrics survey.

Statistical Analysis

The survey construct data was analyzed using Smart PLS (Partial Least Squares) 4.0 because our predictive model was comprised of latent variables.[35] Demographic data was analyzed with R statistical software version 4.1.2.[36] The response rate is unknown. There were 194 valid responses from individuals over age 18 and living in the US that were analyzed. To ensure that our sample size was sufficient, we used Soper's [37] Post-Hoc Statistical Power for Multiple Regression calculator. Soper's [37] calculator indicated that our sample size was more than efficient based on our number of latent variables (n = 6), our R^2 of .50, and our sample size of 194. See Appendix A for the survey questions**.**

Results

Demographics

Survey respondents included 94 females (48 percent), 99 males (51 percent), and one other (1 percent). Approximately 23.7 percent of the respondents were represented by groups ages 18-34, and the 35-50 age group accounted for 34.5 percent. The largest age group was over age 50 (41.8 percent). The largest percentage of participants held a baccalaureate degree (31.4 percent), followed by those with a high school degree (17.5 percent). The majority were employed (60.3

percent). Most had a primary care physician (95.4 percent), and 88.1 percent reported having regular doctor's visits. Table 1 presents demographic information about respondents.

Next, study demographics are considered in comparison to the US Census 2021 data [38] and the US Census education table.[39] The demographic age groups and percentages for the study respondents were 20-34 (23.7 percent) and 35-50 (34.5 percent), in comparison with the most similar Census findings the group percentages are 20-34 (20.0%) and 35-54 (25.5%). Regarding education above high school, the US Census reports high school graduates (28.3 percent), some college (17.1 percent), associate degree (9.9 percent), 4-year degree (22.2 percent), master's degree (9.6 percent), and doctorate (1.9 percent). As expected, the current study had more respondents with associate, bachelor, master, and doctorate degrees than the US Census.

When comparing gender to the US population, Census data showed that 54.9 percent of the population are females and 45.1 percent are males. By comparison, females made up 48.5 percent of the respondents in this study, which was lower than the population, but 51 percent were males. When examining the employment rate for study respondents, 75.3 percent were employed, and 24.7 percent were unemployed. Census results for over 16 years in the civilian labor force reported lower employment (59.6 percent). There were 65.4 percent reporting annual household income less than or equal to $89,999. In similar categories, the Census found 64.2 percent reported income less than or equal to $99,999.

Table 1. Demographic Information

Characteristics	**Number**	**Percentage (%)**
Age, years		
18-34	46	23.7
35-50	67	34.5

Over 50	81	41.8
Education (highest level)		
Less than High School	3	1.6
High school graduate	34	17.5
Some college	22	11.3
2-year degree	29	15.0
4-year degree	61	31.4
Master’s degree	33	17.0
Professional Degree	5	2.6
Doctorate	7	3.6
Gender		
Female	94	48.5
Male	99	51.0
Other	1	0.5
Employment Status		
Full-time	117	60.3
Part-time	29	15.0
Unemployed	48	24.7
Employment Industry		
Education	11	5.7
Financial Services	15	7.7
Healthcare	15	7.7
IT/Computing	33	17.0
Professional and Business Services	10	5.2
Retail	17	8.8
Other	93	47.9
Household Income		
Less than $10,000	7	3.6
$10,000 - $99,999	22	11.3
$30,000 - $49,999	41	21.1
$50,000 - $69,999	28	14.4
$70,000 - $89,999	29	15.0
$90,000 - $149,999	44	22.7
More than $150,000	23	11.9
Primary Care Physician		
Yes	185	95.4
No	9	4.6
Regular Doctor Visits		
Yes	171	88.1
No	23	11.9

Measurement Model

Before analyzing the model, we assessed the constructs and survey questions for reliability and validity. To establish convergent validity, we removed items with factor loadings less than 0.70 and utilized a stepwise approach.[40] A full collinearity assessment determines whether a model violates the common method bias (CMB) principles, which is variance attributed to constructs measured with the same method (e.g., the survey method). The concern is that CMB introduces false effects related only to the measurement instrument when we seek to measure the effects related to the construct being measured. Therefore, items with a variance inflation factors (VIF) value greater than 5 were removed;[41] see the Factor Loadings and VIF Table located in Appendix B.

