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State Consent Policies and the Meaningful Use of Electronic Health Records Among Nonfederal Acute Care Hospitals in the United States

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Abstract

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MJ, Loyola University, Chicago, 2010

BS, UT Southwestern Medical Center, Dallas, 1995

Proposal Submitted in Partial Fulfillment
of the Requirements for the Degree of
Doctor of Healthcare Administration

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Abstract

The less-than-nationwide use of electronic health record (EHR) systems to send, receive, and integrate (SRI) patient summary of care (PSC) records limits the ability of hospital administrators to maximize efficiency and improve quality in the continuum of care. Despite obvious differences in state health information exchange (HIE) consent policies, there is no known research that has determined if and what aspects of state-level HIE legislation affect the use of EHR systems to SRI PSC records. Guided by the unified theory of acceptance and use of technology (UTAUT), the purpose of this quantitative cross-sectional research study was to examine the relationship between one independent variable (type of HIE consent policy) and three dependent variables: percent of nonfederal acute care hospitals that electronically (a)send (b) receive (c) integrate PSC records from and into their EHR from outside providers respectively. Data analysis using multivariate analysis of variance (MANOVA) statistical test found that Opt-in policy states had the lowest percentage of hospitals engaging in the three domains. The study also found that the use of EHR systems was most rampant in states with relatively less stringent HIE policies., there was a non-statistically significant relationship between HIE policy type and the dependent variable. However, the relationship between year (secular trend) and the dependent variable was statistically significant as there was incremental changes in the independent variable between 2015 and 2017. The study contributes to positive social change by providing increased research within the (HIE) field aiming to promote government and private sector investment to understand and address technological, practice, and policy barriers regarding EHR-to-EHR system integrations.

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Dedication

First and foremost, I praise and thank the Almighty, the Supreme Allah, who gave me life, strength, knowledge, and good health throughout my course work. It is also dedicated to my grandmother, “Iya alakara,” for instilling in me very early in life the value of education when she enrolled me in elementary and secondary schools many years ago. I also thank my husband, who inspired and supported me through this journey.

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Section 1: Foundation of the Study

Introduction

An electronic health record (EHR) is a digital format of patients' medical information, which includes physical examinations, health history, treatment, and investigations (Lim et al., 2018). Hospitals are increasingly adopting EHR technology due to the benefits associated with it. In the United States, the federal government has been encouraging the adoption of EHR technology through an EHR incentive program authorized by the Health Information Technology for Economics and Clinical Health (HITECH) Act of 2009 (Health IT, 2020). The incentive program provides payments to eligible professionals and hospitals for adopting and meaningfully using certified EHR technology. Certified EHR technology has capabilities that allow healthcare providers to organize and integrate patients' health information among healthcare providers such that the information can be accessed from multiple sources. Despite these benefits and political support for the meaningful use of certified EHR systems, many (about 59%) nonfederal acute care hospitals in the country do not use their EHR systems to send, receive, and integrate patient summary of care (PSC) records for patients transitioning from one setting of care or provider to another (Eval, 2016; Office of the National Coordinator for Information Technology [ONC], 2017; Riordan et al., 2015; World Health Organization [WHO], 2017). This has led to an increased gap in the continuum of care, especially for people with chronic health conditions (De Regge et al., 2017; Waibel et al., 2016).

Over the years, stakeholders have raised concerns over the privacy and confidentiality of the information they share with their healthcare providers. These concerns appear to have increased with the push for interoperability of electronic health records (EHRs). As a result, the federal government developed the Health Insurance Portability and Accountability Act (HIPAA) privacy rule (Health IT, 2020). This is the federal law that sets the bar for the protection of health information. At the state level, there are also privacy regulations that require healthcare providers to obtain patients' written permission before disclosing information to other organizations or other people, even when the purpose of disclosure is treatment. It is commonly assumed that the HIPAA privacy rule preempts or overrides other state laws that are not as protective (Health IT, 2020), but the influence of state legislatures regarding patient consent for information exchange on the meaningful use of certified EHR systems to receive, share and integrate PSC records is not clear (Henry et al., 2016; Klosek, 2011; ONC 2013; Palabindala et al., 2016; Weiser, 2019).

In this section, I discuss the research problem, purpose, core questions, and approach. I also present a summary of observations from my review of the literature on the relationship between state Health Information Exchange (HIE) consent policies and the meaningful use of certified EHR systems among nonfederal acute care hospitals. I discuss the theoretical foundation of the study, as well as studies related to the variables and methodology used in this study. I conclude by presenting a summary of what is known, controversial, and unknown regarding the variables in focus for this study.

Problem Statement

The problem is that the U.S. government has made significant investments to promote the meaningful use of certified electronic health records (EHR) systems, yet many (about 59%) nonfederal acute care hospitals in the country do not use their EHR systems to send, receive, and integrate summary of care records for patients transitioning from one setting of care or provider to another (Eval, 2016; ONC, 2017; Riordan et al., 2015; WHO, 2017). The lack of the meaningful nationwide use of certified EHR systems to send, receive, and integrate PSC records limits the ability of hospital administrators to maximize delivery of patient-centered e-health solutions, increase efficiency, improve quality of patient care, and facilitate the transformation of healthcare organizations into learning centers (Centers for Disease Control [CDC], 2019; Eval, 2016; Haux et al., 2018; Lin et al., 2018). In 2019, for example, the Office of the National Coordinator for Information Technology (ONC) reported from the HINT survey that about one in 20 individuals who had been to the doctor the year before reported having to redo a test or procedure because their prior data were unavailable. About one in five individuals also had to bring prior test results to an appointment (HINT, 2018; ONC, 2019).

Another problem that exists due to a lack of nationwide meaningful use of certified EHR systems to transfer and receive patient information between different levels of care and locations is an increased gap in the continuum of care, especially for people with chronic health conditions (De Regge et al., 2017; Mansukhani et al., 2015; Waibel et al., 2016). The gaps in the continuum of care contribute to increases in healthcare administrative errors such as poor transitions and miscommunication among care providers, cause confusions regarding treatment plans, increase duplicative testing, discrepancies in medications, missed physician follow-up, fragmented treatment, patient dissatisfaction, and increased healthcare cost (Mansukhani et al., 2018; Waibel et al., 2016).

In addition, researchers who explored the factors that influence the adoption and meaningful use of EHRs highlighted cost, lack of industry collaboration, a culture of fragmentation, and physician burden as important factors that affect the meaningful use of EHR systems in hospitals (Council for Affordable Quality Healthcare, 2020; Reisman, 2017). These factors have been more organizational, structural, and environmentally centered than they have been policy and patient-centered. There has been little research emphasis on the role of state policies related to patient consent for information exchange, even though such policies exist and differ from state to state (Henry et al., 2016; Klosek, 2011; ONC, 2013; Palabindalaet al., 2016; Weiser, 2019). Despite the obvious differences in state HIE consent policies, there is no known research that has determined whether and what aspects of state-level HIE legislation affect the meaningful use of EHR systems to send, receive, and integrate PSC records.

Purpose of the Study

The purpose of this quantitative cross-sectional research study was to determine if there are significant differences in the percentage of nonfederal acute care hospitals that send, receive, and integrate patient summary of care (PSC) records electronically in U.S. states that identify as implementing opt-in health information exchange (HIE) policies versus those that implement opt-out policies. I examined the relationship between one independent variable (type of HIE consent policy) and three dependent variables (percent of nonfederal acute care hospitals that electronically send PSC records, percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, and percent of nonfederal acute care hospitals that electronically integrate PSC records into their EHR from outside providers). Points about whether HIE consent policies affect the use of certified EHR systems to send, receive, and integrate patient summary of care PSC records can provide context for healthcare administrators on how and where policy development and investments can streamline the complexity of exchange and address barriers to interoperability. This can, in turn, contribute to promoting wider use of certified EHR systems by healthcare administrators in acute care settings to send, receive and integrate PSC records, and corresponding improvements in quality of care.

Research Questions and Hypothesis

Research Question 1 (RQ1): What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals in that state that electronically send patient “summary of care” (PSC) records to outside providers, as reported in the American Hospital Association (AHA) survey between 2015 and 2017?

Null Hypothesis ($H_0$1): There is no statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically send PSC records to outside providers, as reported in the AHA survey between 2015 and 2017.

Alternative Hypothesis (H_a1): There is a statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically send PSC records to outside providers, as reported in the AHA survey between 2015 and 2017.

Research Question (RQ2): What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017?

Null Hypothesis (H_02): There is no statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

Alternative Hypothesis (H_a2): There is a statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

Research Question 3 (RQ3): What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers, as reported in the AHA survey conducted between 2015 and 2017?

Null Hypothesis (H_03): There is no statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

Alternative Hypothesis (H_a3): There is a statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

Theoretical Foundation for the Study

The theoretical framework for this study was the unified theory of acceptance and use of technology (UTAUT). The UTAUT model was put forth by Venkatesh et al. (2003). The theory seeks to explain the intentions of users in adopting an information system (IS) and the behaviors that follow. The theory identifies four fundamental constructs as the determinants of information system (IS) usage intention and action. The primary constructs include effort expectancy, performance expectancy, social influence, and facilitating conditions (Khalilzadeh et al., 2017; Venkatesh et al., 2003). Effort expectancy, performance expectancy, and social influence directly influence usage intention while facilitating conditions directly influence user behavior (Lai, 2017). Venkatesh et al. (2003) posited that gender, experience, age, and voluntariness of use moderate the impact of the four central constructs identified by the theory. The theory was a result of a review and consolidation of constructs that had already been employed by earlier models. The other eight models had earlier explained the usage behavior of an IS (Khalilzadeh et al., 2017). The early IS models include the technology acceptance theory, motivational model, the theory of reasoned action, the theory of planned behavior, the combined theory of planned behavior and technology acceptance, diffusion of innovation theory, social cognitive theory, and the model of personal computer use (Lai, 2017). In a longitudinal study to validate the UTAUT model, Venkatesh et al. (2003) found that it makes up 70% of the variance in usage intention.

The Main Theoretical Proposition of the UTAUT

The UTAUT has three main constructs and five facilitating conditions. The first major construct is *performance expectancy.* This construct is defined by the extent to which an individual perceives that the use of technology benefits him or her (Venkatesh et al., 2003). It refers to the perception of usefulness a user has of an IS, the intrinsic motivation one has to implement a technology, its usefulness to the related job, and the relative advantage compared to other technologies (Lai, 2017). Performance expectancy also relates to extrinsic motivation to use a technology an individual has, such as expected improved performance and other benefits that the technology is likely to bring into a job or workplace if implemented (Khalilzadeh et al., 2017). The second construct of the UTAUT is called *effort expectancy*. This is the level of easiness related to the adoption of the IS. It is the perceived complexity and ease of implementation (Venkatesh et al., 2003). Perceived ease tests the level one considers the implementation of a system as extra effort. Perceived complexity, on the contrary, involves examining the extent to which users find an IS complex to understand and implement (Khalilzadeh et al., 2017). The third construct of the UTAUT is the *social influence* construct. This construct refers to a person's belief that other people with influence believe he or she should adopt new technology (Venkatesh et al., 2003). This construct includes subjective norms, image factors, and social factors. When a user decides to adopt an IS due to the opinion of someone they perceive to be important, they are said to be influenced by the subjective norm (Khalilzadeh et al., 2017; Lai, 2017). *Social factor* refers to a situation in which a person's decision to adopt a technology is based on the influence of the prevailing social situation. Lastly, the *image factor* occurs when a user's decision to use an innovation is influenced by the perception that doing so will enhance their status in society (Lai, 2017).

Social influence includes the analysis of the role that organizational and technical infrastructures play in the decision to adopt new technology (Venkatesh et al., 2003). It offers additional information about the surrounding environment, which includes the rule and technical aspects that may encourage or discourage an individual from adopting a new IS. Social influence consists of the compatibility factor, which refers to the compatibility of the IS to existing structures, and includes the values, experiences, and needs of the users (Lai, 2017). The four main facilitating conditions proposed in the UTAUT theory are gender, age, experience, and voluntariness.

Gender influences effort expectancy, performance expectancy, and social influence. It has been established that men have higher performance expectations than women because they are task-oriented and consider task achievement to be important (Brauner et al., 2017; Venkatesh et al., 2003). Men develop this inclination through socialization and the gender roles in the societies in which they are raised. They are most likely to accept a technology when they perceive that the technology will enhance their performance or task outcomes (He & Freeman, 2019). He and Freeman argued that women tend to be influenced more by effort expectancy than men. The difference is caused by gender roles in society (Brauner et al., 2017). As a result, women will readily accept a technology when they expect that it will lead to a reduction in the effort required to meet their goals. Women also tend to be more sensitive to what other people say, which means that social influence is a significant factor in the adoption of technology among women compared to men (Brauner et al., 2017; Venkatesh et al., 2003). Social influence is about how other people in society perceive the technology, their opinion, and how they perceive users of the technology. Women adopt technology to gain social influence, acceptance by peers, or improve their image in the social system. Men are less likely than women to be influenced by these factors, meaning that social influence is a weak determinant among men (Brauner et al., 2017; Venkatesh et al., 2003).

Age influences all the four primary constructs of UTAUT. Young people are more likely to be motivated by extrinsic rewards than old people, which affects the performance expectancy determinant (Brauner et al., 2017; Lai, 2017; Venkatesh et al., 2003). External rewards such as the use of less effort, improving one's social image, improved job performance, and hence promotion or higher-earning, are among the factors that can make younger people accept innovation. Effort expectancy is higher among older people, and therefore, it is a significant determinant in the adoption of technology among older people. They are likely to accept a new technology when they perceive that they require little effort to implement and when the technology is expected to increase the ease of their work (Lai, 2017). Old people are also likely to view social influence as important. However, the effect of this determinant declines with experience (Brauner et al., 2017). Finally, old people are more impacted by their environments than others because their learning depends on experience and is passive (Brauner et al., 2017). Therefore, facilitating factors is a significant determinant of the adoption of new technology.

Experience affects effort expectancy and social influence. For relatively inexperienced users of technology, effort expectancy is a major determining factor of their behavioral intention. Inexperienced users of technology are likely to adopt new technology when they perceive that doing so will require no extra effort (Brauner et al., 2017). However, effort expectancy may not have much effect if the experience is at later stages. This is because, in later stages, the users have mastered the use of the technology, making it easy to implement (Brauner et al., 2017; Venkatesh et al., 2003).

The same effect is observed in social influence. The construct has a more significant impact when the experience is at earlier stages. Relatively inexperienced users are likely to accept a new technology to improve their social image. As people gain experience with new technology, the effect of social influence fades because the technology is normalized in the social system (Brauner et al., 2017). Facilitating factors determine behavioral intention as users' experience with the technology increases, and obstacles in the environment can be removed (Venkatesh et al., 2003).

Voluntariness is the degree to which the use of technology is perceived to be done out of free will or voluntary. It only mediates the social influence factor in the UTAUT model. In a mandatory implementation of technology, social influence has the highest influence on behavioral intention. According to Venkatesh et al. (2003), the social influence factor is the degree to which users perceive that others of importance believe they should adopt the technology. Therefore, when an individual perceives that the implementation of the technology is not voluntary, they are likely to adopt the technology because of those advocating or enforcing the implementation of the new technology (Lai, 2017). However, it is unlikely to influence users’ behavioral intentions in a voluntary implementation context (Lai, 2017; Venkatesh et al., 2003). Based on Venkatesh et al.’s (2003) definition of the social influence factor, voluntary implementation lacks the correct effect due to the opinions of other important members of society or an organization. Hence, there is no motivation for people to voluntarily accept the technology.

Rationale for Choice of Theory

My goal was to identify the relationship between state consent policies and EHR implementation among nonfederal acute care hospitals. Two considerations made the UTAUT suitable for this study to determine the influence of state EHR consent policies on the percentage of nonfederal acute care hospitals that use their EHR system electronically SRI PSC records to outside providers. Firstly, the UTAUT construct of social influence, was of relevance to this study Venkatesh et al. (2013) defined social influence as the degree to which an individual perceives that important others believe he or she should use the new system. The central tenet of this assumption aligned with the purpose of this study because, in this case, the type of EHR patient consent policy present in a state may be considered a form of important others. UTAUT social influence constructs suggest that healthcare administrator’s use of an EHR system to SRI PSC records may be determined by the degree to which they perceive that patients consent legislature should involve the use of EHR systems to electronically transfer, receive, and integrate PSC records. The findings of this study support, refute, and add to the UTAUT assumption.

Secondly, the UTAUT has been extensively used since its inception on studies that explain factors affecting individuals' adoption and use of emerging technologies (Venkatesh et al., 2013). These studies have focused on innovations in multiple fields, including healthcare, education, international business, and communication. Cimperman et al. (2016) applied the UTAUT model in the analysis of older users' behavior of accepting home telehealth services. The researchers sought to develop and test factors that affect the reception of home telehealth services among elderly people. Effort expectancy was found to be negatively influenced by computer anxiety, and the doctor's opinion was found to influence performance expectancy. The researchers established that social influence is irrelevant as a predictor of technology acceptance among elderly users.

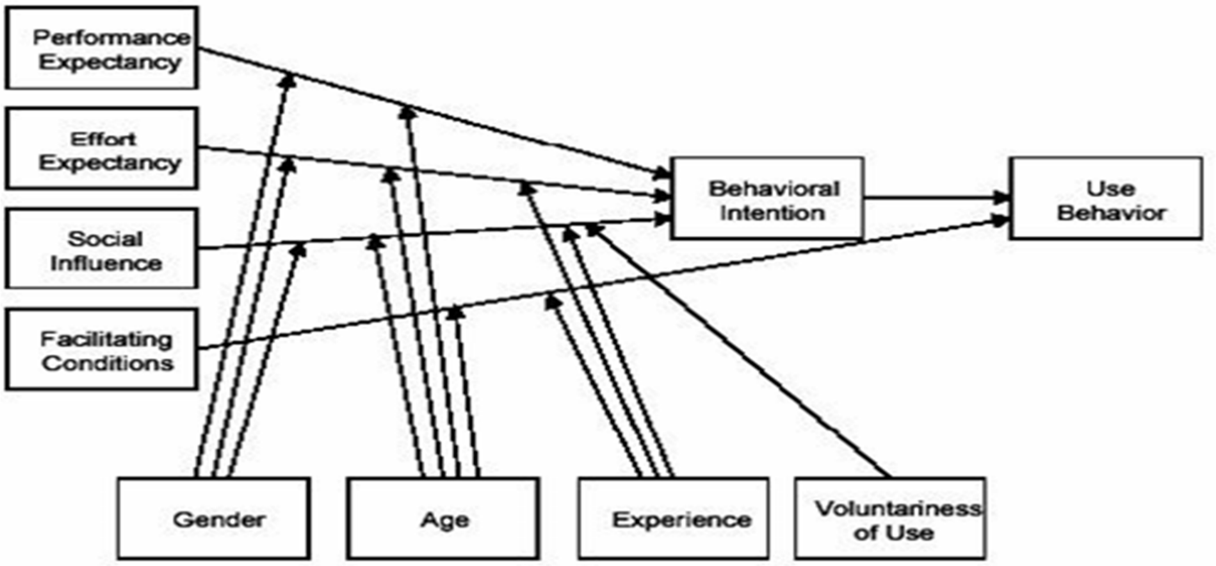
Researchers in the education sector mainly focus on adopting e-learning to determine why technology is either adopted or rejected. In the healthcare industry, the theory is mostly applied in relation to the adoption of electronic medical records technologies. Ishola et al. (2016) used UTAUT in modeling the behavioral intention of adopting broadband technology adoption among youths. In this research, the scholars proposed the use of the UTAUT model for measuring intentions to adopt broadband technology among teenagers in Malaysia. According to Ishola et al. (2016), youths are frequent users of mobile internet carriers.

Logical Connection Between Key Elements of the UTAUT

According to Venkatesh (2013), UTAUT theory is that four constructs directly determine the acceptance and use of technology: (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. According to Venkatesh et al. (2013), the first three constructs are direct determinants of usage intention, and the fourth is a direct determinant of user behavior. Four other mediating factors (age, gender, experience, and voluntariness of use) moderate the four central constructs of the theory. Figure 1 below presents a graphical illustration of the UTAUT theory.

Figure 1

Graphical Representation of UTAUT Theory



Source: Venkatesh et al. (2003)

Relationship with Study Approach

In this quantitative cross-sectional study, I sought to determine the extent to which HIE policies predict the meaningful use of EHR technology. The theory illustrates predictors of IS acceptance and usage. These predictors pinpoint key decision-making considerations for the adoption and use of innovations (Venkatesh et al., 2013). Also, offer guidance on facilitating wider adoption and use of new or existing innovation (Lai, 2017; Muraina et al., 2016; Venkatesh et al., 2013). I designed the research questions to focus on the relationship between the consent policies in a state and the percentage of the acute care hospitals in the specific state that SRI patient information through an EHR.

The independent variable of this study, state consent policies, falls under the social influence, effort expectancy, and facilitating conditions construct of UTAUT.

Application of the UTAUT to Similar Studies

Jewer (2018) used UTAUT to examine patients' intention in the adoption of online postings of emergency department (ED) wait times. The study provided empirical support for the modified UTAUT model in the context of a patient's intention to use the ED technology. The author sought to adopt the model to the context of online ED wait times acceptance. The findings revealed that the modified UTAUT model significantly affected performance expectancy and facilitated people's intention to use the ED online postings. Hoque and Sorwar (2017) sought to understand the elements affecting the adoption of mobile health by the elderly. The authors aimed to develop a model based on UTAUT and testing it empirically for suitability in the determination of basic factors that influence the adoption of m-banking. According to the study, performance expectancy, effort expectancy, social influence, technology anxiety, and resistance to change are key determinant factors of users' behavioral intention to adopt m-health services.

