FACTORS INFLUENCING THE ADOPTION OF CLOUD-BASED EHR/EMR SYSTEMS BY PRIMARY CARE PROVIDERS: A CORRELATIONAL STUDY

by

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Abstract

This study investigated factors influencing the adoption of cloud-based electronic health record/electronic medical record (EHR/EMR) systems by primary care providers (PCPs). EHR/EMR systems enable PCPs to create and manage patient medical histories, to satisfy legislative requirements for security and privacy of patient information, and to support federal initiatives for improving the effectiveness of healthcare services. Despite federal incentives for using EHR/EMR systems and severe penalties for non-compliance with federal mandates for their meaningful use, the adoption of EHR/EMR by PCPs in the United States has not kept pace with industry and regulatory requirements. This quantitative non-experimental study was purposed to answer the omnibus research question which asked to what extent do PE (performance expectancy), EE (effort expectancy), SI (social influence), and FC (facilitating conditions) predict BIU (behavioral intention to use cloud-based EHR/EMR systems) of primary care providers in the United States? The theoretical foundation for this study was the unified theory of acceptance and use of technology (UTAUT). The target population was PCPs responsible for implementing EHR/EMR systems in the United States. Participants for this study were randomly selected from a pool of volunteers recruited by a third-party survey administrator. Evaluation of sample data using Pearson correlation revealed statistically significant relationships between each independent variable (PE, EE, SI, and FC) and the dependent variable BIU. Multiple linear regression analysis indicated that SI and FC were significant predictors of BIU. The research model explained 32% of the variance in BIU, indicative of opportunities for further investigation to identify other factors and thereby extend the research model and provide stronger answers to the research questions.

Dedication

I dedicate this dissertation to my late daughter, Alethia, who taught me the true meaning of excellence and inspired me to strive continuously for personal enrichment.

Acknowledgments

I wish to thank faculty members for reviewing my manuscripts, for sharing their insight, and for their instructive comments. Thanks to my mentor and chairman of my dissertation committee, Dr. Werner Gottwald, for informative, thought-provoking comments that guided me throughout the dissertation process, and to Dr. Bernard Sharum for sharing his insight. Thanks to the other members of my dissertation committee, Dr. Christopher Lucarelli and Dr. Vanessa Wood for invaluable support. To Dr. Josè Nieves and all other faculty members who have inspired and supported me on this journey, thank you.

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CHAPTER 1. INTRODUCTION

The topic of this study is: factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers: a correlational study. This chapter explains the purpose of this study, describes the background of the research problem and presents the problem statement. The chapter also discusses the significance of the research topic in information technology, describes the research design, discusses assumptions made in this study, and identifies limitations arising out of its execution. The chapter concludes with a synopsis highlighting the main points addressed.

Background of the Problem

Increasing dependence on digitized healthcare data has impelled the evolution of innovative cloud-based EHR/EMR systems (Jardins et al., 2016). As contemporary EHR/EMR systems are optimized to enhance healthcare delivery in primary care settings, state and industry regulators have collaborated to regulate their capabilities and use (Carey et al., 2016; Wei & Denny, 2015). HIPAA, which was established in 1996, introduced legislation to protect the privacy of patient health information and included mandatory penalties for violations (Chen & Benusa, 2017; Yarachi & Gopal, 2018).

The Office of the National Coordinator (ONC) was established in 2004 to improve healthcare by promoting the use of health information technology (U.S. Department of Health & Human Services, Office of the National Coordinator, 2019). Enactment of the Health Information Technology for Economic and Clinical Health (HITECH) Act in 2009 introduced significant legislative support for the development of a national Health Information Technology (HIT) infrastructure (Sherer, Meyerhoefer, & Peng, 2016). Under the provisions of HITECH, the ONC was expanded to support the development of HIT by providing administration and oversight for the adoption, implementation, and optimization of information technology throughout the healthcare industry (Mello, Adler-Milstein, Ding, & Savage, 2018; Savage, Gaynor, & Adler-Milstein, 2019). HITECH provisions also included federal funding to promote the adoption of EHR/EMR systems via incentives to healthcare providers who satisfy usage criteria established by the Centers for Medicare and Medicaid Services (CMS) and the Office of the National Coordinator for Health Information Technology (ONCHIT) (Cohen et al., 2018; Mason, Mayer, Chien, & Monestime, 2017). EHR/EMR usage requirements, designated as meaningful use by CMS and ONCHIT, were developed to improve healthcare services by supporting five core strategies: effectiveness and availability, collaborative care, care coordination, public health, and the privacy and security of health information (U.S. Department of Health & Human Services, Centers for Medicare and Medicaid Services, 2010).

The HITECH mandate also included penalties for non-compliance with meaningful use requirements (Wang, Wang, Shen, Rastegar-Mojarad, & Liu, 2019). Cloud-based EHR/EMR systems facilitate availability, integrity, privacy, and security of patient data. Their use enables providers to satisfy requirements of HIPAA and HITECH as well as criteria developed by CMS for meaningful use (Balestra, 2017; Endo et al., 2016; Xhafa, Zhao, Li, Chen, & Wong, 2015). As principal agents in initial healthcare intervention or purveyors of ongoing health maintenance, PCPs have become vital custodians of patient electronic health information (Frogner, Wu, Park, & Pittman, 2017). Consequently, their adoption and effective use of EHR/EMR systems create rapid inflows of data to EHR/EMR databases that fellow professionals, medical organizations and researchers can use to expedite improvements in healthcare delivery (Kaplan, 2016; Lee, Sikula, Lee, Dodds, & Na, 2016). However, PCPs have not adopted EHR/EMR systems at a rate required to meet industry and regulatory requirements (Kruse, Kristof, Jones, Mitchell, & Martinez, 2016).

This study was theoretically undergirded by the unified theory of acceptance and use of technology (UTAUT). The theory posits that four primary constructs predict behavioral intention to use technology: 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions (Venkatesh, Morris, Davis, & Davis, 2003). The first three directly influence usage intention and behavior, and the fourth is a direct determinant of user behavior. UTAUT asserts that the effects of the four primary constructs on usage intention and behavior are moderated by sex, age, experience, and voluntariness of use (Chao, 2019; Šumak & Šorgo, 2016).

Statement of the Problem

The research literature indicates that, despite their potential to support improvements in the quality of healthcare services, primary care providers have been slow to adopt and use cloud-based EHR/EMR systems (Bae & Encinosa, 2016; Gentil et al., 2017; Palabindala, Pamarthy, & Jonnalagadda, 2016). Although Medicare eligible physicians who failed to adopt EHR/EMR systems by 2015 faced severe penalties, the rate of adoption of EHR/EMR systems by primary care providers has been inadequate to satisfy HIPAA and HITECH requirements (Hawkinson, 2016; Mason et al., 2017). Although federal funding allocated in the American Recovery and Reinvestment Act (ARRA) and HITECH provide significant financial incentives to providers who adopt EHR/EMR, the implementation of EHR/EMR requires significant additional investments by PCPs in software systems and training (Mason et al., 2017). The literature also revealed that primary care providers face challenges implementing and using cloud-based EHRs/EMRs and uncertainty regarding a return on their investment (O’Donnell, Kaner, Shaw, &

Haighton, 2018). The slow rate of adoption of cloud-based EHR/EMR systems by PCPs has created significant technological disparities between PCP operations and the healthcare infrastructure that has been established to store, protect, process, and share electronic health records/electronic medical records (Blagec, Romagnoli, Boyce, & Samwald, 2016; Caine et al., 2015; Mack et al., 2016). A comprehensive review of the literature revealed that the factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers have not been exhaustively investigated (Heisey-Grove & King, 2017; O'Donnell et al., 2018).

Purpose of the Study

The purpose of this non-experimental correlational study was to determine the extent that performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI) predict the adoption of cloud-based EHR/EMR systems by primary care providers in the United States, as required by HITECH and CMS regulations. Despite their capabilities to improve diagnostics, optimize health maintenance, and manage detailed patient information used in precision medicine, the rate of adoption of cloud-based EHR/EMR systems by PCPs in the United States has been lower than required to keep pace with industry demand and regulatory compliance obligations (Beckmann & Lew, 2016; Gurupur & Gutierrez, 2016; Palabindala et al., 2016; Wei & Denny, 2015). A slow rate of EHR/EMR adoption has prevented a significant percentage of the PCP population in the United States from participating in data-driven innovations such as real-time monitoring and alerts, enhanced collaborative care enabled by sharing EHR/EMR data, and advances in diagnostics and health maintenance derived from analytics of EHR/EMR data (Wang, Zhao, Sun, & Zhou, 2016; Deverka et al., 2017).

The focus of this study is the adoption and use of cloud-based EHR/EMR systems in primary healthcare in the United States, and its goal is to assess the impact of contributing factors and deliver insight on their significance. This study is purposed to deliver a deeper understanding of factors influencing the adoption of cloud-based EHR/EMR systems by PCPs and to provide guidance to stakeholders in the healthcare and information technology arenas. Moreover, this study is intended to uncover information that could contribute towards accelerating the rate of adoption of cloud-based EHR/EMR systems by PCPs in the United States, which could lead to significant improvements in the delivery of healthcare services (Car, Woan, Huang, Sloot, & Franklin, 2017). Accelerated adoption of cloud-based EHR/EMR systems could also expedite the accumulation of complete patient medical profiles in EHR/EMR data archives to enable PCPs to perform more precise diagnostics and efficient patient care (Ben-assuli, Ziv, Sagi, Ironi, & Leshno, 2016; Metherell, 2016; Murphy et al., 2015; Nimkar, 2016). More effective healthcare services could significantly improve the health and well-being of the United States population (Davidson, Østerlund, & Flaherty, 2015; Delespierre, Denormandie, Bar-Hen, & Josseran, 2017; Jardins et al., 2016).

Significance of the Study

The significance of this study is its anticipated contribution toward narrowing a knowledge gap in the scientific literature regarding factors influencing the adoption of cloud-based EHR/EMR systems by PCPs. The findings of this study may provide improved clarity regarding the challenges facing PCPs as they adopt and use EHR/EMR systems and raise awareness among vendors and developers of EHR/EMR systems, leading to more effective collaboration and the development of more efficient EHR/EMR systems (Høstgaard, Bertelsen, & Nøhr, 2017; Lyles, Schillinger, & Sarkar, 2015). The study may also provide direction for government agencies towards the development of more precise strategies to support EHR/EMR adoption (Yadav, Steinbach, Kumar, & Simon, 2018). More effective support for EHR/EMR adoption may accelerate the adoption of cloud-based EHR/EMR systems by PCPs and expedite higher HIPAA, HITECH, and CMS compliance requirements for using EHR/EMR systems (Wang et al., 2019). Increased EHR/EMR usage may also speed the accumulation of medical health data available for clinical research, leading to more effective health maintenance and lowering the cost of health services (He, Ge, & He, 2017). This study is also purposed to add to the scientific literature and identify avenues for continued research to refine UTAUT theory in its application to explain the impact of factors influencing the adoption of cloud-based EHR/EMR systems by PCPs in the United States.

Research Questions

The omnibus research question that guided this investigation was the following:
To what extent do PE, EE, FC, and SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

The following four sub-questions were developed from RQ1 to enable investigations of the influence of each predictor variables (PE, EE, SI, and FC) on user intention to adopt cloud-based EHR/EMR systems.

Sub-question 1: To what extent does PE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

Sub-question 2: To what extent does EE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

Sub-question 3: To what extent does SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

Sub-question 4: To what extent does FC predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

Definition of Terms

Behavioral Intention to Use (BIU) is the likelihood that an individual will use the technology being considered (Venkatesh et al., 2003; Wagaw, 2017).

Effort Expectancy is an anticipation of the ease of using the technology, and may be defined as the degree to which a user expects job-related tasks to be made easier by using the technology under consideration (Krishnaraju, Matthew, & Sugumaran, 2016).

EHRs/EMRs are electronic health records or electronic medical records consisting of structured patient medical information. The term is also used to denote the software programs used to create and manage electronic health records/electronic medical records.

E-prescription is a feature of EHR/EMR systems which enables providers to submit prescriptions to pharmacies electronically on behalf of patients (Sun & Qu, 2015).

Experience using technology is the number of years the participant has designed, developed, implemented, or used the technology being considered, represented as an ordinal value (1 – 3) reflected in the categories 1 or less, 2 – 5, and 6 or more.

Sex is a dichotomous variable capable of two possible values, male or female.

Facilitating Conditions reflect the magnitude of an individual's belief that an organization's technical resources can support the use of the technology being considered for adoption (Kolog, Sutinen, Vanhalakka-Ruoho, Suhonen, & Anohah, 2015).

Performance Expectancy is the extent that members of an organization anticipate that the use of technology can improve their performance of job-related tasks. Scholarly research has revealed this as the most significant determinant of user intention to adopt a given technology (Krishnaraju et al., 2016).

Population is the group of individuals targeted for this study, namely primary care providers in the United States and their information technology decision-makers who are authorized to choose or influence the decision to adopt EHR/EMR systems. Members of this population are also required to be residents of the United States.

Primary Care Providers are medical professionals who may be nurse practitioners, physician assistants, or physicians such as an internists, obstetricians/gynecologists, geriatricians, pediatricians, or family practitioners (Wood et al., 2017).

Social Influence is the extent to which an individual perceives that others who are influential affirm the use of the technology being considered (Kolog et al., 2015).

Voluntariness of Use is the degree of autonomy which can be exercised by a user in choosing whether to adopt a technology (Venkatesh et al., 2003).

Research Design

The research questions dictated the use of a quantitative research method which was executed using a non-experimental correlational design to investigate the extent that performance expectancy, effort expectancy, facilitating conditions, and social influence predict the adoption of cloud-based EHR/EMR systems by primary care providers in the United States. (Fox, Mooney, Rosati, Paulsson, & Lynn, 2018; Flynn & Kramer, 2019; Krishnaraju et al., 2016; Sabi, Uzoka, Langmia, & Njeh, 2016). Correlation was used to support the development of a model to explain the relationships identified in the research questions (Wagaw, 2017). The target population consisted of primary care providers and IT decision-makers responsible for implementing EHR/EMR systems for primary care providers in the United States. Essential criteria include adequate sample size, and randomized selection of participants to allow each member of the target population an equal opportunity for inclusion (Claydon, 2015; Haegele & Hodge, 2015).

This study involved evaluations of relationships between the IVs (PE, EE, FC, and SI) and the DV (BIU). A non-experimental correlational design was chosen as the appropriate vehicle for executing this study because these relationships can be effectively investigated using correlation (Apuke, 2017; Fives, Canavan, & Dolan, 2017). Similar studies have also demonstrated the efficiency of non-experimental research design, and its capability for preserving external validity (Flynn & Kramer, 2019). Correlation was assessed as suitable for evaluating the influence of predictor variables on EHR/EMR usage intention, the key determinant of technology use in the UTAUT framework (Kolog et al., 2015; Maruping, Bala, Venkatesh, & Brown, 2017).

An a priori calculation using G*Power 3.1 was performed to determine the minimum sample size necessary to support hypothesis testing. Sample selection was randomized by a recruitment process used by a third-party survey administration service which enabled probabilistic sampling of volunteers. Data collection was performed using an online survey hosted by Qualtrics, the third-party survey administration service. Access to the survey was secured by credentials, which were distributed only to qualified volunteers. The criteria for inclusion, as described in the informed consent form, required participants to be primary care providers or IT decision-makers in the United States who are responsible for making decisions regarding the adoption and implementation of cloud-based EHR/EMR systems. Participants were also required to have the knowledge and expertise to answer questions related to the implementation and use of cloud-based EHR/EMR systems. Volunteers were instructed to review the informed consent form and record their agreement to its terms and conditions as a prerequisite for being allowed to complete the survey.