Next, we evaluated the convergent validity. Examining Table 2, we note that Cronbach's alpha and composite reliability for all items were greater than 0.70 as recommended by Nunally and Bernstein.[42] These results indicate the conditions for convergent validity are met. We used two tests to confirm discriminant validity. First, the Average Variance Extracted (AVE) values are all above 0.05.[43] Discriminant validity was also confirmed using the Fornell-Locker Criterion by verifying that the square root of every AVE value for each latent construct, located on the table diagonal, was larger than the correlations with the other constructs as shown in Table 2. The results in this section offer evidence that the constructs and survey questions are reliable and valid.

Table 2. Construct reliability and validity

	Cronbach's Alpha	rho_A	Composite Reliability		Average Variance Extracted (AVE)	VIF Squared						
						Attitude	Continuance Intention	. Usefulness	Perceived Behavior Control	Privacy Beliefs	Security Concerns	Subjective Norm
Attitude	0.88	0.90	0.92		0.69	0.83						
Continuance Intention	0.93	0.93	0.94		0.77	0.61	0.88					
Useful	0.84	0.86	0.89		0.67	0.74	0.70	0.82				
Perceived Behavior Control	0.75	0.78	0.86		0.66	0.60	0.50	0.54	0.82			
Privacy Beliefs	0.86	0.88	0.90		0.70	0.52	0.57	0.63	0.48	0.84		
Security Concerns	0.88	0.89	0.93		0.81	-0.18	-0.18	-0.22	-0.12	-0.37	0.90	
Subjective Norm	0.74	0.80	0.85		0.67	0.18	0.26	0.11	0.16	0.11	0.15	0.82

Hair, Hult, Ringle and Sarstedt [44] recommend assessing discriminant validity with the Heterotrait-Monotrait Ratio of Correlations (HTMT) as shown in Table 3. The HTMT ratio correlations are all less than 0.90, confirming discriminant validity.

Table 3. Heterotrait-Monotrait Ratio of Correlation

	Attitude	Continuance intention	Perceived Behavior Control	Privacy Beliefs	Security Concerns	Subjective Norm	Usefulness
Attitude							
Continuance intention	0.661						
Perceived Behavior Control	0.720	0.584					
Privacy Beliefs	0.589	0.627	0.585				
Security Concerns	0.405	0.426	0.387	0.658			

Subjective Norm	0.232	0.394	0.379	0.109	0.569		
Useful	0.840	0.782	0.654	0.726	0.494	0.202	

