2021

Medical Practitioners' Intention to Use Secure Electronic Medical Records in Healthcare Organizations

Omar Enrique Sangurima
Walden University

Walden University

College of Management and Technology

This is to certify that the doctoral study by

Omar Sangurima

has been found to be complete and satisfactory in all respects,
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Review Committee
Dr. Jodine Burchell, Committee Chairperson, Information Technology Faculty
Dr. Gary Griffith, Committee Member, Information Technology Faculty
Dr. Gail Miles, University Reviewer, Information Technology Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
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Abstract

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MS, Keller Graduate School of Management, 2016

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Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Medical practitioners have difficulty fully implementing secure electronic medical records (EMRs). Clinicians and medical technologists alike need to identify motivational factors behind secure EMR implementation to assure the safety of patient data. Grounded in the unified theory of acceptance and use of technology model, the purpose of this quantitative, correlational study was to examine the relationship between medical practitioners' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention to use secure EMRs in healthcare organizations. Survey data ($N = 126$) were collected from medical practitioners from the northeastern United States. The results of the multiple regression analysis were significant, $F(4, 121) = 13.87$, $p < .001$, $R^2 = 0.31$. The model predicted approximately 31% of the variation in medical practitioners' intention to use secure EMRs. In the final model, performance expectancy (ß = .20, $t = 2.16$, $p = .03$) and effort expectancy (ß = .29, $t = 2.77$, $p = .01$) were the only significant contributors. One recommendation is for practitioners to make training in the use of secure EMRs more focused on ease of use and job role applicability. The implications for positive social change include the potential for medical practitioners to increase proliferation of EMR-enhanced patient care and lowering the associated costs with digitally supplemented medical care.

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Dedication

I dedicate this entire endeavor to my wife, family, colleagues, and friends who provided the support to see me through the process. Finishing this study is a testament not to any innate ability but rather to my inability to allow failure and setbacks to delay forward progress. Obstacles are then not seen as unwelcome but embraced as the mile markers on the road to achievement.

“If I have seen further, it is by standing on the shoulders of giants.” —Sir Isaac Newton

Acknowledgments

I want to first thank Dr. Jodine Burchell for her pivotal role as my dissertation committee chair. Her mentorship and guidance made what could have been an overwhelming process manageable and eminently rewarding. I would also like to thank Dr. Gary Griffith and Dr. Gail Miles for their invaluable insights and notes throughout this dissertation’s creation and refinement. Additionally, I would like to offer my sincere gratitude to all my classmates during my time at Walden University; their encouragement, feedback, and inspirational work ethic helped keep me on the path toward dissertation completion. Finally, I thank my employer, Memorial Sloan Kettering Hospital, for its generous financial support of my doctoral journey.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

In modern medical care facilities, regulatory and other stakeholders call for greater use of medical record digitization, but the implementation, adoption, and use of such digitization leaves an information security gap (Abouelmehdi et al., 2017). Researchers have presented various possible explanations for these use impediments, citing a lack of medical record design parameters that consider practitioner ease of use and overall training time before implementation (Alqahtani et al., 2017). Thus, a better understanding of the factors that contribute to or detract from a medical practitioner's intent to use electronic medical record (EMR) security best practices is needed before the proliferation of this digital paradigm across medical practices and facilities continues. The purpose of this study was to examine factors that shape secure EMR practitioner use intent. In this chapter, I present the background, purpose statement, research question, definitions, theoretical frameworks, and significance of this study.

Background of the Problem

Healthcare organizations are under increasing scrutiny from both regulators and the patients they serve to provide efficient yet secure EMR solutions (Barr & Randall, 2019). Organizations that do not maintain minimum acceptable EMR security levels are at risk of losing patient trust due to breaches stemming from improperly secured EMRs; these organizations also face progressively stringent compliance and corrective regulatory actions from governing bodies (Terry, 2017).

EMRs are a modern technology that can enhance the delivery efficacy of medical care across demographics and can be a driving force for keeping the costs of care down

(Narattharaksa et al., 2016). However, adopter and subject apprehension (and consequently, propensity to adopt) remain high due to the occurrence and impact of EMR breaches (Feldman et al., 2018).

EMRs are a source of increased efficiency and throughput in varied healthcare settings, with the goal of boosting levels of care for cross-sections of patient demographics (Zhou et al., 2018). However, security concerns with continuously aggregating medical record data into digital formats have arisen on both the practitioner and patient side of the healthcare field (Tavares & Oliveira, 2018). With best practices continuously developed but with no apparent downturn in reported breaches (U.S. Department of Health and Human Services Office of Civil Rights, 2019), the disconnect between practitioners who ostensibly know the secure manner to handle EMRs and the actions taken serves as an identified gap in practical scholarship.

Problem Statement

The dearth of practical and intuitive information security guidelines for small to medium medical organizations has contributed to these firms failing to implement information security best practices (Angst et al., 2017). The U.S. Department of Health and Human Services' Office of Civil Rights (2019) reported that data breaches involving the improper securing of EMRs across 34 separate entities affected over 200,000 individuals in 2017. The general information technology (IT) problem is that some healthcare organizations lack the requisite knowledge of the determinants that influence the intention to use secure EMRs. The specific IT problem is that some IT managers lack knowledge of the relationship between medical practitioners' perceptions of performance expectancy, effort expectancy, social influence, facilitating conditions, and the intention to use secure EMRs in healthcare organizations.

Purpose Statement

The purpose of this quantitative, correlational study was to examine the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMR in healthcare organizations. The dependent variable was the intention to use secure EMR in healthcare organizations. The independent variables were medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. The target population was healthcare practitioners in the greater Northeast region of the United States. Healthcare practitioners were the selected population based on the Office of Civil Rights' increased enforcement efforts regarding HIPAA privacy violations. The implications for positive social change include increased privacy protections for patients in practices serviced by the target population and the potential transferability of this increase to medical practices nationwide.

Nature of the Study

I chose a quantitative methodology to investigate the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions and medical practitioners' intention to use secure EMRs. Quantitative research originates from a theoretical or hypothetical position and employs formalized instrumentations to gather numerical data for statistical analysis (Almalki, 2016). The quantitative methodology became more appropriate than a qualitative methodology because the variables were readily measurable and identifiable. In contrast, a qualitative investigation leverages naturalistic and inductive methodologies based on interpreting and observing the study subjects' perceptions (Cypress, 2018). Because the variables were observable and measurable rather than necessitating inference from interviews or direct interactions with subjects, qualitative design was not appropriate. Additionally, with a mixed research methodology a researcher uses practical contextual understandings of the study subjects by introducing and surveying various data types (Johnson, 2019). Mixed methodologies are more appropriate for studies involving multiple data types and sources; thus, with this study only involving quantitative analysis of survey results, mixed methods were not necessary. The four independent variables are identified in the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) and are easily measurable in the study population; therefore, a quantitative methodology was deemed most appropriate for this study.

I applied a correlational design to this study. Correlational design is a research method in which a researcher investigates the statistical relationship between measurable and observable variables (Martin et al., 2019). Because the study subject was a single group and I was investigating the relationship between variables and components, the data were best examined under the lens of a quantitative correlational study. An experimental design is used to carefully examine and strive to uncover any causation between variables instead of merely determining any relationship between them (Turner & Hasford, 2016). Because this study was not intended to determine causation, an experimental design was not appropriate. A descriptive quantitative design was also considered; this design does not begin with a hypothesis; instead, a hypothesis develops postdata collection while relaying the current state of a given phenomenon (Solheim et al., 2017). The descriptive quantitative design was not appropriate because of the measurable and observable nature of the collected data and the study's aim to explore any relationships between the variables. A correlational design was chosen due to the desired outcome of collecting data that assist in observing concrete details surrounding given phenomena while also using mathematical tools to gauge any responsive changes in the examined variables.

Research Question

What was the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations?