Assumptions and Limitations

The following sections discuss the assumptions and limitations that were made to facilitate this investigation.

Assumptions

The following describes general methodological assumptions, theoretical assumptions and topic-specific assumptions that were made to expedite the execution of this investigation.

General methodological assumptions. This study is implemented using a quantitative method, which is supported by the assumption that knowledge can be attained by investigating observable phenomena, and exists independently of the observer (Claydon, 2015; Rita & Priyanto, 2017). This investigation also relies on the assumption that the study can be executed without being influenced by the beliefs or biases of the researcher and that survey participants answered all questions honestly (Kýlýnç & Fırat, 2017). It is also assumed that the randomized sampling technique used in the study yielded a sample that is representative of the entire target population (El Ouirdi, El Ouirdi, Segers, & Pais, 2016). It is further assumed that conclusions can be drawn about the entire target population by a quantitative evaluation of the data provided by the study participants (Haegele & Hodge, 2015; Watson, 2015).

Theoretical assumptions. UTAUT is assumed to be suitable for providing the theoretical foundation for this study and facilitate an assessment of the variables and relationships proposed in its synthesis (Venkatesh et al., 2003). Empirical data collected for this investigation was used to test UTAUT theory in the context of EHR/EMR adoption by PCPs in the United States. The validity of this evaluation rests on the assumptions that the participants in this study truthfully represented their ability to understand and answer all survey questions, and that recruitment and data collection performed by the third-party data procurement company were in strict adherence to the ethics of academic research (Kline, 2017).

Topic-specific assumptions. The topic of this investigation was derived from extensive reviews of the literature, and was synthesized from an identified gap in the scientific knowledge. It is assumed that the tools identified in this study were capable of comprehensively searching the specified academic databases and could be used to identify a significant gap in the scientific literature. It is assumed that the topic selected for this study is significant in information technology and that its investigation could add to the academic literature, provide a deeper understanding of cloud-based EHR/EMR adoption by PCPs, and offer guidance for developers and vendors of cloud-based EHR/EMR systems (Ali, Shrestha, Soar, & Wamba, 2018; Gurupur & Gutierrez, 2016; Hong et al., 2018). This topic was narrowed to focus on PCPs in the United States. It is assumed that the use of cloud-based EHR/EMR systems by PCPs is a crucial prerequisite for improving the quality of healthcare in the United States and that this study could have a positive impact on the adoption of cloud-based EHR/EMR systems (de Grood, Raissi, Kwon, & Santana, 2016; Heisey-Grove & King, 2017).

Assumptions About Measures

The UTAUT survey instrument, which was synthesized and validated in Venkatesh et al. (2003), is assumed to be appropriate for this study. Previous research has revealed that the UTAUT survey instrument has been widely used to effectively assess predictors of technology adoption (Šumak & Šorgo, 2016; Taherdoost, 2018). It is assumed that the UTAUT survey questions can be used for measuring independent variables used in this study, namely, PE, EE, SI, and FC and the response variable BIU. It is further assumed that ordinal survey responses scored on a 7-point Likert scale can be considered as interval (Maruping et al., 2017). It is also assumed that the measures used in the UTAUT instrument accurately reflect the characteristics of the constructs being investigated in this study (Zuiderwijk, Janssen, & Dwivedi, 2015; Nur, Faslih, & Nur, 2017).

Limitations

The following sections discuss design limitations and delimitations that may have impacted the execution of this study.

Design limitations. The scope of this study was limited to an investigation of factors influencing the adoption of cloud-based EHR/EMR systems primary care providers in the United States, and its findings may not be generalized for physicians in other specializations or in other countries. Additional constraints were imposed by the sampling strategy, which involved the use of email and social media. The sample was assigned randomly from a panel of professionals who responded to the online recruitment solicitations used by the third-party data collection company. These methods may not be ideal for engaging some members of the target audience, however, and could potentially limit the participation of these individuals. This factor was not investigated in this study.

Delimitations. The UTAUT framework includes moderating variables consisting of age, experience, sex, and voluntariness of use as essential factors for a complete understanding of how BIU is influenced by its predictors PE, EE, FC, and SI (Reyes-Mercado, 2018; Wagaw, 2017). Although demographic information was collected, the effects of moderating variables on the predictor variables (PE, EE, SI, and FC) were not investigated in this study. The study was executed using a non-experimental design, supported by a single sample. Sample data reflected a cross-sectional representation of the population at a specific point in time. Although there is an inherent assumption that this sampling technique captures behavior that is generally representative of the population, this study did not incorporate mechanisms for assessing variations in behavior over periods of time as would be performed in a longitudinal study.

Organization of the Remainder of the Study

A review of the scientific literature is described in Chapter 2. Chapter 3 describes the rationale for pursuing this research topic and the methodology used to execute the investigation. Chapter 4 presents the research findings synthesized from statistical analysis involved in testing the research hypotheses. Chapter 5 contains a summary of the entire study, a discussion of its findings and conclusions, and recommendations for future research.

CHAPTER 2. LITERATURE REVIEW

The basis for this study was a comprehensive review of extant literature. The literature described research factors that influence the adoption of cloud-based EHR/EMR systems by PCPs. This chapter presents a structured appraisal of the literature, which addresses the state of contemporary cloud-based EHR/EMR systems and the challenges associated with their adoption and use. Technological innovations involved in the evolution of cloud-based EHR/EMR systems create a backdrop for explaining a gap in the literature. An examination of research methods and theories also provides a rationale for the methodological and theoretical choices that guide this investigation. A synopsis of the main points addressed concludes this chapter.

Methods of Searching

This literature review began with an in-depth search of the academic literature to identify gaps in the knowledge related to adoption and use of cloud-based EHR/EMR systems by primary care providers. Keywords and phrases were combined to query academic databases accessible from the Capella Library and Google Scholar. Searches were restricted to scholarly peer-reviewed articles accessible online and published between 2015 and 2019; dissertations, newspaper articles, and book reviews were excluded. The following academic databases yielded multiple source articles: Academic Search Premier, Computers & Applied Sciences Complete, ProQuest databases, and ScienceDirect. Filters were used in queries to eliminate duplicate listings; however, the query formats supported by some databases did not accommodate filters, and results were manually evaluated. The search for seminal literature revealed significant stages in the evolution of technology adoption theories as well as the adoption and use of EHR/EMR systems. These searches identified 201 sources, of which nine were seminal (1971–2005).

Although the primary objective of the literature review was to identify a gap in the literature that could provide a rationale for pursuing this investigation, the review was also purposed to identify an appropriate theoretical model, which could be used as the framework for pursuing this investigation. This comprehensive search of the literature also revealed methodologies that were feasible options for guiding the investigation. The methodologies were critically examined to determine an optimal approach.

Theoretical Orientation of the Study

This study examined the adoption of cloud-based EHR/EMR systems by primary care providers through the theoretical lens of the unified theory of acceptance and use of technology (UTAUT). The UTAUT framework was first presented in Venkatesh et al. (2003), and is a synthesis of extensive research that unified dominant principles and constructs from eight previous theories (Šumak & Šorgo, 2016). Venkatesh et al. (2003) used UTAUT to explain 70% of the variance in user intention, which was a significant improvement over the eight theories used in its synthesis (Maruping et al., 2017). The effectiveness and flexibility of the UTAUT framework to explain user intention in investigations of technology adoption has been affirmed in a wide array of technological contexts (El Ouirdi et al., 2016; Reyes-Mercado, 2018; Venkatesh, Thong, & Xu, 2016).

The UTAUT theoretical framework asserts that behavioral intention is a principal predictor of user behavior, and is directly influenced by performance expectancy, effort expectancy and social influence (Arif & Rafiq, 2018). UTAUT also posits that facilitating conditions impose directs effects on use behavior, but does not influence behavioral intention (Hoque & Sorwar, 2017). Previous studies have used UTAUT to investigate the significance of factors influencing the adoption of technology, and have affirmed its effectiveness to facilitate investigations of intention and use in a wide range of technological contexts (Almaiah, Alamri, & Al-Rahmi, 2019).

As illustrated in Figure 1, UTAUT incorporates four independent variables (IVs): performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI). The dependent variable (DV) BIU, which is the primary predictor of technology use behavior, is influenced by the four IVs (Venkatesh et al., 2012). The effects of IVs on BIU are moderated by four factors: age, experience, sex, and voluntariness of use (Wagaw, 2017). Consumer-oriented extensions were proposed for UTAUT in Venkatesh et al. (2012), namely hedonic motivation, price value, and habit, were introduced to improve support for investigations of technology acceptance for personal use.

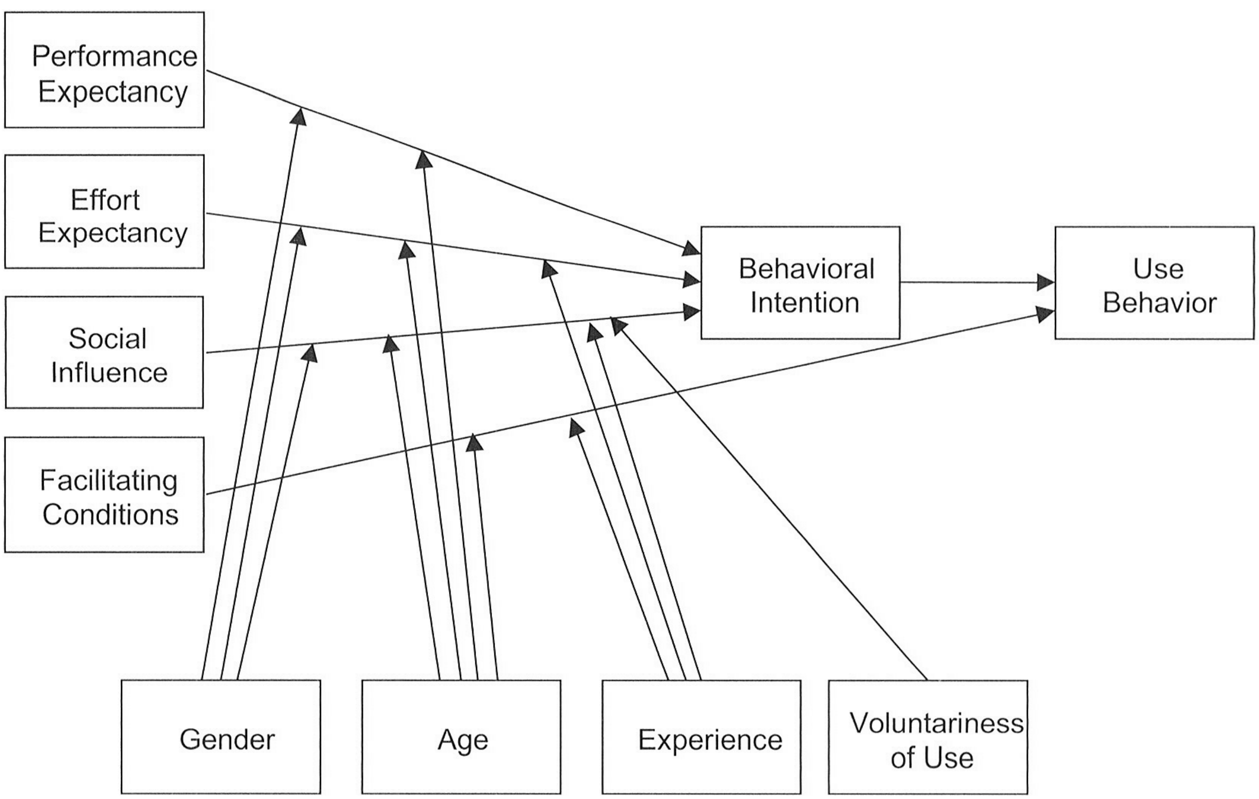

Figure 1: Unified theory of acceptance and use of technology. From "User Acceptance of Information Technology: Towards a Unified View," by V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, 2003, *MIS Quarterly*, *27*, p. 447. Copyright 2003 by Regents of the University of Minnesota. Reprinted with permission.

Since its synthesis, UTAUT has provided a versatile framework for examining the effects of factors involved in the adoption of technology (Alam, Hu, & Barua, 2018). In previous studies, researchers have leveraged the effectiveness of UTAUT constructs and variables to represent factors influencing technology adoption, and used the relationships between predictors and the dependent variable to model the relationships being investigated (Hossain, Quaresma, & Rahman, 2019). The empirical evaluations in this study were also executed to assess the significance of relationships between predictors of behavioral intention, PE, EE, SI, and FC and the dependent variables BIU.

The technology acceptance model (TAM) has also been used in investigations of technology adoption; however, the TAM framework was developed for supporting investigations of consumer-oriented user acceptance of technology (Lai, 2017). Extensions in UTAUT2, namely hedonic motivation and price value, were proposed to improve support for investigations of personal adoption and use of technology (Venkatesh et al., 2012; Venkatesh et al., 2016). UTAUT was more suitable for this investigation because its constructs and variables provide the elements for investigating the factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers. Sample data collected for this study included data for four moderating factors, namely age, experience, sex, and voluntariness of use; however, this information was only used for demographics.

Review of the Literature

EHR/EMR systems enable healthcare providers to create, maintain, and share detailed digital medical profiles (Mack et al., 2016; Palabindala et al., 2016). EHR/EMR systems are also capable of extracting from patient records vital information that can be used to optimize patient care and support clinical governance (Wang, Kung, & Byrd, 2018). The use of EHR/EMR systems has created voluminous reservoirs of medical information, which have been analyzed by researchers to derive guidance for developing more effective patient-centered medical services (Hiller, 2016; O'Malley, Draper, Gourevitch, Cross, & Scholle, 2015). However, increasing reliance on EHR/EMR systems has exacerbated concerns regarding their effectiveness, impelling healthcare providers and system vendors to collaborate closely on their design to meet provider, regulatory, and industry requirements (Ballaro & Washington, 2016; Lyles et al., 2015). Consequently, their continued evolution has delivered improved capabilities for healthcare providers, albeit with increased complexity and higher cost (Kruse, Kristof et al., 2016).

The invention of the "Automated Medical History Taking System" by Harvey R. Worthington Jr. and Daniel B. Schwarzkopf in 1971 was a significant milestone in the advance towards capable EHR/EMR systems (Haessler, Elshtain, & Holland, 1978). This innovative device was equipped with complex electronics to create patient medical histories from answers to pre-programmed questions, was capable of operating in several languages, and safeguarded the privacy of patient information by the use of a coded identity card (Worthington & Schwarzkopf, 1971)**.** Although this system used paper as its recording medium and was prohibitively priced, it demonstrated the immense potential of computerized medical records management. Among the first commercially available EHR/EMR systems, Computer-Stored Ambulatory Record was developed between 1968 and 1978 at the Massachusetts General Hospital by their Laboratory of Computer Science. More affordable systems were developed contemporaneously, such as the Indiana University's Regenstrief Medical Information System, which could generate reminders to physicians, and The Medical Record developed at the Duke University Medical Center, which stored cardiac information for use in clinical investigations (Barnett, 1984).

The early EHR/EMR systems were designed for mainframe computers, and were complex, unreliable, and only affordable for large corporations and government institutions. However, with the advent of the mini-computer and ethernet-enabled networking, developers could create EHR/EMR at price ranges accessible to smaller enterprises such as hospitals (Metcalfe & Boggs, 1976). The modern EHR/EMR system, however, was a confluence of synergistic technologies including inexpensive hardware platforms available in cloud systems, cost effective data storage using Storage Area Networks (SANs), high speed networking delivered by fiber-optics, ubiquitous wireless networking, and AI-enabled Big Data analytics for speedy processing of high-volume data stores (Allaert, Mazen, Legrand, & Quantin, 2017; Aziz, 2016; Cirillo & Valencia, 2019; Xhafa et al., 2015). Improved capabilities have made EHR/EMR systems compelling enablers for PCPs, key players in the creation and management of accurate patient medical profiles. Available as cost effective solutions, EHR/EMR systems provide ready access to patient information as well as an array of tools that enable providers to perform in-depth knowledge extraction.