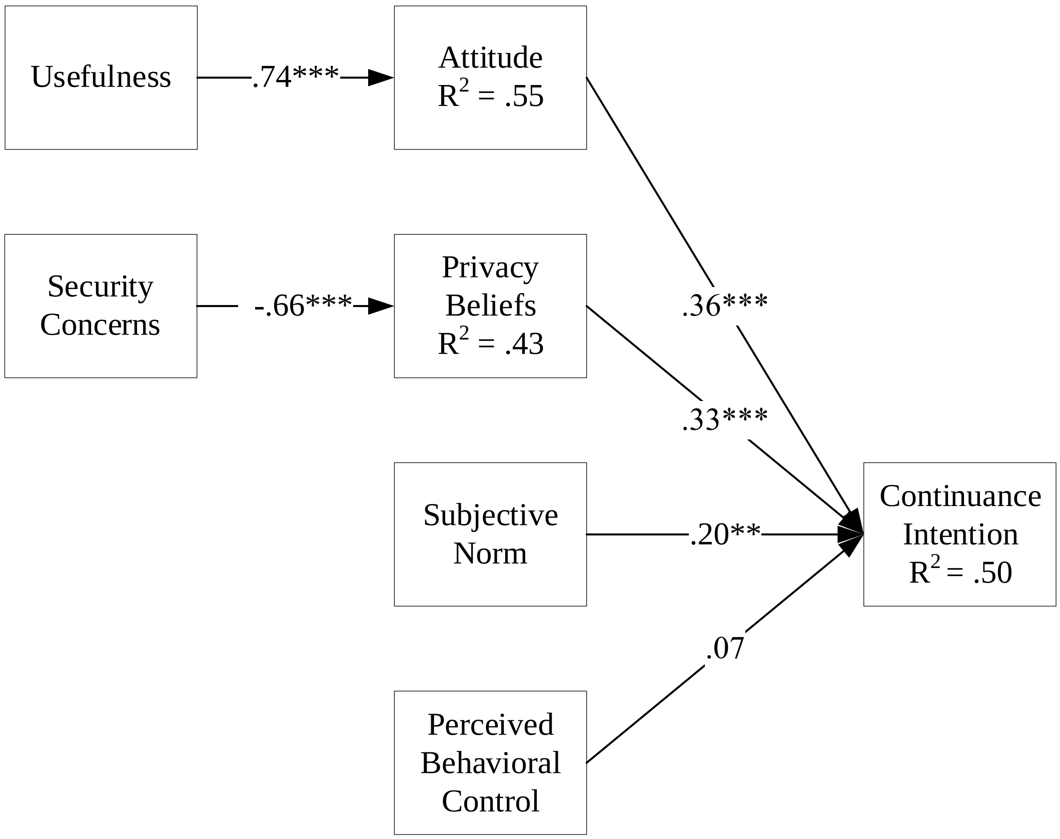
Hypothesis Results

The study results demonstrated that the respondents were influenced to use telehealth by all factors in the study except perceived behavior control. Specifically, usefulness affected attitude, and security concerns influenced privacy. Attitude, privacy beliefs, and subjective norms impacted continuance intention. These results are shown in Table 4, and Figure 2.

Table 4. Hypothesis Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Hypothesis
Useful → Attitude	0.74	0.75	0.05	16.48	0.00	Supported
Security Concerns → Privacy Beliefs	-0.66	-0.66	0.04	18.09	0.00	Supported
Attitude → Continuance Intention	0.36	0.36	0.08	4.55	0.00	Supported
Privacy Beliefs → Continuance Intention	0.33	0.33	0.07	4.96	0.00	Supported
Subjective Norm → Continuance Intention	0.20	0.20	0.07	2.74	0.01	Supported
Perceived Behavior Control → Continuance Intention	0.07	0.08	0.08	0.85	0.39	Not supported

Figure 2. Hypothesis Results



*** $p < 0.001$
** $p < 0.01$

Discussion

This study is one of a small group of behavioral studies that explore determinants of individuals' continuance intention of telehealth. The results from this study can be utilized to reduce the barriers to sustained telehealth use.

Most prior studies on the adoption of telehealth did not explore security and privacy, but we felt it was important since careless security behaviors when using telehealth can cause an individual's health information to be divulged, which invades their privacy. In this study, we found that security concerns negatively influenced an individual's privacy beliefs.

Usefulness positively influenced attitude as previously found by Chau and Hu.[8] These results are important as they indicate that individuals feel that using telehealth is beneficial. Subsequently, usefulness impacts their attitude toward the continuance intention of telehealth. According to Horn [45], a primary care physician for the Division of General Internal Medicine at Massachusetts General Hospital and an assistant professor at Harvard Medical School, healthcare facilities started opening their doors in June 2021. We gathered data in mid-2022. By that time, choosing to use telehealth was more of an option than a requirement. Thus, usefulness and continuance intention were measured after the height of the social distancing period for COVID-19, when individuals were returning to a less isolated existence.

Subsequently, attitude impacts an individual's decision to continuance intention of telehealth in support of prior findings by both Chau and Hu [8] and Ramírez-Correa, Ramírez-Rivas, Alfaro-Pérez and Melo-Mariano [12] Since most individuals were attempting to social distance during COVID-19, telehealth may be seen as useful since one can visit health professionals from a safe environment.