Hypotheses

Venkatesh et al. (2003) presented four main variables that aim to forecast the intention to use technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. Said variables were determined to be enough for investigating the intention of medical practitioners to use secure EMRs. The hypotheses for this study are:

Null Hypothesis (H_0): There is no statistically significant relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

Alternative Hypothesis (H_a): There is a statistically significant relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

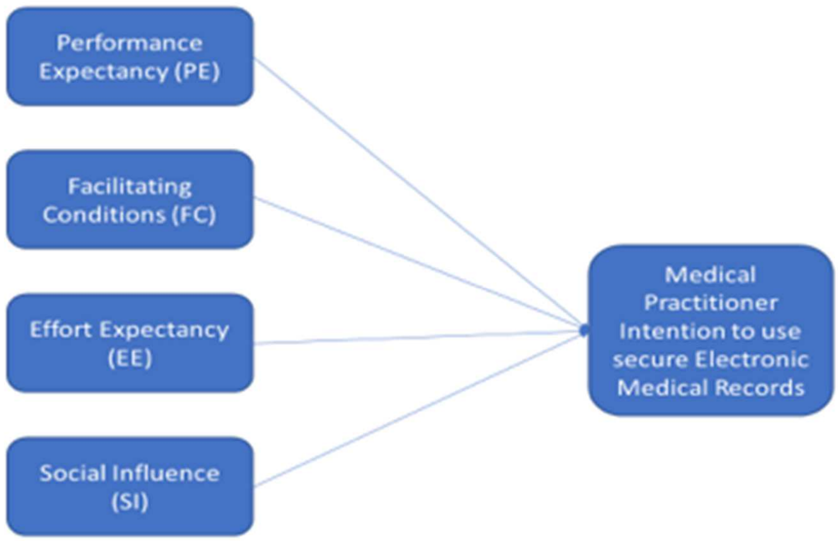
Theoretical Framework

This quantitative study used Venkatesh et al.'s (2003) UTAUT. UTAUT came to fruition in 2003 and built on Davis' (1985) technology acceptance model (TAM). TAM deals similarly with the use of technology and any predictive factors thereof but is used to examine a smaller field of variables (Davis, 1985). UTAUT outlines a theoretical framework consisting of four main components: performance expectancy, facilitating conditions, effort expectancy, and social influence, as shown in Figure 1 (Venkatesh et al., 2003). By leveraging the UTAUT framework, I appraised medical practitioners' intentions in medium to large hospital environments in the northeastern region of the United States to use secure EMRs.

UTAUT supported this study by applying assessable components that allow for the quantifiable measurement of propensity or inclination toward the use of secure EMR technology in the workplace (Venkatesh et al., 2003). UTAUT incorporates more aspects of intentionality than TAM does, particularly in the realm of social constraints and factors that combine to provide insight into the use of technology in a team or community-based setting, making it more supportive of the potential theories for the study to use as a framework.

Figure 1

How the Four UTAUT Variables Relate to Medical Practitioner Behavior



Definition of Terms

Electronic medical record (EMR): A digital version of a paper-based medical record that aids in the management of patient information while also providing for the streamlining of healthcare services and operations; it can represent the medical record of an individual across multiple healthcare organizations or within a single facility (Mijin et al., 2019).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are intrinsic beliefs that a researcher holds to be correct without concrete justification (Soltis-Jarrett et al., 2017). Observers must take care of how assumptions could affect the research process's critical components, from the commencement of crafting hypotheses to the study's discussion and conclusions (Kuchta et al., 2016). The research assumptions for this study were as follows:

- Medical practitioners participating in this study had the choice to follow EMR best practices or not.
- Each returned survey was unique.
- Medical practitioners participating in this study had proficiency in and knowledge of using secure EMRs.
- Medical practitioners participating in this study did so willingly.

Limitations

Limitations represent possible paucities within an inquiry that do not necessarily correspond directly with said inquiry's schema and, hence, are not necessarily introduced by the organizer of the study (Munthe-Kaas et al., 2019). The limitations of this study consisted of:

- Application to a broader population was problematic due to correlative design.
- Results bounded using specific tools for statistical analysis.

- UTAUT specified a set of factors to gauge secure EMR use intent, possibly excluding other prescient factors.
- Lack of open-ended questions allowing for free-form respondent input.

Delimitations

Delimitations denote constraints in the breadth and scope of a study (Wolgemuth et al., 2017). The delimitations for this study were: The study's scope was limited in geographic focus to the northeast region of the United States.

Significance of the Study

Contribution to Information Technology Practice

Electronic health record privacy and security are not yet at generally acceptable levels for ubiquitous EMR adoption, mostly due to incongruencies in best practice implementation rates among medical practitioners (Singh & Dhiman, 2019). Making sure that all human touchpoints for a technological standard within an organization realize and appreciate their potential contributions (and, conversely, what they could cost their firms) to the overall security of operations is one of the best ways to holistically achieve an acceptable level of information security posture (Arain et al., 2019). In this study, I examined the relationship between performance expectancy, effort expectancy, social influence, and facilitating conditions and medical practitioners' propensity to use secure EMRs. By identifying such a relationship, medical practitioners could recognize how they might improve their organizations' complete security profile while also delivering digitized medical care safely. This study contributes to IT practice because by making basic security concepts more immediately approachable in a medical environment, the potential for introducing more advanced practices that could lead to a safer and more efficient proliferation of EMR will be made possible.

Implications for Social Change

This study could introduce the potential for social change because it may lead to the democratization and increased proliferation of EMR-enhanced patient care by lowering the associated costs with digitally supplemented medical care. Demographics that have previously been bereft of the benefits of EMR within their care profiles would have the opportunity to experience better care levels using EMR. Implementation cost has historically been one of the main barriers to widespread adoption of digitized medical care and many of its primary positive externalities, including the provision of services to previously unreachable sectors of society and shorter improvement curves on newer discoveries (Gyamfi et al., 2017). There could also be an increase in disseminating medical innovations in currently underserviced socioeconomic circles, as the secure transmission of electronic health information is essential for such advancement.

A Review of the Professional and Academic Literature

This literature review includes scholarly and peer-reviewed articles with publication dates from 2016 through 2020 and published doctoral dissertations and books. I used Walden University's electronic library database, including ACM Digital Library, Computer Science Database, Computers and Applied Sciences Complete, Emerald Insight, IEEE Xplore Digital Library, The National Science Foundation, ProQuest Central, SAGE Journals, ABI/INFORM Collection, ProQuest Health and Medical Collection, PubMed, and Google Scholar. The following keywords were used as either direct variables or in combination for article searches: *electronic health records* or *EHR, EMRs* or *EMR, information security, internet of things* or *IoT, HIPAA, compliance, enterprise governance, obstacles to adoption, best practices, meaningful use, theory of constraints* or *ToC, technology acceptance model* or *TAM, unified theory of acceptance and use of technology* or *UTAUT,* and *diffusion of innovations* or *DOI*.

In this quantitative, correlational study, I examined the relationship between medical practitioners' perceptions of technology acceptance factors and their intent to use secure EMRs within healthcare organizations. In the literature review, I explain the purpose of the study (and its underlying hypotheses), display the UTAUT theoretical framework and supporting theories such as TAM, as well as examine differing technology adoption theories, including the diffusion of innovations (DOI).

While technological adoption of hardware and software in various settings has been studied at length, there are many differing theories on the specific motivators for adoption by healthcare practitioners (Mijin et al., 2019). Within this study, I describe two substantial theories affecting said adoption: TAM (Davis, 1985) and UTAUT (Venkatesh & Davis, 2000). I used current publications to critically inquire about how factors influence secure EMR practitioner use intent.

For this study, I referenced 248 sources. Ninety percent were published within the last 5 years, with 95% being from peer-reviewed publications. One hundred of the references were included in the literature review, with 86% being from peer-reviewed publications. These references included six books and two doctoral dissertations.

Theoretical Foundation

The theoretical framework for this study was Venkatesh et al.'s (2003) UTAUT. There have been many theories developed to depict the adoption predilections of medical practitioners regarding EMR best practices (Busdicker & Upendra, 2017). From a technological perspective, adoption paradigms have included the TAM (Davis, 1985), DIO (Simpson & Clifton, 2017), and the UTAUT (Venkatesh et al., 2003). Researchers have repeatedly used these theories, among others, to examine varying degrees of EMR adoption within different care environments (Bervell & Al-Samarraie, 2019; Thomas, 2019). Further, with EMRs being in commercialized existence for nearly 30 years at the time of this study, scholarly examination of the field has shifted slightly toward investigating obstacles and issues to mainstream security best practice adoption (Fuad & Chien-Yeh, 2018).