Primary healthcare is defined by the American Academy of Family Physicians as comprehensive care of undiagnosed patients at first contact and may include diagnosis and continuing treatment of health problems (American Academy of Family Physicians, n.d.). Primary care providers may be family practitioners, geriatricians, internists, nurse practitioners, pediatricians, physician assistants, or obstetricians (Lasser et al., 2016). They routinely establish patient medical histories at initial contact and update them during subsequent consultations, creating a detailed chronology of medical events (Balestra, 2017). A major component of the meaningful use strategic objectives is a new trend in healthcare that involves processes optimized to meet the needs of specific patients and has revealed immense potential for elevating the quality of patient care (Cowie et al., 2017; O'Donnell et al., 2018). This strategy is also aligned with the federal precision medicine initiative launched in January 2015, which was developed to more precisely target disease treatment (McGrath & Ghersi, 2016). EHR/EMR systems can play a defining role by enabling detailed medical records to be created, which is crucial for efficient personalized care, and supporting transformational improvements in medical services (Vitalari, 2016).

EHR/EMR Systems

Contemporary EHR/EMR implementations often leverage cloud-based infrastructure to meet performance requirements in primary care settings because cloud architectures combine cost-effective processing power, high availability, reliability, and scalability (Hertzog et al., 2019; Jain, Gyanchandani, & Khare, 2016; Mues et al., 2018). However, cloud-based systems are susceptible to security vulnerabilities that could jeopardize compliance with HIPAA and HITECH standards for securing personal health information (Luna, Rhine, Myhra, Sullivan, & Kruse, 2016; Pandeeswari & Kumar, 2016). As developers of contemporary cloud services continue to make significant progress in addressing security challenges, cloud-based EHR/EMR systems have garnered broad acceptance by providing compelling capabilities such as rapid access to patient medical information, streamlined referrals, clinical workflow efficiencies, support for provider collaboration, and high capacity storage for patient data (Ahmadi & Aslani, 2018; Ali et al., 2018; Babrahem & Monowar, 2018; O'Malley et al., 2015).

The stringent data management requirements for voluminous EHR/EMR data repositories are beyond the capabilities of traditional relational database management systems (Hong et al., 2018). Data science innovations are being leveraged to manage these large reservoirs of patient information, enabling EHR/EMR systems to provide real time access to patient data. Real time access is a critical prerequisite for supporting services such as e-visits, which are virtual consultations involving physician and patient access to EHR/EMR (El aboudi & Benhlima, 2018). Significant investments have targeted technologies such as Big Data analytics by using Big Data processing engines implemented on cloud platforms or massively parallel hardware architectures that can support their demanding challenging requirements (El-Seoud, El-Sofany, Abdelfattah, & Mohamed, 2017; Wang et al., 2018). Big data platforms are being used to manage patient data, effectively storing, processing, and managing extremely large data sources efficiently in real time by using highly optimized algorithms to share the storage and processing load across a distributed architecture (Abouelmehdi, Beni-Hessane, & Khaloufi, 2018). Big Data technologies are implemented as scalable platforms that are optimized for efficient storage of data, implementing innovative methods to facilitate fast access to information, supporting analysis, and enabling EHR/EMR systems to deliver meaningful results to their healthcare providers (Li, Hu, Li, Wu, & Yang, 2016).

Popular big data platforms include Map Reduce, which implements algorithms to map data elements and eliminate redundancy, thereby reducing the size of the database (Austin & Kusumoto, 2016; Usman, Jan, He, & Chen, 2019). Although originally developed by Google, the MapReduce programming model has been implemented in other Big Data processing engines (Li et al., 2016). Data analysis may also be performed by analytics engines such as Storm, a real time open source platform developed by Twitter (Yang, Liu, Chen, & Lu, 2017). Apache Spark enables batch and stream processing of large data repositories, emulating the architectures of distributed file systems such as Hadoop Distributed File System (HDFS), Cassandra, and HBase (Díaz, Martín, & Rubio, 2016). Cassandra and HBase are HDFS compliant platforms and are available as open source platforms from Apache (Pramanik, Lau, Demirkan, & Azad, 2017; Um et al., 2016). Spark was equipped with machine-learning capabilities, capable of helping providers improve their performance in a wide variety of services such as reducing diagnostic errors (Wang & Byrd, 2017).

Big Data analytics may be used to deliver innovative knowledge extraction to support healthcare services by leveraging the capabilities of data streaming platforms, AI-enabled data analysis, and distributed data storage systems (Qi et al., 2017). Biomedical imaging and image processing may be used proactively to identify disease and guide treatment strategies. Because of the extreme noise-sensitivity of image processing, distortions must be detected and discarded to prevent their influence on clinical decision-making (Pouyanfar, Yang, Chen, Shyu, & Iyengar, 2018; Usman et al., 2019). Although sensors may provide more reliable information**,** social network analysis involving the use social network sites as sources of medical data provides an opportunity to explore large data sources in the public domain that could provide valuable information regarding public health issues (Chen et al., 2018).

However, using social network information demands caution because its reliability is questionable, particularly in scenarios where important decisions can be misdirected, such as designing predictive strategies to detect infectious diseases (Ristevski & Chen, 2018). Sensors embedded in medical devices such as those used to monitor heart rate, body temperature, blood pressure, or cardiovascular status may also deliver patient medical information to EHR/EMR datastores using wired or wireless connectivity (Qi et al., 2017). Rapid data accumulation because of the potential for frequent information uploads from sensors requires the use of specialized processing, capable of efficient data analysis and redundancy elimination (Zhang, Qiu, Tsai, Hassan, & Alamri, 2015). Optimization techniques are also essential during data collection to prevent unnecessary duplication, such as monitoring multiple vital signs for a patient (Ray, 2018).

Data cleaning, essential for sustaining the high reliability required for medical information, requires precision to preserve data integrity. The software that performs this function may implement algorithms to fill in missing data or detect and correct data distortion caused by noise (Stiglic, Kocbek, Fijacko, Sheikh, & Pajnkihar, 2017). Data filtering uses predefined criteria to eliminate erroneous or redundant information. Although recognized for its perceived potential to limit the unrestricted growth of medical information, extreme caution is essential to avoid discarding vital patient information (Baig, Gholamhosseini, Moqeem, Mirza, & Lindén, 2017).

Data storage requirements for healthcare information poses severe challenges for data management systems because of its sheer size. Specialized frameworks may include HDFS, (non-relational) NoSQL data management systems such as MongoDB, (relational) SQL databases, or various combinations of these (Venkatraman, Fahd, Kaspi, & Venkatraman, 2016). Acquiring input from sources such as EHR/EMR interfaces, social media, wearable medical devices (WMDs), mobile sensors, and lab information, Big Data architectures support healthcare operations by providing tools and resources to deliver an array of innovative services including visualization, prediction, dashboards, alerts and support for emergency services (Wang et al., 2019). Incorporating these tools enables EHR/EMR systems to support enhanced care such as seamless collaboration and real time medical alerts for improved patient outcomes (El aboudi & Benhlima, 2018). Because of extreme reliance on health information, improved data governance has emerged as a critical imperative for preserving the integrity and security of EHRs/EMRs and for enhancing their value as sources of intelligence for healthcare decision-makers (Wang & Byrd, 2017).

Medical imaging has become a significant contributor to medical diagnostics and clinical research. Image data can be derived from a variety of sources such as radiography, computed tomography scans, magnetic residence imaging, or picture archive communication systems (Erdal et al., 2018). High resolution images required for medical procedures may be large and may require specialized platforms for efficient management and processing (He et al., 2017). The complex processes involved in large scale image processing are ideal for AI optimization, and storage requirements for the large image files involved require high capacity architectures such as cloud infrastructure or SANs (Chen & Benusa, 2017). The Ohio State University Wexner Medical Center REMIX, which was developed to store and process *big imaging data*, is an example of a big data image processing system. The REMIX combines an array of capabilities including storage optimization, image repair, image-based pathology, anonymization, business intelligence, AI, and in-depth analysis of image topologies (Erdal et al., 2018). Powerful guidance can be derived when multiple types of data are used in clinical analysis. Consequently, imaging analysis is highly ranked because of its potential as a source for extracting multiple data sets (Pramanik et al., 2017).

WMDs are miniaturized medical appliances equipped with sensors that are capable of monitoring patient vital signs and transmitting health information via wireless networking (Terry, 2017). Wearables provide continuous monitoring, and by providing continuous monitoring, their role as early detectors of health problems is vital for proactive diagnosis at disease onset. They may also be used to dynamically tailor patient care based on reported health status (Alemayehu & Berger, 2016). Medical information from wearables can be directed to data management systems where they can be combined with information from other sources and used for health maintenance. The effectiveness of WMDs may be impacted by the activities of the user, who must ensure they remain fully operational under all circumstances. Other factors, such as network latency, noise, loss of connectivity, or discharged batteries can affect the reliability of the information wearables provide (Sethi & Sarangi, 2017).

Although capable of storing information while offline, their limited capacity severely restricts the quantity of data they can retain, which could jeopardize the retention of life-preserving information. Resource limitations also inhibit their capability to perform intrusion protection, rendering the device vulnerable to hacking (Rathore, Mohamad, Al-Ali, Du, & Guizani, 2018; Stern, Gordon, Landman, & Kramer, 2019). Devices may become easy targets for clandestine exploits when wearers are unable to monitor them or when the devices are connected to insecure wireless networks (Sun et al., 2018). Although authentication is essential for securing data uploads from devices, lack of standardization among device manufacturers creates widespread interoperability issues among devices and with the data infrastructure (Davidson et al., 2015). However, despite the challenges, wearables remain an important source of health information, contributing to the acquisition of detailed health records, a critical resource for patients whose survival could depend on immediate intervention in a medical crisis.

The Internet of Things (IoT) consists of networked appliances that, equipped with sensors, are capable of collaboration over wireless or wired connections (Kaur & Kaur, 2017). IoT devices can participate in sophisticated collaboration by sharing, pooling or retransmitting information. They are also capable of orchestrating autonomous responses to input information (Ray, 2018). However, their vulnerability to privacy and security challenges have elicited grave concerns among experts (Dimitrov, 2016). Although a 2013 International Data Corporation report estimated that the market for IoT devices and applications would be approximately $8.9 trillion in 2020, IoT manufacturers have not implemented resilient security countermeasures to protect the devices from being exploited by rogue operators (Yang, Wu, Yin, Li, & Zhao, 2017). This lack of security was demonstrated by a researcher who discovered the first IoT botnet in 2013 (Yang, Wu et al., 2017). Despite these challenges, the proliferation of IoT devices continues as investors, manufacturers, and service providers in healthcare and other industries seek to leverage the potential of the IoT to deliver transformational innovations (Rathore et al., 2018).

The IoT adds flexibility and accessibility to healthcare monitoring, enabling devices and sensors to provide highly detailed information about the health status of patients and their environments (Qi et al., 2017). The Internet of Medical Things (IoMT) originates patient information that may be submitted to cloud-based EHR/EMR databases where they supplement the vast archives of medical information used in knowledge acquisition to improve the health and well-being of patients (Anandarajan & Malik, 2018). IoMT endpoints may also be designed to control actuators to effect changes on behalf of patients such as activating an insulin pump for diabetics who may be disabled (Schukat et al., 2016).

Decades of research have revealed the power of visualization to enable faster, more precise clinical diagnosis and improved outcomes for patients (Elhoseny et al., 2018). As healthcare providers are required to use increasingly higher volumes of complex medical information and make faster decisions, the tools developed for analysis, interpretation and visualization of healthcare data have yielded inadequate results (Bahri, Zoghlami, Abed, & Tavares, 2018; Ker, Wang, Rao, & Lim, 2017). However, the introduction of clinical instrumentation to transform EHRs/EMRs for real time visual display are making a striking impact in healthcare. These tools may be used to generate alerts and are being deployed to facilitate speedy intervention in response to adverse changes in patients' health status (Badgeley et al., 2016).

Typical EHR/EMR system displays conform to static tabular formats and may not reveal trends in the progression of diseases, response to treatment, or other aspects of patient pathologies (Chen et al., 2018). These EHR/EMR systems may incorporate the management of biomedical information in hospitals and new track and trigger systems that can fire alerts based on specific status thresholds (Wuytack et al., 2017). EHDViz is an open source visualization toolkit that can be used to speed development of dashboards, significantly reducing development and maintenance cost. This toolkit facilitates rapid application prototyping and testing and supports scalable solutions featuring real time interactive dashboards. These dashboards may be used to retrieve, analyze, and consolidate EHR/EMR data from multiple sources into a single display. They are suitable for clinical units, hospitals, or healthcare systems (Erdal et al., 2018; Wang & Hajli, 2017).

The following are among the most established alerting systems that use vital signs and neurological updates: Modified Early Warning System (MEWS), Standardized Early Warning System (SEWS), and National Early Warning System (NEWS) (Arnold et al., 2019; Downey, Tahir, Randell, Brown, & Jayne, 2017). Contemporary research has revealed that systems based on predictive strategies can more accurately detect the onset of adverse conditions than those relying on vital signs only (Redfern, 2018). Advances in imaging techniques also enable healthcare providers to perform more non-invasive procedures, reducing hospitalization and recuperation time. Technology-driven diagnostics also facilitate proactive protocols that may prevent or reduce the severity of common medical conditions. Innovations in wireless technologies have also facilitated the development of mobile health services (Sajid & Abbas, 2016).

Healthcare data retrieval can be performed using a variety of tools such as MySql, Java Database Connectivity (JDBC), Open Database Connectivity (ODBC), or Not only SQL (NoSQL). Support for each type of data source is implemented in (reusable) EHDViz packages (Badgeley et al., 2016). Searching EHR/EMR data is challenging because of its sheer volume. Storage, retrieval, and processing require special techniques, and the use of Big Data technologies has become the norm for managing patient information (Wang et al., 2018). Enhanced relational models such as OpenEHR have been explored because relational databases may not deliver optimal performance for EHR/EMR data because of the volume and complexity of medical information. OpenEHR leverages the flexibility of storing path information in special tables (Haartbrandt, Tute, & Marschollek, 2016).

Similarly, archetype relational mapping (ARM) uses path information, but it also uses storage structures independent of archetypes. Another solution involves rebuilding the relational schema based on the archetypes and the database tables (Wang, Min, Wang, Lu, & Duan, 2015). There has been insufficient research on the use of NoSQL databases for medical data. However, based on extensive testing involving MySQL, a popular relational database management system (DBMS), MongoDB, a document-based NoSQL DBMS, and eXist, a native XML DBMS, NoSQL may have the potential for superior performance relative to relational databases (Sanchez-de-Madariaga et al., 2017). Testing was done using data sources of various sizes that contained patient data extracts. The patient data originated from several Spanish hospitals whose queries searched the data source for identical patient information.

Although the EHR/EMR information created databases of differing sizes for each DBMS, response times for queries revealed superior performance by the NoSQL DBMSs and indicated that MongoDB, the document-based NoSQL DBMS, outperformed eXist, its XML based NoSQL counterpart (Sanchez-de-Madariaga et al., 2017). The tests also revealed modest linear increases in execution times for MongoDB queries as the sizes of the database increased from 5,000 to 10,000 and 20,000 EHR/EMR extracts. MySQL (relational DBMS) execution time increased rapidly, revealing that NoSQL may provide more scalable database solutions for voluminous EHR/EMR data stores. The NoSQL DBMS also outperformed the relational DBMS in tests of concurrent execution. Superior performance for concurrent query execution may be further improved by implementing NoSQL on parallel hardware architectures (Patel, Verma, Arpaci-Dusseau, & Arpaci-Dusseau, 2018). The value of EHR/EMR data analysis in health maintenance was validated in a longitudinal cohort study that included participants from several countries. This study identified precursors of the following conditions: cardiac arrest, unexpected transfers to intensive care units, and death while hospitalized (Badgeley et al., 2016).