Their privacy beliefs positively impacted whether they intended to continue to use telehealth services. A related barrier is that the patients are often responsible for acquiring the technical skills necessary for enabling and maintaining the telehealth software connection to ensure secure, private telehealth sessions. For example, in this study, over 40 percent of the respondents were over age 50, and this age group may have more difficulty managing the technical aspects of remote telehealth sessions. Thus, it is important to include privacy and security in studies on telehealth adoption.

Moqbel, Hewitt, Nah and McLean [15] found that subjective norms in the form of physicians' and other health professionals' encouragement impacted individuals' decisions to use patient portals. Our results supported those prior findings. Thus, the subjective norm can be important to the adoption of systems, especially if the physician and other healthcare professionals are suggesting that patients use telehealth. We suggest that physicians continue to promote telehealth to their patients.

Surprisingly, perceived behavioral control was also not significant in our study, which contradicts the results from Chau and Hu [8] who found perceived behavior control significant but its influence was moderate. Ramírez-Correa, Ramírez-Rivas, Alfaro-Pérez and Melo-Mariano [12] also found it insignificant when exploring the adoption of telehealth in a study comparing TPB with TAM. Trafimow, Sheeran, Conner and Finlay [46] suggest that perceived behavioral control may need to be broken into two variables including perceived control and perceived difficulty. Terry and O'Leary [47] suggest that researchers should consider the differences between perceived behavioral control and self-efficacy through Ajzen [10] and Ajzen and Driver [48] propose the variables are synonymous. Thus, regardless of whether we included perceived behavior control or self-efficacy, these variables may influence the adoption and/or continuance intention of telehealth with a different group of subjects. Perhaps, COVID-19 had an impact on the individuals' perception that they did not have control over using telehealth. In many instances, physicians were requiring patients to use telehealth during this period.

Study method and design limitations are considered when interpreting any research results. Data for this study was collected with a Qualtrics Survey Service online survey instrument on a general population. Survey data is self-reported data and has an inherent bias that makes it less reliable than measured data. Specifically, respondents may underreport or overreport their reactions. They may not accurately judge the severity of the security threat or the privacy issue. Second, while efforts were made to remove those who appeared to be rushing to get through the survey, respondents may have randomly selected answers due to survey fatigue. Another limitation is that study data was only collected from an online survey.

Another limitation is the population sample size. The 194 individuals who responded to the survey were sufficient. However, larger sample sizes might have provided a better approximation of the population due to the reduction in the standard error. The respondent demographic mix must also be considered. Respondents were distributed evenly per age, employment field, and other fields as shown in Table 1.

Future research could explore other factors that might influence individuals to continue to use telehealth. One may also want to explore why perceived behavioral control was not significant. Perceived behavior control might be significant if broken into perceived difficulty or self-efficacy were used. Additionally, since fears of COVID-19 have lessened, future studies should determine individuals' intentions to use telehealth or to continue to use telehealth, especially after this pandemic ends. Future research could include asking patients if they have any concerns about accurate diagnosis and the completeness of their physical examination when the provider uses telehealth versus in-person patient visits where the provider can conduct a hands-on examination.

Conclusion

The goal was to examine the factors that influence individuals to use telehealth. The study results indicated that privacy, security, attitude, subjective norm, and usefulness were important predictors of the continuance intention of telehealth. While perceived behavioral control was not significant in this case, the significant factors might best explain the continuance intention of telehealth. Security initiatives for telehealth should include technology and human factors. Most telehealth visits are conducted remotely, or private information is sent through a secured format to the users over the internet using encryption or other security measures. Perhaps, healthcare organizations should educate users on security protocols when inviting individuals to telehealth sessions. The information can discuss ways to keep the session private as well as how to ensure the security of the individual's computing device during the session.

Telehealth can provide many benefits, especially in the remote management of chronic diseases. However, privacy and security concerns of healthcare consumers create barriers to telehealth use that must be reduced to facilitate repeated telehealth usage in future healthcare settings.