My study reflects the disparity between actual practices and proposed security best practices within hospital care environments. Grasping EMR security elements is fundamental to healthcare organizations seeking to close this gap between current and best practices, ensuring a fast and complete shift to EMRs. In the following sections, I discuss UTAUT in-depth and analyze supporting and contrasting theories.

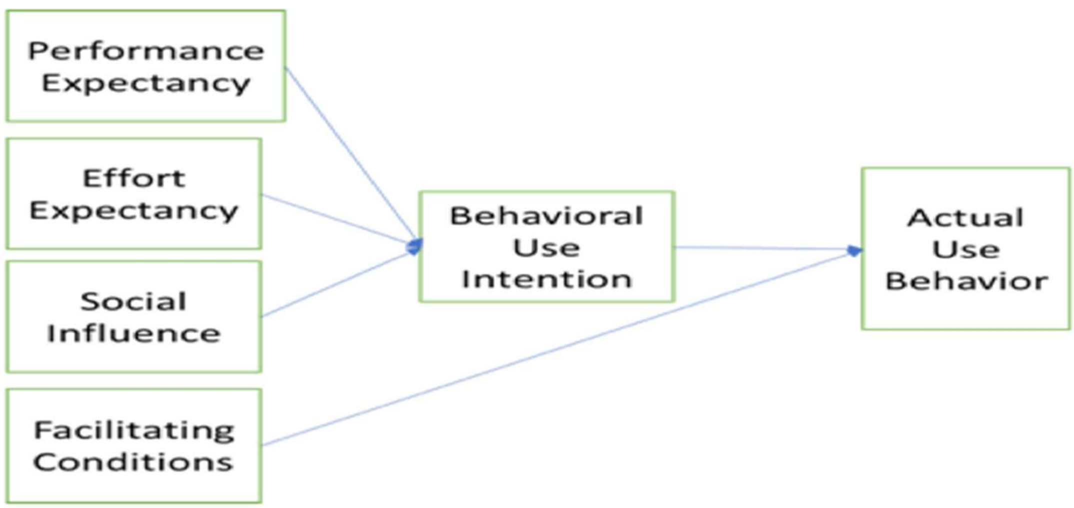
Unified Theory of Acceptance and Use of Technology

Venkatesh and Davis first postulated UTAUT in 2000 as an expansion of Davis' (1985) TAM as well as a combination of other prior models examining the propensity for technology use in individuals. UTAUT has been used extensively to study IT innovation and innovation adoption rates (Venugopal et al., 2016). Venkatesh et al. (2003) reasoned that the four principal components of UTAUT were (a) performance expectancy, (b) facilitating conditions, (c) effort expectancy, and (d) social influence. Venkatesh's primary concern was on these four components to capture enough of a spectrum of motivations for user behavior while still maintaining enough discursive flexibility to enable practical research. Investigators have repeatedly used UTAUT to study IT innovation adoptions across both individual actor environments and enterprise settings (Hui-Lung et al., 2016).

While TAM, and even its slightly more inclusive follow-up TAM2, has been used in attempts to list a more significant number of factors for dissecting behavioral intention, UTAUT can go further in arranging many previously studied considerations into sets of direct precursors for use intent and other contributory dynamics (Venkatesh et al., 2003). Primary variables of performance expectancy, facilitating conditions, effort expectancy, and social influence were posited as the primary driving factors behind subject behavioral intention to use a technology (Venkatesh & Davis, 2000). However, rather than stopping at the identification of further factors (as in TAM or TAM2), UTAUT presents a flexible theoretical framework that includes whichever factors a specific researcher is seeking to control for in a given population or within a given potential relationship (Fuad & Chien-Yeh, 2018). The four primary variables can be calibrated to be specific lenses of inquiry regardless of the breadth and disposition of the additional factors that a researcher chooses to measure. By only formulating the theory after an exhaustive analysis of prior adoption paradigms, Venkatesh et al. (2012) crafted a theory suitable for measuring behavioral factors in a field as constantly in flux as technology. However, this does not discount the crucial, foundational work that TAM framed within the field of technology usage and motivation. TAM formalized relationships between nontechnical behavioral motivators and propensity to adopt technological instruments or practices, and without it, Venkatesh's unified theory would not as easily find room for inquisitive expansion into further motivators and their potentially recursive relationships (Vermaut, 2017).

Figure 2

Unified Theory of Acceptance and Use of Technology



Note. Adapted from "User acceptance of information technology: Toward a unified view," by Venkatesh et al. (2003). MIS Quarterly, 27 (3), 425-478. Copyright 2003 by the Management Information Systems Research Center. Reprinted with permission.

Performance expectancy describes the degree to which users believe using a given technology will enhance their ability to perform a task (Venkatesh et al., 2003). This primary variable of UTAUT represents a combination of five other motivational constructs: (a) relative advantage, (b) outcome expectations, (c) job-technology fit, (d) extrinsic motivation, and (e) perceived usefulness (Venkatesh et al., 2012). As with its constituent parts, performance expectancy researchers propose that users measure technologically facilitated task execution as a function of the relative net positives (easier or more efficient performance of tasks) and net negatives (outlays of time, money, or mental bandwidth; Curtis & Payne, 2008). Should the positive factors outweigh the negative factors, the overall usefulness of technology would be enhanced and so too would use intent be promoted. Venkatesh proposed that performance expectancy was a suitable proxy for the grouping mentioned above of other factors, allowing for an extension of previous adoption models while not introducing too many constituent variables into a predictive analysis tool (Venkatesh & Davis, 2000).

Facilitating conditions are the collection of external factors (outside of behavioral or motivational drivers) such as organizational constructs or technical infrastructures that influence the intention to use a technological item or service (Venkatesh et al., 2003). As with performance expectancy, facilitating conditions is itself a composite of previous TAM paradigms: (a) compatibility, (b) facilitating conditions, and (c) perceived behavioral control (Venkatesh et al., 2012). The degree to which these factors are beneficially available to prospective users of a technology is the level to which facilitating conditions are attributed to influencing technology use intent (Sobti, 2019). Facilitating conditions represents the inclusion of factors present in the surrounding environment, decreasing or removing use obstacles or, conversely, increasing the ease of accomplishing a task with a given technology (Venkatesh et al., 2003).

Effort expectancy is the individual assessment of the degree to which the use of technology is free from effort (Venkatesh et al., 2003). Again, three explicatory components from previous models combine into the UTAUT version of effort expectancy: complexity, ease of use, and perceived ease of use (Celik, 2016). Effort expectancy presents the more internal factors influencing technology use, divorced from the outcome of said use, and examining instead how much effort a user foresees expending while learning how to and utilizing a discrete piece of IT (Dulle & Minishi-Majanja, 2011). Particularly in voluntary contexts, effort expectancy is an important predictive factor on user behavior, even when accounting for secondary factors (such as demographic or experience-based criteria) on technology use (Alwahaishi & Snášel, 2013).

UTAUT defines social influence as the level that a user perceives other people of importance believe that they should use new technology or systems (Venkatesh et al., 2003). This factor encompasses social considerations, perceptions of social image, and normative pressures that encourage users to equate social approval or participation in shared social meaning using a given technology (Venkatesh et al., 2012). As with the other primary variables in UTAUT, mandatory or voluntary circumstances affect the degree to which social influence can impact behavioral intent (Venkatesh et al., 2012). Social influence factor strength is more easily observable in voluntary settings that include socially motivated behaviors (Celik, 2016); this does not discount social influence's usefulness in conceptualizing use motivators and behavioral intention in mandatory settings or individual-focused environments (Almaiah et al., 2019).

UTAUT has been used (either as initially proposed or after slight to extensive modification) to examine technology use in both organizations (Khan et al., 2020) and individuals (Alam et al., 2020). Tavares and Oliveira (2018) postulated a reintegration of prior models into an extended version of the UTAUT to measure influencing factors on electronic health record adoption within the Portuguese national health system. The propensity for use and adoption of animation technologies was studied in Malaysian classrooms, leveraging a more traditional application of the UTAUT as a foundation for inquiry (Suki & Suki, 2017). Findings from this study presented that performance expectancy was the most pertinent motivator for technological use in a classroom environment, with facilitating conditions and effort expectancy being the next two factors in order of influence (furthering the notion of a disconnect between mandatory and volitional circumstances on chief observable primary UTAUT factors).