Federal Support for Using EHRs/EMRs

In the United States, federal organizations such as CMS have embraced a strategy to improve the health and well-being of the population at large and, in particular, of children requiring complex therapy by promoting large scale adoption of EHRs/ERMs to modernize the delivery of medical services (Kercsmar et al., 2017; Kroning, 2018). A report from the Agency for Healthcare Research and Quality indicated a critical requirement for HIT support of healthcare management coordination (Bruns, Hyde, Sather, Hook, & Lyon 2016). Federal guidance regarding provisions for Medicaid Health Homes in the Patient Protection and

Affordable Care Act also encourages effective use of HIT (Buehler, Snyder, Freeman, Carson, & Ortega, 2018; Feldman et al., 2018).

Legislative support for healthcare as a national priority was demonstrated in the enactment of the American Recovery and Reinvestment Act (ARRA) in 2009, which provided an $840 billion stimulus package for economic development (Carley, Nicholson, & Fisher, 2015). Financial support for this healthcare initiative, designated as HITECH, was tailored to provide administrative assistance and oversight for the adoption and use of interoperable EHRs/EMRs (Kroning, 2018; Mennemeyer, Menachemi, Rahurkar, & Ford, 2016; Williams & Shah, 2016). Financial incentives were designed to elevate the quality of healthcare services by supporting the development of a national HIT infrastructure, and maximizing the benefits of using EHRs/EMRs (Gopalakrishna-Remani, Jones, & Camp, 2018; Snyder & Oliver, 2014). The assimilation of EHR/EMR technologies into the healthcare ecosystem requires significant investment, IT governance, training, and effective policies to promote efficient use of this technology (Kruse, Kothman, Anerobi, & Abanaka, 2016). Although return on investment cannot be guaranteed, the effectiveness of EHRs/EMRs to elevate the quality of care and improve the efficiency of healthcare delivery may depend on well-orchestrated management and governance of systems as well as stringent controls to meet standards imposed by regulatory mandates such as HIPAA and HITECH (Bhavnani et al., 2017; Wang & Byrd, 2017).

In recognition of their potential to facilitate modernization of the healthcare industry and hasten improvements in the quality of medical services, federal support for the adoption of EHR/EMR systems was instituted in Title IV of the ARRA (American Recovery and Reinvestment Act, H.R.1, 111th Cong., 2009; Savas, Smith, & Hay, 2019). Funding for HITECH infrastructure development was allocated from an ARRA appropriation of $27 billion, which included significant provisions for meaningful use of EHR/EMR systems (Wani & Malhotra, 2018). Major EHR/EMR usage requirements were introduced by the CMS in 2010 with the launch of the EHR/EMR certification program, which was originally designated Certified EHR Technology and renamed in 2011 to Promoting Interoperability (PI) (U.S. Department of Health & Human Services, Centers for Medicare and Medicaid Services, 2019). Federal commitment to support the adoption of EHR/EMR systems was further demonstrated in an amendment of the Patient Protection and affordable Care Act in 2013 to include mandatory EHR/EMR use by providers (U.S. Department of Health & Human Services, Centers for Medicare and Medicaid Services, 2010).

The CMS has also established prerequisites for meaningful use of EHR/EMR systems, including the adoption of certified EHR technologies (CEHRT) by healthcare providers and medical institutions (Bullard, 2016; Kroning, 2018; Understanding Certified IT, n.d.). Providers were also required to attain mandatory levels of meaningful use before the designated deadlines (Barnett, Mehrotra, & Jena, 2016). The deadline established by the CMS for attaining Stage 1 meaningful use certification was 2011, two years after its launch in 2009, the deadline for achieving Stage 2 was postponed to 2014, and Stage 3 requirements were scheduled for 2017 (Levine et al., 2016; Lesley & Shmerling, 2015). Requirements for Stage 1 meaningful use of EHR/EMR include structured documentation**.** Stage 2 criteria include computerized order entry, implementation of e-prescription, and recording of clinical details such as vital signs and smoking status (Snyder & Oliver, 2014; Bae, Ford, Kharrazi, & Huerta, 2018). Stage 2 requirements also included the creation of patient EHR/EMR portal by providers and institutions to facilitate secure administration of personal health information, and enable efficient communication by secure messaging with at least 5 % the patients they serve (Snyder & Oliver, 2014). The deadline for meeting Stage 3 requirements was delayed until 2017 to allow time for providers and institutions to address challenges related to the adoption of CEHRT, and the implementation of advanced features such as e-prescribing (Estes, Kelemen, Liang, & Constantine, 2016).

Although providing important benefits, the adoption of EHR/EMR systems introduces new challenges for providers, such as the lack of interoperability between systems from different vendors (Curtis et al., 2018). EHR/EMR adoption also involves strategic re-engineering of business processes, and the probability of significant loss of productivity during implementation (Kruse, Kothman et al., 2016). PCPs have emerged as important agents in the creation of electronic health records/electronic medical records, and although severely handicapped by challenges related to the adopting complex EHR/EMR systems, their contribution to the maintenance of accurate and complete EHR/EMR databases is critical for supporting transformation in essential services to improve the health and well-being of the population (Harle et al., 2015).

Data Governance for EHR/EMR Information

The acquisition of complete EHRs/EMRs is an essential prerequisite for maintaining accurate healthcare chronology. Patient data archived in medical databases can be used for analysis, and may yield valuable guidance for improving health services and clinical outcomes for the population at large (Konnoth, 2016). However, such usage of EHR/EMR data poses significant ethical challenges for participants and may be a cause of concern for the patients whose EHRs/EMRs are used in this manner (Yarachi & Gopal, 2018). Patients are vulnerable to severe risks of exposure of their personal information because security and privacy safeguards implemented by EHR/EMR custodians provide no guarantee against clandestine exploits (Krisby, 2018).

For low-income individuals, the elderly, and patients battling severe health problems, disparities in the security and privacy protection of personal health information is placing them at even greater risk (Levine et al., 2016). However, individuals who can forego public assistance can avoid sharing their health information while benefiting from knowledge derived from the EHR/EMR data of recipients of public assistance programs such as Medicaid and Medicare (Konnoth, 2016). Effective data governance must therefore be applied to EHR/EMR data to establish ethical integrity in the protection, use, and sharing of patient healthcare information while ensuring its availability for deriving significant clinical benefits for everyone (He et al., 2017).

Data Requirements in Primary Settings

Primary care providers create medical profiles to facilitate effective patient care. Patient records include critical details for assessing health status, such as immunizations, risk factors for diseases, potential exposure to pathogens, and previous and ongoing medical treatment (Carey et al., 2016; Casey, Schwartz, Stewart, & Adler, 2016; Gurupur & Gutierrez, 2016). Medical information may be initially typed by the provider; however, because this may be too time-consuming during clinical consultations, providers may use scribes to input patient information into EHR/EMR systems during consultation with patients, which has exacerbated concerns about patient privacy (Kroth et al., 2019). Human error may also introduce significant inaccuracies in clinical updates that must be identified and corrected to maintain the integrity of patients' records (Monteith, Glenn, Geddes, Whybrow, & Bauer, 2016; Vimalachandran, Wang, Zhang, Heyward, & Whittaker, 2016). Patients can also use an EHR/EMR web portal to review and validate their personal medical information (Rogers & Jeanty, 2017). EHR/EMR systems facilitate all these processes by enabling users to create records in formats which can be processed by a wide range of medical systems (Rosenbloom, Carroll, Warner, Matheny, & Denny, 2017). Consequently, maintaining the accessibility of EHR/EMR data is critical for sustaining the effectiveness of key innovations in healthcare; however, securing their privacy is a critical prerequisite for gaining stakeholder confidence in EHRs/EMRs (Jayabalan & O'daniel, 2016; Pussewalage & Oleshchuk, 2016).

Synthesis of the Literature

Primary care providers use EHR systems to digitize patient information, a prerequisite for technological transformation throughout the healthcare industry (Frogner et al., 2017). Federal support for adoption of EHR/EMR systems has led to their increased implementation and use by PCPs; however, the need for improved interoperability between EHR/EMR systems from different vendors, and the additional workload to document clinical events, remain significant challenges for providers (Kroth et al., 2019; Young & Nesbitt, 2017). PCPs who use medical scribes to perform data entry may avoid excessive loss of productivity, but increased labor costs are inescapable (Sulmasy et al., 2017). HIPAA and HITECH privacy stipulations, and the complexity of EHR/EMR systems, have also created a need for IT training and for hiring more IT professionals, creating additional financial burdens for PCPs, who often serve in small practices with modest budgets (Chen & Benusa, 2017).

Using EHR/EMR systems creates large data archives from which researchers extract meaningful guidance for diagnosing and treating diseases (Hong et al., 2018; Murphy et al., 2019). Using machine learning and AI supplement provider capabilities; however, HIPAA privacy stipulations require safeguarding patient privacy by deidentifying patient records

(Rathore et al., 2018). However, HIPAA needs to be modified to adequately protect patient privacy in settings where data may be accessible outside of healthcare providers' control. ONCHIT created a certification standard for identifying EHR/EMR systems that are capable of supporting strategic objectives to improve healthcare services; their use is required for participation in federal incentive programs (U.S. Department of Health & Human Services, Office of the National Coordinator, 2018).

However, this has created challenges for PCPs who are required to transition from uncertified EHRs/EMRs. Although the CMS meaningful use requirements were created to support healthcare optimization, stage 2 requirements were postponed to 2014, and stage 3, the most challenging stipulations, were scheduled for 2017 (Levine et al., 2016; U.S. Department of Health & Human Services, Centers for Medicare and Medicaid Services, 2019). Providers may petition the CMS for additional time to satisfy EHR/EMR meaningful use requirements by requesting a hardship exception (U.S. Department of Health & Human Services, Centers for Medicare and Medicaid Services, 2019). Meaningful use of EHRs/EMRs streamlines the documentation of patients' clinical events and allows fast access by authorized healthcare providers (U.S. Department of Health & Human Services, Centers for Medicare and Medicaid Services, 2010). The goal is to eliminate the need for duplicate information. Achieving these efficiency goals could enable PCPs to offset the additional cost of implementation, maintenance and training required to use EHRs/EMRs; however, these challenges continue to delay their attainment.

HIT investment inequities in poorer neighborhoods, reflected in lower EHR/EMR usage, are creating healthcare disparities (Jardins et al., 2016). Elevating the levels of EHR/EMR adoption in distressed communities could improve general health, increase the rate of early detection in the treatment of cancer, and reduce susceptibility of underserved communities to health threats such as the Ebola crisis or the Zika virus. (Gilbert, Degeling, & Johnson, 2019; Morain et al., 2018; Murphy et al., 2019).

Technological convergence in healthcare has led to increasing complexity in EHR/EMR systems and to highlighting the need for IT governance and controls to safeguard the healthcare infrastructure and sensitive patient information **(**He et al., 2017**).** Voluminous EHR/EMR repositories containing detailed patient records may be viewed by rogue agents as prime targets for exploits such as ransomware attacks or data pilfering to facilitate identity theft scams (Abouelmehdi et al., 2018; Kaplan, 2016; Yarachi, & Gopal, 2018). Countermeasures require continuous revision to remain effective against a continuously evolving wave of malicious attacks (Stern et al., 2019). Critical infrastructure also requires protection from vulnerabilities in all layers of the EHR/EMR system and requires robust standards for interoperability among EHR/EMR vendors and hardware manufacturers, network service providers (Krisby, 2018).

Critique of Previous Research Methods

This literature review revealed that quantitative research methods were primarily used in investigating the adoption of cloud-based EHR/EMR systems. However, challenges involved in their use undermine the validity of their findings. These challenges have also created opportunities for further investigation to advance knowledge creation. An overview of these issues follows.

Although sampling enables access to information about a target population from a subset its constituents, a representative sample is required for generalizing findings for the entire target population (Kline, 2017; Park & Park, 2016). Techniques used to procure representative samples include randomizing the selection of participants for the study (Hayat & Knapp, 2017). However, practical constraints may undermine sample randomness, leading to bias or overrepresentation of segments of the population (Smyk, Tyrowicz, & Van der Velde, 2018). Sampling bias may be introduced by selection processes which do not allow all participants an equal opportunity for inclusion. The use of convenience sampling introduced potential bias and undermined the generalizability of research findings in Abd-Alrazaq, Bewick, Farragher, and Gardner (2019). Online recruitment of survey participants may also be susceptible to sample bias when individuals in the target population do not have equal access to the online recruitment environment (Tavares & Oliveira, 2017). Sampling bias was not examined in depth in a number of studies reviewed (Emani et al., 2017; Gopalakrishna-Remani et al., 2018; Redd et al., 2015). Unless the researcher investigates the potential of such recruitment techniques to skew participant representation, their effects remain unknown (Laher, 2016).

Post hoc power analyses may be used to evaluate the statistical power attained in an investigation; however, they cannot provide proactive guidance regarding sampling and are, therefore, only used for verification (Gopalakrishna-Remani et al., 2018; Zhang et al., 2019). Using surveys in quantitative studies may also introduce imprecision because of the limited choices available. A pilot study can be used to provide guidance for selecting a sample frame; however, the value of such studies is sometimes overlooked (Jindal & Raziuddin, 2018; Redd et al., 2015). Tests such as Cronbach's alpha may be used to assess internal consistency of sample data; however, inherent imprecision of Cronbach's alpha evaluations should also be addressed (Gagnon et al., 2016; Tavares & Oliveira, 2017).

Although quantitative methods often use statistical analysis for hypothesis testing, they lack the broad scope of qualitative studies that facilitate freedom of expression to expose issues related to research problems (McCusker, & Gunaydin, 2015). Qualitative research often seeks answers to questions in face-to-face interviews that solicit opinions and is, therefore, subjective, and may include documenting and interpreting nuances such as non-verbal cues (Oltmann, 2016). Interview settings may also introduce unintended effects such as the influence of the researcher on participants, particularly in situations where the participants may be reluctant to express opinions on sensitive issues (Flynn & Kramer, 2019). In the initial stages of research qualitative methods are, therefore, more effective for developing a deeper understanding of the research problem (McCusker & Gunaydin, 2015; Meigs & Solomon, 2016; Park & Park, 2016). Qualitative studies may also provide guidance for aspects of research design, such as defining the sample frame or refining research questions; however, in qualitative studies, the researcher may impose unintended effects on participants which may be difficult to quantify (Flynn & Kramer, 2019; Meigs & Solomon, 2016; Park & Park, 2016; Trudel et al., 2017). Analysis of unstructured data derived from participants' responses also introduces additional challenges (Ramani & Mann, 2016). In Ladan, Wharrad, and Windle (2019), these limitations of qualitative investigations were eliminated by the use of a quantitative pilot study to validate sample statements for subsequent research.

Summary

Primary care providers have emerged as principal custodians of electronic health records, using cloud-based EHR/EMR systems to maintain complete and accurate patient medical histories (Frogner et al., 2017). Contemporary cloud-based EHR/EMR systems leverage advanced technologies to provide high availability, high capacity storage, and fast secure access to patient information (Ahmadi & Aslani, 2018; Endo et al., 2016). PCPs adopt cloud-based EHR/EMR systems to support improvements in the effectiveness of healthcare services, and to facilitate compliance with HIPAA privacy requirements (Cohen & Mello, 2018; Woodside & Amiri, 2018).