Al-Qeisi et al. (2015) also examined the feasibility of UTAUT in non-Western contexts. The researchers examined the plausibility of UAUT in predicting the behavior intentions of adopters of mobile banking technology in developing countries. The results show that the effects of facilitating conditions variable on behavioral intent are insignificant. Additionally, the authors established that social influence was a weak determinant of usage behavior. They demonstrated that effort expectancy is the major determinant of mobile banking adoption and that this determinant is influenced by experience. Kim et al. (2015) also analyzed the factors that influence healthcare professionals to adopt mobile electronic medical record (EMR) technologies in tertiary hospitals. The study used UTAUT to confirm the users' intentions to adopt and use ISs in healthcare. The study established that the intention to use EMRs was high because of the influence of performance expectancy on users' attitudes. Both doctors and nurses used the system to view inpatient lists, patients' clinical data, and alerts with a high frequency. The authors suggested that when determining EMR systems implementation, functions related to workflow and can enhance performance should be considered first.

Venugopala et al. (2016) cross-validated UTAUT in the examination of user acceptance of EHR. The authors compared the healthcare systems of India and the United States, revealing the gaps that still exist in the Indian healthcare system. The authors suggest that using technology can help in bridging the gap in healthcare. The authors aim to identify the perception of doctors in the adoption of the use of EHR. The study notes that in a qualitative study of the factors influencing the adoption of EHR systems, direct interviews would be enough. However, in the quantitative study, the authors empirically validate the UTAUT model by administering a questionnaire to doctors and analyze the data to identify the purpose. The authors concluded that the success of an EHR depends on the positive mindsets of hospital employees. Finally, Alsyouf and Ishak (2018) seek to create an understanding of factors that impact nurses' sustained intention to implement the EHR system in Jordan. The authors justify their focus on nurses by arguing that nurses are the key healthcare providers and the primary users of the ISs. They argue that nurses' reception and implementation of the EHR is key to its success. The framework of the study was based on an extended UTAUT model and the Top Management Support. A fully implemented EHR system in public hospitals was surveyed using a cross-sectional survey. The results reveal that performance expectancy, effort expectancy, and facilitating conditions positively influence nurses' continuance intention to use the EHR. They also reveal that the connection between social influence and continuance of implementation is insignificant.

The UTAUT model has been criticized for being inflexible, making it difficult to adapt to different contexts (Lai, 2017). The theory poses a challenge when there is a difference in culture, meaning that it cannot be modified to fit into a situation in a culture different from the culture in which it is applied initially (Al-Qeisi et al., 2015). Critics also say that given that the theory is applied initially to Western countries, it can be challenging to apply it in Middle Eastern countries with different values and beliefs (Al-Qeisi et al., 2015; Lai, 2017). Despite these critics, UTAUT remains suitable for the study because, despite its inflexibility, it is comparable to a complete model. This is because the theory is a product of the experience drawn from previous theories of IS technology. Because it unifies constructs from other theories, it provides a more accurate explanation of the determinants of behavioral intentions and usage (Lai, 2017). As established by Venkatesh et al. (2003), the theory has the highest rate of accuracy in explanation compared to other technology acceptance theories. With an accuracy rate of up to 70%, UTAUT remains the best choice for use in the current study.

Additionally, the limitation of the theory, as highlighted in the literature, does not change the decision to use the theory because the theory has been applied to various industries. It can be applied to e-commerce, education, and healthcare (Lai, 2017). The multidisciplinary application of the theory makes it suitable as the topic under investigation is in the healthcare industry. The context of the current study is the United States, which is a Western country. The identified limitation of the theory, therefore, does not affect the present study.

Nature of the Study

The nature of this study will be based on a quantitative cross-sectional research design consistent with assessing the association of HIE consent policies on the percent of nonfederal acute care hospitals that use HIE systems to send, receive, and integrate patient summary of care PSC records nationwide. A MANCOVA statistical test was used to identify the relationship between state HIE consent policy types and the percentage of nonfederal acute care hospitals that use EHR systems to send, receive, and integrate patient summary of care (PSC) records in the United State between 2015 and 2017. The approach of this study will be to examine the percentage of nonfederal acute care hospitals that send, receive, and integrate PSC records using their EHR systems in that state and study if the type of HIE consent policy present in a state affects the percentage. The results of this study may inform the administrators of provisions in state EHR policy that stand as facilitators or barriers to the meaningful use of EHR systems to foster interoperability in nonfederal acute care.

Literature Search Strategy

The publications that I examined in this review included scholarly peer-reviewed journal articles published within the last 5 years and a few nonpeer-reviewed publications relevant to the topic. I located relevant literature by searching the following databases: Academic Source Premier, EBSCOhost, ProQuest, Hein Online, Emerald, Sage, and Business Source Premier, Questia, and Google Scholar. The keywords employed for the search included: EHR, interoperability, meaningful use, HIE, HIE policies, HIE and EHR, EHR privacy, EHR security, EHR adoption, EHR benefits, history of EHR technology, Unified theory of adoption, and use of technology.

Literature Review Related to Key Concepts

Historical Background of EHR Meaningful Use

The electronic health records (EHR) technology started to gain prominence in the 1960s and 1970s when developments were made in the computer technology fields (Evans, 2016). At that time, the Institute of Medicine called for a shift from the paper system of medical records to the use of EHR. The EHRs were developed first as part of clinical policies aimed at improving Medicare and research work in the healthcare sector (Entzeridou et al., 2018). Their use was based on different merits, such as the ease of storing and reading patients' medical records from any location in the world (Entzeridou et al., 2018).

At its inception, most of the EHR was developed in mainframe computers and rarely used with minicomputers. This presented many drawbacks to such records: there was limited storage because practitioners had to use the parts and tapes of the removable disk for purposes of extra storage. The systems experienced downtime and proved ineffective in backing up data. Physicians were also not trained to use and access the EHRs. They relied on clerical officers to input such information, which led to significant data entry errors (Entzeridou et al., 2018). Getting data from such records was done through pulling charts, which became complicated when some records were stored electronically while others were in paper formats (Kruse et al., 2016). Accessing patients' medical records in one institution by other institutions was also relatively difficult because providers had to copy emails or use fax to transfer the information. Juhlin et al. (2015) further reported that earlier EHR systems were viewed as a hybrid of paper and electronic data. They were mainly used for purposes of billing, scheduling, and handling clinical systems. The personal computers equipped with graphics were used as monitors, and data entry was mainly through the keyboards and mouse. EHR systems relied on local area networks and the minimal web-based systems applied to them, and this meant that they were exposed to fewer security risks (Juhlin et al., 2015). The format in which medical records and health data are kept in EHR systems have since changed (Evans, 2016).

Despite advances in the use of EHR technology, limitations remain. Physicians and hospitals still struggle to share, receive, and integrate patients' records electronically. Reasons cited for this include the fact that records are hosted in different technological platforms that have fully or partially different systems standards or contain errors that make the records nontransferable (Juhlin et al., 2015). Despite the presence of electronic records technology, many stakeholders are not willing to share the data without regulations that compel individuals to do so (Kruse et al., 2016). Many medical providers are not willing to share their data. For them, the information is proprietary and something of high commercial value (Ratwani et al., 2015). Notwithstanding these limitations, there has been remarkable growth in the use of EHR, and now it has become part of the universal medical language (Juhlin et al., 2015). EHR technologies are now used on a wide area network, and this has led to the development of regulations on how the EHRs and related systems should be handled.

With the increasing use of EHR technology, there was a need for prudent standards and regulations on how they should ensure stakeholder rights are not violated. Independent EHR systems had resulted in more access to people's medical information by third-party applications (Shull, 2019). To ensure privacy and confidentiality of the information shared through these systems, there arose a call for the development of specific standards and interfaces that can be viewed as interoperable. The industry required a consistent message format to be used, and all protocols were to be observed before the information was shared within the systems. The first standards developed in the United States were the health level seven (HL7) while the IEEE (Institute of Electrical and Electronic Engineers) P1157 became the primary interface standards for regulating EHR use. The HL7 standards were useful in reducing the ambiguity related to data element definitions (Evans, 2016). They were later refined and expanded to other domains to aggregate the ancillary systems associated with the medical sector. The ancillary systems are the laparotomy, electrocardiogram, microbiology, echocardiography, which should all operate through the central EHR systems (Hammer et al., 2019). The EHR message format should have standardized dictionary codes of semantics to be able to communicate with other systems (Hammer et al., 2019). Accordingly, the National Librarians of Medicine and Universal Medical Language

Systems have been working on developing the semantic that can be used in EHR. Juhlin et al. (2015) argued that the process of developing the semantics to be used within EHR is a continuous process and will be part of the standardization process now and in the future.

At the federal level, the Insurance Portability and Accountability Act of 1996 and the Recovery Act section dealing with information technology guide nationwide utilization of the EHR (Evans, 2016; Shull, 2019). States also have varying laws that deal with consent issues on the utilization of the information contained in EHR systems and how HIE. The Milken Institute School of Public Health (2016) provided a summary of the state HIE consent policies. The laws were enacted via legislators and agencies governing HIE in those states. The policies fall under the opt-out or opt-in policies. With opt-in policies, the patients can automatically enroll within the HIE. However, they are provided with the chance to opt out. Opt-out policies require individuals to consent to their data being stored or disclosed by the provider. Policies in some states fall outside these two broad categories, and under such circumstances, the descriptions of such policies are provided in addition to the federal ones. With the implementation of standards and a legislative framework, the digital records from patients should move seamlessly from one healthcare provider to and another.

Studies Related to the Constructs of Interest

Multiple researchers have examined the current state of EHR adoption, the meaningful use thereof, and the factors that influence it. The influence of physician perspectives, hospital and patient characteristics, laws, and policies are among the major buckets that researchers examined. For instance, Heath and Porter (2019), Asan (2017), and Iqbal et al. (2013) studied physician perspectives about EHR use as well as their usage intentions and how this influences the extent and prevalence of EHR use. They also examined the influence of hospital and patient characteristics. Scholars have also explored the role of government policies and incentives on EHR adoption and meaningful use (Cohen, 2016; De Pietro, 2018; Dranove et al., 2015; Wani & Maholtra, 2018). The specific legislative considerations that have been discussed include the HITECH Act in 2009 and corresponding incentives. Other researchers examined the role of resource availability, vendor characteristics, and market competitiveness in the extent of EHR meaningful use in the United States (Holmgren et al., 2017; Rumball-Smith et al., 2018; Sherer et al., 2016; Sorace et al., 2020).

Earlier researchers also focused on developing models, frameworks, and tools to guide research on EHR technology and meaningful use, and support practice focused efforts to expand adoption and improve the usability of EHR technology (Azarm et al., 2017; Gomes et al., 2018; McGeorge et al., 2015; Legaz-García et al., 2016; O'Sullivan, 2018; Plastiras & Rasmy et al., 2019; Zhu et al., 2019). Other types of models and frameworks that researchers have explored include those for improving implementation of interoperable EHR systems, strengthening the security, privacy, efficient use, and management of EHR (Baskar et al., 2020; Cui et al., 2018; Dagher et al., 2018; Karapiperis et al., 2019; Mačinković & Aničić, 2016). Some researchers have also proposed models for examining the capability, impact, and privacy of EHR systems and data.

The impact of the interoperable EHR systems has also gained much attention. In this regard, researchers assessed the impact of interoperable EHR systems on healthcare safety, physician experience and productivity, and hospital effectiveness and efficiency. Although the authors of some studies focused on examining the beneficial impact of interoperable EHR systems (Austin et al., 2020; Finet et al., 2018; Wilson-VanMeter & Courtney, 2019), others explored the disadvantages of implementing of these systems. However, both categories of investigations have examined interoperable EHR systems' effects on telemedicine, data quality, safety and quality of care, professional satisfaction, and clinical decision making. These studies have also explored the effects of these systems on patient processes and flows and financial performance in resource-constrained settings.

Some literature includes an analysis of why EHR projects fail or stall, and what strategies may be implemented to address EHR implementation roadblocks, improve interoperability of EHR systems, and expand meaningful use of these systems (Aldosari, 2017; Khajouei et al., 2018; Kirkendall, 2016; Maxhelaku & Kika, 2019; Rangachari, 2018; Rangachari & Rethemeyer, 2017; Rey, 2015, Shahnaz et al., 2019). Some researchers discuss approaches for integrating EHR data electronically. These studies explore evidence-based strategies and approaches for making EHR integrable and interoperable (Jiang et al., 2020; O'Connor et al., 2017; Sun et al., 2015). Some studies have particularly explored and proposed approaches and methods to utilize and manage EHR data in research and practice (Agrawal et al., 2019; Juhn & Liu, 2020; Krahe et al., 2019; Taggart et al., 2015).

Finally, there has been considerable emphasis on the landscape of EHR privacy, security, and consent policies and how they affect current and future levels of EHR adoption and the interoperable functionality of EHR systems. Some researchers have proposed tools and techniques for preserving EHR privacy and maintaining record security in healthcare. They propose approaches like automated privacy auditing, semantic privacy frameworks, e-consent tools, computational modeling, and a hybrid technique (Carter, 2020; Hathaliya & Tanwar, 2020; Iwaya et al., 2019; Kundalwal et al., 2019; Lu & Sinnott, 2018). Some researchers also examined HIE preferences, including patient and public attitudes toward different informed consent models (Apathy & Holmgren, 2020; Riordan et al., 2015; Turvey et al., 2020). Researchers examined the mechanisms and practices used to protect EHR privacy. Some mechanisms discussed include hospital internal ISs, EHR publishing, blockchain-based secure EHR system (Huang et al., 2019; Stablein et al., 2018; Tseng et al., 2016; Wang et al., 2019; Yogarajan et al., 2018). Another aspect of EHR security, privacy/consent policies, meaningful use minimally researched relates to the impact of privacy regulation on EHR interoperability and meaningful use.

Methodologies in Studies that are Consistent with the Scope of Research

Three types of study designs were commonly used in the studies I reviewed: quantitative, qualitative, and interventional designs. The quantitative studies were more often experimental or quasi-experimental analyses of data than primary surveys. For instance, Rasmy et al. (2019) used a dataset that included over 150,000 heart failure patients and over 1,000,000 controls from nearly 400 hospitals and demonstrated the power of more expressive deep learning models for EHR predictive modeling that can be applied to other hospitals with only about 3.6% of reduction of AUC. Sorace et al. (2020) similarly determined the Part A and Part B Medicare-expenditure weighted market shares of EHR vendors and estimated the rate of attestation of meaningful use (MU) for EHRs among Medicare Part A & B providers from 2011 to 2016. They then calculated the Herfindahl–Hirschman index based on the data they obtained to quantify the competitiveness of the EHR market and the number of vendors' individual Medicare beneficiaries' medical records that were stored from 2014 through 2016.

In addition, Karapiperis et al. (2019) proposed four methods. The first method, SkipBloom efficiently, involves summarizing the participating datasets, using their blocking keys to allow for very fast comparisons among them. The second method, BlockSketch, summarizes a block to achieve a constant number of comparisons for a submitted query record, during the matching phase. The third method, SBlockSketch, operates on data streams, where the entire dataset is unknown a-priori but, instead, there is a potentially unbounded stream of incoming data records. The fourth method, PBlockSketch, adapts BlockSketch to privacy-preserving settings.

Concerning their preferred approaches to data analysis, similar cross-sectional studies applied multivariate logistic regression and MANOVA. Rumball-Smith et al. (2018) applied multivariable logistic regression models to estimate the odds of the outcomes of interest, controlling for key covariates with a study sample of 17,163 children under 13 years of age evaluated at one of 13 EDs within the University of Pittsburgh Medical Center health system. Weech-Maldonado et al. (2018) also applied survey data on EHR implementation among a national sample of 242 high-Medicaid nursing homes in 2017 merged with secondary data (LTCFocus, area resource file, and Medicare cost reports) and performed data analysis using multivariable regression with state fixed effects. Shu et al. (2014) applied the model of EHR grading to assess the level of EHR adoption across 848 tertiary hospitals. Shu et al. (2014) applied multivariate analysis to explore the factors that influence total score (including hospital characteristics and information technology [IT] investment) and the scores for nine roles.

Studies that used the MANOVA include those of Zhu et al. (2019), who applied a methodology that included the construction of communication networks among healthcare professionals (HCPs). In each patient's virtual care team, the measurement of communication linkages between HCPs, social network analysis, and nonparametric MANOVA with 100 surgical colorectal cancer patients as the sample size. Yogarajan et al. (2018) similarly applied an e-mailed questionnaire survey, using New Zealand's Official Information Act to request information on the policies and practices of each DHB: 19/20 DHBs (95%) responded to the survey, one of which reported that it did not provide patient information for research.

Ways Researchers Have Approached the Problem

The implications of stand-alone EHR systems can be far-reaching into the future. The poor coordination that arises due to the lack of interoperability can have detrimental impacts on the efficiency of the larger healthcare systems due to poor coordination of patient care records. It is difficult to guarantee high-quality care services unless patient data, such as medical history, is available to healthcare practitioners throughout the entire healthcare system (Patel & Chatterji, 2015). The lack of a coordinated healthcare database also means limited or lack of access to the data needed for research and monitoring of public health patterns. On the contrary, an integrated electronic health system will go a long way in ensuring patient safety and improved quality of care. An integrated EHR system could mean that healthcare facilities will have an organized and secure way to capture, store, retrieve, and utilize patient data for optimal outcomes (Shull, 2019). The current state of EHR indicates a need to improve and strengthen the capacity of EHR systems to send, receive, and integrate a PSC records. The need for nationwide adoption of systems with this level of functionality is also evident.

To address the issue of the low nationwide meaningful use (MU) of EHR systems, many researchers have examined various operational, administrative, and research dimensions of EHR systems and their use. There has been a significant emphasis on developing and testing models, frameworks, and tools for facilitating the wide adoption and functionality of EHR systems. Many researchers have also paid attention to examining the extent of EHR adoption and MU, the impact of EHR systems on the quality of care and research, and strategies for managing electronic health records. They have also studied the landscape of EHR security, privacy/consent policies, and MU and how these dimensions of EHR use relate to each other. EHR implementation roadblocks and strategies for expanding the MU of EHR systems are also discussed extensively. However, the influence of HIE consent policies on the use of EHR for SRI PSC records is unknown. The paragraphs that follow the sections on these dimensions are presented in additional detail, along with the methodological approaches that researchers implemented in related studies.

Current Trends in the Adoption and Meaningful Use (MU) of EHR Technology

EHR adoption rates have been studied in different countries and across levels of healthcare institutions. Some researchers also focused on determining and predicting the extent of EHR adoption and use. These studies have particularly explored the prevalence and rate of EHR adoption and factors that influence these rates. The extent of user adoption and use patterns, practices, effectiveness, and usability problems have also been frequently studied (Sahama et al., 2019). Some studies in this regard examined the availability and use of inpatient EHR systems in hospitals and physician offices located in developed countries, including China and Saudi Arabia (Qazi et al., 2018; Sahama et al., 2019). Others examined the use pattern of EHR systems among office-based physicians' practices (Ekezue et al., 2019) while others determined the extent to which EHR systems meet MU criteria. Another aspect of EHR use investigated those related to the usability, effectiveness, acceptance, and use continuance of EHR systems (Aldosari, 2017). Researchers investigated the usability problems commonly encountered by physicians across healthcare sectors (Amoah et al., 2017; Kiapio et al., 2017) and the effectiveness of EHR systems in improving the quality and efficiency of care (Amoah et al., 2017). Some researchers also assessed the extent of EHR acceptance among physicians and their continuance intentions (Ayanso et al., 2015; Steininger & Stiglbauer, 2015).

Adoption and Meaningful Use (MU) Rates

Despite the near-nationwide adoption of EHR, it had not been meaningfully used for clinical intervention and research outcomes (Agrawal et al., 2019). Mukherjee et al.'s (2019) findings indicate an acceleration in EHR adoption rates in different countries, including the United States (Shu et al., 2014). Even as the current trends and projections about the use and adoption of healthcare electronic systems have shown an upward trajectory, Shu et al. (2014) also observed low adoption rates across tertiary hospitals in China. Hospitals ineligible for incentives also experience lower adoption rates than eligible hospitals (Walker et al., 2016). Additionally, existing research suggests that the rich array of machine learning, predictive analytics, data analysis, and wellness applications that could drive the intended outcomes might not feature EHR systems.

Currently, EHR systems are majorly encounter-based systems that are incapable of supporting real-time point-of-care health and clinical decisions. The systems are not built to support the analysis needed before resorting to a given clinical decision or choice (Patel & Chatterji, 2015). For instance, Thompson and Graetz (2019) suggested that only a small proportion of hospitals had implemented all six PI3 MU functionalities: to find, SRI information throughout the entire healthcare system. Walker et al. (2016) also asserted that throughout the United States, only about 50% of all healthcare facilities have reported their intentions and taken the initiative to implement EHR systems with the capacity for integration. Parasrampuria and Henry (2019) noted that the current design of EHR systems might require major redesigns for integration with many of the other digital resources needed for seamless recording, storage, transmission, and interpretation of clinical data. Policymakers and health system executives are consistently exploring the issue of interoperability, given that the limitations of the traditional EHR systems are rather obvious.