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Appendix A

Survey Questions on Telehealth Use

Construct	Variable	Description
Demographics	Age	Age in years
	EdLvl	Highest level of education completed
	gender	Gender
	EmpStat	How would you describe your employment status?
	EmpIndustry	What is your occupation? - Selected Choice
	Income	Household income level
	PCP	Do you have a primary care physician?
	DocReg	Do you regularly see a doctor?
	CovidTelImpact	COVID-19 has changed how I plan to use telehealth.
	UseTH	Have you used telehealth?
Attitude	Att1	My experience using telehealth to visit with my physician is positive.
	Att2	Using telehealth to visit with my physician is valuable.
	Att3	Using telehealth to visit with my physician allowed me to avoid getting COVID-19.
	Att4	Using telehealth to visit with my physician was beneficial.
	Att5	Using telehealth to visit with my physician was important.
	Att6	Using telehealth to visit with my physician was satisfying.
Perceived Behavioral Control	PBC1	I have the necessary resources to use telehealth.
	PBC2	I have the ability to use telehealth.
	PBC3	I used telehealth because I am knowledgeable about the technology needed.
	PBC4	I used telehealth because it was entirely within my control.
Subjective Norm	SubNorm1	I used telehealth because my physician suggested I use it.
	SubNorm2	I used telehealth because a healthcare professional suggested I use it.
	SubNorm3	I used telehealth because a friend suggested I use it.
	SubNorm4	I used telehealth because a family member suggested I use it.
	SubNorm5	I used telehealth because someone in my physician's office suggested I use it.
Usefulness	Useful1	I used telehealth because I could use it after business hours.
	CUseful1	I used telehealth when my physician was closed due to COVID-19.
	Useful2	I used telehealth even when I can’t go to the provider.
	Cuseful2	I used telehealth to avoid being exposed to COVID-19.

	CUseful3	COVID-19 made telehealth a useful way to see my physician.
	Useful3	I used telehealth anytime I can't go to the doctor's office.
	Useful4	I benefitted from using telehealth.
	Useful5	The advantages of telehealth outweigh the disadvantages.
	CUseful4	Telehealth was a convenient way to meet with my physician during COVID-19.
Privacy Beliefs	Private1	I believe that the information provided at a telehealth session is kept private.
	Private2	When I share information during a telehealth session, it will be kept private.
	Private3	When using telehealth, one is able to share information since it will be kept private.
	Private4	I feel comfortable sharing information at a telehealth session because I know it is kept private.
Security Concerns	Secure1	I do not feel my health information is secure when using telehealth.
	Secure2	I use telehealth because I feel that my protected health information is kept secure.
	Secure3	I do not perceive that my health information is secure when using telehealth.
	Secure4	I am worried that others can access my health record when using telehealth.
Continuance Intention	Continuance Intention 1	I intend to continue to use telehealth.
	Continuance Intention 2	I plan to continue to use telehealth.
	Continuance Intention 3	Even after COVID-19 is no longer a threat, I will continue to use telehealth.
	Continuance Intention 4	I will use telehealth again.
	Continuance Intention 5	Since the COVID-19 virus (coronavirus) makes it hard to see my physician, I will continue to use telehealth.