Legislative support for the adoption of EHR/EMR systems was provided in the HITECH Act which was enacted to support improvements in the health and well-being of the population at large by promoting the use health information technologies (Mennemeyer et al., 2016). Incentives for meaningful use of CEHRT were introduced by CMS (Cohen et al., 2018). ONCHIT provides administrative assistance to support their implementation (Thorpe, Gray, & Cartwright-Smith, 2016). Despite significant penalties for non-compliance with HIPAA, HITECH and CMS requirements, the adoption of EHR/EMR systems by PCPs has not kept pace with regulatory demands (Cohen et al., 2018; Mack et al., 2016; Mason et al., 2017). This study was purposed to address a gap in the literature regarding the factors influencing the adoption of cloud-based EHR/EMR systems by PCPs (Heisey-Grove & King, 2017).

CHAPTER 3. METHODOLOGY

The focus of this chapter is the research methodology that was used to investigate factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers in the United States. This study was purposed to narrow a knowledge gap regarding inadequate adoption of EHR/EMR systems by PCPs to satisfy regulatory and operational requirements for leveraging health information technologies to improve the health and well-being of the population at large (Balestra, 2017; Wani & Malhotra, 2018). This objective was pursued by investigating the extent that performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI) predict the adoption of cloud-based EHR/EMR systems by primary care providers in the United States, as required by HITECH and CMS regulations (Barnett et al., 2016; Bruns et al., 2016). This chapter also presents the research questions and hypotheses that were used to guide this investigation and describes the target population and sampling strategy. The chapter also describes data collection procedures and data analysis techniques. The chapter concludes with an evaluation of the survey instrument used in this study, ethical considerations, and a chapter summary.

Purpose of the Study

The purpose of this non-experimental correlational study was to determine the extent that PE, EE, FC, and SI predict the adoption of cloud-based EHR/EMR systems by primary care providers in the United States, as required by HITECH and CMS regulations. This study was also purposed to address a gap in the literature regarding factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers. This study examined relationships between UTAUT constructs in the context of EHR/EMR adoption by PCPs in the United States to answer four research questions and to evaluate support for the four related hypotheses that were developed to facilitate this investigation. This study may also deliver insight and provide guidance for PCPs implementing cloud-based EHR/EMR systems as well as inform vendors and developers of EHR/EMR systems regarding essential requirements for improving the effectiveness of cloud-based EHR/EMR systems to better serve PCP needs. This study was also pursued to increase awareness of challenges facing PCPs in their adoption of cloud-based EHR/EMR systems and potentially promote improved collaboration between vendors, developers, implementers, users and the government agencies responsible for oversight of EHR/EMR adoption. This could lead to improved orchestration of policies, legislation, and standardization to improve the efficiency and interoperability of cloud-based EHR/EMR systems to support modernization of healthcare and quality improvements in the delivery of primary care.

Research Questions and Hypotheses

The following research questions and hypotheses, developed using the UTAUT framework, were used to guide this investigation and to facilitate evaluations of the relationships between predictors (PE, EE, FC, and SI) and BIU (behavioral intention towards using EHR/EMR systems):

Omnibus Research Question (OQ): To what extent do PE, EE, FC, and SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

HO_0: There is no statistically significant relationship between PE, EE, FC, and SI with BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

HO_A: There is a statistically significant relationship between PE, EE, FC, and SI with BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

RQ1: To what extent does PE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0 1$: There is no statistically significant relationship between PE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

$H_A 1$: There is a statistically significant relationship between PE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

RQ2: To what extent does EE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0 2$: There is no statistically significant relationship between EE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

$H_A 2$: There is a statistically significant relationship between EE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

RQ3: To what extent does SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0 3$: There is no statistically significant relationship between SI and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

$H_A 3$: There is a statistically significant relationship between SI and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

RQ4: To what extent does FC predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0 4$: There is no statistically significant relationship between FC and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

$H_A 4$: There is a statistically significant relationship between FC and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

Research Design

This quantitative study was executed using a non-experimental correlational design theoretically undergirded by the unified theory of acceptance and use of technology (UTAUT). A quantitative method was dictated by the research questions which required evaluations of relationships between multiple independent variables and a dependent variable (Haegele & Hodge, 2015). This design is philosophically anchored in post-positivism, relying on evidence, while acknowledging that the continuous evolution of theory is an integral aspect of scholarly advancements via research (Kuhn, 2012). The study was purposed to evaluate the extent that performance expectancy, effort expectancy, facilitating conditions, and social influence predict the adoption of cloud-based EHR/EMR systems by primary care providers in the United States (Kruse, Kristof et al., 2016; Levine, Linder, & Landon, 2018).

The sample for this study consisted of participants selected from a pool of volunteers recruited by Qualtrics from a target population consisting of primary care providers and their IT professionals responsible for implementing cloud-based EHR/EMR systems. Although randomized selection was used to recruit the sample for this study, some groups may have been underrepresented because of their reluctance to participate in an online survey (Tavares & Oliveira, 2017). This issue was not investigated. The number of participants required for this study was determined by power analysis using G*Power 3.1, which revealed a minimum requirement of 89 participants. Data for this study was created when participants completed an online survey which was administered by Qualtrics. The survey instrument was derived from the instrument published in Venkatesh et al. (2003) and adapted for cloud-based EHR/EMR systems.

This study employed empirical evaluations of discrete quantitative data to test four hypotheses developed for investigating the adoption of EHR/EMR systems by PCPs. The target population for this study was PCPs and their IT professionals who implement cloud-based EHR/EMR systems in primary care settings. The sample used was a randomly selected subset of the target population. The use of probability sampling to acquire discrete quantitative data from which meaning can be inferred for a larger population has garnered significant support in the literature and has been widely used in investigations of technology adoption (Monteith et al., 2016; Savage et al., 2019; Scheuner et al., 2017). This technique requires a representative sample, which involves using a sufficiently large random subset of the target population to retain statistical properties of the entire population (Leppink, O’Sullivan, & Winston, 2017).

This study involved evaluations of relationships between the IVs (PE, EE, FC, and SI) and the DV (BIU). Correlation was assessed as suitable for evaluating the influence of predictor variables on EHR/EMR usage intention, the key determinant of technology use in the UTAUT framework (Kolog et al., 2015; Maruping, et al., 2017). A non-experimental correlational design was chosen as the appropriate vehicle to execute this study because correlation can be used effectively to investigate these relationships (Apuke, 2017; Fives et al., 2017). Similar studies have also demonstrated the effectiveness of non-experimental research design, and its ability to preserve external validity (Flynn & Kramer, 2019).

An a priori power analysis using G*Power 3.1 was performed to determine the minimum sample size required to support hypothesis testing. Probabilistic sampling was achieved by Qualtrics, the third-party survey administrator, by using a randomized selection process to procure the sample from volunteers recruited from the target population. Data collection was facilitated by using an online survey, which was administered by the third-party survey administrator. The survey administrator distributed, via email, the informed consent form, which listed the inclusion criteria for this study to each volunteer. Criteria required participants to be primary care providers or their IT professionals responsible for implementing cloud-based EHR/EMR systems in the United States. Participants were also required to have the knowledge and expertise to answer questions related to the implementation and use of cloud-based EHR/EMR systems. Volunteers were instructed to review the informed consent form and record their agreement to its terms and conditions as a prerequisite for participation in the survey.

Target Population and Sample

This section described the sample, and target population from which it was obtained.

Population

The target population for this study consisted of primary care providers and their IT decision-makers responsible for implementing EHR/EMR systems in the United States. Primary care providers may be physician assistants, nurse practitioners, or physicians with the following specializations: pediatrics, obstetrics/gynecology, internal medicine, family medicine, or geriatrics (Wood et al., 2017). The Kaiser Family Foundation reported that in 2019 there were 479,856 active primary care physicians in the United States (State Health Facts, 2019). There were also more than 25,445 physician assistants and over 196,020 nurse practitioners working in primary care settings (NCCPA Certification Excellence, 2019; NP Fact Sheet, 2019). Although the target population also included IT designees responsible for implementing cloud-based EHR/EMR systems, statistics for their level of participation in EHR/EMR adoption decision-making was not available. Because of the large investment required to adopt EHR/EMRs, the decision to adopt may be primarily reserved for the primary care physicians (O’Donnell et al., 2018). Participants were also required to have the expertise and knowledge to understand the technical challenges involved in the adoption of EHR/EMR systems, the requirements to comply with HITECH and HIPAA mandates, and the business implications of using them in primary care settings.

Sample

The sample used in this study was randomly chosen from a pool of PCPs and IT designees recruited by Qualtrics who were responsible for implementing cloud-based EHR/EMR systems in the United States. Volunteers were prescreened to verify that they met the requirements for participation. The survey also included questions that were tailored to eliminate volunteers who did not satisfy all the criteria for inclusion.

Power Analysis

Power analysis has been used effectively to estimate minimum sample sizes to achieve a specified statistical power to support hypothesis testing for quantitative investigations (Kyonka, 2019). These techniques are supported by computational principles that are encapsulated in the algorithms used to develop the G*Power application (Lininger & Riemann, 2018). In this study, the statistical test chosen was the two-tailed t-test. UTAUT theory posits that the four predictor variables — PE, EE, SI, and FC — are primary predictors of the dependent variable BIU (behavioral intention to use technology). A statistical power (1- β) of 0.95 was specified to detect a small effect of 0.15 in BIU. The value of α (the probability of a type 1 error) was 0.05, and the number of predictor variables was 4. The analysis indicated that a minimum sample size of 89 participants was required.

Procedures

This section describes the processes involved in the selection of participants for this study, protection of participants, data collection, and data analysis.

Participant Selection

Participants were randomly selected from a panel recruited by Qualtrics. The selection process identified primary care providers and their IT professionals responsible for implementing cloud-based EHR/EMR systems in the United States. Additional criteria were implemented in the screening section of the survey, which also required participants to affirm their eligibility for participation or terminate the survey.

Protection of Participants

Protecting the privacy of participants is a critical ethical requirement of research involving human subjects (Colosi, Costache, & Colosi, 2019). This study collected no personally identifying information (PII). The survey administrator created a unique ID for each survey participant, which was used to enforce a single attempt and eliminate the need to use PII in survey responses. Qualtrics enabled access to the survey, and distributed access information to participants via email. Participants were instructed to access the survey to record their responses. The administrator closed the survey after the minimum sample size requirement had been exceeded. The survey administrator collected participant responses which were indexed by their session IDs. Survey responses included demographic information which consisted of age ranges, sex, years of experience using EHR/EMR systems, voluntariness of use of EHR/EMR systems, U.S. employment, and area of specialization. This researcher did not request participants' contact information and received no PII in the data that was transmitted from the survey administrator.

Data Collection

Data collection was initiated after the number of completed error-free surveys exceeded the minimum sample size. The survey administrator closed the survey, eliminated incomplete responses, and created a data file in .csv format which was delivered to this researcher via email.

This researcher created backups of the data, which were archived on secure servers. Raw response data were inspected to ensure that all survey questions were answered. Records containing inconsistent responses were also discarded. The 94 remaining responses satisfied the minimum sample size requirement of 89 participants.

Data Analysis

Data analysis was initiated after importing the .csv data file into the SPSS version 26.0 statistical analyzer. The SPSS Transform/Compute Variable function was used to create composites of the factors used in the survey instrument to measure each variable. Although Likert type variables used in this study are by nature ordinal, the following assumption allows them to be considered as interval. Field (2013) stated, “To say that [ordinal] data are interval, we must be certain that equal intervals on the scale represent equal differences in the property being measured” (p. 9). Interval variables may be considered continuous if this requirement is satisfied (Maruping et al., 2017).

Initial data analysis involved using descriptive statistical tests to explore data characteristics, including calculations of the mean, mode, median, and standard deviation for each variable. Z-scores were also calculated to detect the existence of extreme outliers. Histograms and distribution graphs were also created to display the characteristics of data distribution for all independent variables (Lee, 2017). These evaluations were used to identify extreme outliers, skewness, and kurtosis of the distribution. Normal Q-Q plots were used to detect conformance with a normal distribution as required for the t-test that was used to calculate the sample size for this study (Kwak & Kim, 2017). Scatter plots were used to verify that linear relationships existed between the predictor variables and user intention to use cloud-based

EHR/EMRs required for using Pearson's correlation. Scatter plots were also used to verify homogeneity of variance (homoscedasticity) for predictor variables (Laher, 2016).

Statistical analysis was also used to investigate the magnitude of relationships between the IVs (PE, EE, SI, and FC) and the DV (BIU) using the SPSS linear regression function. A model was developed using multiple linear regression to calculate regression coefficients for each IV, and to estimate the variance explained by this model (Bujang, Sa'at, & Bakar, 2017).

Instruments

The instrument used in this study was the UTAUT survey questionnaire published in Venkatesh et al. (2003) and adapted for cloud-based EHR/EMR systems. The researcher requested permission to use this instrument from the owner of the copyright. Permission was granted by the Regents of the University of Minnesota on May 24, 2018. This instrument was empirically validated using the original data that was used to test the eight other theoretical frameworks from which it was derived (Chao, 2019). The independent variables represented in this instrument explained 70% of variance in user intention to adopt new technology (Šumak & Šorgo, 2016; Venkatesh et al., 2003).

Validity. Validity of measures was investigated using partial least squares (PLS) based on assessments of the UTAUT model to measure predictor impact on intention to use technology (Koral Gümüsoglu & Akay, 2017; Chao, 2019). Continued research has affirmed that the UTAUT model is an effective framework for investigating technology adoption across a wide range of technological contexts (Nikou & Economides, 2017; Zuiderwijk et al., 2015).

Reliability. The reliability of the UTAUT instrument has been affirmed by rigorous evaluations of confirmatory factor analysis, assessments of internal consistency, composite reliability, and convergent validity (Šumak & Šorgo, 2016). Convergent and discriminant validity was examined by using 48 tests, which yielded internal consistency and internal reliabilities greater than 0.70 for all measures (Venkatesh et al., 2003). Composite reliability coefficients were greater than .70, which indicated the reliability of variables and also revealed the absence of collinearity between independent variables (Rahi, Ghani, Alnaser, & Ngah, 2018). These tests also affirmed that performance expectancy is the principal predictor of user intention to use technology (El Ouirdi et al., 2016).

Ethical Considerations

This study was conducted in accordance with the ethical requirements of the Capella Internal Review Board (IRB). Ethical principles required informed consent by all study participants. An informed consent letter, which was distributed to each volunteer, outlined the expectations of the study. The inclusion criteria and participant responsibilities were also approved by the IRB. Participants were allowed to opt out at any point during the survey by terminating their session.

The third-party administrator recruited participants for the survey, and this researcher obtained no personal information for any participant. Qualtrics used participant IP addresses as a factor for preventing multiple survey sessions by any participant; however, IP addresses were excluded from the data file that was delivered to this researcher. The survey administrator also verified that survey participants were capable of understanding survey instructions and providing informed answers to all questions.

There were no conflicts of interest between participants, the survey administrator, or this researcher. This researcher was not acquainted with any participant, and there was no attempt to influence participants to provide answers that did not truly reflect their own perspectives.

Incomplete and inconsistent responses were eliminated, and only error-free surveys were used for analysis.

Every effort was made to protect the identity of survey participants, and no personal information was requested or collected. Participants were also assured that their privacy would be protected. This researcher had no access to participant email addresses, and the memo expressing thanks for their participation was sent by email from Qualtrics.

Summary

This chapter outlined the methodology that guided this non-experimental quantitative correlational investigation of factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers in the United States. Characteristics of the target population, sample, and the sampling technique were described. The details of the sample size calculation were also presented, and the method used to select participants. The validity of the processes involved in participant selection was also discussed.