Models, Framework, and Tools

Many researchers developed, tested, or proposed models, frameworks, and tools to guide research on EHR technology and MU, and support practice focused efforts to expand adoption and improve the usability of EHR technology (Azarm et al., 2017; Gomes et al., 2018; Legaz-García et al., 2016; McGeorge et al., 2015; Plastiras & O'Sullivan, 2018; Rasmy et al., 2019; Zhu et al., 2019). Other types of models and frameworks explored include those that improve implementation of interoperable EHR systems, strengthen EHR security, privacy, and the efficient use and management of EHR (Baskar et al., 2020; Cui et al., 2018; Dagher et al., 2018; Karapiperis et al., 2019; Mačinković & Aničić, 2016). Some researchers have also proposed models for examining the capability, impact, and privacy of EHR systems and data. These models can be applied to EHR research and practice settings, and are discussed in the following paragraphs:

The Semantic/Harmonization Framework

Speaking on the importance of semantic frameworks, Cornet (2017) observed that EHR infrastructure depends on legal, technical, and semantic aspects that are frequently reciprocally related. Sun et al. (2015) also proposed the use of semantics for the synchronization of large-scale data. Jaulent et al. (2018) discussed how semantics could improve information sharing and address the problem of data mediation with domain ontologies. They introduced the main steps for building domain ontologies as they could be implemented in the context of forensic and legal medicine. Semantic interoperability can be improved by applying a formal concept analysis method (Detro et al., 2016). These models appear to emphasize the importance of standardizing EHR data semantics as this can facilitate data sharing and synchronization across hospitals and physician offices. Integration of semantics frameworks into EHR systems can enable synchronization of large-scale data and improve information sharing (Jaulent et al., 2018; Sun et al., 2015). The finding suggests that formal concept analysis should be applied to improve semantic interoperability (Detro et al., 2016). Other models that may aid in the processing and storage of large-scale data include MongoDB, which allows for the easy storage of structured and unstructured data to foster heterogeneity (Dodeja et al., 2018). The capability of RNN for use in predictive modeling with large heterogeneous EHR data was determined (Ramsy et al., 2019).

Models for Improving EHR Interoperability

Models to improve EHR interoperability, specifically those related to supporting the exchange, integration, and preservation of health records are proposed. Li et al. (2019) proposed the novel model of distributed noise contrastive estimation (D-NCE) for learning from multiple databases and building predictive models based on distributed noise contrastive estimation (NCE). According to them, the D-NCE can preserve the model structure, achieve comparable prediction accuracy, and build predictive models in a distributed manner with privacy protection. The model has also been implemented as a stand-alone Python library available on Github. Mishra et al. (2016) proposed a prototype that can be used to edit different fields in the patient file and add comments to the CDA document while preserving the validity of the documents. They observed that other systems could parse the generated CDA documents while the semantic meaning and structure is preserved, which provided proof of the efficacy of the interoperability approach. An enactment model has also been proposed to address the required level of institutional cross-boundary collaboration in healthcare (Chiahsu et al., 2019). Jiang et al. (2016) proposed a harmonization with the models developed in HL7 Fast Healthcare Interoperability Resources (FHIR) and Clinical Information Modeling Initiatives (CIMI) to enhance the QDM specification and enable the extensibility and better coverage of the data element repository (DER). They also demonstrated the scalability and extensibility of the DER-based approach by comparing it with the existing QDM implementation utilized within the measure authoring tool. These frameworks improve EHR interoperability by preserving the model structure, achieving comparable prediction accuracy, and building predictive models in a distributed manner with privacy protection (Li et al., 2019), enabling editing of patients' records and addition of comments while preserving the validity of the documents (Mishra et al., 2016).

Models for Managing Large-Scale Data

Models to manage large-scale EHR data are also proposed. These models focus on processing large-scale heterogeneous data, preserving data, and evaluating the quality and fitness of data. Dodeja et al. (2018) proposed using MongoDB because it allows for easy storage of structured and unstructured data to aid heterogeneity. Sun et al. (2015) proposed using semantic data visualization for processing large-scale EHR data. Ramsy et al. (2019) also demonstrated the capability of RNN for predictive modeling with large heterogeneous EHR data. Loft and Greene (2018) had presented findings of a data and fitness evaluation framework. These models reveal the capacity of interoperability models to process and store large-scale data in EHR systems.

Models for Assessing Interoperable EHR Systems

These frameworks and tools support evaluating the social impact of EHR, EHR acceptance, EHR communication capabilities, and changes in complex practices proposed. Steininger and Stiglbauer's (2015) model can be used to explain physicians' acceptance of EHR systems and identify social influences to EHR experience and the perception of the usefulness of EHR systems. Belaryan et al. (2019) derived model identifies factors that influence behavioral attitudes to novel technology. Alkureishia et al. (2018) validated the use of e-CEX as a reliable tool for assessing patient-centered EHR communication capabilities. Rangachari (2018) noted integrating the SKN tool as a reporting tool in the EHR system and the SKN ability to enable interprofessional learning. The presence of clinical ethics consultation notes has been identified as the basis of the process of EHR systems (Russo et al., 2018). These models reveal the need to evaluate factors that influence EHR MU. These Frameworks and tools support evaluation of EHR social impact and acceptance. They can explain physicians' acceptance of novel technology and identify social influences to EHR experience and perception of the usefulness of EHR systems (Belaryan et al., 2019; Steininger & Stiglbauer, 2015). Tools like the CEX are reliable tools with which to assess patient-centered EHR communication. The integration of the SKN tool as a reporting tool within the EHR system could enable interprofessional learning (Alkureishia et al. 2018; Rangachari, 2018; Russo et al., 2018).

Tools for Improving EHR Capabilities

Tools that may improve EHR usability and achieve more precise and user-centric results have also been identified. Yip et al. (2019) demonstrated that NoSQL systems such as Neo4j graph databases have more technical and financial advantages than relational database systems and are suitable for data visualization, data storage, and the management of large-scale data-intensive applications, such as EMR database systems. Kanade et al. (2019) found out that an HL7 parser can be designed to achieve highly precise and user-centric results. They also noted the vital role analytics plays in maintaining health records. To improve EHR capabilities, the NoSQL and HL7 tools improve precision and user-centric results because they allow for the data visualization and management of data-intensive EHR systems (Kanade et al., 2019; Yip et al., 2019).

Improving EHR System Usability

The usability of EHR systems may be determined by factors of EHR system brand, safety, training, and user experience. Kiapio et al. (2018) found that EHR system usability may be determined by differences in EHR brands and differences between healthcare sectors. Aldosari (2017) highlighted the importance of properly training physicians in the use of EHR safety functions to avoid medical errors that can be fatal. Jiang et al. (2020) proposed that the LATTE (a knowledge-based method for transforming various expressions of laboratory test results into a normalized and machine-understandable format) may effectively transform various expressions of patient records for effective EHR sharing and for supporting EHR-based applications. Their study demonstrates the effectiveness of LATTE for normalizing various expressions of laboratory test results in free-text EHRs and facilitating EHR-based applications such as patient clustering, cohort querying, and machine learning. Training physicians about the safety functions of EHR can reduce the possibility of fatal medical errors (Aldosari, 2017). The proposed use of the LATTE model may normalize laboratory test results and facilitate EHR-based application (Jiang et al., 2020).

Strengthening the security of EHR

Shoja and Maraka (2019) indicated that hospitals with complementary IT applications were less likely to experience security failures than other hospitals. Security breach patterns were observed to change as a result of MU and IT investments. They also proposed the use of multi-expert ABE (MA-ABE), which allows for the authorization of individual access to improve the security of health records (Sowmya & Suresh, 2019). Another approach proposed for strengthening the security of EHR data is the DEM, which was proposed by Kundalwal et al. (2019). This privacy preservation technique can protect EHRs from inference attacks, linking attacks, and impersonation attacks. They simulated the proposed technique and showed that the average processing time per tuple and the amount of information loss were lower than those of other techniques. The use of blockchain technology in EHR systems was also proposed to secure the storage of electronic records and ensure regulated access to records. Huang et al. (2019) noted that blockchain-enabled MedBloc enables the regulation of access to patient records using encryption mechanisms. Shahnaz et al. (2019) also propose a framework that implements blockchain technology into EHR to secure electronic records.

The models reveal that implementing blockchain technology into EHR systems could improve the security of the system and could be a potentially scalable and secure solution to interoperability. These models reveal the use of EHR systems in preserving data and in interoperability. To strengthen EHR security, stakeholders consider the complementary use of EHR with IT systems in the hospitals may reduce risks of data breaches (Shoja & Maraka, 2019). The use of MA-ABE and DEM can also preserve privacy and protect EHR from attacks (Kundalwal et al., 2019; Sowmya & Suresh, 2019). The use of blockchain technology in EHR systems was also proposed to secure the storage of electronic records and act as a scalable and secure solution to interoperability issues (Huang et al., 2019; Shahnaz et al., 2019).

The EHR models, frameworks, and tools presented in earlier studies appear focused on advancing interoperability in practice. They specifically tend to tilt toward supporting the capability of EHR systems for real-time sharing of EHRs and addressing privacy and security concerns. The multitude of these kinds of models and frameworks discussed in the literature suggests that researchers and practitioners alike still struggle to find the right framework to foster EHR interoperability, ensure the data privacy, security, management, and assessments, and examine the capabilities, impact, and privacy of EHR. The need for guidance on the most effective and efficient approach for adopting, implementing, and maximizing the power of interoperable EHR systems is evident.

The Impact of EHR Technology

Establishing the integrated system of EHRs, however, has proven a tall order. The existence of more barriers than facilitators to the MU of EHR in primary care and rural practices has also been observed (Holden & Davidson, 2017). Several researchers find the discussion on the benefits and disadvantages of EHR systems interesting. They have assessed the impact of interoperable EHR systems on healthcare safety, physician's experience and productivity, and the hospital's effectiveness and efficiency. Although some researchers focused on examining the beneficial impact of interoperable EHR systems (Austin et al., 2020; Finet et al., 2018; Wilson-VanMeter & Courtney, 2019), others explored negative outcomes associated with the implementation of these systems. However, both categories of investigations have examined interoperable EHR systems' effects on telemedicine, data quality, safety and quality of care, professional satisfaction, and clinical decision making.

Researchers have also explored the impact of these systems on patient processes and flows and financial performance in resource-constrained settings. Finet et al. (2018), for instance, showed the benefits of EHR interoperability in telemedicine while Austin et al. (2020) determined EMR interventions that improved the safety and quality of therapeutic anticoagulation in an inpatient hospital setting. Wilson-VanMeter and Courtney (2019) also described the positive impact of EHR by linking patient data to patient outcomes and explained its role as a communication tool between healthcare providers and staff. The relationship between EHRs and data quality was investigated by Darko-Yawson and Ellingsen (2016) in the Pentecost Hospital Madina-Ghana. Lastly, Ayaad et al. (2019) identified the quality of healthcare services' differences between adopted EMR and paper-based record hospitals and how the quality of electronic medical records affects the quality of healthcare services.

Regarding the impact of EHR interoperability on clinician decision making, patient processes flow on records and errors, Ben-Assul et al. (2015) evaluated the effects of accessing EHR in an ED on improved decision making by clinicians while Jacobs et al. (2019) studied the number of disruptions in patient processes in a radiotherapy center after the replacement of an EHR. Bushelle-Edghill et al. (2017) discussed the effects of EHR implementation on patient flow by investigating EHR implementation on patient flow for operations within a pediatric practice. Yabut et al. (2017) confirmed the positive impact of EHR on childhood obesity.

Benefits of EHR technology. Overall, many researchers assert that EHR technology benefits physicians' work processes, patient flow, and hospital performance. Bushelle-Edghill et al. (2017) observed significant improvements in patient flow after an EHR system was adopted, and this resulted in improved operational efficiency. EHR also supports effective knowledge-sharing among employees as well as training (Bushelle-Edghill et al., 2017). EHR implementation and functionalities were also associated with positive financial performance in one study (Weech-Maldonado et al., 2018).

EHR Benefit to Quality of Care

Several researchers have identified EHR benefits to the quality of healthcare. Ayaad et al. (2019) observed that the adoption of high-quality EMR has a significant impact on improving the quality of healthcare services. Rey (2015) also noted that as more small physician practices integrate into the EHR system, the implications for social change are that the quality of healthcare may increase. Their positive influence on diagnostic metrics, treatment plan development, healthcare providers' productivity, and improved survival rates have been highlighted. Kevin et al. (2019) noted that physicians participating in an EHR program for a single year had better cancer-screening metrics than others while those who participated for multiple years reported having better medication-related metrics and chronic disease management metrics than others. Cheriff et al. (2010) indicate that provider productivity as measured by patient visit volume, charges, and RVUs modestly increased for a cohort of multispecialty providers that adopted a commercially available ambulatory EHR. They also suggested that there were fundamental differences between the adopters and non-adopters. Findings also indicate the use of EHR data to develop treatment plans (Walji et al., 2014). Han et al. (2016) also observed a survival benefit following EHR implementation with computerized physician order entry in a critical care setting and a concomitant decrease in severe medication errors. Austin et al. (2020) observed the presence of limited benefits and indicated that optimal, evidence-based methods have not been determined to improve EMR utilization.

EHR Interoperability Benefits

As a benefit, EHR systems could support patient record sharing, improve health synergy, and interoperability. Information sharing can improve services and reduce misunderstandings in healthcare systems (Mačinković & Aničić, 2016). Also, the use of interoperability standards for telemedicine systems might enable the development of platforms with multiple medical devices (Finet et al., 2018). Wu et al. (2016) provided evidence that increased integration efforts drive e-health synergy and have overall effects on hospital performance.

Benefits of EHR Use in Data Management and Research

The benefit of using EHRs as a tool for measuring, accessing, and capturing data in social settings has been identified. Researchers identify the use of EHR databases in social care systems, assessing trends, measuring ECNs, and population outcomes. Rumball-Smith et al. (2018) report that the integration of child screening tools hero the EHR system ensured positive screening and improved reporting in child protective services. Rashotte et al. (2016) used MCICS as an assessment tool to identify the consequences of EHR deployment in clinical social settings. Zhu et al.'s (2019) findings reveal that EHR access log data can be used to measure and examine electronic communication networks and to propose models that capture salient communication patterns in care teams. Amoah et al.'s (2017) findings about the cyclical trends of BP control and their associations with diabetic patients demonstrated that her use is beneficial in determining health population outcomes.

EHR Benefit to Data Quality, Physician Efficiency, Herd Effectiveness

EHR also supports improved data quality and interpretation for improved clinical decisions. The researchers highlighted that EHR systems help improve health records quality, interpretability, and clinical decisions, and treatment quality. Horton et al. (2019) noted the improvement in data quality obtained from EHR compared to administratively-sourced data and stated that such data is the better indicator of health status between the two. The findings from another study indicate that using EHR can improve physicians' treatment efficacy and data interpretability (Hoang & Ho, 2019). Ben-Assul et al. (2015) highlighted the benefit of easy EHR data access and its resultant increase in the quality of clinical diagnosis and decisions. However, Taggart et al. (2015) indicated that although the presence of feedback and structured data quality reports (SDQRs) improve the recording of patient data, it does not improve the quality of data.

EHR technology benefits hospitals' performance, quality of care, data management research, and physician efficiency. The adoption of EHR improves medical care metrics, provider productivity, quality of healthcare, and aid development of treatment plans (Cheriff et al., 2010; Khern et al., 2019). EHR technology also improves hospital performance, which is demonstrated by improved patient flow and financial performance (Weech-Maldonado et al., 2018; Bushelle-Edghill et al., 2017). Interoperability standards may also enable the development of multiple-access telemedicine platforms. The integration of EHR systems could also enable information sharing and e-health synergy, which have overall effects on hospital performance (Finet et al., 2018; Mačinković & Aničić, 2016; Wu et al., 2016). The use of EHR was also noted in improved data records, data collection, assessment, and capture in social settings (Rumball-Smith et al., 2018). Physicians' efficiency also improves with EHR use, as do improvements in diagnostic metrics, treatment plan development, the productivity of healthcare providers, patient survival rates, and consequently improved quality of healthcare (Ayaad et al., 2019; Han et al., 2016; Rey, 2015; Walji et al., 2014).

EHR Disadvantages and Drawbacks

Researchers also attempted to understand why EHR projects fail or stall, and what strategies may be implemented to address EHR implementation roadblocks. Khajouei et al. (2018) identified the errors and causes of communication failures between hospital ISs and EHRs systems. Aldosari (2017) similarly investigated EHR project managers' practices to understand why EHR projects fail or stall. Khennou et al. (2018) also presented a case study of the implementation process of an EHR-based Open EHR and investigated the adoption of health analytics in each step of the methodology. Jaulent et al. (2018) discussed the challenges of enforcing EHR interoperability standards in forensic and legal medicine.

Similarly, Rey (2015) presented the challenges that small physician practices in the Central Valley, California Region face in implementing EHR systems. Kuziemsky and Peyton (2016) identified process interoperability issues in a two-year case study of a palliative care IS (PAL-IS) to understand process interoperability and health IT. Aldosari's investigated why the authors of EHR projects failed to write about the development of practices for EHR implementation success.

The findings from the above studies indicate that there are disadvantages to using EHR technology. Obstruction to physicians' efficiency, loss of interprofessional understanding of the patient's story, and threats to security and privacy account for EHR disadvantages. According to Varpio et al. (2015), physicians' uses of EHR obstructed their ability to build the patient's story by fragmenting data interconnections. They also observed that limited numbers and sizes of free-text spaces available for narrative notes inhibit clinicians' ability to read the why and how interpretations of clinical activities from other team members. These limitations result in the loss of shared interprofessional understanding of the patient's story and increased time required to build the patient's story. The integration of medical information can improve the quality of care at a serious risk of privacy and security (Heart et al., 2017). McGeorge et al. (2015) also showed that EHRs did not consistently improve efficiency or eliminate paper use from work processes. The disadvantages to EHR technology relate to its tendency to obstruct physicians' efficiency when building a patient's story, and this may result in losses of interprofessional understanding of a patient's situation (Varpio et al., 2015). The integration of EHR technology was also observed to not completely improve efficiency and lead to serious privacy and security risks (Heart et al., 2017; McGeorge et al., 2015).

Strategies for Improving and Expanding EHR MU

In one study, Eliadou et al. (2019) discussed the characteristics/architecture of EHR that allows for interoperable functionality. Weiner (2019) recommended the use of other strategies for improving the current state of EHRs. Shahnaz et al. (2019) emphasized how blockchain technology can be used to transform the EHR systems and could be a solution for issues regarding data security, integrity, and management. Maxhelaku and Kika (2019) analyzed standards for improving interoperability and integration of patient data between different hospital services. To understand why EHR projects fail, researchers worked to identify errors and causes of EHR systems communication failures. They also examined the practices of EHR project managers and observed EHR implementation processes in small physician offices (Aldosari, 2017; Khajouei et al., 2018; Khennou et al., 2018; Rey, 2015).

Other researchers examined strategies that relate to improving the workflow process and data quality of EHRs technology that implement MU functionality. Spooner and Kirkendall (2016) summarized efforts to create standard quality measures and discussed the rise in EHR-based registry systems as one of such strategies. Other approaches to facilitating the MU of EHR discussed in the literature include addressing Technology and SKN implementation. For instance, Rangachari and Rethemeyer (2017) investigated the role of SKN Technology-based strategy for promoting/facilitating MU and successful implementation of EHR. Similarly, Rangachari (2018) examined user engagement in the SKN system and the associations between “SKN use” and “meaningful use” Risk Management and Healthcare Policy. Rangachari et al. (2019) go further to describe AU Health’s experiences with the novel initiative to pilot an SKN system for enabling MU of EHR MedRec technology and discussed lessons learned regarding the potential of an SKN system to enable interprofessional learning and practice improvement in the context of EHR MedRec.

To achieve the desired level of EHR sharing, receiving, and integration, EHR systems must be interoperable. Shull (2019) notes that, at its core, interoperability is primarily about aggregating the crucial and rich data generated from health plans, vendors, health systems, and patients and leveraging it to improve clinical processes, such as patient diagnosis, prescriptions, and treatment. The rich data from health systems, vendors, health plans, and patients are generated through analytic systems, EHRs, biometric recordings, and any other digital system in place. Essentially, interoperability is desirable because it is the key determinant of whether clinicians through the healthcare system can optimize current and emerging technologies for better or improved healthcare outcomes (Moor et al., 2015). The desired level of optimization cannot be achieved unless the digital systems used in different clinical systems can exchange, interpret, and use electronic information without necessarily requiring the user's intervention, in this case, the healthcare personnel.

An integrated electronic health system must save time and enable nurses and other healthcare practitioners to spend additional time with patients. Parasrampuria and Henry (2019) insist that the need for improved efficiency necessitated the shift from the traditional systems, which were primarily manual and involved a great deal of paperwork, to an electronic or automated one. Whether at the sending or receiving end, users of EHR systems must be able to access, retrieve, and use data and information for clinical purposes (Patel & Chatterji, 2015). Importantly, the systems must be flexible enough to receive and send data or information from third-party systems such as independent IT vendors. EHR integration also entails having seamless automatic access to patient's healthcare records and other types of clinical information from within and without the healthcare system (Parasrampuria & Henry, 2019). Importantly, integrated systems are a key factor in improved patient outcomes. According to Shull (2019), integrating electronic health systems, which culminates into a higher level of interoperability, can turn out as the enabler of a global population-based payment system, patient data, and information harmonization, delivery forms, and performance measurement metrics.

To expand the adoption and MU of EHR technology, Sahama et al. (2019) proposed the application of OECD data and ITS analysis for creating simulations.

Cohen’s (2016) demonstrated that HITECH financial incentives accelerated EHR adoption among small practices in the United States. However, small healthcare practices are less likely than others to qualify for incentives and meet the MU of EHR criteria (Ekezue et al., 2019). Reform policies that make EHR adoption requirements for hospitals and allow for voluntary adoption by private practice may influence EHR adoption (De Pietro, 2018), even though the evidence also revealed growth in EHR adoption rate in the absence of incentives (Dranove et al., 2015).