Beglaryan et al. (2017) proposed a tripartite model describing user intention to use technology, arranging primary UTAUT factors within the patient, practitioner, and organizational groups. This research projected to both address gaps in the theoretical antecedents/similar theories to UTAUT as well as uniquely position itself as applicable to an overall healthcare setting (Beglaryan et al., 2017). Further extensions or modifications of the UTAUT primarily focus on similar arrangements, choosing to highlight specific constituent variables of UTAUT's primary four (Tsai et al., 2019) or instead on principle applicability of the UTAUT to a distinctive setting (Cresswell et al., 2019; Harlie et al., 2019). At the same time, organizational adoption of technology has been repeatedly successfully examined in organizations through the UTAUT (Baird & Boak, 2016; Rahi & Abd. Ghani, 2018); critiques of the theory center around the need for extension through additional primary factors (Magsamen-Conrad et al., 2019) or the integration of additional models, contexts, and predictive factors into classical UTAUT (Zwain, 2019).

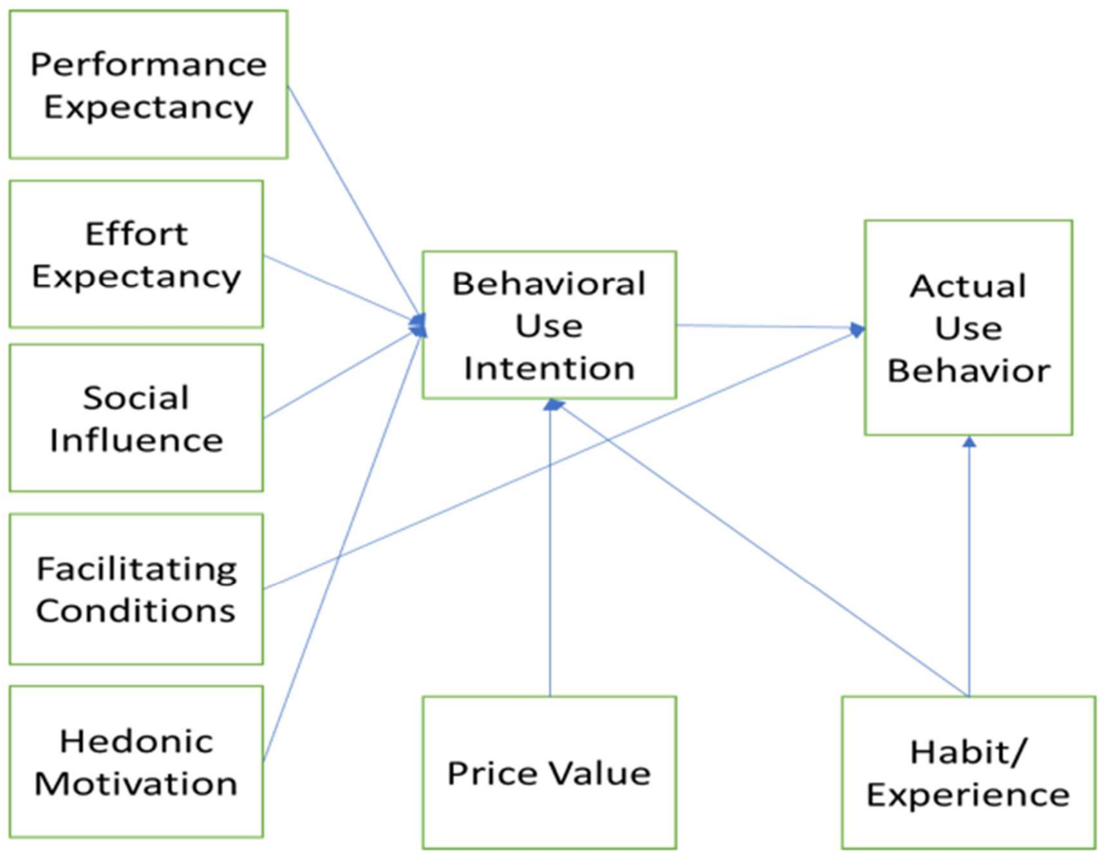
Analysis of Supporting Theories

Within this literature review, analysis of security best practices regarding EMRs, and the implementation of select practices (with their accompanying rationale), alongside healthcare technology in general, was presented by varied researchers with theoretical underpinnings complimentary to the UTUAT scope leveraged as the basis of this study. These supporting research perspectives represent alternative yet not altogether divergent viewpoints to this study's main theoretical framework. In the subsequent paragraphs, I submit specifics on two supporting theories.

Unified theory of acceptance and use of technology 2 (UTAUT2). Introduced in 2012, UTAUT2 is a model that extends original UTAUT inquiries more squarely into the realm of consumer attitudes on the acceptance and use of technology (Venkatesh et al., 2012). Focusing the scope of study within the setting of a particular demographical intention (in this case, that of consumers), the proponents of the extension can posit additional conceptual models for gauging the intention to use a given technology, as well as potentially increase the predictive power of said theories. The new primary additions to UTAUT that constitute its nominal augmentation were price value, experience/habitual factors, and hedonic motivation (El-Masri & Tarhini, 2017). The first of these, price value, was defined as the cognitive interchange consumers partake in between possible perceived benefits from the technology and the economic cost associate with using the technology (Munyoka & Maharaj, 2017). The second of these additional factors, experiences, and habits, were defined as both the familiarity of a consumer with the use of technology as well as how persistent erudition guides consumer intentions on use (Cassia de Moura et al., 2017). Finally, hedonic motivation was defined as the enjoyment or gratification resulting from consumer use of a technology or application (Venkatesh et al., 2012).

Figure 3

The UTAUT2 Model With the Additional Factors Extending the Unified Theory of Acceptance and Use of Technology



Note. Adapted from "Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology," by Venkatesh et al. (2012). MIS Quarterly, 36(1), 157-178. Copyright 2012 by MIS Quarterly. Reprinted with permission.

The extension of UTAUT works to broaden the scope of potential theoretical applicability deep into the commercial/consumer-centric realms; while UTAUT can be used for consumer motivation inquiries, UTAUT2 was constructed with the consumer in mind (Alalwan, 2020). With the additional criteria that UTAUT2 introduced, the theory became much more malleable for use in various contexts that UTAUT would not have initially addressed (Zaini et al., 2020). Hedonic motivation itself was such a broad topic, presenting more abundant elements from the social sciences and psychology into the UTAUT set of components that its sole addition to the initial theory would have been a sizeable extension on its own. This one factor was now facilitating the study of a motivation/decision/action loop that was far tighter than would have been possible with UTAUT alone, although with mixed results (S. W. Lee et al., 2019). While hedonistic motivation was a notable factor in certain use cases (namely purchases along the spectrum of impulse buying and discretionary spending), it can complicate dissection of the other UTAUT2 additives or even the baseline motivational factors described in the original UTAUT (Harandi et al., 2017). Use of hedonic motivation has thus proven a complex issue: On the one hand, it enhanced UTAUTs original premises for the prevalence of internal factors potentially governing activity motivation (Tamilmani et al., 2019); on the other hand, deciphering the discursive line between where proposed explanations on motivation were to be traced back to hedonic motivation and where explanatory variables should be sought elsewhere (either in the price value/habits/experience factors found in UTAUT2 or within another theory entirely) proved problematic and became a discounting factor in a given set of research (Rahi & Abd. Ghani, 2018).