Details of data collection and data analysis were also described, including techniques to preserve data quality by screening and removing incomplete and inconsistent responses. The use of data analysis in hypothesis testing was also presented. The chapter concluded with a description of procedures employed to preserve the ethical integrity of the study.

CHAPTER 4. RESULTS

The purpose of this chapter was to present a detailed report of the data analysis that was performed to support this investigation of factors influencing the adoption of cloud-based EHR/EMR systems. The chapter discusses characteristics of the sample and also describes data-cleaning procedures used to eliminate extreme outliers. This chapter also discusses assumptions made about the data and describes the statistical tests that were used to test the four hypotheses that guided this investigation. The chapter also reported inferential statistics that satisfied the requirements for using the statistical analysis used for hypothesis testing. The sizes of effects and the power attained in each statistical test were also presented. The chapter also reported details of results of the hypotheses that were tested using the methodology described in Chapter 3. The chapter concludes with a summary of the answer to each research question derived from the results. In Chapter 5, these results are discussed and analyzed to assess their effectiveness to provide answers to the research questions.

Description of the Sample

The sample used in this study consisted of responses from primary care providers who participated in an online survey that was developed for this investigation. After responses were examined for completeness, checked for consistency, and cleaned, a sample of 86 responses remained. Descriptive statistics for all variables in the sample was explored in SPSS. Initial results are displayed below in Table 1.

Table 1

Descriptive Statistics for All Variables

Variable	N	Min	Max	Mean	Standard Deviation	Skewness/ Standard Error	Kurtosis/ Standard Error
PE	94	5	28	19.57	4.78	- 0.59 / 0.25	0.08 / 0.49
EE	94	4	28	20.55	5.40	- 1.04 / 0.25	0.95 / 0.49
SI	94	6	28	19.13	5.39	- 0.51 / 0.25	- 0.31 / 0.49
FC	94	9	28	19.63	3.59	- 0.40 / 0.25	1.00 / 0.49
BIU	94	3	21	16.71	4.85	- 1.30 / 0.25	1.25 / 0.49

Table 1 revealed that, for PE, the minimum value of 5 was marginally less than 3 standard deviations below the mean (5.23) and the maximum value of 28 was less than 3 standard deviations above the mean (33.91). An examination of the raw data revealed 1 marginal outlier, 1 value (5), which was less than 5.23. This record was excluded from further analysis. The minimum value of EE, 4, was marginally less than 3 standard deviations below the mean (4.35), but the maximum value of 28 was less than 3 standard deviations above the mean (36.75). An examination of the raw data revealed two marginal outliers, two values (4 and 4), which were less than 4.35. These two records were excluded from further analysis. The minimum value of SI, 6, was greater than three standard deviations below the mean (3.04), and the maximum value, 28, was well within three standard deviations of the mean (35.30). This result identified no outliers. The minimum value of FC, 9, was marginally greater than three standard deviations below the mean (8.86), and the maximum value, 28, was less than three standard deviations above the mean (30.50). No outliers were identified by this result. The minimum value of BIU, 3, was greater than three standard deviations below the mean (2.16), and the maximum value, 21, was less than three standard deviations above the mean (31.26). No outliers were identified by this result. After all outliers were removed, descriptive statistics were recalculated. Results are displayed in Table 2 below.

Table 2

Revised Descriptive Statistics for All Variables

Variable	N	Min	Max	Mean	Standard Deviation	Skewness/ Standard Error	Kurtosis/ Standard Error
PE	86	10	28	20.14	4.19	- 0.30 / 0.26	- 0.56 / 0.51
EE	86	9	28	21.24	4.51	- 0.63 / 0.26	0.11 / 0.51
SI	86	7	28	19.90	4.85	- 0.51 / 0.26	- 0.10 / 0.51
FC	86	11	28	20.08	3.12	0.15 / 0.26	0.40 / 0.51
BIU	86	7	21	17.40	3.75	- 0.86 / 0.26	- 0.01 / 0.51

The demographics of participants were examined by the four criteria used in the survey, namely age, sex, experience using EHR/EMR systems, and specialization. Table 3 presents a summary of survey participation categorized by sex.

Table 3

Survey Participants Categorized by Sex

Sex	Participants	Percent
Female	22	25.58
Male	64	74.42
Total	86	100.0
Ratio (Female:Male) = 1:2.91		

The specializations of participants were examined and are summarized in Table 4.

Table 4

Survey Participants Categorized by Specialization

Specialization	Participants	Percent
Family Practitioner	26	30.23
Internist	52	60.46
Nurse Practitioner	5	5.81
Obstetrician/Gynecologist	1	1.16
Pediatrician	1	1.16
Physician Assistant	1	1.16

The ages of participants were also examined and are presented in Table 5.

Table 5

Survey Participants Categorized by Age

Age of Participants (years)	Number of Participants
18 – 32	12
33 - 45	40
46 - 55	16
55 and over	18

The number of years of experience of participants using EHR/EMR systems was summarized and is shown below in Table 6.

Table 6

Survey Participants Categorized by Years of Experience Using EHR/EMR Systems

Experience Using EHR/EMR	Participants
1 year or less	5
2-5 years	23
6 years or more	58

The distribution for each variable in the sample was investigated. A normal P-P plot of standardized residuals was generated and is displayed in Figure 2.

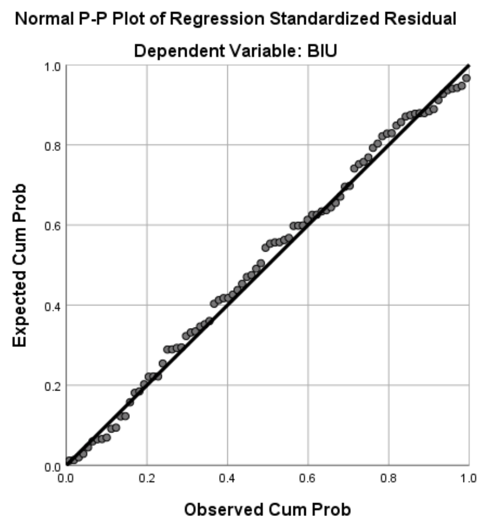

Figure 2. Normal P-P plot (standardized residuals), independent variables – PE, EE, SI, and FC

All four independent variables (PE, EE, SI, and FC) conformed to a normal distribution, as illustrated in Figure 2.

An investigation of the relationships between independent variables and BIU was also performed. A scatter plot for PE/BIU, displayed below in Figure 3, was created.

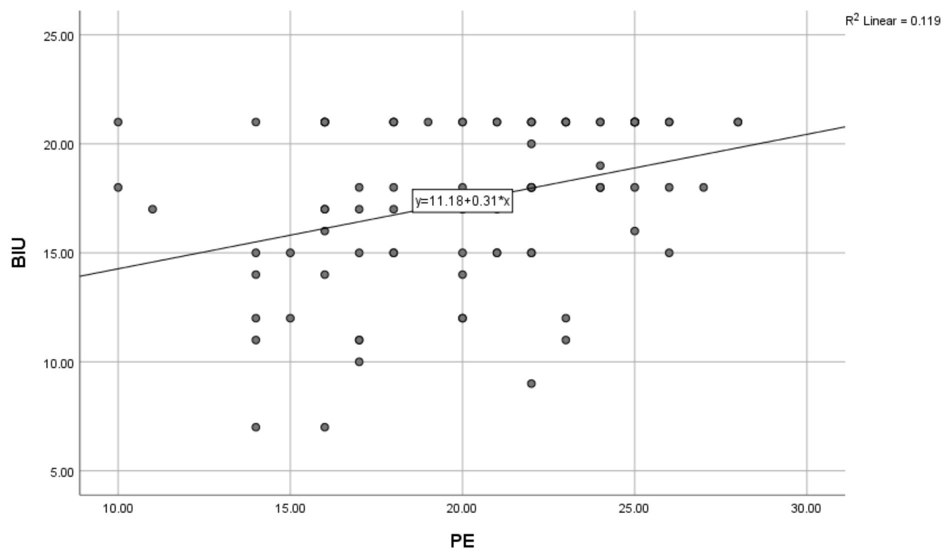

Figure 3. Scatter plot: PE with BIU

The requirements for linear relationships between independent variables and BIU were met, as indicated in Figure 3, which shows that a majority of the points in the scatterplot are arranged around the fit line. This indicates a linear relationship between PE and BIU, satisfying the linearity requirements for multiple linear regression and for the use of the two-tailed t-test power analysis to determine the minimum sample size. Similar scatter plots for EE with BIU, SI with BIU, and FC with BIU are presented in Figure 4, Figure 5, and Figure 6, respectively.

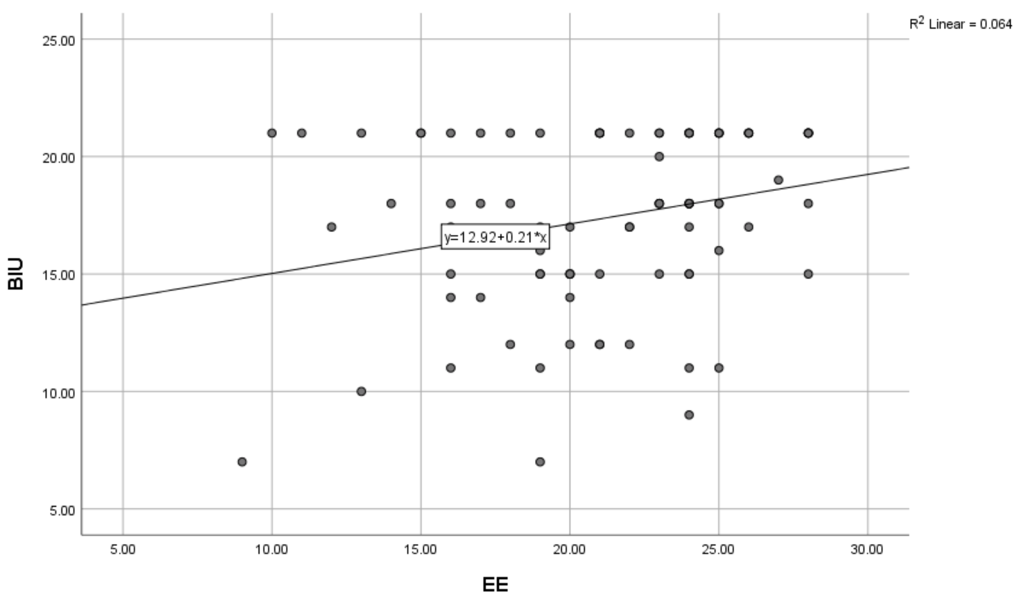

Figure 4. Scatter plot: EE with BIU

Figure 4 confirms the existence of a linear relationship between EE and BIU, satisfying the linearity requirement for using multiple linear regression.

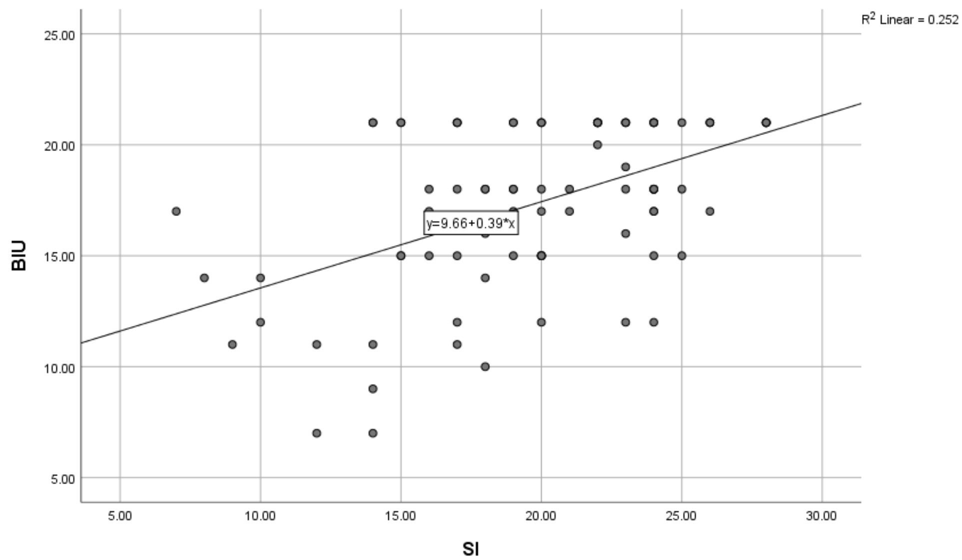

Figure 5. Scatter plot: SI with BIU

Figure 5 confirms the existence of a linear relationship between SI and BIU, satisfying the linearity requirement for using multiple linear regression.

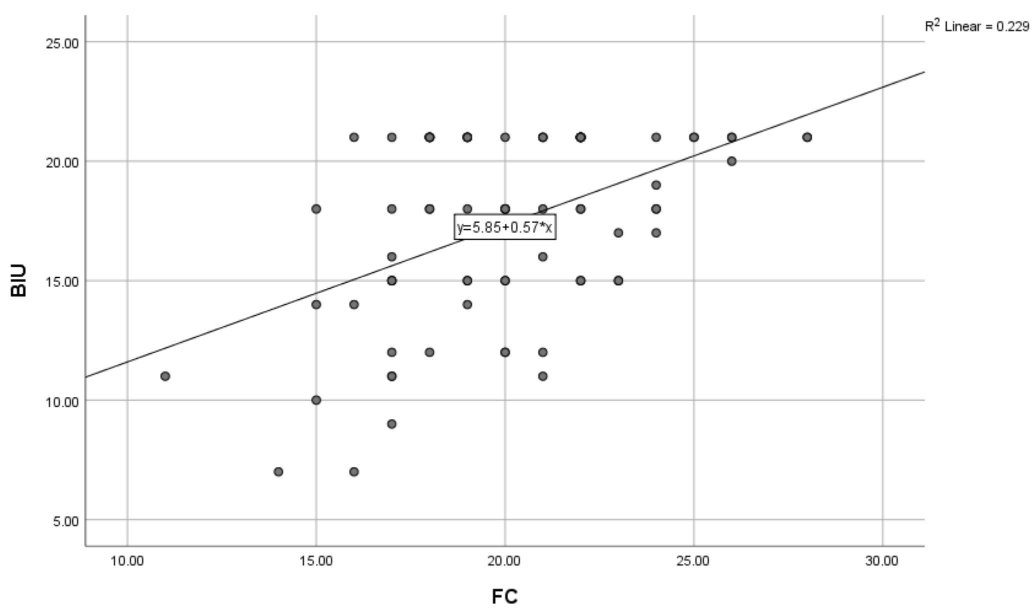

Figure 6. Scatter plot: FC with BIU

Figure 6 indicates the existence of a linear relationship between SI and BIU, satisfying the linearity requirement for using multiple linear regression (McKim & Velez, 2015). An a priori power analysis performed for a small effect size of .15, α (error prob) of .05, power (1 - β) of .95, using four predictors for a two-tailed t-test for multiple linear regression, indicated a minimum requirement of 89 participants. The post-hoc analysis revealed that the sample of 86 respondents attained a statistical power greater than 0.99, indicating that it was adequate for detecting a small effect.

Hypothesis Testing

Testing the four hypotheses developed for this study required verification that criteria were satisfied for using multiple linear regression and Pearson's correlation to investigate relationships between the independent variables, PE (performance expectancy), EE (effort expectancy), SI (social influence), and FC (facilitating conditions), and the dependent variable, BIU (behavioral intention to use EHR/EMR systems). The ensuing tests of each hypothesis were executed to determine if they should be accepted or rejected.

Multiple linear regression (MLR) was used to model relationships between four independent variables (PE, EE, SI, and FC) and the dependent variable (BIU). MLR was executed to calculate regression coefficients for each IV involved in a linear relationship with the DV. The value of R^2 was indicative of the variance explained by the regression model (Oguntunde, Lischeid, & Dietrich, 2018). Pearson's correlation, denoted Pearson's r, was evaluated to determine whether statistically significant relationships existed between each independent variable and the dependent variable.