Factors that Influence EHR Adoption and MU

Multiple researchers have also explored factors that influence EHR adoption and MU. The influence of physician perspectives, hospital, and patient characteristics, laws, and policies are among the major buckets that researchers examined. For instance, Heath and Porter (2019), Asan (2017), and Iqbal et al. (2013) examined physicians’ perspectives on EHR use as well as their usage intentions and how this influences the extent and prevalence of EHR use. They also examined the influence of hospital and patient characteristics.

Physicians’ perception and user intentions can influence the adoption and MU of EHR technology. Jacobs et al. (2019) observe that the initial experiences of physicians may influence the MU of EHRs. Other factors that may influence physicians’ use of EHR are social influence, work experience, medical specialty, and resistance to change (Al-Rayes et al., 2019). Iqbal et al. (2013) identified the intention to use EHR, perceived usefulness, and ease to use primary care physicians as key factors to EHR adoption. This finding was substantiated by Abdekhoda et al.’s (2015) findings that point to perceived ease of use (PEOU), perceived use (PU), and organizational contextual factors influence physicians' attitudes toward EMRs. In Swedish hospitals, the slow rate of adoption of EHR technology despite government requirements has been attributed to a lack of agreement and financing strategy by stakeholders (De Pietro, 2018). Organization-level seems to have no significant impact on physicians' adoption of EHR systems in Quebec (Gagnon et al., 2016). Sharp and Steven (2019) identified other factors that contribute to EHR use experience to include undue clerical burden, loss in sense of autonomy, excessive time with computer interactions, fewer meaningful interactions, inadequate proficiency, and changing relationships with patients. They noted the sparse availability of evidence for interventions that would specifically improve physician wellness. Although there has been significant acceleration in the rate of EHR adoption, challenges remain, especially for small and rural clinics and hospitals. The perception of physicians, as well as their intentions, significantly affect rates of EHR adoption. Physician perceptions and use intentions are influenced by multiple factors, including perceived usefulness, ease of use, and organizational level dynamics in hospitals and practices. Policies, incentives, and data may be instrumental in facilitating the wider adoption of EHR systems.

Facilitators of EHR Use

Facilitators of EHR usage among physicians' have been identified as the perception of ease of use, perceived usefulness, MU certification, government laws, incentives, and CDSS interoperability. MU and PU of EHR have been attributed to physicians' continued use of EHR (Ayanso et al., 2015; Holmgren et al., 2017; Peterson et al., 2015; Sherer et al., 2016). Barriers to EHR interoperability in health institutions relate more to external factors beyond the hospital's control. Complexities of medicine and clinical terminologies and errors in communication were also noted to limit interoperability usage and hamper communication between EHR systems (Braunstein, 2018; Khajouei et al., 2018). EHR capacity for documentation is sometimes inefficient and may enable inconsistency and undesirable variations with resultant effects on clinical care (Walton et al., 2019; Weiner, 2019). Physicians' use of EHR systems may also be deterred by factors such as stringent MU criteria, resource availability, and perception about the MU of EHRs. For instance, costs associated with upgrading MU-certified EHR systems may prevent family physicians with MU-certified EHRs from meeting the successively stringent MU criteria. Physicians also continue to express negative beliefs about the MU of EHRs (Peterson et al., 2015; Stuttgart, 2017).

Barriers to EHR Use

Researchers have also highlighted some barriers to EHR use. Stringent MU criteria, resource availability, and physicians' perception about the MU of EHR might deter the use of EHR systems. For instance, Peterson et al. (2015) observed that costs associated with upgrading MU-certified EHR systems prevent family physicians with MU-certified EHRs from meeting the successively stringent MU criteria. Stuttgart (2017) found that only one-fifth of the physicians in their study believed that the MU of the EHR would improve the quality of care, patient-centeredness of care, or the care they provide. Stuttgart (2017) also noted that primary care physicians expressed more negative beliefs about the MU of the EHR in Stage 2 than in Stage 1. Another barrier to EHR use highlighted relates to the issue of compromising interoperability standards during EHR integration. Yuksel et al. (2016) observed that it is impossible to sustain the integration of EHRs with other healthcare IT systems in a proprietary way without exploiting promising interoperability standards and profiles. Holmgren et al. (2017) also noted that a nontrivial proportion of variation in hospital MU performance is explained by vendor choice. Certain vendors are more often associated with better MU performance than others.

Complexities of medicine and clinical terminologies and errors in communication have been identified as limitations to interoperability usage and sharing of data. Braunstein's (2018) findings, for instance, reveal that a large extent of the limitations in the use of EHR to share, receive, and integrate patients' records can be attributed to the complexity of medicine and clinical terminologies. Khajouei et al. (2018) identified a large number of system and operator-dependent errors hampering communication of information from HIS to SEPAS and obtained results that revealed that the same hospital ISs used in different hospitals could face dissimilar types and levels of errors when communicating with other ISs.

EHR systems also suffer from gaps that limit their efficiency as documentation tools. Inconsistencies in the functional capability of EHR systems account for its limitation as a documentation tool. Walton et al. (2019) report that the poor capturing of genomic data by the EHR systems accounts for ineffective clinical care for patients requiring such documentation. Weiner (2019) also noted that current EHR systems are still far from being effective documentation tools for facilitating the effective healthcare of individuals and populations. Weiner (2019) identified the inefficiencies of EHR systems to include their ability to enable inconsistency and potentially undesirable variation in the documentation and, sometimes, even the clinical care associated with it. These findings reveal that the capability of current EHR systems is limited in their insufficient ability to record genomic health data and effectively facilitate documentation of health records.

EHR adoption and MU by health institutions may be influenced by factors of practice size, financial incentives, and complete use of EHR functionalities. For instance, despite an acceleration in EHR adoption, challenges to its use exist notably in a small and rural hospital. Shu et al. (2014) also observed low adoption rates across tertiary hospitals in China. This may be substantiated with findings that reveal that organization-level seems to have no significant impact on physicians' adoption of EHR systems in Quebec (Gagnon et al., 2016). Also, only a small proportion of hospitals have effectively utilized all functionalities in the EHR system. Compliance to government reform policies and financial incentives have also been observed to influence adoption rates (Cohen, 2016; Dranove et al., 2015; De Pietro, 2018). Physicians' perceptions, which may be influenced by their initial experience with EHR systems, PEOU, EOU, and poor user experience, could influence the continued use of EHRs (Jacobs et al., 2019). These researchers, however, present different findings on the influence of incentives on the EHR adoption rates. While Cohen (2016) identified the influence of HITECH financial incentives in accelerating EHR adoption among small practices in the United States, this contrasts with evidence about the growth of EHR adoption in the absence of financial incentives

(Dranove et al. (2015). Sharp and Steven (2019) noted the availability of sparse evidence for interventions that will specifically improve physician wellness.

EHR Data Privacy and Security

Evidence from mobile health applications shows insufficient attention to privacy policy despite privacy regulations (Parker et al., 2019). Robillard et al.'s (2019) findings also reveal information collection on mental health applications that do not include a PP or ToA. Flaumenhaft and Ben-Assuli (2018) observed existing variance in government policies such as the EU's general data protection regulation (GDPR) concerning the degree of compliance to EHR service systems. These findings demonstrate the presence of weak data policies, which might not be adhered to if variance in legal terminologies and adoption of privacy regulations issues are not addressed. Kalesanwo (2019) identified location-based information access by third parties without user consent as a data privacy violation. Hecht (2019) highlighted possible data breaches as an area of concern in the use of EHRs. Data breaches of sensitive healthcare data may occur if secure techniques for healthcare are not implemented. Common threats to data loss and theft are identified as third-party disclosures, which are said to have increased with the advent of electronic IT (George & Bhila, 2019). Campbell et al. (2019) observed that participants voiced concerns about balancing patient safety with 42 CFR Part 2 privacy protections. Numerous workarounds have been deployed to manage communication and care within hospitals. EHR privacy and security may be threatened by a lack of attention to privacy policies and regulations, the presence of weak data policies, and noncompliance to these policies. For instance, the nonadherence of mental applications to privacy regulations and variances in government policies concerning EHR system compliance may pose risks to EHR privacy and security. Concerns have also been noted in balancing patients' safety with some privacy regulations, such as the CFR Part 2 privacy protections (Campbell et al., 2019; Flaumenhaft & Ben-Assuli, 2018; Parker et al., 2019; Robillard et al., 2019). Implementing insecure techniques and third-party disclosures, which lead to data breaches and unauthorized access to sensitive data, were also considered areas of concern to EHR use (George & Bhila, 2019; Hecht, 2019; Kalesanwo, 2019).

Protecting EHR Privacy

Privacy concerns and consent rules may influence health record efficiency, increase administrative burdens, and affect personal health information disclosure and care. To address these concerns, Zhang et al. (2018) highlighted that coping appraisals and threat appraisals influence privacy concerns. Shen et al. (2019) also found that patients' perceptions of healthcare may mitigate privacy concerns. Findings from studies on the use of e-Consent tools indicate its importance in providing users awareness of consent policy (Iwaya et al., 2019), which in turn, helps allay related concerns. Krahe et al. (2019) indicated that user willingness to share data is dependent on the type of data, and information sharing is influenced by trust. In addressing concerns of EHR privacy, measures and tools have been proposed to identify the influences of privacy concerns. Coping and threat appraisals, patient perceptions of healthcare, and use of e-Consent tools may influence and mitigate privacy concerns (Iwaya et al., 2019; Shen et al., 2019; Zhang et al., 2018). Trust and data types may also determine the user's willingness to share data.

Approaches to protecting data privacy and guarding against violations of data privacy have been proposed in several studies. McSherry (2018) highlighted measures by government bodies, such as the European Union, to regulate automated profiling of large databases and Australia's introduction of a data breach notification scheme for cases where personal information held by an organization is lost or subjected to unauthorized access or disclosure. They also reviewed and summarized the known approaches reported in the literature, specifically concerning the integration of EHRs. Jiang et al. (2020) similarly developed a knowledge-based method, LATTE, for transforming various expressions of laboratory test results into a normalized and machine-understandable format. Jiang et al. (2016) also developed and evaluated a DER to provide machine-readable QDM data element service APIs. They used ISO/IEC 11179 metadata standards to capture the structure for each data element and leverage semantic web technologies to facilitate semantic representation of the metadata. An approach to integrating EHRs from heterogeneous resources and generating integrated data in different data formats or semantics to support various clinical research applications was presented by Sun et al. (2015). A novel way of visualizing and linking EMR data by developing a NoSQL graph database using Neo4j was proposed by Yip et al. (2019). O'Connor et al. (2017) also proposed practical approaches that should be considered when designing and developing IoT for data collection and data sharing within the health domain.

Some researchers particularly explored and proposed approaches and methods to utilize and manage EHR data in research and practice. Juhn and Liu (2020), for instance, reviewed the literature on the secondary use of electronic health record data for clinical research concerning allergy, asthma, and immunology and highlighted their approaches to advancing EHR research. Agrawal et al. (2019) discovered that obstructive sleep apnea and related comorbidities are clinically correlated. An approach for applying EHR data analytics was discovered in the process of their study. Taggart et al. (2015) also examined how structured data quality reports (SDQR) and feedback sessions with practice principals and managers can improve the quality of routinely collected data in EHRs. Patients Perceptions regarding the use of personal health information for research were assessed by Krahe et al. (2019). They determined that investigating EHR data usage plays a key role in EHR adoption. They also proposed the Artificial intelligence approach that uses natural language processing to advance EHR-based clinical research and highlighted the secondary use of electronic health record data.

Sher et al.'s (2017) evaluation of privacy policy compliance by Health IT staff indicated that health records are handled without behavioral intentions, deterrent approaches to ensure compliance has also been observed by nursing staff. Taylor and Wilson (2019) argued that conformity with a reasonable expectation of privacy provides an alternative account for the lawful disclosure of CPI and may provide a more sustainable and authentic approach to meeting obligations under the law of confidence than the standard account. To guard against privacy violations, government bodies have put measures to regulate automated database profiling and have introduced the use of schemes that notify users about data breaches or losses or unauthorized access to data (McSherry, 2018). Measures to ensure health staff comply to privacy regulations include the use of deterrent approaches and the evaluation of privacy policy compliance among health IT staff (Sher et al., 2017).

Tools, models, and frameworks are also proposed to ensure privacy and data protection in EHR systems. The integration of confidentiality codes, semantic frameworks, cloud-based solutions, and middleware solutions are examples of tools and frameworks that researchers propose. For example, Tseng et al. (2016) observed that the use of confidentiality codes on Taiwan’s EMRs ensured stronger security in personal health record exchange, even though it increased healthcare professionals’ workloads. Lu and Sinnott (2018) suggested that the use of semantics frameworks helped to preserve EHRs. They demonstrated this through their use of eXtensible Access Control Markup Language (XACML) with semantic framework to improve access control and risk disclosure functions. Yesmin and Carter (2020) also evaluated the performance of tools that monitor audited user access. Karapiperis et al. (2019) proposed a framework for integrating EHR can perform privacy preservation of large-scale data in healthcare, Cloud-based solutions for management and securing of patient information have been highlighted to provide improved data protection (Chirilla et al., 2015). Middleware solutions compatible with EHR or PHR could strengthen EHR user access privacy (Plastiras & O’Sullivan, 2018).

Additionally, Campbell et al. (2019) indicated that use of sensitive note designation in the healthcare system “breaks the glass” technology. Yogarajan et al. (2018) noted compliance to privacy ethics in research use and data sharing among DHBs, use of confidentiality agreements, encryption, and cybersecurity procedures were also highlighted as measures to ensure compliance. Badr et al. (2018) proposed PBE-DA framework is also aimed at enabling patient's private access and updating of sensitive data on EHR systems. Privacy protection within the EHR system may be achieved through the use of confidentiality codes, integration of semantic frameworks, proposed frameworks, cloud-based and middleware solutions. For instance, the use of proposed frameworks, semantic models, and cloud-based solutions could ensure preservation and security of large-scale data as well as strengthen user access privacy (Chirilla et al., 2015; Karapiperis et al., 2019; Lu & Sinnott, 2018; Plastiras & O'Sullivan, 2018; Tseng et al., 2016). Health systems have also been observed to ensure compliance to privacy regulations and ethics in research use and data sharing (Badr et al., 2018; Yogarajan et al., 2018).

Studies Related to HIE Consent Policies

There has been significant emphasis on the landscape of EHR privacy and consent policies and how these affect current and future levels of EHR adoption and interoperable functionality of EHR systems. Earlier researchers proposed the use of tools and= techniques for preserving EHR privacy and maintaining record security in healthcare. They propose approaches like automated privacy auditing, semantic privacy frameworks, e-consent tools, computational modeling, and a hybrid technique (Carter, 2020; Hathaliya & Tanwar, 2020; Iwaya et al., 2019; Kundalwal et al., 2019; Lu & Sinnott, 2018). Some studies have also examined the HIE preferences, including patient and public attitudes toward different types of informed consent models (Turvey et al., 2020; Apathy & Holmgren, 2020; Riordan et al., 2015). There are also studies that examined mechanisms and practices used to protect EHR privacy. Some mechanisms discussed include hospital internal ISs, EHR publishing, blockchain-based secure EHR system (Huang et al., 2019; Stablein et al., 2018; Tseng et al., 2016; Wang et al., 2019; Yogarajan et al., 2018).

The findings of these studies suggest that consent and privacy policies may impact HIEs. Existing privacy policies, compliance to these policies, and legal variance in data policies influence EHR adoption and MU. Kosseff (2019) noted that privacy law limits companies' collection, use, sharing, and retention of personal information. Mulder and Tudorica (2019) highlight obscure processing activities of privacy laws in Europe and the gaps that exist between privacy policy regulations and practical reality. However, some regulations experience gaps in legal variance and practical compliance, which may influence HIE, EHR adoption, and MU (Mulder & Tudorica, 2019).

Patients' privacy concerns can also influence patients' confidence and use of EHR systems. They have been observed to limit data sharing and EHR usage. Xu's (2019) findings indicated that privacy concerns for HIaaS significantly affect patients' trust belief, perceived privacy risk, and consent intention. On the contrary, Park and Shin et al. (2020) observed that privacy concerns and confidence had weak effects on people's behavior. Stablein et al. (2018) also noted that confidentiality concerns due to EHR's longevity increased access and multidimensional use. Zhang et al. (2018) also observed that health information privacy concerns significantly influence personal health information disclosure, and the fear of data breach of sensitive medical information may impact patients' confidence in seeking treatment. Spooner (2016) noted the challenging security and privacy concerns of adolescents' data. Complex privacy and security challenges exist in children adolescents' health record privacy and may affect how data is stored in EHR systems (Spooner, 2016). Privacy concerns have been observed to limit confidence in data sharing and EHR usage. For instance, confidentiality concerns have been observed to influence personal health information disclosure, and one's confidence to seek treatment may be influenced by fears about the loss of sensitive data. Clemens (2012) also noted privacy and security concerns are more noted in data records of minors and adolescents. This may affect data storage in EHR systems. Findings that reveal how privacy concerns of EHR systems affect patients' trust, belief, perceived privacy risks, and consent intention (Xu, 2019) contrasts with findings that observed weak behavioral effects of privacy concerns and confidence (Park & Shin et al., 2020).

Studies Related to Research Questions

Opt-in privacy rules have been observed to create administrative burdens that are borne by hospitals that are not technologically advanced (Apathy & Holmgren, 2020). Gaps in care continuity by demographics indicate an influence of consent policy preferences (Turvey et al., 2020). Aldjerid et al. (2016) noted that privacy regulation alone can result in a decrease in planning and operational HIEs and that, when coupled with incentives, could positively impact the development of HIE efforts. Anwar et al. (2015) observed the challenges of cross-country data protection to EHR interoperability. Goldstein et al. (2020) observed that although providers were aware of the confidential features within their EHR systems, they lacked training on how to ensure confidentiality of patients' records and had low confidence in their EHR's ability to maintain confidentiality. These findings reveal factors that facilitate and impede the usability of

EHR. Regulations like opt-in privacy rules have been found to place administrative burdens on hospitals that are not technologically advanced. Privacy regulations could also be coupled with incentives to positively impact HIE (Apathy & Holmgren, 2020; Aldjerid et al., 2016). Providers were also observed to lack training on how to ensure confidentiality of patients' records despite being aware of EHR confidential features.

Navigating the Consent Policy Barrier

Findings from some studies indicate that the development of EHR schemes might outpace stringent privacy measures and consent policies and lessen the effects of stringent privacy regulations (Riles, 2020). Edward et al. (2019) observed the use of well-written consent forms as well as blanket consent treatment forms in pediatric departments. Riordan et al. (2015), for instance, reported that although a large patient population in the UK was unaware of EHRs, the requirement of consent to use EHRs was strongly preferred in populations that were previously aware of EHRs. O'Connor et al. (2017) expressed concerns about the challenges the IoT may cause in the informed consent process. The importance of full awareness of the extent of consent is further emphasized by privacy requirements associated with the forthcoming GDPR. Secure techniques in healthcare can provide satisfaction to patients and healthcare givers (Hathaliya & Tanwar, 2020). Barriers to consent policy were addressed through the use of blanket consent at pediatric departments, lessening the effects of privacy regulations, and challenges the IoT may also influence the informed consent process. Improving awareness of consent is considered an important requirement in forthcoming regulations, such as the GDPR.

Definitions

Basic EHR System

An EHR system with at least a basic set of EHR functions (typically 10 core functionalities are determined to be essential to an EHR system, including clinician notes, as defined in Table 1) (Blumenthal et al., 2006; Henry et al., 2016).

Certified EHR System

A certified EHR is EHR technology that meets the technological capability, functionality, and security requirements adopted by the Department of Health and Human Services. This includes the capability to securely work with other certified EHR systems to share information (interoperability). The "possession" of certified EHR technology is considered to be either the physical possession of the medium on which a certified EHR system resides or a legally enforceable right by a healthcare provider to access and use, at its discretion, the capabilities of a certified EHR system. Table A1 shows the electronic functions required for hospital adoption of a Basic or Comprehensive EHR system, which a consensus expert panel established (Blumenthal et al., 2006; Henry et al., 2016).

EHR

An EHR is a digital version of a patient's paper chart. EHRs are real-time, patient-centered records that make information available instantly and securely to authorized users. One of the key features of an EHR is that health information can be created and managed by authorized providers in a digital format capable of being shared with other providers across more than one healthcare organization (Health IT, 2020).

EHR MU

MU is defined by the use of certified EHR technology that connects with other EHR technologies to provide for the electronic sharing, receiving, and integration of health information between both technologies to improve the quality of care. MU sets the specific objectives that eligible professionals and hospitals must achieve to participate in the national EHR incentive programs (CDC, 2020; Center for Medicare and Medicaid Services, 2020).

Interoperability

Interoperability is the capability to securely work with other certified EHR systems to share information (interoperability) (Henry et al., 2016).

Nonfederal Acute Care Hospital

This category includes acute care general medical and surgical, general children's, and cancer hospitals owned by private/not-for-profit, investor-owned/for-profit, or state/local government and located within the 50 states and District of Columbia. The inclusion of children's general and cancer hospitals in this category makes this definition different from that in previous peer-reviewed research. However, it is consistent with the population of hospitals eligible for federal Health IT adoption incentives (Blumenthal et al., 2006; Henry et al., 2016).

PSC Records

Patient Summary care records are electronic records of important patient information created from GP medical records. They can be seen and used by authorized staff in other areas of the health and care system involved in the patient's direct care.

Type of State HIE Consent Policy

This refers to the respective state-designated HIE policy adopted. Broadly, these policies fall under two categories: opt-in and opt-out. Opt-out-patients may be automatically enrolled in the HIE but are given the opportunity to opt-out of having their information stored and/or disclosed by the HIE while with opt-in, patient consent is required for patient health information to be stored and/or disclosed by the HIE (ONC, 2019c).