The introduction of price value as a variable was where UTAUT2 made the most considerable inroads into consumer research applications as an extension of the original UTAUT (Ramírez-Correa et al., 2019). Additionally, the concept of price value in UTAUT2 takes into consideration the relative costs of a given technology, albeit with a different emphasis than in UTAUT: For the former, technology costs were examined from the perspective of the individual (with expected downward trends) as opposed to the latter's focus on technology costs at the organizational level, with expected trends upwards as rates of adoption call for increased purchasing activity (Chipeva et al., 2018). The pricing structure, as well as who (or what), bears most of the monetary cost of technological use and was considered a distinguishing focus of UTAUT2 (Venkatesh et al., 2012). For nearly any consumer-based setting (market adoption of new technology in the face of lower-priced substitutes, for example), examining the trade-off between perceived benefits derived from technology and the financial costs for their use grants insights into adoption that examination of hedonic motivation and habits/experience alone was unable to consider fully (Herrero et al., 2017). Even when the overall benefits of a technological adoption fall firmly into the category of nonmonetary, use of price value within a UTAUT2 context was still relevant: The comparison of loss versus gain from using a technology remains a pertinent variable for examining and possibly predicting user adoption behaviors (Shaw & Sergueeva, 2019).

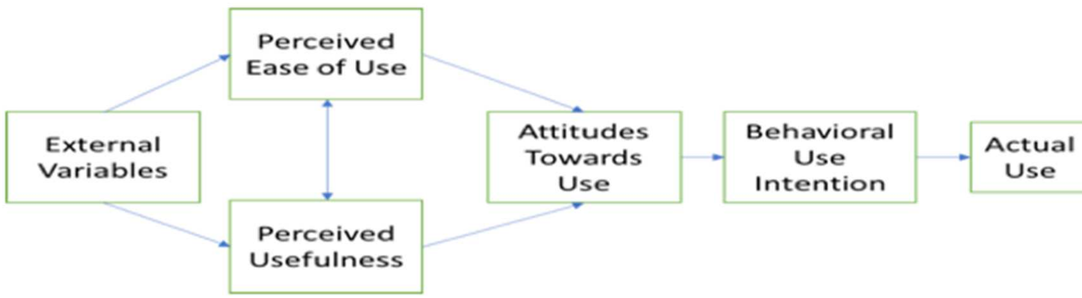
The addition of experience and habit as a variable to the original UTAUT further codifies the theory's handling of factors external to the organization itself (Venkatesh et al., 2012). The combined concept were two separate factors that Venkatesh et al. combined into a single metric within UTAUT2: Experience describes the chance or chances to use a specific technology; habit designates an individual's ability to perform tasks with a given technology automatically due to learning. While again, this was a set of factors (like price value) that were more applicable to studying technology adoption at an individual level, experience and habit do fill in potential theoretical gaps within UTAUT2 that stem from a focus on consumer adoption of new-to-market technologies by focusing more on how much prior use is a predictor of future use with established technologies or successive iterations of existing technologies (Talukder et al., 2020). This combination of incorporating past familiarity and proficiency in the use of technology into consideration for the likelihood of adoption on an individual basis presents insightful research opportunities in fields that repeatedly combine newer technologies with established use tropes, such as education and healthcare (Tavares et al., 2018; Wang et al., 2020c). Such a blend, in turn, has aided in the understanding of why specific demographics have or have not adopted a new technology within a given set of circumstances, based in part on how much of an opportunity the individual has had to familiarize themselves with the technology or based on how many familiarities exist at all, in the case of entirely new technologies (Kalinić et al., 2020) and whether or not this time has solidified habits influencing intent to use (Merhi et al., 2019).

While introducing additional factors to the UTAUT list of variables was a welcome expansion of research avenues, UTAUT2's focus on technology adoption's individual perspective would not have aided efforts in this proposed study. The present study was concerned at least equally with the variables at both organizational and individual levels that impacted technological adoption. Additionally, price value was more suited to discussions of individual adoption behaviors (Eneizan et al., 2019); since this study examined technological adoption in a setting that considers technology cost as sunk or already invested (and thus not incrementally a variable in potential adoption or replacement), UTAUT was deemed the more appropriate framework. Finally, a more immediate and measurable consumer context would have been a fit for UTAUT2 instead of the original UTAUT; with the study's setting being removed somewhat from market externalities, UTAUT was considered more readily applicable than its extension and second iteration.

Technology acceptance model (TAM). According to Davis, perceived ease of use, as well as perceived usefulness, were the main drivers for subjects' propensity to use a given technology (Davis, 1985). Taking forward postulates of the Theory of Reasoned Action, Davis arrived at this initial bifurcation of motivators for individual user intention to use technology (Davis et al., 1989). Perceived usefulness was the level of enhancement to job performance improvement that an individual believes is attainable from adopting a given technological artifact or system (Davis et al., 1989). Perceived ease of use was the level of effort lessening attainable from adopting a given system (Rezaei et al., 2020). Perceived usefulness and perceived ease of use contribute to attitudes (and future use case decisions) towards using a specific technology, notions which themselves coalesced into actual behavioral intentions to use said technology (Venugopal et al., 2016).

Figure 4

The Technology Acceptance Model Showing the Relationships Between Factors Motivating Adoption



Note. Adapted from "Technology anxiety and resistance to change behavioral study of a wearable cardia warming system using an extended TAM for older adults," by Tsai et al. (2020). PloS ONE, 15(1), 1-24. Copyright 2020 by PloS ONE. Reprinted with permission.

TAM has been referenced and utilized, either in original or through various extended models, to grant insights into the motivations underpinning individuals' use and acceptance of technology (Tsai et al., 2020). TAM is among the most ubiquitous models used to analyze the individual's favorable reception of new IT and communication systems (Sangkaew et al., 2019). TAM has also been a theoretical foundation for studies on e-commerce (Ha et al., 2019; Sukno & Pascual, 2019), brand engagement (Florenthal, 2019), social media use (Florenthal, 2019; Tripopsakul, 2018), and EHR adoption (Martins et al., 2019). Other areas of study that utilized TAM within its study perspectives include internet banking (Rahi et al., 2017), mobile payment adoption (Bailey et al., 2017), and consumer satisfaction modeling (Cho, 2017). One point on which these studies differed was the degree to which external variables influenced the noted levels of perceived ease of use and perceived usefulness amongst examined individuals. This potential reintroduction of subjectivity through consideration of external variables is somewhat in conflict with the development of TAM in the first place: As a derivation from the theory of reasoned action (and to some extent the theory of reasoned behavior), TAM eschewed the subjective norm variable (Davis et al., 1989). With external variables, depending on what they were and how much they were measured as precursors for TAM's pair of primary factors, TAM or its extensions allowed researchers to regulate somewhat the presence of subjective norms in both perceived ease of use and perceived usefulness (Chi, 2018; Mijin et al., 2019).

TAM detractors cite the limited amount of factors established and studied through the theory as a leading inhibitor against broader applicability (Poellhuber et al., 2018). The lower factor counts were some of the main reasons UTAUT was chosen instead, as it provides a wider-reaching level of applicability to both individual and organizational cases (Kaye et al., 2020). Additional problematizing of original (or even just slightly expanded) TAM centers around the role of normative motivational factors and issues that were not adequately addressed by an unassisted interpretation of TAM (Yoon, 2018). Further arguments against the technology acceptance model's use find potential shortcomings in the predictive power of TAM sans additional primary variables or correctly structured (and studied) external ones (Rahi et al., 2017). Social influencers (including economic ones), as well as structural imperatives governing technology use, were also not given enough credence in the two-factor investigatory instrument proposed by TAM (Bagozzi, 2007). All use intent-influencing variables manifest into actual, observable uses of technology (Tounekti et al., 2020). The main differentiators among TAM, its initial extension into TAM2, and the evolution into UTAUT were primarily a matter of factor breadth.

Through an avowed choice by Davis, TAM does not discuss as many sociological or behavioral factors that may indeed influence technology acceptance (Venkatesh & Davis, 2000). Therefore, studies that utilize TAM were often cited and expounded upon by those that hold UTAUT as the primary investigatory focus (Zwain, 2019). Even then, the aggregate mix of which factors provide possible explanations for which indicators of technological use was still very much in the format of a further extension of TAM rather than any outright refutations (Kim et al., 2016). However, by recognizing the foundations upon which UTAUT was built, further studies can also mitigate attempts to include too many potential influencing factors, which was a criticism leveled at increasingly complex UTAUT-driven inquiries (Venkatesh & Zhang, 2010). This mixture was the specific balance I chose to strike by analyzing TAM as a supporting theory and leveraging UTAUT as another, but not including more straightforward extensions of TAM (such as TAM2) or further extensions of UTAUT (such as UTAUT2 or UTAUT3) within this study. By focusing on the four primary variables of UTAUT concerning the two primary variables of TAM, this study was based on a more manageable yet adequately descriptive composition of influencing factors.