Hypothesis HO0

Omnibus Research Question (OQ): To what extent do PE, EE, FC, and SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

HO_0: PE, EE, FC, and SI do not have a statistically significant relationship with BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

HO_A: PE, EE, FC, and SI have a statistically significant relationship with BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

The requirements for linear relationships between independent variables PE, EE, SI, and FC were investigated using scatterplots. Results, as presented in Figure 3–Figure 6, reveal linearity relationships between independent variables PE, EE, SI, and FC with the dependent variable BIU. The absence of multicollinearity was verified by investigating collinearity diagnostics in SPSS, which revealed that variance inflation factor (VIF) statistics for all independent variables were less than 10 (max = 2.323), therefore indicating that there was no significant collinearity between the independent variables (PE, EE, SI, and FC) (Thompson, Kim, Aloe, & Becker, 2017). These tests confirmed that the requirements for multiple linear regression were satisfied.

Multiple linear regression was executed to test $HO_{0.}$ The results are shown below in Table 7 and Table 8. Table 9 summarizes regression model results.

Table 7

Multiple Linear Regression: Model Summary

Variable	B	Standard Error	Beta	t	Sig.	VIF
(Constant)	4.542	2.388		1.902	0.061	
SI	0.231	0.090	0.298	2.563	0.012	1.615
PE	0.145	0.121	0.162	1.196	0.235	2.175
FC	0.348	0.145	0.289	2.402	0.019	1.729
EE	-0.077	0.113	-0.093	- 0.682	0.497	2.197

Result: $F(4, 81) = 9.548$, $p < 0.001$, $R^2 = 0.32$

Table 7 reveals that the regression model indicates that two of the independent variables, SI and FC, were significant predictors of BIU (behavioral intention to use cloud-based EHR/EMR systems), based on significance values of 0.012 and 0.019, which were less than 0.05.

Table 8

Regression Model Statistical Summary

	Model	Sum of Squares	df	Mean Square	F	Sig
1	Regression	383.400	4	95.850	9.548	0.000[b]
	Residual	813.158	81	10.039		
	Total	1196.558	85			

Using dependent variable BIU
b. Predictors (Constant, FC, PE, SI, EE)

The regression model indicated that independent variables PE, EE, SI, and FC imposed significant effects on dependent variable BIU, as is evident in the result, $F(4, 81) = 9.548$, $p < 0.001$, $R^2 = 0.32$. However, the results displayed in Table 7 revealed that SI ($\beta = 0.30$, $p < 0.05$) and FC ($\beta = 0.30$, $p < 0.05$) were significant predictors of BIU. The value of R^2, 0.32 revealed that the four independent variables were responsible for 32 % of the variance in BIU (behavioral intention to use EHR/EMR systems), as displayed in Table 8. Based on this result, the null hypothesis HO_0 should be rejected. An a priori calculation performed in G*Power 3.1 indicated that a minimum of 89 participants were required to attain the required power of 0.05. A post-hoc power analysis using G*Power 3.1 for a sample size of 86, effect size of 0.32, α (err prob) of 0.05, and four predictors for a two-tailed t-test indicated that the power attained was greater than 0.99. The values of the t statistic in Table 7 for independent variables SI and FC, 2.56 and 2.40 respectively also indicated that only independent variables SI and FC were statistically significant predictors of BIU.

Table 9

Regression Model Summary

R	R Square	Adjusted R Square	Std. Error of Estimate	R Square Change	F Change	df1	df2	Sig. F Change
0.586[a]	0.320	0.287	3.17844	0.320	9.548	4	81	0.000

a. Predictors: (Constant), FC, PE, SI, EE

Hypothesis $H_0 1$

RQ1: To what extent does PE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0 1$: There is no statistically significant relationship between PE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

$H_A 1$: There is a statistically significant relationship between PE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

Pearson's correlation results: Correlation of PE with BIU is significant ($p < 0.01$), based on results for a two-tailed test, displayed in Table 10, indicating that the null hypothesis $H_0 1$ should be rejected.

Table 10

Pearson Correlation: PE/BIU

Independent Variable	Statistic	Dependent Variable: BIU
PE	Pearson Correlation	0.344**
	Sig. (2-tailed)	0.001
	N	86.000

** indicates $p < 0.001$
$r(84) = 0.34$ $p < 0.001$

Hypothesis $H_0 2$

RQ2: To what extent does EE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0 2$: There is no statistically significant relationship between EE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

$H_A 2$: There is a statistically significant relationship between EE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

Pearson's correlation results: Correlation of EE with BIU is significant ($p < 0.001$), based on results for a two-tailed test, displayed in Table 11, indicating that the null hypothesis H_02 should be rejected.

Table 11

Pearson Correlations: EE/BIU

Independent Variable	Statistic	Dependent Variable: BIU
EE	Pearson Correlation	0.253*
	Sig. (2-tailed)	0.019
	N	86.000

* indicates $p < 0.05$
$r(84) = 0.25$, $p < 0.05$

Hypothesis H_03

RQ3: To what extent does SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

H_03: There is no statistically significant relationship between SI and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

H_A3: There is a statistically significant relationship between SI and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

Pearson's correlation results: Correlation of SI with BIU is significant ($p < 0.01$), based on results for a two-tailed test, displayed in Table 12, indicating that the null hypothesis H_03 should be rejected.

Table 12

Pearson Correlations: SI/BIU

Independent Variable	Statistic	Dependent Variable: BIU
SI	Pearson Correlation	0.502**
	Sig. (2-tailed)	0.000
	N	86.000

** indicates $p < 0.01$
$r(84) = 0.50, p < 0.001$

Hypothesis $H_0$4

RQ4: To what extent does FC predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?

$H_0$4: There is no statistically significant relationship between FC and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

H_A4: There is a statistically significant relationship between FC and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.

Pearson’s correlation results: Correlation of FC with BIU is significant ($p < 0.01$), based on results for a two-tailed test, displayed in Table 13, indicating that the null hypothesis $H_0$4 should be rejected.

Table 13

Pearson Correlation: FC/BIU

Independent Variable	Statistic	Dependent Variable: BIU
FC	Pearson Correlation	0.478**
	Sig. (2-tailed)	0.000
	N	86.000

** indicates $p < 0.01$
$r(84) = 0.48, p < 0.001$

Summary of Hypothesis Testing

Multiple linear regression was used to test the hypothesis derived from the omnibus research question, HO_0 (Bujang et al., 2017; McKim & Velez, 2017). The regression summary revealed the relationships between the independent variables, PE, EE, SI, and FC, which are illustrated in Table 5.

Hypothesis $H_0$1was tested using Pearson correlation to investigate the relationship between PE and BIU. The results displayed in Table 10 revealed a statistically significant relationship between PE and BIU. The null hypothesis $H_0$1 was rejected.

Pearson correlation was used to test hypothesis $H_0$2. Results in Table 11 revealed a statistically significant relationship between EE and BIU (Ibrahim, Sanni, & Nsereko, 2018). Null hypothesis H02 was rejected. Similarly, Pearson correlation was used to test hypothesis $H_0$3. Results in Table 12 revealed a statistically significant relationship between SI and BIU. Null hypothesis $H_0$3 was rejected. Pearson correlation was also used to investigate the relationship between FC and BIU, which was also found to be statistically significant as indicated in Table 13. Hypothesis $H_0$4 was also rejected, based on this result. Table 14 provides a detailed summary of the results of hypothesis testing.

Table 14

Hypothesis Testing: Summary

Research Question	Hypothesis	Test Performed	Result
Omnibus research question: To what extent do PE, EE, FC and SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?	HO_0: There is no statistically significant relationship between PE, EE, FC and SI with BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.	Multiple Linear Regression: $F(4, 81) = 9.548$, $p < 0.001$, $R^2 = 0.32$	HO_0 rejected
RQ1: To what extent does PE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?	H_01: There is no statistically significant relationship between PE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.	Pearson Correlation: $r(84) = 0.34$, $p < 0.001$	H_01 rejected
RQ2: To what extent does EE predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?	H_02: There is no statistically significant relationship between EE and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.	Pearson Correlation: $r(84) = 0.25$, $p < 0.05$	H_02 rejected
RQ3: To what extent does SI predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?	H_03: There is no statistically significant relationship between SI and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.	Pearson Correlation: $r(84) = 0.50$, $p < 0.001$	H_03 rejected
RQ4: To what extent does FC predict BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems?	H04: There is no statistically significant relationship between FC and BIU of primary care providers in the United States to adopt cloud-based EHR/EMR systems.	Pearson Correlation: $r(84) = 0.48$, $p < 0.001$	H04 rejected

Summary

This chapter presented the results of data analyses performed to provide empirical support for this non-experimental correlational investigation of factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers in the United States. The UTAUT survey instrument, published in Venkatesh et al. (2003) and adapted for cloud-based EHR/EMR systems, was used to collect data for this study. The data collected by Qualtrics, a third-party survey administrator, yielded 94 responses. After data-cleaning, outliers were identified and removed. The remaining sample of 86 was marginally less than the minimum sample size of 89 participants, determined by an a priori analysis using G*Power 3.1. The sample for this study consisted of primary care providers responsible for implementing cloud-based EHR/EMR systems in the United States.

The omnibus research question was developed to determine whether a statistically significant relationship existed between the independent variables, PE (performance expectancy), EE (, effort expectancy), SI (social influence), and FC (facilitating conditions), and the dependent variable, BIU (behavioral intention to use cloud-based EHR/EMR systems). Multiple linear regression was used to determine that a statistically significant relationship was detected and that PE and SI were statistically significant predictors of BIU. The use of multiple linear regression was validated by demonstrating that the following requirements were satisfied: linearity relationships between the independent variables (PE, EE, SI, and FC) and the dependent variable (BIU), normal distribution of IVs, homoscedasticity, and the absence of multicollinearity. Multiple regression analysis yielded the result: $F(4, 81) = 9.548$, $p < 0.001$, $R^2 = 0.32$. The regression analysis revealed that this model explained 32 % of the variance in behavioral intention to use cloud-based EHR/EMR systems. The null hypothesis, $HO_{0,}$ was therefore rejected.

The relationships between each independent variable (PE, EE, SI, and FC) and the dependent variable (BIU) were investigated using Pearson correlation. Statistically significant relationships were identified between PE, EE, SI, and FC with BIU, revealing Pearson's r values of $r(84) = 0.34$, $p < 0.001$, $r(84) = 0.25$, $p < 0.05$, $r(84) = 0.50$, $p < 0.001$, and $r(84) = 0.48$, p <

0.001, respectively. These results dictated that null hypotheses H01, H02, H03, H04 should be rejected. These results will be further discussed in chapter 5 and will provide support for the findings presented. Chapter 5 will also explore the significance of these findings, implications, and recommendations for future research in this area of study.

CHAPTER 5. DISCUSSIONS, IMPLICATIONS, RECOMMENDATIONS

In this chapter, the results presented in Chapter 4 were analyzed and interpreted in the context of current literature to assess their effectiveness to provide answers for the research questions posed in this study. This chapter provides a summary of results from testing four hypotheses that were developed to facilitate an investigation of factors influencing the adoption of cloud-based EHR/EMR systems. The chapter also presents a discussion of the results and provided conclusions based on the results. The effects of limitations on the execution of the study, the results and findings were also examined. This chapter also discusses implications for practice in information technology, and concludes with recommendations for continuing future research.

Summary of the Results

This investigation was purposed to narrow a gap in the literature regarding the failure of PCPs in the United States to satisfy industry and regulatory requirements for increasing the implementation and use of EHR/EMR systems (Graboyes & Bryan, 2018). Despite significant provisions of the HITECH ACT to support the adoption of EHR/EMR systems, the failure of PCPs to adequately adopt and use certified EHR/EMR systems has created technological disparities between PCP operations and the electronic health records/electronic medical records infrastructure (Blagec et al., 2016; Cohen & Mello, 2018; Lyles et al., 2015). Consequently, the realization of HITECH objectives to improve the quality of healthcare services have been delayed (Heisey-Grove & King, 2017; Rathert, Porter, Mittler, & Fleig-Palmer, 2019).

A review of the literature revealed several challenges primary care providers face relative to the implementation of EHR/EMR systems. These challenges include the financial strain on the modest budgets of small practices, the cost of transitioning from uncertified EHR/EMR systems to CEHRTs, resources to retrain staff and revise business processes, and the uncertainty of realizing a return on their substantial investment (O'Donnell et al., 2018). Inconsistent interoperability among EHR/EMR systems poses severe challenges, inhibiting seamless data access for sharing and processing information across systems from different vendors. Significant challenges also inhibit archiving data from sources such as internet of things and WMDs, and the large image files obtained from scans such as EMR have influenced HITECH and CMS regulators to modify the requirements and postpone deadlines for achieving the highest levels of EHR usage certification (El-Miedany, 2017; Levine et al., 2016; Wu, Li, Cheng, & Lin, 2016).

Despite these challenges, PCPs leverage the analytical efficiency of AI and deep learning used in big data analytics using cloud-based architectures to perform knowledge extraction from EHR/EMR databases to support early medical diagnosis and to expedite medical research and to improve personalized care (Abul-Husn & Kenny, 2019; Wang & Hajli, 2017). Advanced features, such as e-prescription and electronic laboratory reporting (ELR), employ automation to improve the efficiency of repetitive or extremely time-sensitive processes involved in health maintenance or emergency procedures (Revere, Hills, Dixon, Gibson, & Grannis, 2017; Sun & Qu, 2015). Integration of cloud-based EHR/EMR systems with other sources of medical information such as IoT and IoMT endpoints enhance rapid delivery of detailed health status information to support patient-centered care for vulnerable individuals (Cirillo & Valencia, 2019). AI-enabled EHR/EMR systems have also been implemented to deliver detailed reports derived by analyzing images developed from medical scans (Allaert et al., 2017; Banerjee, Hemphill, & Longstreet, 2018; Ker et al., 2017).

This non-experimental correlational study was executed using a quantitative method, as described in Chapter 3. The theoretical framework for this study was provided by the unified theory of acceptance and use of technology (UTAUT), which posits that four constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, predict behavioral intention to use technology (Koral Gümüsoglu & Akay, 2017; Taherdoost, 2018). UTAUT asserts that the effects of the four primary constructs on usage intention and behavior are moderated by sex, age, experience, and voluntariness of use (Chao, 2019). This investigation examined the influence of four predictor variables, PE (performance expectancy), EE (effort expectancy), SI (social influence), and FC (facilitating conditions), on BIU (business use intention to adopt cloud-based EHR/EMR systems).

G*Power 3.1 was used to calculate the minimum sample size essential for providing statistical power to detect a small effect. The designated population consisted of primary care providers in the United States. The sample was randomly selected from a pool of volunteers recruited by Qualtrics, the third-party survey administrator. The UTAUT instrument was administered in an online survey. Participants' responses provided the data used to test the hypotheses, as described in Chapter 4. Sample data was analyzed to determine the statistical significance of relationships between the four predictor variables PE, EE, SI, and FC and the outcome variable BIU using Pearson correlation. Multiple linear regression was used to evaluate the influence of predictor variables PE, EE, SI, and FC on the outcome variable BIU.

The primary hypothesis was derived from the omnibus research question and was tested using multiple linear regression. A regression model was developed and used to compute their combined contribution on the total variance in the outcome variable. Four hypotheses that were derived from the sub-questions facilitated testing to investigate correlation between PE, EE, SI, and FC and the outcome variable BIU. Statistical analysis was used to evaluate the significance of the effects imposed by predictor variables PE, EE, SI, and FC on the outcome variable BIU. Multiple linear regression analysis was used to examine the statistical significance of the variance in BIU attributable to PE, EE, SI, and FC. The relationships between each predictor and BIU were also investigated by computing Pearson correlation. Pearson's r was computed to determine whether statistically significant relationships existed between each predictor and BIU.