Appendix B

Factor Loadings and VIF

	Attitude	Continuance Intention	PBC	Privacy Beliefs	Security Concerns	Subjective Norm	Useful	VIF
Att1	0.74	0.35	0.32	0.34	-0.27	0.09	0.52	1.94
Att2	0.86	0.55	0.50	0.45	-0.37	0.17	0.65	2.71
Att4	0.90	0.60	0.56	0.55	-0.42	0.14	0.69	3.27
Att5	0.77	0.45	0.47	0.39	-0.35	0.15	0.58	1.90
Att6	0.86	0.53	0.59	0.41	-0.40	0.18	0.62	2.62
ContinuanceIntention 1	0.56	0.92	0.45	0.49	-0.42	0.28	0.64	4.55
ContinuanceIntention 2	0.63	0.93	0.49	0.56	-0.49	0.26	0.69	4.71
ContinuanceIntention3	0.49	0.86	0.43	0.44	-0.33	0.29	0.54	2.66
ContinuanceIntention 4	0.51	0.88	0.40	0.55	-0.52	0.23	0.62	2.99
ContinuanceIntention 5	0.47	0.80	0.40	0.45	-0.35	0.30	0.56	2.05
PBC1	0.43	0.31	0.71	0.35	-0.35	0.02	0.36	1.43
PBC3	0.47	0.42	0.88	0.39	-0.29	0.29	0.42	1.95
PBC4	0.55	0.47	0.84	0.43	-0.32	0.28	0.51	1.55
Private1	0.48	0.49	0.46	0.88	-0.61	0.02	0.58	2.48
Private2	0.43	0.46	0.39	0.84	-0.55	0.05	0.53	2.14
Private3	0.36	0.38	0.33	0.76	-0.37	0.08	0.43	1.74
Private4	0.46	0.55	0.40	0.87	-0.63	0.12	0.56	2.19
Sec2Rev	-0.56	-0.63	-0.53	-0.70	0.72	-0.19	-0.65	1.06
Secure1	-0.12	-0.17	-0.06	-0.30	0.72	0.33	-0.15	2.34
Secure3	-0.15	-0.14	-0.15	-0.33	0.76	0.32	-0.20	2.47
Secure4	-0.21	-0.17	-0.11	-0.36	0.78	0.42	-0.24	2.75
SubNorm2	0.15	0.23	0.14	0.08	0.02	0.57	0.07	1.03
SubNorm3	0.12	0.27	0.25	0.06	0.20	0.88	0.15	3.34
SubNorm4	0.14	0.20	0.22	0.04	0.20	0.85	0.14	3.32
Useful4	0.76	0.64	0.52	0.60	-0.52	0.16	0.87	1.99
Useful5	0.57	0.61	0.45	0.42	-0.34	0.13	0.81	1.78
CUseful3	0.55	0.50	0.42	0.54	-0.42	0.15	0.79	1.73
CUseful4	0.52	0.52	0.33	0.49	-0.41	0.05	0.81	1.92

References

1. Gajarawala SN, Pelkowski JN. Telehealth Benefits and Barriers. Article. *The Journal for Nurse Practitioners*. 02/01/February 2021 2021;17(2):218-221. doi:10.1016/j.nurpra.2020.09.013

2. Bestsennyy O, Gilbert G, Harris A, Rost J. Telehealth: A quartertrillion-dollar post-COVID-19 reality? https://www.mckinsey.com/industries/healthcare/our-insights/telehealth-a-quarter-trillion-dollar-post-covid-19-reality

3. Kaiser Family Foundation. Health Coverage and Insurance. https://www.kff.org/state-category/health-coverage-uninsured/

4. Medicaid.Gov. Telemedicine. https://www.medicaid.gov/medicaid/benefits/telemedicine/index.html

5. Majerowicz A, Tracy S. Telemedicine: Bridging Gaps in Healthcare Delivery. *Journal of AHIMA*. 2010;81(5):52-53,56.

6. Chacko A, Hayajneh T. Security and Privacy Issues with IoT in Healthcare. *EAI Endorsed Transactions on Pervasive Health and Technology*. 2018;4(14)doi:10.4108/eai.13-7-2018.155079

7. Elkefi S, Layeb S. Telemedicine's future in the post-Covid-19 era, benefits, and challenges: a mixed-method cross-sectional study. Article. *Behaviour & Information Technology*. 2022:1-15. doi:10.1080/0144929x.2022.2137060

8. Chau PYK, Hu PJH. Investigating healthcare professionals' decisions to accept telemedicine technology: An empirical test of competing theories. Article. *Information and Management*. 2002;39(4):297-311-311. doi:10.1016/S0378-7206(01)00098-2

9. Ajzen I, Fishbein M. Attitudes and normative beliefs as factors influencing behavioral intentions. *Journal of Personality and Social Psychology*. January 1972 1972;21(1):1-9. US: American Psychological Association.