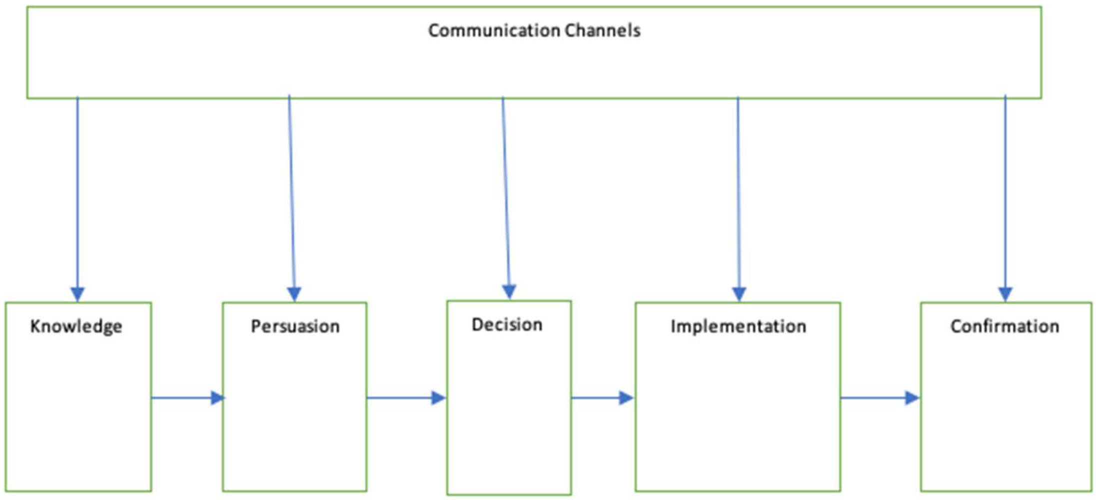
Analysis of Contrasting Theories

Throughout the scope of the literature review, healthcare tech, EMR security, and adoption of technology within medical settings were studied by multiple researchers with multiple theoretical foundations. These different discursive lenses present potential substitutions for the previously outlined theories. In the ensuing paragraphs, I present specifics on two such alternative theories.

Diffusion of Innovation Theory (DOI). The diffusion of innovations theory was developed by Rogers throughout iterative publications through the early 1960s and has been utilized to investigate IT advances (as well as their contexts within both groups and in individual settings) in a wide array of industries (Boehmke et al., 2017). Rogers posited that the four main foundational concepts affecting the diffusion of innovations were communication channels, innovation, social systems, and time (Rogers, 2003). Within these four factors, Rogers was primarily concerned with the elements shaping the adoption of innovations, going so far as to sketch a decision process tracking user adoption across five stage-gates (Rogers, 2003).

Figure 5

Diffusion of Innovation Model of the Five Stages in the Innovation-Decision Process



Note. Adopted from Diffusion of Innovations (p. 170), by E.M. Rogers, 2003, New York, NY: Free Press. Copyright 2003 by E.M. Rogers. Reprinted with permission.

Within these five stages, there was a proposed observable process through which users (both individuals and organizations) arrive at either a reject or adopt decision regarding innovation (Rogers, 2003). Purposefully employing this developed decision-making model would, according to Rogers (2003), assist both levels of users in grasping innovation-adoption influencers more clearly, eventually transitioning the spread of technology through a system from haphazard, ad-hoc progression to a process that introduces far less uncertainty into an organization or at the individual level. Rogers purported that at least half and up to near-90 percent of such innovation adoption could be explained (but not outright predicted) by five common observable attributes of innovation: relative advantage, compatibility, complexity, trialability, and observability

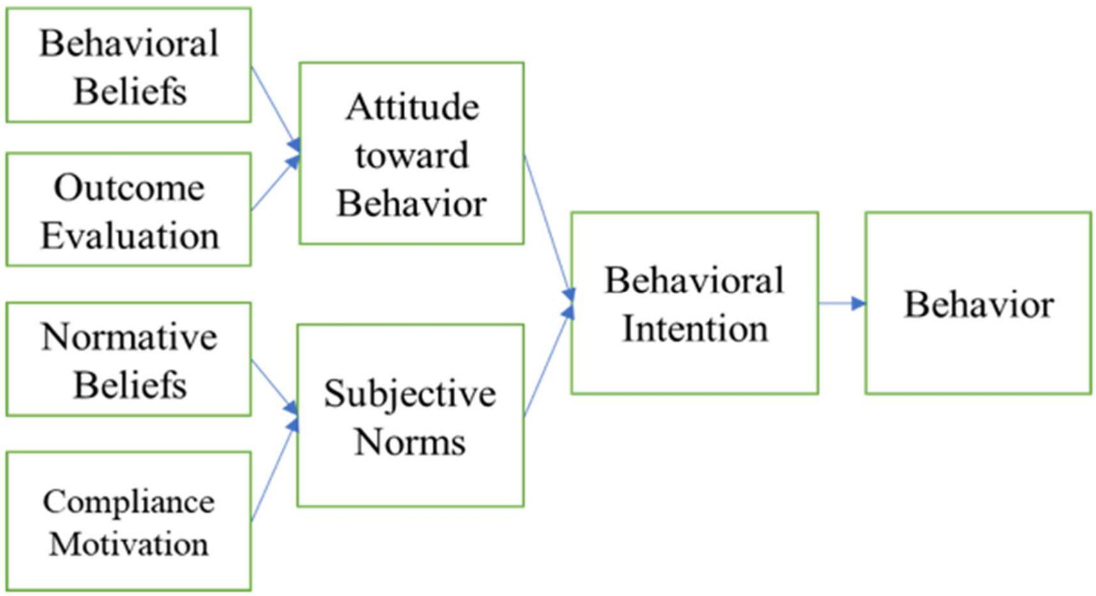
(Rogers, 2003). Variability on the strength of influence was further based on what a given adopter perceived to be most prominent among these five factors (Rogers, 2003).

While researchers have widely utilized DOI to examine the motivations behind technology adoption (McEnroe-Petitte & Farris, 2020; Wang et al., 2020b), there remain some potential criticisms of the approach such that it was not chosen in place of UTAUT. Primarily, the fashion in which DOI-based exploratory models can either diminish or significantly negate the varied nuances within social constructs that play a role in adopting sophisticated technologies (Venkatesh et al., 2003). Furthermore, the perspective of innovation adoption as artifacts involving a mixture of intense individual or organization learning, coupled with additional internal/external factors as well as environmental variables, does detract from DOIs applicability in this specific study ("Erratum to: Diffusing Software Product and Process Innovations," 2017). Institutional factors, process histories, and other constituent influences in the specific diffusion arena would be more straightforward to trace back to DOI in solely an innovation adoption setting, rather than an exploratory examination of both adoption of innovation and any preventative forces impeding or preventing adoption behavior in organizations and users ("Erratum to: Diffusing Software Product and Process Innovations," 2017). Finally, when inquiry focuses specifically on the individual level, factors such as socioeconomic resources and external social support elements can be more closely examined through UTAUT (Alblooshi et al., 2019).

Theory of Reasoned Action. Martin Fishbein and Icek Ajzen first proposed the theory of reasoned action in 1967 as an outgrowth of attitude theories, social psychology theories, and persuasion models (Fishbein & Ajzen, 1975). The theory's primary purpose was an inspection of individual voluntary action, particularly concerning investigating foundational motivators for said actions (Wong & Chow, 2017). The concepts of behavior, attitudes, intentions, and the conditions affecting these functions were described in detail throughout the early-to-mid theory of reasoned action exposition (Baki et al., 2018). A crucial addition by the theory of reasoned action to broader research discussions on motivation was the concept of intention to perform an action preceding actual performing of the action, as well as the inclusion of normative factors (a predecessor of overall "social factors" in subsequent theories) into behavior analysis (Liu et al., 2017). Additionally, notions of disparities between verbal responses to questions on proposed behavior and the actual behavior itself were seen in later iterations of this theory (Paquin & Keating, 2017).