The primary null hypothesis HO_0 asserts that no statistically significant relationship exists between PE, EE, SI, and FC and the outcome variable BIU. Multiple linear regression was used to model the relationship between PE, EE, SI, and FC and the response variable BIU. The analysis revealed that PE, EE, SI, and FC explained 32% of the variance in BIU. Two variables, SI and FC, were identified as significant predictors of BIU. HO_0 was therefore rejected.

Correlation between each predictor PE, EE, SI, and FC and the outcome variable BIU were investigated. Hypothesis H_01 asserts that there is no statistically significant relationship between PE and BIU was tested by using Pearson correlation. The result revealed a statistically significant relationship. Hypotheses H_02, H_03, and H_04 were also tested by performing similar evaluations determine if statistically significant relationships existed between predictor variables EE, SI and FC and the outcome variable BIU. These results also revealed statistically significant correlation coefficients, indicative of statistically significant relationships. Hypotheses H_01, H_02, H_03, and H_04 were therefore rejected.

Discussion of the Results

This investigation examined the combined effects of four predictor variables (PE, EE, SI, and FC) on behavioral intention to use EHR/EMR systems (BIU) to answer the primary research question. Multiple linear regression analysis was performed to test the primary null hypothesis, HO_0, which asserts that no statistically significant relationship exists between the four predictors PE, EE, SI, and FC and the outcome variable BIU. The results revealed a statistically significant relationship. The primary null hypothesis was therefore rejected; however, only two predictor variables, namely SI (Beta = 0.30, $p < 0.05$) and FC (Beta = 0.29, $p < 0.05$), were assessed as significant predictors, as reported in Table 7. Four sub-questions that asked whether statistically significant relationships existed between each predictor and the outcome variable were investigated by testing four hypotheses. H_01, H_02, H_03, and H_04, each asserting that no statistically significant relationship exists between the outcome variable BIU and predictor variables PE, EE, SI, and FC, respectively, were evaluated by computing Pearson correlation. All four tests revealed statistically significant relationships. H_01, H_02, H_03, and H_04 were therefore rejected.

The evaluations using Pearson correlation to analyze the relationships between the predictor variables and BIU indicated that all four predictor variables investigated in this study (PE, EE, SI, and FC) were positively correlated with the outcome variable BIU. These results affirm findings from similar studies of technology adoption using the UTAUT theoretical framework (Hossain et al., 2019; Isa, Nasrul, Senan, & Mohamad, 2017). However, there was disagreement with the magnitude of the correlation coefficients for predictors, particularly PE and EE, which were found to be only moderately correlated with BIU (bin Arshad, Mat, & Ibrahim, 2018; Hernandez & Hernandez, 2020; Savić & Pešterac, 2018). Findings of previous studies also provided support for PE and EE as significant predictors of BIU; however, results from regression analysis in this study indicated that they are not significant predictors of BIU (Arif & Rafiq, 2018; Reyes-Mercado, 2018). The results in this study were obtained from a marginal sample of 86, derived from 94 completed surveys, because of the elimination of eight extreme outliers as the sample was cleaned. G*Power analysis had revealed a minimum requirement of 89 participants to support the detection of a statistically significant effect. Internal consistency was assessed using a computed value of 0.79 for Cronbach's alpha, indicating good internal consistency. This is also indicative of good reliability of the measurements and scaling of the variables represented in the sample (Nur et al., 2017; Sarfaraz, 2017). Although these factors may have limited the magnitude of the variance that was detected by the sample, the statistically significant relationships between performance expectancy, effort expectancy, social influence, and facilitating conditions are aligned with other studies of technology adoption using the UTAUT theoretical framework (Alam et al., 2018; Koral Gümüsoglu & Akay, 2017; Venkatesh et al., 2003**)**

The primary research question asked whether a statistically significant relationship exists between predictors PE, EE, SI, and FC and the response variable BIU. Multiple linear regression analysis revealed that 32% of the variance in BIU was explained by the predictor variables at a significance level expressed as $p < 0.001$. This result constitutes an affirmative answer to the primary research question and is consistent with previous studies of technology adoption based on the UTAUT theoretical framework. The result of multiple linear regression analysis also indicated that FC and SI are significant predictors of BIU; however, PE and EE were not significant. Although Pearson correlation evaluations revealed significant correlation between all four predictors (PE, EE, SI, and FC) and BIU, moderate correlation with BIU was detected for SI

(r (84) = 0.50, $p < 0.001$)) and FC (r (84) = 0.48, $p < 0.001$)). Correlation between BIU and PE (r (84) = 0.34, $p < 0.001$)) and between BIU and EE (r (84) = 0.25, $p < 0.05$)) was found to be weak. Consequently, although the study provided answers to the research questions that were aligned with previous studies, the variance explained by the four predictor variables (PE, EE, SI, and FC) was 32%, which was less than reported in several studies based on the UTAUT theoretical model (Venkatesh et al., 2003; Zuiderwijk et al., 2015).

Conclusions Based on the Results

The results of this study indicated that primary care providers in the United States were influenced by the combination of UTAUT constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions, to adopt cloud-based EHR/EMR systems. Previous research concluded that all four factors were significant predictors of technology adoption. Findings in this study revealed that social influence and facilitating conditions were significant predictors of adoption of cloud-based EHR/EMR systems, but performance expectancy and effort expectancy were not found to be significant (Arif & Rafiq, 2018). This study also revealed significant correlation between all four predictor variables and behavioral intention to use cloud-based EHR/EMR systems, indicating that the four factors capture intrinsic elements in the outcome variable.

Comparison of the Findings with the Theoretical Framework and Previous Literature

The UTAUT theoretical framework has been widely used to facilitate investigations of technology adoption. The following compares findings from previous studies that were based on the UTAUT theoretical model with findings of this study.

Previous studies have affirmed the significance of performance expectancy, which can be defined as the expectation of potential users' improved job performance as a consequence of using technology, as a predictor of behavioral intention to use the technology (Yusof, Qazi, & Inayat, 2017). In the seminal work by Venkatesh et al. (2003), performance expectancy was assessed as the strongest predictor of behavioral intention to use technology in environments where technology use was required or optional. In this study, performance expectancy was found to be a significant predictor of adoption of cloud-based EHR/EMR systems. However, correlation of performance expectancy with behavioral intention to use cloud-based EHR/EMR systems was significant, as previous studies also found (Hoque & Sorwar, 2017; Sarfaraz, 2017).

Effort expectancy, the perceived ease of using new technology, was not a significant predictor of behavioral intention in this study, which was also demonstrated in Mensah, Mi, and Feng (2017). However, in previous studies, effort expectancy was found to be a significant predictor of behavioral intention (Almaiah et al., 2019; Nizar, Rahmat, Maaruf, & Damio, 2019). In this study, effort expectancy was significantly correlated with behavioral intention to use cloud-based EHR/EMR systems (Madigan et al., 2016).

Social influence, which can be defined as potential users' perception that important individuals believe they should use a technology, has been widely demonstrated as a significant predictor of behavioral intention to adopt technology (Arif & Rafiq, 2018; Lopez-Perez, Ramirez-Correa, & Grandon, 2019). The findings in this study also provided empirical support for this assertion. This conclusion is not unanimous among researchers, particularly for environments in which technology adoption is voluntary and social influence was not assessed as significant (El Ouirdi et al., 2016; Madigan, et al., 2016).

Facilitating conditions, defined as potential users' perceived organizational support for the use of technology, was found to be a significant predictor of behavioral intention to use technology in this study and in previous investigations of technology adoption, based on the

UTAUT theoretical framework (Chauhan & Jaiswal, 2016; Khechine & Augier, 2019). In this study, facilitating conditions also correlated significantly with behavioral intention to use technology, as assessed in previous studies (Rahi et al., 2018).

Interpretation of the Findings

Facilitating conditions represent the expectation that elements in the infrastructure in the work environment support the adoption of cloud-based EHR/EMR systems. This includes the management and oversight for the implementation of EHR/EMR provided by ONCHIT. ONCHIT and CMS also provide certification criteria for EHR/EMR systems which can support strategic HITECH objectives for using information technology to elevate the quality of healthcare services (Abubakar & Sinclair, 2018).

Based on the results of this investigation, PE and EE were not found to be significant predictors of behavioral intention to use cloud-based EHR/EMR systems. This result suggested that primary care providers in the United States were not significantly influenced by the anticipation of system performance (PE), or by their apprehension because of the severe challenges of adopting EHR/EMR (EE), but rather by the conditions conducive to adoption (FC) and the influence of individuals or groups (SI). This assessment must also acknowledge the potential financial challenges small practices face; however, no data was collected to facilitate an assessment of the financial resources available to the providers in the study. The significance of SI and FC may also be reconciled with primary care physicians' mandatory use of EHR/EMR systems, enforced by industry and regulatory groups (Wani & Malhotra, 2018). The study also revealed that anticipated performance was not a significant predictor; however, the investigation did not evaluate the role of experience using EHR/EMR. Questions such as whether knowledge of EHR/EMR could familiarize providers with the challenges of using them productively, or of the potential effects of security and privacy concerns for systems which providers may perceive as extremely complex, were not fully addressed (Sherer et al., 2016).

Limitations

This non-experimental study used a cross-sectional approach by using data retrieved from a single sample, generated at a single point in time. Although the validity of this approach has been affirmed in the literature, findings derived from a sample obtained in this manner should be large and representative (Smyk et al., 2018). This sample was marginal, particularly after six responses were discarded as the sample was cleaned, potentially undermining its capacity to provide stronger support for the study findings. Participant recruitment also used online solicitation via email and social media. Although a randomized selection was used to select the sample from this pool of volunteers, some groups among the target population may have been underrepresented (Redmiles, Acar, Fahl, & Mazurek, 2017).

The quantitative methodology used in this study involved the analysis of numeric data derived from participant responses which were coded as ordinal based on selections on a 7-point Likert scale. The data used for this study was regarded as continuous, and was used in Pearson correlation analysis, which requires that sample data is continuous. Although the rationale for converting ordinal Likert data to continuous is supported by the literature, the degree of imprecision may be reduced by increasing the number of points on the scale (Field, 2013; Wu & Leung, 2017).

The sample consisted of participant responses to an online survey hosted by a third-party administrator. The underlying assumption was that volunteers read all the questions, had the knowledge and experience to understand them, and provided meaningful responses to all questions. The lack of controls to validate participant responses may have allowed the inclusion of questionable data in the sample that was used (Dewitt et al., 2018).

The target population for this study was primary care providers in the United States. The findings should not therefore be considered applicable to providers in other specializations or in other geographical regions. There was no assurance that the recruitment process used by Qualtrics was designed to ensure equal representation from every state in the U.S., thereby introducing the potential for regional biases in the selection of participants.

The adoption and use of EHR/EMR systems by primary care providers pose many complex challenges for providers and their staff. In environments where the focus has traditionally been on processes designed to improve the health and well-being of patients, medical professionals are being asked to use information technology, reengineer their workflows to optimize its effectiveness, retrain staff to operate the new systems, and cope with high implementation cost. Many providers are concerned about system security and the high cost of data breaches. They are also required to choose from among various systems which provide a variety of advantages and disadvantages. However, this study was not designed to accommodate investigations of these issues.

Implications for Practice

Researchers can benefit from this investigative study by using its findings to guide further study into the issues and challenges faced by implementers of EHR/EMR systems in healthcare. The findings indicate that performance expectancy and effort expectancy are not significant predictors of primary care providers' behavioral intention to use cloud-based EHR/EMR systems. This represents an opportunity for researchers to investigate whether other variables or moderators are responsible for the variance unexplained by the variables used in this study. Further investigation should also assess whether the factors influencing primary care providers are unique to their peculiar environments, such as the compelling influence of people and groups in their enterprise who promote the use of EHR/EMR (SI). These investigations could also examine elements in their business environment that are conducive to the adoption of EHR/EMR (FC), as opposed to the less dominant effects of system complexity and challenging implementations or the expectation of improved healthcare quality from the use of EHR/EMR. Severe challenges in implementing EHR/EMR are well documented in the literature. Such challenges include system complexity, requirements for retraining staff, the disruptive effects of reengineering workflow, and the high cost of implementation. For PCPs in the United States, however, these issues may not be neutralized by the mandatory implementation requirement. EHR/EMR vendors, developers, and implementers may find that system complexity and implementation challenges may not significantly influence the decision of PCPs to adopt.

Recommendations for Further Research

The following recommendations for further research were developed based on characteristics of the data used and on delimitations of this study.

Recommendations Developed Directly from the Data

The data in this study was analyzed using multiple linear regression to determine if a statistically significant relationship existed between PE, EE, SI, and FC and the outcome variable BIU. The analysis revealed that SI and FC were significant predictors of behavioral intention to use cloud-based EHR/EMR systems, but PE and EE were not found to be significant. Previous research provides considerable support for PE as a significant predictor of behavioral intention to use technology. This represents an opportunity for further study to explore the moderating effects of age, gender, experience, and voluntariness of use. The research model explained 32% of the variance in business. This also presents opportunities for investigating the effects of other factors that were not identified in this study. Such exploratory research could use qualitative methods to reveal hidden factors. Further research could therefore propose and test extensions to the UTAUT framework to determine their significance.

Recommendations Based on Delimitations

The moderating effects of age, gender, experience and voluntariness of could be investigated to assess their effects on the predictor variables, and to determine whether they can explain why PE did not significantly predict BIU in this investigation. Descriptive statistics reported in Chapter 4 revealed that the ratio of female to male participants was 1:2.91; however, future research could determine what ratio would constitute proportionate representation for both sexes. Other potential biases could also be explored relative to disproportionate representation from all PCP specializations.

Cloud-based EHR/EMR systems must satisfy stringent security and privacy standards mandated by HIPAA, and violations incur severe penalties. With respect to potential vulnerabilities in cloud infrastructure and mobile networking, further research could also investigate the effects of these requirements on providers' actual use of EHR/EMR and collaboration with WMDs.

The study was focused on primary care providers in the United States. Further study should investigate other adoption of cloud-based EHR/EMR systems by providers in other medical specialties, and should also investigate populations in other locales.

Conclusion

This study investigated factors influencing the adoption of cloud-based EHR/EMR systems by primary care providers in the United States. The study was executed using quantitative methodology and guided by a non-experimental design, theoretically undergirded by the unified theory of acceptance and use of technology (UTAUT). The study was guided by the primary research question, which asked whether a statistically significant relationship exists between four predictors, PE, EE, SI, and FC and the outcome variable, BIU. Findings identified SI and FC as two significant predictors of BIU. However, PE and EE were not assessed as significant predictors of BIU. This was a departure from the findings of a significant collection of previous studies technology adoption which found that PE and EE were dominant predictors of technology adoption (Hoque & Sorwar, 2017; Wang, Tao, Yu, & Qu, 2020). Using SPSS, multiple linear regression analysis revealed that the four predictors, PE, EE, SI, and FC, accounted for 32% of the variance in BIU. From this significant result, it was inferred that other factors not included in this investigation were influencing BIU.

This study gave a definitive answer to the research question by providing empirical support for rejecting the primary null hypothesis; however, the findings of this investigation also identified avenues for further research. Although the predictors used in this study explained 32% of the variance in BIU, in the synthesis of UTAUT, Venkatesh et al. (2003) asserted that the UTAUT framework explained 70%. It is therefore conceivable that the research model used in this study could be further enhanced by exploratory research to reveal hidden factors influencing PCPs to adopt cloud-based EHR/EMR systems in the United States and thereby provide a stronger answer to the research questions.

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