10. Ajzen I. The Theory of Planned Behavior. *Organizational Behavior & Human Decision Processes*. 1991;50(2):179.

11. Bell WF. *Factors determining the behavioral intention to use a web-based appointment system: An application of the theory of planned behavior (TPB)*. 2022.

12. Ramírez-Correa P, Ramírez-Rivas C, Alfaro-Pérez J, Melo-Mariano A. Telemedicine Acceptance during the COVID-19 Pandemic: An Empirical Example of Robust Consistent Partial Least Squares Path Modeling. *Symmetry*. 2020;12(1593):1593-1593. doi:10.3390/sym12101593

13. Wang T, Wang W, Liang J, et al. Identifying major impact factors affecting the continuance intention of mHealth: a systematic review and multi-subgroup meta-analysis. *NPJ Digital Medicine*. 2022;5(1):145.

14. Hsieh FY, Bloch DA, Larsen MD. A simple method of sample size calculation for linear and logistic regression. *Statistics in medicine*. 1998 1998;17(14):1623-1634. doi:doi.org/10.1002/(SICI)1097-0258(19980730)17:14<1623::AID-SIM871>3.0.CO;2-S

15. Moqbel M, Hewitt B, Nah FF-H, McLean RM. Sustaining Patient Portal Continuous Use Intention and Enhancing Deep Structure Usage: Cognitive Dissonance Effects of Health Professional Encouragement and Security Concerns. *Information Systems Frontiers: A Journal of Research and Innovation*. 2022;24(5):1483-1496. doi:10.1007/s10796-021-10161-5

16. Myers J, Frieden TR, Bherwani KM, Henning KJ. Ethics in public health research: privacy and public health at risk: public health confidentiality in the digital age. *American Journal of public health*. 2008;98(5):793-801.

17. Runy L. The best line of defense: Hospitals take a proactive approach to data security threats. *Hospitals and Health Networks*. 2008;7(3):22-26.

18. Johnson VL, Kiser A, Washington R, Torres R. Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. *Computers in Human Behavior*. 2018;79:111-122. doi:10.1016/j.chb.2017.10.035

19. Kisekka V, Goel S, Williams K. Disambiguating Between Privacy and Security in the Context of Health Care: New Insights on the Determinants of Health Technologies Use. *CyberPsychology, Behavior & Social Networking*. 2021;24(9):617-623. doi:10.1089/cyber.2020.0600

20. Luciano E, Mahmood MA, Mansouri Rad P. Telemedicine adoption issues in the United States and Brazil: Perception of healthcare professionals. *Health Informatics Journal*. 2020;26(4):2344-2361. doi:10.1177/1460458220902957

21. Smith SJ, Smith AB, Kennett W, Vinod SK. Exploring cancer patients', caregivers', and clinicians' utilisation and experiences of telehealth services during COVID-19: A qualitative study. Article. *Patient Education and Counseling*. 10/01/October 2022 2022;105(10):3134-3142. doi:10.1016/j.pec.2022.06.001

22. Houser SH, Flite CA, Foster SL. Privacy and Security Risk Factors Related to Telehealth Services -- A Systematic Review. *Perspectives in Health Information Management*. 2023:3-3.

23. Pool J, Akhlaghpour S, Fatehi F, Gray LC. Data privacy concerns and use of telehealth in the aged care context: An integrative review and research agenda. *2022*. 2022:160. doi:10.1016/j.ijmedinf.2022.104707

24. Hirani SP, Rixon L, Beynon M, et al. Quantifying beliefs regarding telehealth: Development of the Whole Systems Demonstrator Service User Technology Acceptability Questionnaire. *J Telemed Telecare*. 2017;2023(4):460–469. doi:10.1177/1357633X16649531

25. Zhang X, Guo X, Guo F, Lai K-H. Nonlinearities in personalization-privacy paradox in mHealth adoption: The mediating role of perceived usefulness and attitude. *Technology & Health Care*. 2014;22(4):515-529. doi:10.3233/THC-140811