Figure 6

Theory of Reasoned Action Model of the Four Stages in the Behavioral Decision Process



Note. Adopted from Belief, attitude, intention, and behavior: An introduction to theory and research (p. 186), by Martin Fishbein and Icek Ajzen, 1975, Boston, Massachusetts: Addison-Wesley. Copyright 1975 by Fishbein and Ajzen. Reprinted with permission.

The theory of reasoned action has been utilized in various academic and applied professional fields, including consumer purchase motivation, commodities consumption, healthcare, and education (Calderón-Mora et al., 2020; Canova et al., 2020; Gregorio-Pascual & Mahler, 2020; Lee & Chow, 2020). Developed initially by its foundational proponents to examine health-related behaviors (Fishbein & Ajzen, 1975), applicability to a more expansive set of individual behaviors soon followed and was seen in broader research scopes to this day. The reasoning behind why this theory was not appropriate as support for this study was multitiered: Environmental conditions were not given as much influential credence as in UTAUT (Mi et al., 2018), the effect of organizations on individual behaviors were not researched as thoroughly as others (Buabeng-Andoh, 2018), and the reasoning behind stated intent to act differing from actions taken was not fully developed (Dippel et al., 2017). With my proposed study centering on adoption motivations for individual practitioners within a larger healthcare setting, the theory of reasoned action was a suitable contribution to the study's theoretical foundation.

Critical Analysis and Synthesis of Independent Variables

As shown in Figure 1, UTAUT consists of four significant constructs that were utilized to examine both an individual's behavioral use intention regarding a given technology, as well as their actual use of said technology. These constructs were performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs were considered independently of each other and represent a combination of variables that have been used in other models on technology adoption (Venkatesh et al., 2003).

Performance Expectancy

Performance expectancy referred to as the degree to which an individual believes that using the system helped them make job performance gains (Venkatesh et al., 2003). Affirmative effects on performance expectance positively influence motivations to adopt new technologies, systems, or technical best practices (Almetere et al., 2020). Technological innovations that enhance personal job or task performance were influential forecasters of adoption, both in professional as well as personal settings (Suki & Suki, 2017). In the analysis of literature studies utilizing UTAUT, performance expectancy was one of the strongest predictors of technological adoption (Angeli et al., 2020; Tambe, 2020; Yoon et al., 2020). Ha1a; There was a statistically significant relationship between medical practitioners' perceptions of performance expectancy and the intention to use secure EMR in healthcare organizations.

Effort Expectancy

Effort expectancy is categorized as the level of ease associated with using a system (Venkatesh et al., 2003). Typically, the easier a given technology was, or at least seemed to be, to use, the more likely a user was to exhibit positive motivations or intentions to adopt that technological product, service, or practice (Rakhmawati et al., 2020). Novel technologies or established best practices regarding such technologies that were presented in new ways or in conjunction with the adoption of other technological innovations that increase an individual's ability to perform a task with ease, or at least reduce the effort with which the task is performed, were more likely to be adopted (Panhwer et al., 2020). Within both mandatory and voluntary environments, lessened effort expectancy (or increase in ease of use) led to increased adoption by both individuals and at the organizational level (Brandsma et al., 2020). Ha1b; There was a statistically significant relationship between medical practitioners' perceptions of effort expectancy and the intention to use secure EMR in healthcare organizations.

Social Influence

Social influence is demarcated as the level at which an individual or collection of individuals considers it essential that others (whomever they may be, given differing contexts) suppose that they should use the new technology, system, or practice. This variable represents the shift from internally to externally originating, adoption-affecting factors, in conjunction with Facilitating Conditions discussed below. A notable distinction was that said external social factors do not overly influence voluntary use, and thus use cases where technology adoption was mandatory become better environments for tracing social influence as an independent variable (Venkatesh et al., 2003). There were also notable differences in the level of influence that social factors exhibit during the timing of new technology adoption: Earlier on, in mandatory settings, social influence plays a more significant role than later with consistent use (He et al., 2020). Social influence is leveraged as an observable independent variable in both individuals (Sobti, 2019) as well as organizational (Thomas, 2019) contexts. Ha1c; There was a statistically significant relationship between medical practitioners' perceptions of social influence and the intention to use secure EMR in healthcare organizations.

Facilitating Conditions

Facilitating conditions are the extent to which an individual or an organization perceives that there was a technical or metaorganizational support system for the use of a technology, system, or best practice. Facilitating conditions are variables that, along with social influence, measure various constructs of external factors that would affect the motivators for technological adoption within a given population (Venkatesh et al., 2003). Significant in both mandatory as well as voluntary environments, facilitating conditions were examined across a variety of research contexts: Mobile commerce (Marinković et al., 2020); eHealth initiatives (Alam et al., 2020); and eLearning platforms (Zwain, 2019) have all employed UTAUT-based research with the use of facilitating conditions as likewise independent variables. Ha1d; There was a statistically significant relationship between medical practitioners' perceptions of facilitating conditions and the intention to use secure EMR in healthcare organizations.

Critical Analysis and Synthesis of Dependent Variables

Secure EMR practitioner use intent was the dependent variable in this study. The notion of secure EMR use has been in consideration for nearly as long as medical records have been electronic and indeed became a more immediate issue for the domestic healthcare industry when national legislation concerning the proper digitization of medical records (among a broad host of other relevant sector topics) went into effect August 21, 1996 (Mbonihankuye et al., 2019). Over the last decade (into the start of the present one), security issues surrounding EMR implementations became increasingly heightened, especially in conjunction with the rising illicit profitability from the illegal sale, both online and off, of health records to the highest bidders (Kamerer & Mcdermott, 2019).

EMR use continues to proliferate in the healthcare sector, which itself is growing into a more individualized set of care services both up and downstream from the practitioner/patient interface points (Crameri et al., 2020). While there were salient security concerns with this increase in both actual use and scope of potential use cases (Kalambe & Apte, 2017), the overall industry drive towards consolidated (i.e., more efficient) care models spearheaded by secure EHR implementation remains unabated (Hung et al., 2019; Zanaboni et al., 2019). In particular, decreasing the cognitive load on patients regarding personal interfacing with their care providers away from the medical facility (Dendere et al., 2019), navigating medical information portals (Mehta et al., 2019), and enhanced patient support community engagement (Manias et al., 2020) were each avenues of overall care that benefit from the continued and advanced adoption of EMRs. However, the potential damage that unsecured EMR implementations can wreak throughout an increasingly connected healthcare environment (Razaque et al., 2019) makes the need for sound technical and operational controls more pressing than ever.

Secure EMR best practice adoption is influenced by multiple factors, such as ease of use, adaptability of the platform, training methodologies, and onboarding time/cost. These were among factors that favorably influenced secure EMR best practice adoption (Akinsanya et al., 2019; Al-Issa et al., 2018; Alqahtani et al., 2017; Colicchio et al., 2019; Mathai et al., 2020). Barriers remain, however, to the adoption of secure EMR best practices (Park et al., 2017). For the adoption of EMR best practices to increase, security and privacy limitations need to be sustainably addressed for a reliable, widespread EMR paradigm to emerge. Critical factors must be pinpointed to facilitate the likelihood of secure EMR best practice adoption across the healthcare industry.

Measurement of Variables

This quantitative correlational research study statistically analyzed numeric data procured from Likert-scale responses to survey questions crafted to uncover a correlation between UTAUT variables. I used an instrument by Kim et al. (2017) that was tested beforehand to assure the validity and reliability of data. I used Statistical Package for the Social Sciences (SPSS) version 25 statistical analysis software for Windows to generate descriptive statistics, assess validity and reliability, and run a correlational analysis on the data. Findings are presented in Section 3.

Current Research With Similar Variables

Researchers remain divided on which of the four independent variables studied (performance expectancy, effort expectancy, social influence, and facilitating conditions) can have more of an influence in general as well as in specific (to this study) medical environment. On their own, each variable saw equally strong relational forces on differing independent variables (Alam et al., 2020; Kim & Hall, 2020; Zwain, 2019). However, there were nuances to just what types of relationships were uncovered based on the environmental situations in each study.