Assumptions

Five assumptions underpin this study. The first assumption is that the theoretical framework accurately reflects the hypothesis being tested in this study. The second assumption of this study is that the variables of state EHR consent policy have been clearly defined and are measurable. Thirdly, it is assumed that the participants who participated in the primary survey from which data is being drawn for this study are representative of the population and responded to questions honestly without biases. This assumption is necessary to make because I used information from a reliable source. The fourth assumption is that the results of this study will be generalizable beyond the sample of nonfederal acute care hospitals being studied.

Scope and Delimitations

Delimitations are conditions deliberately imposed by the researcher to limit the scope of a study. According to Bloomberg and Volpe (2012), a researcher can achieve delimitation by establishing the parameters for the participants and location of the study. Kirkwood and Price (2013) supported this view. The present study includes only U.S.

nonfederal acute care hospitals that (a) specifically reported on the extent to which they share, receive, and integrate PSC records were collected between 2015 and 2017, and (b) are located in states that fall within the two broad HIE opt-in or opt-out policies. Nonfederal acute care hospitals that do not report on the extent to which they share, receive, and electronically integrate PSC records between 2015 and 2017 will not be included in the study to maximize standardization of data utilized for analysis.

Limitations

The limitations of a study refer to gaps in the feasible intent and procedural weaknesses of the study (Morse, 2015). A limitation anticipated in this study relates to the validity and generalizability of the study's findings (Katz, 2015). Because I drew conclusions about the phenomenon without empirically analyzing primary data or the direct participation of physicians and patients from all U.S. nonfederal acute care hospitals, questions regarding generalizability may arise. Despite these limitations, findings from this study may contribute to the body of knowledge regarding the effects of EHR consent policies on the MU of EHR systems, specifically for SRI PSC records. Another limitation anticipated for this study relates to the availability of a recent dataset on state EHR policies. The most recent data on EHR consent policies were collected in 2016 and did not include data on when policies were enacted. As a result, the findings from this study may not reflect policy changes that may have occurred within the last three years. However, to address the problem of lack of information on when policies were enacted, web pages of institutions that manage implementations of these policies will be reviewed to determine the year they were enacted. Another limitation relates to the scarce availability of recent studies on the role of consent policies on provider adoption of EHR systems. The scarcity of evidence in this regard may affect the robustness of findings from the literature to support or refute findings from this study.

Significance, Summary, and Conclusion

The U.S. government has made significant investments to promote the MU of certified EHR systems, yet many (about 59%) nonfederal acute care hospitals in the country do not use their EHR systems to SRI PSC records for patients transitioning from one setting of care or provider to another (Eval, 2016; ONC, 2017; Riordan et al., 2015; WHO, 2017).

What is Known

Wider EHR adoption and MU by health institutions may be influenced by factors of practice size, financial incentives, and effective use of EHR functionalities. For instance, despite the acceleration in EHR adoption rates, challenges involved in the use of EHRs notably exist in small and rural hospitals. Low adoption rates have also been observed across tertiary hospitals in China and may substantiate the findings that organization-level seems to have no significant impact on physicians' adoption of EHR systems in Quebec (Gagnon et al., 2016; Shu et al., 2014). Furthermore, all functionalities of the EHR system are only effectively used in a small proportion of hospitals. Compliance to government reform policies and financial incentives have also been observed to influence adoption rates (Cohen, 2016; Dranove et al., 2015; De Pietro, 2018). Physicians' perceptions, which may be influenced by their initial experience with EHR systems, PEOU, EOU, and poor user experiences, can influence their continued use of EHR technology (Jacobs et al., 2019).

One proposed way to expand EHR adoption and MU is the application of OECD data and ITS analysis to the creation of simulations (Sahama et al., 2019).

The impact of EHR technology on healthcare quality, patients, and medical personnel is apparent from earlier studies. EHR technology benefits hospitals' performance, quality of care, data management research, and physician efficiency. The adoption of EHR technology was observed to improve medical care metrics, provider productivity, quality of healthcare, and aid development of treatment plans. For instance, improved hospital performance, which is associated with improved patient flow and financial performance, was observed upon adoption of EHR (Bushelle-Edghill et al., 2017; Weech-Maldonado et al., 2018). Physician efficiency was also observed to improve with EHR use. Improvements in diagnostic metrics, treatment plan development, the productivity of healthcare providers, and patient survival rates, which also contribute to improving the quality of healthcare was also found to be associated with EHR adoption (Ayaad et al., 2019; Han et al., 2016; Rey, 2015; Walji et al., 2014). Furthermore, an increase in provider productivity, measured by patients' visit volumes and charges, indicates the benefits of EHR adoption over non-adoption (Cheriff et al., 2010; Kevin et al., 2019). The use of EHR also improves data collection, assessment, and capture in social settings (Rashotte et al., 2016; Rumball-Smith et al., 2018). EHR interoperability standards may enable the development of multiple-access telemedicine platforms. The integration of EHR systems could also enable information sharing and e-health synergy, which have overall effects on hospital performance (Finet et al., 2018; Mačinković & Aničić, 2016; Wu et al., 2016). Despite these many benefits, EHR technology can obstruct physicians' efficiency. In one study, EHR systems were found to make it difficult for physicians to build comprehensive patient stories, which in turn, limited interprofessional understandings of patients' medical situations (Varpio et al., 2015). The integration of EHR technology did not completely improve efficiency and poses serious privacy and security risks (Heart et al., 2017; McGeorge et al., 2015).

Regarding facilitators and barriers, factors such as how physicians perceived the ease of use of EHRs, EHR usefulness, and MU can facilitate EHR adoption. Other factors are MU certification, differences in EHR brands, government laws, and incentives. MU and positive PU of EHR are attributed to physicians' continued use of EHR (Ayanso et al., 2015; Holmgren et al., 2017; Peterson et al., 2015; Sherer et al., 2016). Furthermore, barriers to EHR interoperability in health institutions were also identified in primary care institutions; complexities of medicine and clinical terminologies and errors in communication can limit interoperability usage and hamper communication between EHR systems (Braunstein, 2018; Khajouei et al., 2018; Kiapio et al., 2018) EHR capacity for documentation was noted to be inefficient. For instance, findings agree that EHR was incapable of capturing relevant genomic data and can enable inconsistency and undesirable variations with resultant effects on clinical care (Walton et al., 2019; Weiner, 2019). Factors such as stringent MU criteria, resource availability, and perception about the MU of EHR can deter physicians' use of EHR systems. For instance, costs associated with upgrading MU-certified EHR systems can prevent family physicians with MU-certified EHRs from successively meeting stringent MU criteria. Physicians also continue to express negative beliefs about the MU of the EHR (Peterson et al., 2015; Stuttgart, 2017).

Approaches that improve EHR implementation and interoperability functions include system integration approaches that are responsive to organizational change, and the utilization of generic HISs is essential to EHR adoption efforts (Currie et al., 2016; Sharp & Steven, 2019). The adoption of web service technology may solve EHR interoperability problems, which in turn reduce costs and errors incurred by hospitals. Also, the use of developed PHIPs was found to have strong capacities for HIE (Zeinali et al., 2016; Zhang et al., 2017). Semantics was identified as integral to EHR infrastructure (Cornet, 2017). The integration of semantics frameworks into EHR systems is proposed to enable synchronization of large-scale data and improve information sharing (Jaulent et al., 2018; Sun et al., 2015). Detro et al. (2016) suggested the application of formal concept analysis to improve the semantic interoperability of EHR systems. Other models that aid in the processing and storage of large-scale data include MongoDB, which allows for the easy storage of structured and unstructured data to aid heterogeneity (Dodeja et al., 2018). The capability of RNN for predictive modeling with large heterogeneous EHR data was also determined in this study (Ramsy et al., 2019). Models that improve EHR interoperability have also been proposed. For instance, proposed novel models of distributed noise contrastive estimation (distributed NCE) can preserve model structure, achieve comparable prediction accuracy, and build predictive models in a distributed manner with privacy protection (Li et al., 2019). Proposed prototypes can also enable the editing of patient records and the addition of comments while preserving the validity of the documents (Mishra et al., 2016). Proposed harmonization of FHIR and CIMI could enable the QDM specification and enable better coverage of DER, DER-based approaches have been demonstrated as extensible and scalable (Jiang et al., 2016).

Models and tools that support the evaluation of EHR social impact and acceptance are proposed. Models can explain physicians' acceptance of novel technology and identify social influences of EHR experience, as well as the perception of the usefulness of EHR systems (Belaryan et al., 2019; Steininger & Stiglbauer, 2015). Tools such as the e-CEX have also been validated as reliable tools for assessing patient-centered EHR communications. The integration of the SKN tool as a reporting tool within the EHR system can enable interprofessional learning (Alkureishia et al., 2018; Rangachari, 2018; Russo et al., 2018). To improve EHR capability, tools that achieve more precise and user-centric results, such as the HL7 parser, have been identified (Kanade et al., 2019). The use of Neo4j database systems was found to enable additional data visualization and the management of data-intensive EHR systems (Yip et al., 2019). The proposed use of the LATTE model may normalize laboratory test results and facilitate EHR-based application (Jiang et al., 2020).

EHR privacy and security are threatened by the lack of attention to privacy policies and regulations, the presence of weak data policies, and noncompliance to these policies. For instance, nonadherence of mental applications to privacy regulations and variances in government policies regarding EHR system compliance poses a risk to EHR privacy and security. Concerns have also been noted in balancing patients' safety with some privacy regulations, such as the CFR Part 2 privacy protections (Campbell et al., 2019; Flaumenhaft & Ben-Assuli, 2018; Parker et al., 2019; Robillard et al., 2019). Implementation of insecure techniques and third-party disclosures, which lead to data breaches and unauthorized access to sensitive data, are also considered areas of concern to EHR use (George & Bhila, 2019; Hecht, 2019; Kalesanwo, 2019).

To strengthen the security of EHR, several measures and tools have been proposed. For instance, the complementary use of EHRs with IT systems in hospitals may reduce the risk of data breaches (Shoja & Maraka, 2019). The use of MA-ABE and DEM was observed to preserve privacy and to protect EHR from attacks (Kundalwal et al., 2019; Sowmya & Suresh, 2019). The use of blockchain technology in EHR systems was also proposed to secure the storage of electronic records and act as a scalable and secure solution to interoperability issues (Huang et al., 2019; Shahnaz et al., 2019). Privacy protection within the EHR system may also be achieved with the use of confidentiality codes, integration of semantic frameworks, proposed frameworks, and cloud-based and middleware solutions. For instance, proposed frameworks, semantic models, and cloud-based solutions can ensure preservation and security of large-scale data and strengthen user access privacy (Chirilla et al., 2015; Karapiperis et al., 2019; Lu & Sinnott, 2018; Plastiras & O’Sullivan, 2018; Tseng et al., 2016). Privacy regulations can also be coupled with incentives to positively impact HIE (Aldjerid et al., 2016; Apathy & Holmgren, 2020). To guard against privacy violations, government bodies have implemented measures to regulate automated database profiling. They have introduced the use of schemes that notify users of data breaches, losses, and unauthorized access to sensitive information (McSherry, 2018).

The use of health systems can also ensure compliance with privacy regulations and ethics in research use and data sharing (Badr et al., 2018; Yogarajan et al., 2018). Measures to ensure compliance to privacy regulations by health staff include the use of deterrent approaches and evaluations of privacy policy compliance among Health IT staff (Sher et al., 2017). To address or mitigate concerns of EHR privacy, measures like coping and threat appraisals, responding to patient perceptions of healthcare, and the use of e-Consent tools may be helpful (Iwaya et al., 2019; Shen et al., 2019; Zhang et al., 2018). Proactively building trust can also determine the user's willingness to share data.

Regulations like opt-in privacy rules were observed to place administrative burdens on less technologically advanced hospitals (Apathy & Holmgren, 2020). Providers were also observed to lack training on how to ensure confidentiality of patients' records despite being aware of EHR confidential features (Goldstein et al., 2020). Barriers to consent policy implementation were addressed in the use of blanket consent policies at pediatric departments, lessening effects of privacy regulations, and challenges related to the IoT may also influence the informed consent process (Edward et al., 2019; O'Connor et al., 2017; Riles, 2020). Improving consent awareness is considered an essential requirement in forthcoming regulations such as the GDPR (O'Connor et al., 2017).

What is Controversial

The literature review revealed that there were mixed findings about the influence of her use on healthcare quality. Findings from some studies indicate that EHR improves hospitals' performance and increased efficiencies. For instance, Ayaad et al. (2019) observed that the adoption of high-quality EMR has a significant impact on improving the quality of healthcare services. The findings of Kruse et al. (2016), however, indicate that although EHR functionalities improve the quality of care, it also reduces the quality of patient-physician interactions.

EHR capacity for documentation was noted to be inefficient. For instance, findings show that EHR was incapable of capturing relevant genomic data and enabling inconsistent and undesirable variations with resultant effects on clinical care (Walton et al., 2019; Weiner, 2019). Different findings are also presented on the quality of data obtained from EHR systems. For instance, Horton et al.'s (2019) findings indicate that EHR use improves data quality and is more indicative of health status than administratively-sourced data. In contrast, Taggart et al. (2015) argued that although the presence of feedback and SDQRs improved the recording of patient data, they do not improve the quality of data. This is substantiated by evidence of EHR's limited effect on data quality (Darko-Yawson & Ellingsen, 2016). The following study presents different findings about the influence of incentives on the EHR adoption rates. For instance, Cohen (2016) indicated that HITECH financial incentive accelerates EHR adoption among small practices in the United States, this contrasts with evidence of growth in EHR adoption in the absence of financial incentives (Dranove et al., 2015). Findings that reveal how privacy concerns of EHR systems affect patients' trust, belief, perceived privacy risks, and consent intention (Xu, 2019) contrasts with findings that observed weak behavioral effects of privacy concerns and confidence (Park & Shin et al., 2020).

Gaps in the Literature

Earlier studies that explore factors that influence the adoption and MU of electronic health records have highlighted cost, lack of industry collaboration, a culture of fragmentation, and physician burden as important factors that affect the MU of EHR systems in hospitals (Council for Affordable Quality Healthcare, 2020; Reisman, 2017). These factors have been more organizational, structural, and environmentally centered than they have been policy and patient-centered. Several researchers suggested that there is a relationship between state policies and increased administrative burden on healthcare practitioners, but little is known about whether these burdens influence the use of EHR systems and the sending, receiving, and use of PSC records. HIE consent policies exist and differ from state to state (Henry et al., 2016; Klosek, 2011; ONC, 2013; Palabindala, Parmarthy, & Johnnalagadda, 2016; Weiser, 2019). Despite the obvious differences in state HIE consent policies, there is no known research that has determined if and what aspects of state-level HIE legislation affect the MU of EHR systems to SRI PSC records.

The study addresses the under-researched area of the use of EHR systems for transferring and receiving PSC records among nonfederal acute care hospitals in the United States. The study was not limited to a specific health condition, a single state, or federal privacy legislation as found in related studies (Klosek, 2011; Weiser, 2009). Rather, it covered a broader scope in comparing state-level differences in EHR consent policies to differences in the percentage of nonfederal acute care hospitals that SRI PSC records using their EHR systems. Pointers to whether or not patient consent policies affect the use of certified EHR systems to SRI PSC records can provide context for healthcare administrators on how and where policy development and investments can streamline the complexity of exchange and address barriers to interoperability. This can, in turn, contribute to promoting wider use of certified EHR systems by healthcare administrators in acute care settings to SRI PSC records.

The study contributes to positive social change by providing evidence that could help healthcare administrators, advocates, and policymakers address current gaps in the continuum of care that have been amplified by the 59% of nonfederal acute care hospitals that do not use their EHR systems to SRI PSC records (De Regge et al., 2017; Eval, 2016; Mansukhani et al., 2015; ONC, 2017; Riordan et al., 2015; Waibel et al., 2016; WHO, 2017). These stakeholders may be able to leverage the evidence from this study to (1) addresses policy-related barriers to nationwide use of interoperable systems for sharing, receiving, and integrating PSC records and (2) promote patient consent policies that could support wider use of EHR systems for the said purpose. These could, in turn, increase gains in the quality and efficiency of care delivered (Henry, Pylypchuk, Searcy, & Patel, 2016).

The rationale, purpose of this study, research strategy, and sources of information for the literature review were part of this section on earlier studies on EHR adoption and MU, influencing factors, and the security architectures emplaced to protect EHRs. This section also contains a description of the theoretical framework that will serve as the lens through which the results of this study will be interpreted. The relevance of the theoretical framework was analyzed and synthesized. I concluded this section with a discussion of what is known, controversial, and unknown regarding the role of privacy policies on EHR MU. In Section 2, I discuss the research methodology of the study.

Section 2: Project Design and Process

Introduction

The purpose of this quantitative cross-sectional research study was to determine if the type of HIE consent policy present in a state influence the percentage of nonfederal acute care hospitals in that state that (a) send patients’ summary of care (PSC) records, (b) receive PSC records, and (c) integrate PSC records using their EHR systems. The study examined whether differences exist with the percentage of nonfederal acute care hospitals that send, receive, and integrate patients' PSC records in states that implement opt-in HIE policies versus states with opt-out HIE policies.

In this section, I present the methods I used to implement this quantitative cross-sectional study analysis. I begin with a brief review of my purpose statement, research question, and hypotheses. A description of the method and design and advantages and disadvantages of the method and design follows. I then discuss the dataset, variables I used for data analysis, as well as my plan for ensuring reliability, validity, and addressing missing data. I describe the statistical test I used for the secondary data analysis and discuss data analysis assumptions, including the implications for violating highlighted assumptions and corrective measures. Finally, I discuss the sampling procedure used during primary data collection, as well as the ethical considerations that guided the study, procedures for storing and protecting data, and data identity.

Methods and Design

Methods

The research question and null and alternative hypothesis for this quantitative analysis are as follows:

What is the correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically (a) send (b) receive(c) integrate PSC records from outside providers as reported in the American Hospital Association (AHA) survey between 2015 and 2017? The null hypothesis (H_01) is that there is not a statistically significant relationship between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically (a) send (b) receive (c) integrate PSC records from outside providers as reported in the AHA survey between 2015 and 2017? The alternative hypothesis (H_a1) is that here is a statistically significant relationship between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically (a) send (b) receive (c) integrate PSC records from outside providers as reported in the (AHA) survey between 2015 and 2017?

Research Design and Rationale

The research problem for this study was that the predictive influence of state HIE consent policies on healthcare administrator's use of EHR systems for sending, receiving, and integrating PSC records electronically in U.S. nonfederal acute care hospitals is not clearly understood. The independent variable for this study was "HIE consent policy type." This variable is a categorical variable with four categories: exclusively opt-in, exclusively opt-out, both opt-in and opt-out, and no HIE policy. The no HIE policy served as the base case for this study. The dependent variables were the percentage of nonfederal acute care hospitals in that state that (a) send PSC records, (b) receive PSC records, and (c) integrate PSC records using their EHR systems. The covariate or confounding variable was the year in which the survey was conducted (i.e., 2015 and 2017).

I used a cross-sectional quantitative correlational research to statistically determine whether a statistically significant relationship exists between the variables discussed above. Correlational designs are nonexperimental research designs researchers use to assess the statistical relationship between two or more quantitative variables without manipulating the independent variable (Paul et al., 2015; Setia, 2016). An important characteristic of correlational studies is that they are easy to conduct, generally inexpensive, and involve few ethical concerns (Paul et al., 2015). However, this design is limited due to its inability to establish causation. Despite this limitation, with this correlational research design, researchers can determine the strength and direction of a relationship between variables. Additional experimental studies can be conducted to build on findings to determine causation (Paul et al., 2015). The authors of this study used a correlational research design with a cross-sectional approach because this approach enables researchers to get an accurate representation of the general population. With cross-sectional studies, researchers get a snapshot of a wide area and strengthen the external validity of their study. However, the cross-sectional design is limited because it does not consider what happens before or after the snapshot is taken (Seita, 2016).

Another research design I considered using in this study was the quasi-experimental controlled before and after design. The controlled before and after design is a between-subject design in which I compared changes in the dependent variable between two groups before and after introducing or varying the independent variables (Campbell & Stanley, 2015). Because the controlled before and after design is a quasi-experimental design, it has better internal validity than observational studies and can result in improved estimates of the cause and effect relationship between the independent and dependent variable than observational studies. The design is also cheaper, more time- and cost-saving, and less complicated than traditional experimental designs because it does not require randomization (Bernard & Bernard, 2012; Trochim, 2006). However, this design was not suitable for this study because the purpose of the study was not to assess the impact or effect of the independent variable on the dependent variable but to examine the relationship between both variables. The design is also not suitable because the prospective approach of the controlled before and after design (Campbell and Stanley, 1963; Creswell, 2013) requires the collection of data at multiple points before, during, and after the independent variable (HIE consent policy) is introduced to study groups (nonfederal acute care hospitals that send/do not send, receive/do not receive, integrate/do not integrate PSC records using their EHR systems). The scope of this study does not include the analysis of nonfederal acute care hospitals that SRI PSC records using their EHR systems prior to when their state HIE consent policy was instituted. For this reason, I did not use the quasi-experimental controlled before and after research design in this study.

Methodology

Population

The population for this study was U.S. states that identify as implementing opt-in, opt-out, both opt-in and opt-out, or neither opt-in nor opt-out HIE consent policies. I examined the percentage of nonfederal acute care hospitals in the above categories. This included children’s and cancer hospitals, acute general medical and surgical hospitals owned by private/not-for-profit, investor-owned/for-profit, or state/local government located within the 50 U.S. states and District of Columbia. According to the American Hospital Directory (AHD), there were about 3,906 nonfederal acute care hospitals in the United States as of 2019 (AHD, 2020). The AHD categorizes a hospital as acute care based on the last four digits of its Center for Medicare and Medicaid Services (CMS) certification number, as reported in Medicare cost reports.