26. Ramirez-Rivas C, Alfaro-Perez J, Ramirez-Correa P, Mariano-Melo A. Telemedicine Acceptance in Brazil : Explaining behavioral intention to move towards internet-based medical consultations. Conference. 2020:1-4. doi:10.23919/CISTI49556.2020.9140996

27. Ajzen I. From intentions to actions: A theory of planned behavior. *Action control*. Springer; 1985:11-39.

28. Bandura A. Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review*. 1977 1977;84(2):191-215.

29. Fishbein M, Ajzen I. Predicting and Changing Behavior : The Reasoned Action Approach. 2010;

30. Ezzi S. A theoretical Model for Internet banking: beyond perceived usefulness and ease of use. *Archives of business research*. 2014;2(2):31-46. doi:10.14738/abr.22.184

31. Bailey AA, Pentina I, Mishra AS, Ben Mimoun MS. Mobile payments adoption by US consumers: an extended TAM. JOURNAL. *International Journal of Retail & Distribution Management*. 2017;45(6):626-640. doi:10.1108/IJRDM-08-2016-0144

32. Reid M LY. Integrating Trust and Computer Self-Efficacy with TAM: An Empirical Assessment of Customers Acceptance of Banking Information Systems (BIS) in Jamaica. *The Journal of Internet Banking and Commerce*. 1970;13(13):1-18.

33. Davis F. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. research-article. *MIS Quarterly*. 09/01/ 1989;13(3):319-340. doi:10.2307/249008

34. Dinev T, Hart P. An Extended Privacy Calculus Model for E-Commerce Transactions. *Information Systems Research*. 2006;17(1):61-80. doi:10.1287/isre.1060.0080

35. Ringle CM, Wende S, Becker J-M. SmartPLS 4. 2022;2022(September 28, 2022)

36. R Core Team. R: A language and environment for statistical Computing. R Foundation for Statistical Computing. https://www.R-project.org/

37. Soper DS. Post-hoc Statistical Power Calculator for Multiple Regression [Software]. http://www.danielsoper.com/statcalc

38. Bureau UC. ACS Demographic and Housing Estimates. https://data.census.gov/table?tid=ACSDP1Y2021.DP05

39. Bureau UC. Educational Attainment of the Population 18 Years and Over, by Age, Sex, Race, and Hispanic Origin: 2021. https://www.census.gov/data/tables/2021/demo/educational-attainment/cps-detailed-tables.html

40. Gefen D, Straub D. A Practical Guide To Factorial Validity Using PLS-Graph: Tutorial And Annotated Example. *Communications of the Association for Information systems*. 2005;16(1):5. doi:https://doi.org/10.17705/1CAIS.01605

41. Hair JF, Sarstedt M, Ringle CM. Rethinking some of the rethinking of partial least squares. *European Journal of Marketing*. 2019;doi:https://doi.org/10.1108/EJM-10-2018-0665

42. Nunally JC BI. *Psychometric theory*. McGraw-Hill; 1978.

43. Fornell C, Larcker D. *Structural Equation Models With Unobservable Variables And Measurement Error: Algebra And Statistics*. Los Angles, CA: Sage; 1981.

44. Hair JF, Hult GTM, Ringle CM, Sarstedt M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. 3rd Ed.,Thousand Oakes, CA: Sage.; 2022.

45. Horn DM. It's time to go back to the doctor's office. In person this time. *The Washington Post*. June 16, 2021. https://www.washingtonpost.com/outlook/2021/06/16/doctor-visit-physical-coronavirus-pandemic/

46. Trafimow D, Sheeran P, Conner M, Finlay KA. Evidence that perceived behavioural control is a multidimensional construct : Perceived control and perceived difficulty. *British journal of social psychology*. 2002;41:101-121.

47. Terry DJ, O'Leary JE. The theory of planned behaviour: The effects of perceived behavioural control and self-efficacy. *British journal of social psychology*. 1995;34(2):199-220.

48. Ajzen I, Driver BL. Prediction of leisure participation from behavioral, normative, and control beliefs: An application of the theory of planned behavior. *Leisure Sciences*. 1991;13(3):185–204. doi:https://doi.org/10.1080/01490409109513137