Sampling and Sampling Procedures

Sampling Strategy

In this study, I used a deidentified panel of publicly available datasets containing measures of adoption and use of interoperable EHR systems as well as the characteristics of state privacy legislation related to EHR adoption and use will be extracted from the ONC database **(**ONC, 2019a; ONC, 2019b). However, the original dataset was collected in a survey that was fielded from 2015 to 2017. The AHA used purposive convenience sampling methods in the primary study. The use of purposive sampling enables the researcher to select participants who meet certain inclusion criteria (Frankfort-Nachmias & Nachmias, 2008; Palinkas et al., 2015). Convenience sampling is a nonrandom sampling technique in which only participants that can practically participate in the study do so (Ilker et al., 2016). With convenience sampling, members of the target population that meet practical criteria like accessibility, availability, geographic proximity, and willingness can participate in the study. Both purposive and convenience sampling techniques are effective at anthropological studies and are two of the most efficient and least expensive sampling approaches (Saunders et al., 2012). However, because convenience samples can underrepresent the general population, the study may have insufficient power to detect differences between population subgroups. In turn, this can introduce considerable amounts of variation and produce unstable statistical influence in the analysis (Marc et al., 2013). In the primary study, the AHA purposively sampled hospitals that met the inclusion criteria of being a nonfederal acute care hospital. Only representatives from these hospitals who were available and willing to participate in the study were surveyed.

Sample size calculation**.** An appropriate sample size strengthens the validity of a study (Burkholder, 2009). Researchers consider four criteria in determining the sample size for a study: (a) Population size (i.e., the number of people in the target population that meet the eligibility criteria for participating in a study) (b) the margin of error or confidence interval (i.e., the amount of error between the sample mean, and the population that the researcher is willing to accommodate) (c) the confidence level (i.e., how confident the researcher wants to be that the actual/sample mean falls within the margin of error) (d) standard deviation (i.e., an estimate of how much each participant’s response varies from each other and from the mean number) (Trochim, 2006).

All 50 U.S. states met the eligibility criteria for this study because they had an opt-in, opt-out, both opt-in and opt-out, or no HIE consent policy (Milken Institute School of Public Health, 2016). I used the sample size online calculator at survey systems.com to estimate the minimum sample size for this study. The margin of error or confidence interval for this study was set to 5% while the confidence level and standard deviation were set to 95% and 0.5, respectively, to ensure that the sample size was large enough. Statistical power is the probability of obtaining a statistic that is large enough to reject the null hypothesis when it is false (Rebecca, 2013). Using G*Power software to estimate the statistical power for this study, I estimated the beta (i.e., Type II error at 100% power) value to be 20% (i.e., 0.2), and the statistical power value to be set at 80% (i.e., 0.80). For a test, the predetermined effect size or the power estimation was set at a small level (i.e., 0.2). I also set the parameters in the tool to (a) test family = F test, statistical test = MANOVA, and alpha = 0.05. Based on these parameters, the minimum sample size proposed for this study was 44 U.S. states. The Type II error and power were the criteria used to assess whether the sample size was sufficient for the statistical analysis.

Procedures for recruitment, participation, and primary data collection**.** In the primary survey, the chief executive officers of all nonfederal acute care hospitals in the United States were invited to participate in the survey regardless of AHA membership status. The person who was most knowledgeable about the hospital’s health IT (typically the chief information officer) was asked to provide the information via a mail survey or secure online site. No respondents received follow-up mail or phone calls to encourage them to respond.

Secondary data access**.** I submitted an application to the Walden University institutional review board (IRB) prior to accessing the raw dataset for this study. The application included information regarding the purpose of the study and the strategies I implemented to address ethical concerns in the research and protect the safety and privacy of participants and their data. Upon approval of the IRB, secondary data were accessed from the online publicly accessible database located on the website of the Office of the National Coordinator on Health Information Technology United States.

For this study, dataset containing measures of adoption and the use of interoperable EHR systems, as well as the characteristics of state privacy legislation related to EHR adoption and use, was extracted from the ONC database **(**ONC, 2019b; ONC, 2019c). Data published on the ONC websites were extracted from the AHA Annual Survey/Health IT Supplement implemented from 2011 to 2017. The survey was carried out with nonfederal acute care hospitals from all 50 U.S. states (ONC, 2019a). However, data that specifically report on sharing, receiving, and integrating PSC records were collected in 2015 and 2017. The dataset on adoption and MU of EHR systems in hospitals include measures for EHR adoption, patient HIE, including measures of interoperable exchange, and patient engagement capabilities.

The Office of the National Coordinator collected data on the type of state consent policies for Health IT in coordination with Clinovations and the George Washington University Milken Institute of Public Health (ONC, 2019c). The ONC and its partners collected the data through research of state government and health information organization websites. The dataset provides information on the type of consent policy that the respective state-designated HIE has adopted. Broadly, these policies fall under two categories: opt-out patients may be automatically enrolled in the HIE but are given the opportunity to opt-out of having their information stored and/or disclosed by the HIE, and opt-in patient consent is required for patient health information to be stored and/or disclosed by the HIE. However, some state policies fall outside of these two broad categories in which case descriptions of the policies are included (ONC, 2019c).

One advantage of conducting a secondary analysis of archived data is that doing so enables a researcher to analyze large samples of data without the cost and hassle of contacting potential participants directly, and this, in turn, limits ethical concerns (Cheng & Phillips, 2014; Kelder, 2005). A downside to this, however, is that because data collected were not originally collected specifically to answer the research questions for the study, data may be incomplete (Cheng & Phillips, 2014).

Instrumentation and Operationalization of Constructs

The Independent Variable

Because secondary data were used in this study, there was no researcher-created or published instrument used to collect data. However, in the primary survey, the independent variable—the type of consent policy that the respective state-designated HIE has adopted broadly—fit into four categories. Opt-out -patients may be automatically enrolled in the HIE but are given the opportunity to opt-out of having their information stored and/or disclosed by the HIE. Opt-in patient consent is required for patient health information to be stored and/or disclosed by the HIE. Both opt-in and opt-out have regulations that allow healthcare facilities that implement one of opt-in or opt-out in the state. Below are the operationalizations for the independent variables that was used in this study (see Table 2).

Table 2

Operationalization of the Independent Variables

Variable	Coding
Type of HIE consent policy	1 = opt-out 2 = opt-in 3 = Both opt-in and opt-out 4 = Neither opt-in nor opt-out (No HIE policy)

The Dependent Variables

The measure for the independent variables was calculated from answers to the following questions asked during primary data collection:

1. When a patient transitions to another care setting or organization outside your hospital system, how does your hospital routinely send and/or receive a PSC records? Only responses c through e were used to determine the electronic transmission or receipt of the care record. Mail or fax and eFax using EHRs were not included in the definition of EHR.
2. When a patient transitions from another care setting or organization to your hospital system, how does your hospital routinely receive and/or send PSC records? Only

responses c through e were used to determine electronic transmission or receipt of the care record. Mail or fax and eFax using EHR were not included in the definition.

3. Does your EHR integrate the information contained in PSC records that are received electronically (not eFax) without the need for manual entry?

The AHA aggregated responses c through e and presented them as percentages in the raw dataset that was used for analysis in this study. Below are operationalizations for each of the above dependent variables that will be used in this study:

- Percent of nonfederal acute care hospitals that receive PSC records electronically using an EHR system
- Percent of nonfederal acute care hospitals that send PSC records electronically using an EHR system
- Percent of nonfederal acute care hospitals that integrate PSC records electronically using an EHR system

Control Variable

Secular trends can confound association analysis (Greenland & Neutra, 1980). Accordingly, in this study, I will control for the effect of secular trends using calendar time. This study examines the percent of nonfederal acute care hospitals that SRI PSC records electronically as reported by the AHA between 2015 to 2017. I examined the mean differences in the outcome variables in Year 1(2015) and Year 2 (2017).

Data Analysis Plan

Data analysis was carried out to answer the following research questions and hypothesis:

RQ1: What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals in that state that electronically send PSC records to outside providers, as reported in the AHA survey between 2015 and 2017?

$H_0$1: There is no statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically send PSC records to outside providers, as reported in the AHA survey between 2015 and 2017.

H_a1: There is a statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically send PSC records to outside providers, as reported in the AHA survey between 2015 and 2017.

RQ2: What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017?

$H_0$2: There is no statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

H_a2: There is a statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

RQ3: What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers, as reported in the AHA survey conducted between 2015 and 2017?

$H_0$3: There is no statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

H_a3: There is a statistically significant correlation between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers, as reported in the AHA survey conducted between 2015 and 2017.

The data for this study were analyzed using IBM SPSS Statistics, Version 26. This software was used in compliance with policies and guidelines established by Walden University. Data analysis was carried out with the following steps:

Variable Extraction and Labeling

I extracted the variables in focus for this study from the ONC databases for HIE consent policies and nonfederal acute care hospitals EHR adoption and implementation records. Data were then uploaded into IBM SPSS version 26 for analysis. To gain a clear understanding of each variable, I gave each one a name and label that made sense and could be easily linked to the research question. Next, I checked whether the values for the independent categorical variable (type of HIE consent policy) were appropriately labeled. Each independent and dependent variable was also designated to an appropriate type (e.g., numeric and string). In this study, the independent and dependent variables will be designated as numeric variables (Sweet & Grace-Martin, 1999).

Data Cleaning

Errors within a given dataset may occur during data collection, exploration, and peer review activities (Osborne, 2013). Thus, Frankfort-Nachmias and Nachmias (2008) recommend that researchers should clean and edit raw data prior to conducting analysis of the same (Frankfort-Nachmias & Nachmias, 2008). Accordingly, I carried out the above procedures to the extent possible through repeated cycles of validation and verification (Van den Broek et al., 2005). After extracting and labeling relevant variables from the database, I inspected the dataset to identify or determine system missing values and/or user-defined missing values. System missing values are values (typically presented as a dot or period in SPSS) that are automatically recognized as missing by SPSS because a response was not collected or reported in the dataset. User-defined missing values are values that are either present but unlikely based on the general pattern observed in the entire dataset, unwanted for analysis (as with some categorical variables), or absent (as with string variables). To inspect the dataset for missing values, I ran a frequency distribution analysis on each variable. For missing system variables, based on the observed patterns of missing values, I skipped/deleted cases or responses when I determined they could result in high numbers of missing values or assign values to the missing data. For user-defined missing responses, I recoded or assigned responses as missing accordingly.

Descriptive Statistics

Descriptive statistics were used to understand the characteristics of the study sample. This included the frequencies of each dependent variable for each independent variable group (i.e., opt-in states, opt-out states, states that identify as allowing both opt-in and opt-out, and states that are neither opt-in nor opt-out). The percent, mean, and standard deviation of nonfederal acute care hospitals that a) send, b) receive, c) integrate PSC records electronically were independently determined and for each independent variable group (on the bases of group mean).

One-way MANOVA

One-way MANOVA is used to determine whether there are significant differences between independent groups on more than one continuous dependent variable (Huberty, Olejnik, 2006). In this regard, it differs from a one-way ANOVA, which only measures one dependent variable. It is only appropriate to carry out a one-way MANOVA if the data passes eight assumptions that are required for a one-way MANOVA (Huberty & Olejnik, 2006; Keselman et al., 1998; Nayanajith et al., 2019). Below, I discuss these assumptions, my early analysis of how the data for this study aligns with the assumption and steps I took if data failed certain assumptions:

Assumption 1**.** Your two or more dependent variables should be measured at the interval or ratio level (i.e., they are continuous). In this study, the dependent variables (i.e., the percentage of nonfederal acute care hospitals that a) send (b) receive, c) integrate PSC records electronically in 2015, and 2017) are continuous variables.

Assumption 2**.** The independent variable should consist of at least one categorical variable with two or more levels or independent groups. The independent variable for this study (type of HIE consent policy in the state) is a categorical variable with two independent groups of opt-in and opt-out states.

Assumption 3**.** There should be independence of observations, which means that there is no relationship between the observations in each group or between the groups themselves. In the United States, states adopt either the opt-in HIE policy, the opt-out, both opt-in and opt-out HIE policy. Therefore, the characteristics of the independent variable for this study meets the independence of observations assumption.

Assumption 4**.** The study has an adequate sample size. Although the larger the sample size is, the better the results will be, for MANOVA, it is important that there are more cases in each group than the number of dependent variables you are analyzing. This study had three dependent variables and about 25 cases (i.e., approximately 18 states that identity as opt-out states and seven states that identify as opt-in states with varying statewide applicability; others were neither opt-in or opt-out or both opt-in and optout states) (Milken Institute School of Public Health, 2016).

Assumption 5**.** The fifth assumption was that the data had normal distribution with no univariate or multivariate outliers. The dependent variable should be normally distributed within groups. Overall, the F test is robust to non-normality when the non-normality is caused by skewness rather than outliers. Tests for outliers should be run before performing a MANOVA, and outliers should be transformed or removed. Therefore, prior to performing a MANOVA test, I checked to determine that the “normal distribution” assumption is met by plotting a histogram and examining the skewness ratio. If the histogram demonstrates that there are outliers, then outliers will be transformed or removed.

Assumption 6**.** I assumed there was linearity in the data. Conducting MANOVA involves assuming that all the dependent variables are linearly related to each other. I will test for this assumption by plotting a scatterplot matrix for each group of the independent variable. To do this, I will split my data file in SPSS Statistics before generating the scatterplot matrices for each group.

Assumption 7**.** I assumed the variances were homogeneous. The MANOVA test assumes homogeneity of variance. Homogeneity of variances means that the dependent variables exhibit equal levels of variance across the range of predictor/independent variables. I used Levene’s test to check for homogeneity of variance. A p-value of less than 0.05 indicates a violation of the assumption. When a violation occurred, I conducted the nonparametric equivalent of the MANOVA analysis—ANOVA.

Assumption 8**.** There is no multicollinearity. Multicollinearity generally occurs when there are high correlations between two or more independent variables. In this study, I only focus on one predictor variable.

Once I determined that my dataset met the above eight assumptions, I conducted a one-way MANOVA test in SPSS to determine whether there is a significant difference in the mean percent of nonfederal acute care hospitals that SRI PSC records electronically based on the “type HIE policy” in a state. If the Wilk’s Lambda row of the MANOVA test results table showed a p-value of less than or equal to 0.05, then I concluded that the type of state HIE policy significantly influences the percentage of nonfederal acute care hospitals that SRI PSC records electronically, and will reject the null hypothesis. If not, then I concluded otherwise, accept the null hypothesis, and did not conduct a follow-up analysis.

Post Hoc Test

Because the one-way MANOVA is an omnibus test statistic that is used to identify which specific groups were significantly different from each other, I planned to use a post hoc test to determine where the mean percent difference comes from if the one-way MANOVA shows a statistically significant result (Huberty & Olejnik, 2006). Specifically, Tukey - Kramer test was to be used as the post hoc test. Tukey’s test compares the means of all treatments to the mean of every other treatment.

Controlling for Confounding Variables

Separating the influence of extraneous variables from those of the independent variable under study is one way to strengthen the validity of the study (Greenland & Neutra, 1980). Secular trends can confound association analysis. Accordingly, in this study, I controlled for the effect of secular trends using calendar time (i.e., Year 1, 2015, and Year 2, 2017).

Threats to Validity

External Validity

External validity is the degree to which the findings and conclusions from a study would hold for other populations, settings, and times beyond those of the study (Steckler

& McLeroy, 2008l Trochim, 2006). Threats to external validity may arise from the fact-finding on the relationship between state HIE consent policies, and nonfederal acute care hospitals may not truly represent the relationship between both variables in the broader acute care hospital community nor the EHR utilization practices in U.S. acute care hospitals because this study is limited to only nonfederal acute care hospitals. However, to strengthen the external validity of the results, I ensured that a large enough sample size was used for the study.

Internal Validity

Internal validity is a gage of the strength of the methods used in a research study. The internal validity of this research may be influenced by the presence of possible confounding variables, which cannot be accounted for given that data that will be used for analysis is from secondary sources, and the data were collected for a different purpose. Although the American Health Association performs data quality checks at the time of data collection, checks cannot be verified. It was not possible to draw a random sample because all study cases were included in the study (Creswell, 2013). However, the fact that the data for the independent variables were collected independent of the predictor variable (i.e., all nonfederal acute care hospitals, regardless of the type of HIE consent policy states identify with, were invited to participate in the study) suggested minimal or nonexistent chances of bias and considerable strength in the internal validity of the study.

Construct and/or Statistical Conclusion Validity

Construct and/or statistical validity is “the degree to which a test measures what it claims, to be measuring.” It also refers to the degree to which a researcher can legitimately draw inferences from the operationalization of a study to the statistical tests used (Trochim, 2006). To strengthen the construct validity of the study, I went beyond analyzing the association between opt-in and opt-out states to assess the mean differences in the percentage of nonfederal acute care hospitals that SRI PSC records in states that were identified as implementing opt-in, opt-out, both opt-in and opt-out, and neither opt-in nor opt-out HIE consent policy. I also ensured that the choice of statistical test used for analysis is corroborated by sufficient evidence of its appropriateness from prior studies. I also ensured that the assumptions of the statistical test chosen corresponded with the peculiarity of the dataset that has been chosen for this study.

Ethical Considerations

Because this was a secondary analysis of archived data, I did not have direct contact with study participants. Therefore, there were limited ethical concerns or opportunities to cause potential harm to study participants (Tripathy, 2013). However, to strengthen the ethicality of this study, data for this study was not extracted without seeking and obtaining prior approvals from Walden University IRB. The dataset used for this study was deidentified, and I ensured that they are stored, and password protected on my laptop. Passwords were only known by me, and plans were put in place to ensure that all data extracted will be discarded 5 years after data collection is completed.

Summary

In Section 2, I presented an overview of the research design, rationale, methodology, and threats to validity. I also discussed the ethical considerations I plan to undertake, as well as plans for data analysis. In Section 3, results of data analysis are presented and discussed while the interpretation of findings, study limitations, recommendations, and implications are presented in Section 4.

Section 3: Presentation of the Results and Findings

Sample Characteristics

The sample size consisted of 102 cases, one from each of the 50 states plus the District of Columbia per year data were available (2015 and 2017). There were two cases with missing data: Missouri 2017 (no percentage for send, receive, or integrate) and Wyoming 2017 (no percentage for receive or integrate). These data were collected from the website of the National Coordinator for Health Information Technology. Three cases were identified as outliers via a review of the histograms constructed for each dependent variable, and these cases were removed from the dataset (Arizona 2015, Hawaii 2015, and Missouri 2015). This resulted in 99 total cases. Of these cases, 12 had a flexible HIE policy, 40 had no HIE policy, 10 had an opt-in policy, and 37 had an opt-out policy (Table 1).

Table 2

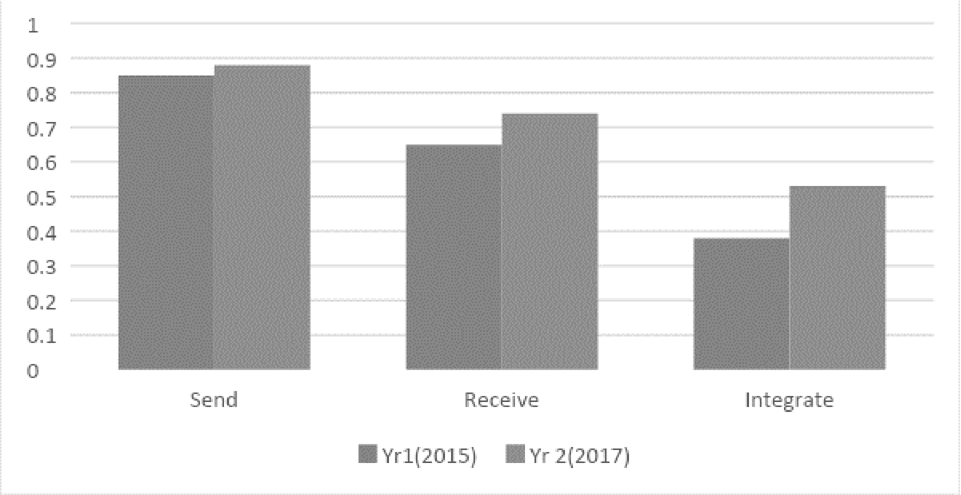
HIE Policy Descriptive Statistics

		Frequency	Percent
Valid	Flexible	12	12.1
	No policy	40	40.4
	Opt-In	10	10.1
	Opt-Out	37	37.4
	Total	99	100.0

Nationally, the percent of nonfederal acute care hospitals that SRI PSC records increased from 85% in 2015 to 88% in 2017. Hospitals that receive PSC records increased from 65% in 2015 to 74% in 2017. Hospitals that integrate PSC records increased from 38% in 2015 to 53% in 2017. Between the two time periods, additional hospitals reported sending and receiving PSC records than integrating the same. However, changes between both years were greater (15%) among hospitals that integrated PSC records compared to those that send (3%) and received 95%) same (Figure 2).

Figure 2

Percent of Nonfederal Acute Care Hospitals that sent, received, and integrated PSC Reports between 2015 and 2017



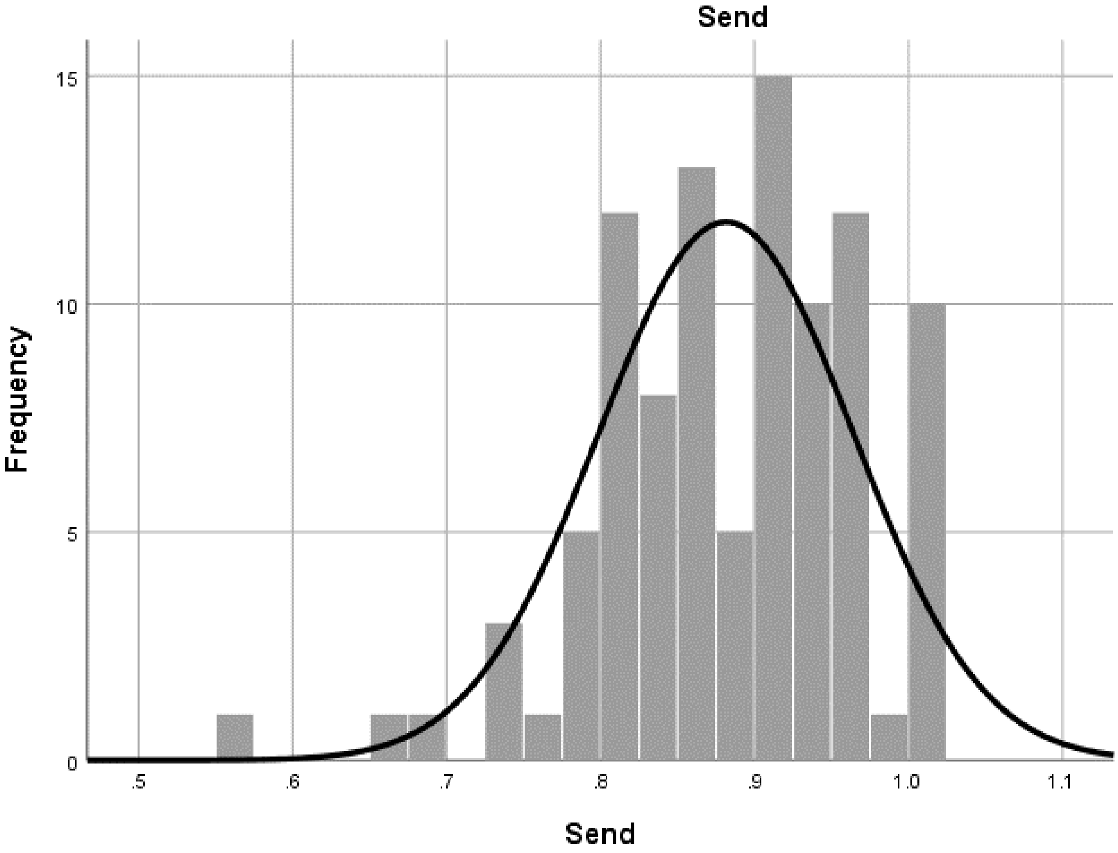
Statistical Assumptions

The data must meet the following conditions to be used in MANOVA: (1) interval or ratio level-dependent variables, (2) a categorical independent variable with at least two or more levels or independent groups, (3) independence of observations, (4) an adequate sample size, (5) normal distribution, (6) linearity of the dependent variables, (7) homogeneity of variance, (8) absence of multicollinearity. These assumptions were checked for the remaining dataset of 99 cases.

The first assumption was that the dependent variables were measured at the interval or ratio level. The dependent variables were measured as percentages, meaning they were, indeed, measured at the ratio level. The second assumption was that the independent variable is categorical with at least two or more levels. The independent variable, in this case, is the HIE policy type, of which there are four levels (flexible, no policy, opt-in, and opt-out). This assumption was also met. The third assumption was that the observations are independent of one another. These observations refer to the percentages of hospitals that SRI patient summary records in each state plus the District of Columbia. Because the states and Washington D.C. are free to set their own policies, the assumption of independence was met. The fourth assumption is that there is an adequate sample size. Given the sample size of 99 cases, this assumption was met with more than three cases in each group. The fifth assumption is that the data are normally distributed. A histogram was constructed for each dependent variable, along with a normal curve for comparison. The distributions were all relatively normal. For the send variable or percentage of hospitals that send patient summary records data, most cases were between 70% and 100%, with an uptick at 100%. These data were relatively normally distributed (Figure 3).

Figure 3

Histogram for Dependent Variable Send

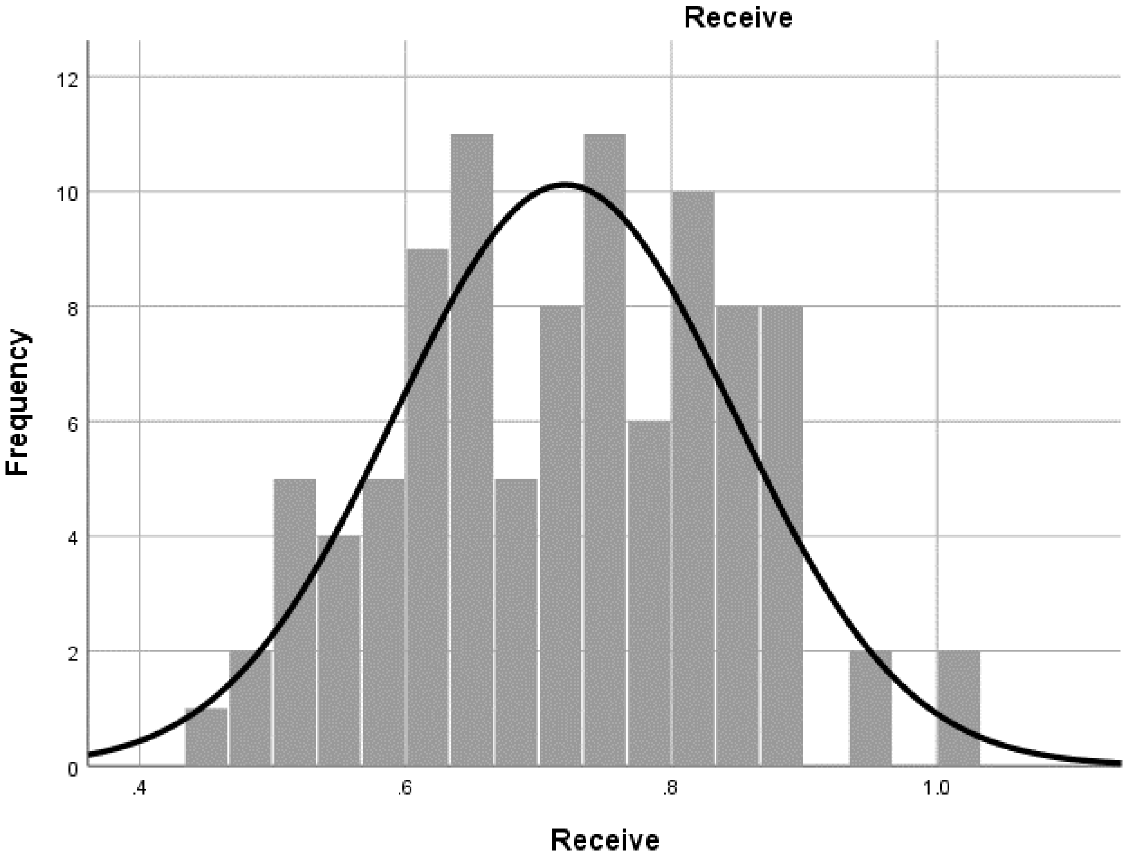


Note. Mean = 0.881523111. St. Dev. = 0.082838305. N = 98

For the receive variable (i.e., the percentage of hospitals that received PSC data) most cases were between 60 and 90%, and the data were relatively normally distributed (see Figure 4).

Figure 4

Histogram for Dependent Variable Receive

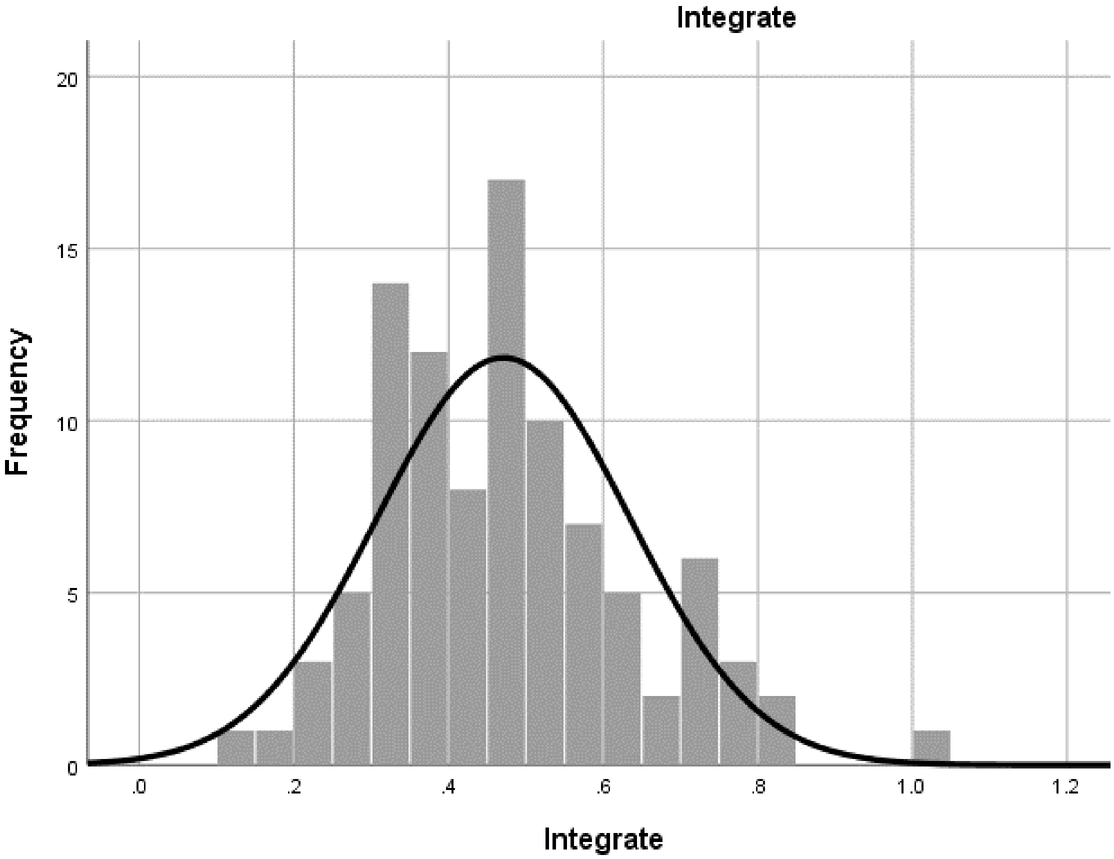


Note. Mean = 0.719959724. St. Dev. = 0.127476353. N = 97

For the integrate variable, or percentage of hospitals that integrate patient summary records data, most cases were between 30% and 60%, with a few cases at 100%. These data were also considered normally distributed (Figure 5).

Figure 5

Histogram for Dependent Variable Integrate



Note. Mean = 0.471053753. St. Dev. = 0.163517578. N = 97

The skewness and kurtosis values of each dependent variable were calculated to further investigate the normality of the data. The skewness values were between -1 and 1 for each variable, and the kurtosis values were between -2 and 2 for each variable. These results are shown in Table 3.

Table 3

Descriptive Statistics of Dependent Variables

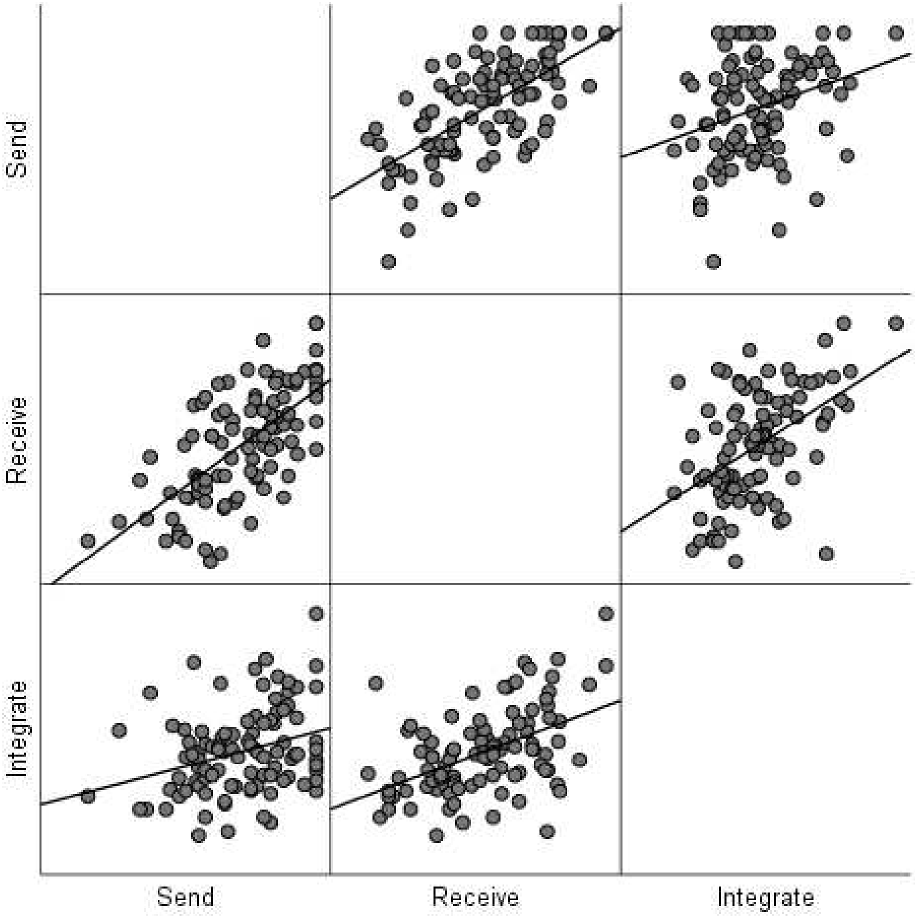
		Send	Receive	Integrate
N	Valid	98	97	97
	Missing	1	2	2
Mean		0.882	0.720	0.471
Skewness		-0.900	-0.049	0.602
Std. Error of Skewness		0.244	0.245	0.245
Kurtosis		1.745	-0.681	0.310
Std. Error of Kurtosis		0.483	0.485	0.485

The skew and kurtosis were within reasonable ranges expected for normality. These values, along with the histograms show a relatively normal distribution for each dependent variable, indicate that the assumption of normality has been met.

The sixth assumption was that the dependent variables are linearly related. A scatterplot matrix was constructed to check for linearity between dependent variables. As Figure 6 shows, the relationship between each dependent variable can be roughly expressed as a line. Thus, these variables are linearly related.

Figure 6

Scatterplot Matrix of Dependent Variables



The scatterplot matrix shows that each dependent variable has a linear relationship with each other dependent variable, meaning that the assumption of linearity held true.

The seventh assumption was about the homogeneity of variance. To check for homogeneity of variance, Levene's statistic was calculated for each dependent variable. None of the statistics reached significance at the 0.05 level for any of the dependent variables (Table 4). Based on the mean, variance was homogeneous for send (F (3,94) = 1.078, $p = 0.362$), for receive (F (3,93) = 1.611, $p = 0.192$), and for integrate (F (3,93) = 0.957, $p = 0.416$).

Table 4

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Send	Based on Mean	1.078	3	94	0.362
	Based on Median	0.839	3	94	0.476
	Based on Median and with adjusted df	0.839	3	80.505	0.476
	Based on trimmed mean	0.960	3	94	0.415
Receive	Based on Mean	1.611	3	93	0.192
	Based on Median	1.513	3	93	0.216
	Based on Median and with adjusted df	1.513	3	91.820	0.216
	Based on trimmed mean	1.602	3	93	0.194
Integrate	Based on Mean	0.957	3	93	0.416
	Based on Median	0.984	3	93	0.404
	Based on Median and with adjusted df	0.984	3	85.736	0.404
	Based on trimmed mean	0.998	3	93	0.397

In each case, Levene's statistic did not reach statistical significance ($p < 0.05$). Thus, the assumption of homogeneity of variance was met.

The eighth and final assumption is of the absence of multicollinearity. Correlations were calculated to check for possible multicollinearity. All three dependent variables were correlated at the $p < 0.05$ level, but none of the correlations were strong (0.8 or greater). Year was found to be positively correlated to the receiving ($r = 0.297$, p

= 0.003) and integration of EHRs ($r = 0.484$, $p < 0.001$), but again, the correlations were weak to moderate. These results indicate that the percentage of hospitals that SRI data are correlated. Those that engage in one of the dependent variables (sending, receiving, and integrating PSC records) are also more likely than others to engage in the other two dependent variables. In addition, the positive correlations with year indicate that hospitals were more likely to SRI patient summary records in 2017 than they were in 2015. See Table 5 for correlations.

Table 5

Correlations Between the Dependent Variables and Year

		Send	Receive	Integrate	Year
Send	Pearson Correlation	1	0.656**	0.307**	0.135
	Sig. (2-tailed)		0.000	0.002	0.187
	N	98	97	97	98
Receive	Pearson Correlation	0.656**	1	0.485**	0.297**
	Sig. (2-tailed)	0.000		0.000	0.003
	N	97	97	97	97
Integrate	Pearson Correlation	0.307**	0.485**	1	0.484**
	Sig. (2-tailed)	0.002	0.000		0.000
	N	97	97	97	97
Year	Pearson Correlation	0.135	0.297**	0.484**	1
	Sig. (2-tailed)	0.187	0.003	0.000	
	N	98	97	97	99

**. Correlation is significant at the 0.01 level (2-tailed).

Given the reasonable, moderate correlations between the three dependent variables, the assumption of absence of multicollinearity is also met.

Results of the Statistical Analysis

Given the data met the assumptions required for a MANOVA, I conducted a MANOVA with the three variables of SRI as the dependent variables and HIE policy type as the independent variable, with year as the control variable. Table 6 shows the variables that were included in the MANOVA.

Table 6

Between-Subjects Factors for the MANOVA

		N
HIE Policy	Flexible	12
	No policy	38
	Opt-in	10
	Opt-out	37
Year	2015	48
	2017	49

The MANOVA resulted in a non-statistically significant result for HIE policy type (F (9, 212) = 0.497, p = 0.875; Wilk's Λ = 0.950, partial η^2 = 0.017). This indicates that HIE policy type does not impact the percentages of hospitals that SRI patient summary records. However, the year variable was significant (F (3, 87) = 8.463, $p <$ 0.001, Wilk's Λ = 0.774, partial η^2 = 0.226), meaning that year did significantly impact the dependent variables.

Because the HIE policy did not significantly impact the dependent variables, between-subjects tests were not conducted for this variable or for the interaction. Results of the multivariate tests are shown in Table 7.

Table 7

Multivariate Tests of the MANOVA

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
Intercept	Wilks' Lambda	0.009	3,123.749	3.000	87.000	0.000	0.991
HIE Policy	Wilks' Lambda	0.950	0.497	9.000	211.886	0.875	0.017
Year	Wilks' Lambda	0.774	8.463	3.000	87.000	0.000	0.226
HIE Policy * Year	Wilks' Lambda	0.958	0.421	9.000	211.886	0.923	0.014

RQ1: What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically send PSC records to outside providers as reported in the AHA survey between 2015 and 2017?

$H_0$1: There is no statistically significant association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically send PSC records to outside providers. The alternative hypothesis is that there is a statistically significant association between the type of HIE consent policy and the percent of hospitals that electronically send patient records.

Descriptive statistics were calculated for the percentage of hospitals sending PSC records and HIE policy. All groups had five or more cases. In each group, the mean was larger in 2017 than in 2015, suggesting that hospitals were more likely to send patient summary records in 2017 than in 2015 (Table 8).

Table 8

Descriptive Statistics for the Percent of Hospitals Electronically Sending PSC Records

	HIE Policy	Year	Mean	Std. Deviation	N
Send	Flexible	2015	0.870	0.089	6
		2017	0.921	0.044	6
		Total	0.896	0.072	12
	No policy	2015	0.874	0.079	19
		2017	0.891	0.075	19
		Total	0.883	0.077	38
	Opt-In	2015	0.894	0.079	5
		2017	0.934	0.132	5
		Total	0.914	0.105	10
	Opt-Out	2015	0.859	0.071	18
		2017	0.892	0.064	19
		Total	0.876	0.068	37
	Total	2015	0.870	0.075	48
		2017	0.899	0.075	49
		Total	0.885	0.076	97

However, the results of the MANOVA for HIE policy type were not significant (F (9, 212) = 0.497, p = 0.875; Wilk's Λ = 0.950, partial η^2 = 0.017). This indicates that the null hypothesis that HIE policy type does not impact the percentage of hospitals that send patient summary records must be accepted.

RQ2: What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers as reported in the AHA survey conducted between 2015 and 2017?

H$_0$2: There is no statistically significant association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017. The alternative hypothesis is that there is a statistically significant association between the type of HIE consent policy and the percent of hospitals that electronically receive patient summary records.

Descriptive statistics were calculated for the percentage of hospitals electronically receiving PSC records and HIE policy. All groups had five or more cases, and, in each group, the mean was larger in 2017 than in 2015. This suggests that hospitals become increasingly likely to electronically receive PSC records as time passes (Table 9).

Table 9

Descriptive Statistics for the Percent of Hospitals Electronically Receiving Patient Summary Records

	HIE Policy	Year	Mean	Std. Deviation	N
Receive	Flexible	2015	0.645	0.141	6
		2017	0.796	0.065	6
		Total	0.720	0.131	12
	No policy	2015	0.693	0.108	19
		2017	0.742	0.130	19
		Total	0.718	0.120	38
	Opt-In	2015	0.694	0.148	5
		2017	0.815	0.189	5
		Total	0.755	0.172	10
	Opt-Out	2015	0.679	0.102	18
		2017	0.745	0.137	19
		Total	0.713	0.124	37
	Total	2015	0.682	0.112	48
		2017	0.757	0.132	49

	Total	0.720		0.127	97

Because the results of the MANOVA indicated that the HIE policy type did not have statistically significantly impacts on the percentage of hospitals that electronically received PSC records (F (9, 212) = 0.497, p = 0.875; Wilk's Λ = 0.950, partial η^2 = 0.017), the null hypothesis must also be accepted for RQ2.

RQ3: What is the association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate into their EHR PSC records received from outside providers as reported in the AHA survey conducted between 2015 and 2017?

$H_0$3 is that there is no statistically significant association between the type of HIE consent policy in a state and the percent of nonfederal acute care hospitals that electronically integrate PSC records from outside providers, as reported in the AHA survey conducted between 2015 and 2017. The alternative hypothesis is that there is a statistically significant association between the type of HIE consent policy and the percent of hospitals that electronically integrate patient summary records.

Descriptive statistics were calculated for the percentage of hospitals electronically integrating PSC records and HIE policy. All groups had five or more cases. In each group, the mean was larger in 2017 than in 2015, suggesting that hospitals were more likely to electronically integrate patient summary records in 2017 than they were in 2015 (see Table 10).

Table 10

Descriptive Statistics for the Percentage of Hospitals Integrating PSC Records

	HIE Policy	Year	Mean	Std. Deviation	N
Integrate	Flexible	2015	0.355	0.135	6
		2017	0.637	0.133	6
		Total	0.496	0.195	12
	No policy	2015	0.393	0.107	19
		2017	0.521	0.142	19
		Total	0.457	0.140	38
	Opt-In	2015	0.380	0.068	5
		2017	0.514	0.180	5
		Total	0.447	0.146	10
	Opt-Out	2015	0.405	0.131	18
		2017	0.558	0.197	19
		Total	0.484	0.183	37
	Total	2015	0.391	0.115	48
		2017	0.549	0.168	49
		Total	0.471	0.164	97

Although means slightly differed by group, the results of the MANOVA showed that HIE policy type did not significantly impact the percentage of hospitals electronically integrating patient summary records (F (9, 212) = 0.497, $p = 0.875$; Wilk's $\Lambda = 0.950$, partial $\eta^2 = 0.017$). Thus, the null hypothesis must be accepted for RQ3.

Alternative Variable: Year (Secular Trend)

Although there were differences between the percentage of hospitals that send, receive and integrate patient summary of care records in states with opt in, opt out, and flexible HIE policies, the differences were not statistically significant. However, year was found to have a statistically significant impact on the percentage of hospitals that sent, received, and/or integrated records (F (3, 87) = 8.463, $p < 0.001$; Wilk's $\Lambda = 0.774$, partial η^2 =.226). This suggest a general trend toward sending, receiving, and integrating patient summary records as means were higher in 2017 than in 2015 for each of the three dependent variables (see Table 11).

Table 11

Means by Dependent Variable and Year

Dependent Variable	Year	Mean
Send	2015	0.870
	2017	0.899
Receive	2015	0.682
	2017	0.757
Integrate	2015	0.391
	2017	0.549

Because year was found to have a statistically significant impact on the percent of hospitals that send, receive, and/or integrate patient summary records, tests of between-subjects effects were conducted. These tests show that year had a statistically significant effect on the percentage of hospitals that electronically receive patient summary records (F (1, 89) = 10.216, p = 0.002, partial η^2 = 0.103) and electronically integrate patient summary records (F (1, 89) = 24.276, p < 0.001, partial η^2 = 0.214), but not on the percentage of hospitals that electronically send patient summary records (F (1, 89) = 3.572, p = 0.062, partial η^2 = 0.039). This indicates that with time, more hospitals choose to electronically receive and integrate PSC records. See Table 12 for additional information.

Table 12

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	Send	0.037[a]	7	0.005	0.912	0.501	0.067
	Receive	0.182[b]	7	0.026	1.680	0.124	0.117
	Integrate	0.683[c]	7	0.098	4.610	0.000	0.266
Intercept	Send	53.779	1	53.779	9,239.308	0.000	0.990
	Receive	35.642	1	35.642	2,302.111	0.000	0.963
	Integrate	14.962	1	14.962	706.904	0.000	0.888
HIE Policy	Send	0.013	3	0.004	0.762	0.518	0.025
	Receive	0.015	3	0.005	0.313	0.816	0.010
	Integrate	0.025	3	0.008	0.389	0.761	0.013
Year	Send	0.021	1	0.021	3.572	0.062	0.039
	Receive	0.158	1	0.158	10.216	0.002	0.103
	Integrate	0.514	1	0.514	24.276	0.000	0.214
HIE Policy * Year	Send	0.003	3	0.001	0.188	0.905	0.006
	Receive	0.030	3	0.010	0.638	0.592	0.021
	Integrate	0.056	3	0.019	0.888	0.451	0.029
Error	Send	0.518	89	0.006			
	Receive	1.378	89	0.015			
	Integrate	1.884	89	0.021			
Total	Send	76.516	97				
	Receive	51.839	97				
	Integrate	24.090	97				
Corrected Total	Send	0.555	96				
	Receive	1.560	96				
	Integrate	2.567	96				

a. R Squared = 0.067 (Adjusted R Squared = -0.006)

b. R Squared = 0.117 (Adjusted R Squared = 0.047)

c. R Squared = 0.266 (Adjusted R Squared = 0.208)

Summary

The purpose of this quantitative cross-sectional research study is to determine if there are significant differences in the percentage of nonfederal acute care hospitals that SRI PSC records electronically in U.S. states that identify as implementing opt-in HIE policies versus those that implement opt-out policies. I used a deidentified panel of publicly available datasets containing measures of adoption and use of interoperable EHR systems and the characteristics of state privacy legislation related to EHR adoption and use, which will be extracted from the ONC database (ONC, 2019b; ONC, 2019c).

I examined the relationship between one independent variable (i.e., type of HIE consent policy) and three dependent variables (i.e., percent of nonfederal acute care hospitals that electronically send PSC records, percent of nonfederal acute care hospitals that electronically receive PSC records from outside providers, and percent of nonfederal acute care hospitals that electronically integrate PSC records into their EHR from outside providers).

As noted above, the results of the MANOVA indicated that the HIE policy type did not have a statistically significant impact on the percentage of hospitals electronically sending, receiving, and integrating PSC records, meaning the interaction between HIE policy type and year was also not statistically significant. These results indicated that HIE policy type and year did not have any significant interaction effects on hospitals.

In Section 4, I provide my interpretation of the findings of the study, discuss the limitations of the study, make recommendations based on the results and the existing literature, and discuss implications of the study results as they pertain to positive social change and the practice of healthcare administration.

Section 4: Discussion, Conclusion, and Recommendations

Introduction

Despite efforts made by the United States Government to promote adoption and MU of EHR systems in U.S. hospitals, many nonfederal acute care hospitals in the country do not use their EHR systems to send, receive, or PSC records for patients transitioning from one setting of care or provider to another (Eval, 2016; ONC, 2017; Riordan et al., 2015; WHO, 2017). Over the years, stakeholders have raised concerns over the privacy and confidentiality of the information they share with their healthcare providers. These concerns appear to have increased with the push for interoperability of EHRs. At the state level, privacy regulations require healthcare providers to obtain patients' written permission before disclosing information to other organizations or other people, even when the purpose of disclosure is treatment. However, the influence of state legislatures regarding patient consent for information exchange on the MU of certified EHR systems to receive, share, and integrate PSC records is not clear (Henry et al., 2016; Klosek, 2011; ONC 2013; Palabindala et al., 2016; Weiser, 2019).

In this study, descriptive statistics and MANOVA statistical test was used to determine the relationship between the type of state HIE consent policy and percent of nonfederal acute care hospitals that use EHR systems to SRI PSC records in the United States between 2015 and 2017. Results from descriptive statistics demonstrate that of the 99 acute care hospitals assessed across all 50 U.S. states, 12 had a flexible HIE policy, 40 had no HIE policy, 10 had an opt-in policy, and 37 had an opt-out policy (Table 1). Additionally, nationally, the percent of nonfederal acute care hospitals that SRI PSC records increased between 2015 and 2017, with the greatest incremental changes seen in the percentage of hospitals integrating PSC records. The results of the MANOVA indicated that the HIE policy type did not statistically significantly impact the percentage of hospitals electronically sending, receiving, and integrating patient summary records. However, year was found to have a statistically significant impact on the percentage of hospitals that send, receive, and/or integrate patient summary records.

Interpretation of the Findings

Information sharing can improve services and reduce misunderstandings in healthcare systems (Mačinković & Aničić, 2016). The findings of this study show increases in the percentage of nonfederal acute care hospitals that engaged in all three EHR interoperability domains over time. The majority of the hospitals that I assessed engaged in the three interoperability domains to facilitate health data exchange: sending, receiving, and integrating. This finding confirms Mukherjee et al. (2019) and Shu et al. (2014) observation that there has been an upward trajectory in the adoption and MU of electronic systems in different countries, including the United States. It further supports arguments that EHR, which has become part of the universal medical language (Juhlin et al., 2015), and interoperability, are desirable because they are the key determinants of whether clinicians through the healthcare system can optimize current and emerging technologies for better or improved healthcare outcomes (Moor et al., 2015).

Interoperability is primarily about aggregating the crucial and rich data generated from health plans, vendors, health systems, and patients, and leveraging it to improve clinical processes, such as patient diagnosis, prescriptions, and treatment. This study demonstrates that fewer hospitals electronically integrate PSC records than those that electronically send and receive. The relatively lower number of hospitals that electronically integrate patients' summary illustrates concerns expressed in the literature regarding the EHR system to EHR system integration and communication barriers related to complexities of medicine and clinical terminologies, errors in communication, and heightened risk of compromising interoperability standards during EHR integration (Braunstein, 2018; Khajouei et al., 2018). Yuksel et al. (2016) for instance, observed that it is impossible to sustain the integration of EHRs with other healthcare IT systems in a proprietary way without exploiting the promising interoperability standards and profiles. The finding also justifies recent research and resource investments into the development of models for improving EHR interoperability, including HL7 standards and standardized dictionary codes of semantics that are useful in reducing the ambiguity related to data element definitions and EHR message format and facilitating communication with other EHR systems (Evans, 2016; Hammer et al., 2019).

States that adopt the opt-in policy regulation recorded the lowest percentage of hospitals engaging in health data exchange through EHR systems. States adopting opt-in policies require patients to give permission before their data may be exchanged with other healthcare facilities. This finding confirms Apathy and Holmgren's (2020) and Aldjerid et al.'s (2016) observation that opt-in privacy regulations impede EHR usability due to the administrative burdens it places on some hospitals that are not technologically advanced. According to them, privacy regulation alone can result in a decrease in planning and operating HIEs.

Furthermore, Parasrampuria and Henry (2019) observed that the current design of EHR systems might require major redesigns for integration with many of the other digital resources needed for the seamless recording, storage, transmission, and interpretation of clinical data. I found that more hospitals engaged in the sending and receiving domains of EHR interoperability than the integrating domain, substantiating the findings of Parasrampuria and Henry (2019).

In addition to confirming knowledge in the discipline, some findings from this study disconfirm certain knowledge in the discipline as presented in peer-reviewed literature. For instance, Thompson and Graetz (2019) suggested that only a small proportion of hospitals had implemented all six PI3 MU functionalities to find, SRI information throughout the entire healthcare system. Walker et al. (2016) also asserted that throughout the United States, only about 50% of all healthcare facilities have reported their intentions and taken the initiative to implement EHR systems with the capacity for integration. In contrast, this study's findings suggest that a considerably higher percentage of hospitals electronically sent (85% in 2015 to 88% in 2017), received (65% in 2015 to 74% in 2017), and integrated (38% in 2015 to 53% in 2017) PSC records in 2017 than 2015.

Another area in which this study disconfirms knowledge from earlier studies relates to the extent to which privacy laws impact MU of EHR systems. The MONOVA analysis results in this study demonstrated that no significant difference was found between the policy type and the percentage of hospitals engaging in EHR interoperability domains. However, previous studies suggest that the privacy law limits companies' collection, use, sharing, and retention of personal information (Cohen, 2016; De Pietro, 2018; Dranove et al., 2015; Kosseff, 2019) mentioned that compliance to government reform policies and financial incentives influence adoption rates. Kosseff (2019) asserted that consent and privacy policies may impact HIE. Existing privacy policies, compliance to these policies, and legal variance in data policies influence EHR adoption and MU. Mulder and Tudorica (2019) also highlighted the obscure processing activities of privacy laws in Europe, as well as the gaps that exist between privacy policy regulations and practical reality.

Earlier studies that explored factors that influence the adoption and MU of EHRs have highlighted cost, lack of industry collaboration, a culture of fragmentation, and physician burden as important factors that affect the MU of EHR systems in hospitals (Council for Affordable Quality Healthcare, 2020; Reisman, 2017). These factors have been more organizational, structural, and environmentally centered than they have been policy and patient-centered. By highlighting the influence of time, and the differences in the percentage of nonfederal acute hospitals that send, receive, and integrate PSC records, this study extends the knowledge on factors that influence adoption and MU of EHR systems in the United States

Furthermore, earlier researchers suggested that only a small proportion of hospitals have effectively utilized all functionalities in the EHR system. This study extends this knowledge in demonstrating that the proportion of hospitals that meaningfully use their EHR system has grown significantly. The growth observed in recent years may serve as evidence for anticipating the EHR landscape in coming years and making related healthcare policy and practice accommodations. Additionally, it is evident from peer-reviewed literature that factors of practice size may influence wider EHR adoption and MU by health institutions, financial incentives, ease of use, and effectiveness in the use of EHR functionalities (Gagnon et al., 2016; Shu et al., 2014). Findings from this study add an important element of time as a predictor of wider MU of EHR systems to SRI PSC records.

Additionally, HIE consent policies exist and differ from state to state. A handful of studies suggest a relationship between state policies and increased administrative burden on healthcare practitioners, but little was known about if these burdens influence the use of EHR systems to SRI PSC records (Henry et al., 2016; Klosek, 2011; ONC 2013; Palabindala et al., 2016; Weiser, 2019). This study adds to the body of knowledge on the influence of state consent policies on interoperability by revealing that although considerable differences in the percentage of hospitals that send, receive, and integrate PSC records in states with opt-in regulations and those with no regulations, opt-out regulations, the type of consent policy in a state may not be as burdensome as to influence MU of EHR systems. The findings corroborate the observations of Rile's (2020), Edward et al.'s (2019), and O'Connor et al.'s (2017) that practitioners reduced the effects of privacy regulations and addressed barriers to consent policy by using blanket consent at pediatric departments. Finally, by highlighting that fewer hospitals integrate PSC records than send and receive them, this study extends current knowledge on where opportunities to strengthen the MU of EHR systems in the United States exist.

The UTAUT Model and Study Findings

The findings of this study revealed that there is no significant correlation between state consent policy type and EHR adoption. State consent policy type was theorized to fall under the social influence, effort expectancy, and facilitating conditions construct of UTAUT. Findings of this study suggest that social influence, effort expectancy, and facilitating conditions do not significantly affect the intention to use EHR technology. Researchers appear to have mixed views regarding the plausibility of the UTAUT model to predict intentions and use of technology. For instance, although Alsyouf and Ishak (2018) Al-Qeisi et al. (2015), and Kim et al. (2015) determined that performance expectancy, effort expectancy, and positively influence intention and attitude toward the use of EHR systems. Hoque and Sorwar (2017) posited that noting that performance expectancy, effort expectancy, and social influence, alongside technology anxiety, and resistance to change are key determinant factors of users' intentions and behavior toward new technology.

The absence of a statistically significant difference between the type of state consent policy and MU of EHR systems observed in this study may not completely negate the position of the UTAUT model, but may, in fact, lend credibility to the model. Similar to Kim et al.'s (2015) findings, an observation from this study is that states with opt-out policies had more nonfederal acute care hospitals using an EHR system to SRI PSC information compared to those with opt-in and mixed policies. This suggests some level of influence of state consent policies on intention, attitude, and behavior toward MU of EHR and in so doing, support the UTAUT model.

Limitations of the Study

First, the study design was cross-sectional in nature. This makes it impossible to draw a causal conclusion from the findings. The sampling strategy from which the secondary data were drawn utilized a purposive convenience sampling method. The reality that estimates might have been affected by selection bias based on certain inclusion criteria that fit into the aim of the primary survey was inherent in this sampling method. However, the study had sufficient power to detect differences in subgroups and the ability to introduce considerable amounts of variation to produce unstable statistical influence in the analysis.

This study was limited to nonfederal acute care hospitals. Therefore, the relationship between the state HIE policies and nonfederal acute care hospitals may not truly represent or be applicable to other care settings. Furthermore, respondents in the primary study were health administrators rather than doctors or other trained physicians. This allowed me to have a narrow perspective of EHR adoption and MU.

Due to time and financial resource limitations, secondary data were used for this study. The use of secondary data limited the scope of the study as only a limited number of predictive factors (policy and time) identified in the literature could be investigated. Furthermore, I highlighted that time is an important predictor of MU of EHR systems in nonfederal acute care hospital settings. In this regard, this study is limited because it does not explain how time influences observed changes.

Recommendations for Further Research

Research and practice in healthcare administration can benefit from the same study that takes a more robust methodology to investigate the relationship between HIE policies and MU of EHR to send, receive, and integrate PSC records. A random sampling or a mixed-methods design that includes healthcare settings beyond nonfederal acute care hospitals, will not only provide a more accurate picture of interoperability in U.S. hospitals, but it will also provide explanatory information about the complex interplay between privacy policies and interoperability in the United States. Other researchers could advance this study by comparatively examining the interplay between privacy policies and interoperability in other clinical settings including rural vs academic medical centers vs urban hospitals, vs community hospitals vs specialty hospitals.

Based on the strength of the current study, states adopting the opt-in policy were found to have the lowest proportion of hospitals that electronically send, receive, and integrate PSC records. States without consent policies and those that had opt-out policies were found to have the highest proportions of hospitals that electronically send, receive and integrate PSC records. Because this study suggests a nonsignificant relationship between both variables, further research should examine what other factors present in states with opt-out policies influence the higher percentage of hospitals that send, receive and integrate PSC records compared to those in states with opt-in policies. Finally, the effect of time (years) on interoperability, as demonstrated by this study, can be further explained in future studies. Other researchers may be able to answer questions such as: are early adopters who test out the EHR technology responsible for influencing other practitioners' use of the technology? Are there other policy and practice interventions, like financial incentives, vendor marketing, and so on, that have occurred over time, which may have influenced growth in MU of EHR systems?

Implications for Professional Practice and Social Change

Implications for Professional Practice

For healthcare administration researchers, the findings of this study provide evidence for additional research into the dimension of time as a predictor of interoperability. For health administrators, the study findings provide context for healthcare administrators on how and where policy development and investments can streamline the complexity of exchange and address barriers to interoperability. Research, policy, and private sector investment into understanding and addressing technological, practice, and policy barriers to EHR-to-EHR system integration may be critical to ensuring universal MU of certified EHR systems to SRI PSC records.

Implications for Positive Social Change

The study contributes to positive social change by providing evidence that could help healthcare administrators, advocates, and policymakers address current gaps in the continuum of care that has been amplified by the percent of nonfederal acute care hospitals that do not use their EHR systems to SRI PSC records. These stakeholders may be able to leverage the evidence from this study to address time and policy-related barriers to nationwide use of interoperable systems for sharing, receiving, and integrating PSC records. These could, in turn, increase gains in the quality and efficiency of care delivered (Henry et al., 2016).

Conclusion

Despite the obvious differences in state HIE consent policies, there is no known research that has determined if and what aspects of state-level HIE legislation affect the MU of EHR systems to SRI PSC records. Grounded on the UTAUT, descriptive statistics and MANOVA statistical test was used to determine the relationship between the type of state HIE consent policy used and the percent of nonfederal acute care hospitals that used EHR systems to SRI PSC records in the United States between 2015 and 2017.

Most of the hospitals assessed in this study engaged in the three interoperability domains–sending, receiving, and integrating to facilitate health data exchange. However, more hospitals engaged in the sending and receiving domains of EHR interoperability, compared to those engaging in the integrating domain. Nationally, the percent of nonfederal acute care hospitals that SRI PSC records increased between 2015 and 2017, with the most remarkable incremental changes seen in the percentage of hospitals integrating PSC records. The majority of nonfederal acute care hospitals assessed (40 out of 99) were located in states that had no HIE policy. States that adopted the opt-in policy regulation recorded the lowest percentages of hospitals engaging in health data exchange through EHR systems.

These findings confirm the earlier observation that EHR has become part of the universal medical language, interoperability is desirable, and there has been an upward trajectory in adopting and MU of electronic systems in different countries, including the United States. They also confirm the accuracy of the observation that opt-in privacy regulations impede EHR usability due to the administrative burdens it places on some hospitals that are not technologically advanced. By demonstrating that there was a considerable increase in the number of hospitals that meaningfully used EHR systems, the findings of this study disconfirm earlier studies that suggest that only a small proportion of hospitals had implemented all six PI3 MU functionalities—to find, SRI information throughout the entire healthcare system. Additionally, in demonstrating that no significant difference was found between the policy type and the percentage of hospitals engaging in EHR interoperability domains, findings from this study also disconfirm previous studies that suggest that the privacy law limits companies' collection, use, sharing, and retention of personal information. However, year was found to have a statistically significant impact on the percent of hospitals that send, receive, and/or integrate patient summary records.

The practice of healthcare administration could benefit from similar studies that incorporate healthcare settings beyond nonfederal acute care hospitals and implement a rigorous research design that will also provide a highly explanatory picture of interoperability in U.S. hospitals.

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