Effort expectancy can play a significant role in how inclined a population even is to try new technology; generally, the more accessible hardware or applications were for early users, the higher the likelihood that first use transpires (Suki & Suki, 2017). There were levels at which participants' intent to use would sustain increased effort expectancy, with researchers in these cases designating organizational pressures (social influences, other facilitating conditions, vocational importance) as avenues for further study (Almetere et al., 2020; Brandsma et al., 2020). Researchers see the most congruent trending in variable behavior between effort expectancy and the following independent UTAUT variable: performance expectancy.

Unlike effort expectancy, performance expectancy does not behave with relative predictability in organizational as well as individual contexts; the more participants conflate the performance expectancy of technology with how well they can do a job or tasks for a job, the higher the likelihood that increased performance expectancy correlates with increased intent to use (Baishya & Samalia, 2020; Beglaryan et al., 2017). This distinction is where researchers are investing a considerable amount of study time: Where and why does performance expectancy wane in its correlation with other independent variables as well as intent to use technology, and in what contexts (mainly within an organization versus the individual use of new hardware, applications, or services) (Beglaryan et al., 2017; Khan et al., 2020; Sohn & Kwon, 2020)?

Social influence is the variable that researchers observe having the most noticeable fluctuations in relative importance based on study context, in some cases, even when the technology observed is similar. EMR use positively correlated with increased social influence to use the technology in both individual and organizational settings (Alam et al., 2020; Brandsma et al., 2020; Feldman et al., 2018). Context has a noticeable influence on the level to which social influences matter: Individuals were initially more susceptible to social influences driving EMR adoption even in the face of increased effort expectancy and performance expectancy (Alam et al., 2020). Whereas organizational users still need at least steady effort expectancy and performance expectancy assumptions before social influence becomes an additional driving factor for use intent (Tsai et al., 2019).

Facilitating conditions affect individual potential technology users and organizational ones similarly: Training and awareness efforts for users in both settings present noticeable influences on intent to use a given technology (Alblooshi et al., 2019; Almaiah et al., 2019; Rahi & Abd. Ghani, 2018). However, there is some debate on how far upstream from the studied use decision point researchers should consider facilitating conditions. For some researchers, medical technical knowledge, in general, was counted among other facilitating conditions (Wang et al., 2020a). For other researchers, external moderating factors were best included in a study by noting effects on facilitating conditions, then indirectly on the intention to use a technology (Kurilovas & Kubilinskiene, 2020). For yet other researchers, facilitating conditions were worth observing at the individual and organizational levels in health IT adoption, but not any more so than other independent variables studied (Fuad & Chien-Yeh, 2018).

Relationship of This Study to Previous Research

Research in the field of EMR security has been steadily expanding into motivational drivers for practitioners at the individual and organizational levels, beyond the strictly technical implementation issues that once dominated the domain of study. Encryption methodologies remain an essential topic for continued study; there remains a need for strategies to decrease the human risk factors associated with EMR use by positively influencing practitioners' intention to adopt secure EMRs (Joshi et al., 2019). Practitioners exhibit varying degrees of adherence to proposed security best practices, with various factors influencing their consistent adoption or adherence, within both organizational and individual contexts.

Some studies contrast security best practices at the societal and organizational levels, primarily in the greater context of overall IT security at an institution, within a group, or for a given market (Kalambe & Apte, 2017; Kim et al., 2017; Ravert et al., 2020; Sorace et al., 2020). Many of the studies conducted investigations through a combination of audiences: Either patient and families within hospital settings (Manias et al., 2020); entire health system performance with health record security as a subset therein (Leslie et al., 2019); clinician and patient interactions within care environments (Mehta et al., 2019); or even as a review of an entire subset of health professions in general (Roth et al., 2019). Whether government services (of which healthcare is a subset in most circumstances outside of the US) (Mansoori et al., 2018; Munyoka & Maharaj, 2017); healthcare-focused wearable technology (Talukder et al., 2020); or EHR portal adoption (Tavares & Oliveira, 2018), there were strong links from previous research into contexts with this study. However, while there is an in-depth exposition on the differences in influencing secure EMR adoption within each context, there is still a lack of indicators for what strategies would best fit across such contexts.

Outside of the pure organization perspective, there were a myriad of potential avenues for research into what drives individuals to adopt given technologies. Alalwan et al. researched a subset of the Jordanian population and their adoption attitudes towards newer internet banking practices (Alalwan et al., 2018). In specific contrast to the Abrar study (but pertinent to a discussion of previous technology adoption research in general), factors such as performance expectancy and hedonic motivation arose as the predominantly essential issues. In this study, social influence proved the least quantifiably measurable influencing factor on internet banking adoption (Abrar et al., 2019). Still, the authors did concede that this had more to do with how the study itself was constructed and recommended further research to investigate the seemingly nonsignificant relationships surrounding social influence variables. Likewise, similar studies still do not address how to maintain a positive influence on best practice adoption strategies when moving from within an individual context to a broader organizational one, nor how to address adoption of technology in a mixed technological environment (where a combination of technology versions or implementations exist irrespective of researchers' focus on one or a small handful of cases).

Within the broader organizational context, secure EMR adoption among various constituent populations is crucial to overall EMR security. Gordon et al. (2019) analyzed patient data at a Boston, USA hospital to examine the propensity for patient populations to adopt electronic health records at all; furthermore, the researchers measured the adopters as either utilizing another technological factor in their adoption (the iPhone, in this case) or if the subjects interfaced without such a familiar device. Mijin et al. investigated the acceptance of EMR systems by examining Korean medical professionals' attitudes (Mijin et al., 2019). This study found record accuracy, security, and compatibility (i.e., interoperability between different supporting technologies) as factors that positively perceived the usefulness of EMRs. Salameh et al. (2019) focused on researching nurses' mindsets towards adopting electronic health information systems in Palestinian hospitals. Researchers have also found that most respondents understand the need for EMR adoption in a professional medical setting and presented guidelines on the early stages of planning for what such an adoption influencing program would look like (Muir, 2019). As with the Mijin study, researchers also suggested a more diverse population set (of not just nurses in developing countries, but also nurses in developed countries, medical doctors in either or both settings, patients, as well as auxiliary staff's attitudes towards implementation) were beneficial to generating guidance on how best to initially present (and eventually implement) any such computerized documentation of health information (Salameh et al., 2019). There was room to expand research on secure EMR adoption within specific demographics to approach a more comprehensive set of strategies for overall best practice adoption.

The discursive space for research into cohesive, secure EMR adoption strategies is considerable. Previous research has focused on an individual versus organizational dichotomy or split studied populations along strict professional boundaries. Strategies that encompass both clinical and technical medical practitioner attitudes, as well as those that investigate more than just technological solutions to human motivational factors, were not readily available in the topic literature. Thus, I have deemed this as an opening in the literature that needed analysis. I used a quantitative, correlational research design to examine the strategies for influencing secure best practice use in EMRs through more cohesive and comprehensive approaches.

Transition and Summary

The purpose of this quantitative, correlational study was to examine factors that shape secure EMR practitioners' use intent in a medium to large Northeastern U.S. hospital setting. EMR adoption has been investigated at length within both an organizational and an individual context; still, medical organizations have yet to consistently adopt secure EMR best practices across most of the target population. The unified theory of acceptance and use of technology is a conventional framework used in use or adoption intent studies within organizations. The utilization of this framework increased the perception of technological best practice adoption. My analysis showed how crucial secure EMR adoption is to U.S. hospitals' overall EMR adoption rate.

Currently, a relatively small number of researchers have examined secure EMR adoption through the UTAUT perspective. This smaller sample size of the research, in turn, exposes a gap in the literature that was evidenced by a dearth of research investigating the factors affecting secure EMR adoption by healthcare practitioners in hospital settings.

Parsing the most influential elements of secure EMR adoption is critical to the healthcare field as both regulatory and market factors call for increased digital technologies within the medical domain. None of the accepted benefits of EMRs (personal privacy assurance, record portability, reduction in care accuracy issues, coordination of and efficiencies among care plans, and lowering of healthcare costs) were safely digitally sustainable even for more socially responsible healthcare organizations without the consistent implementation of secure EMR systems. The consequences to IT practice were assured by the possibility of developing a reproducible model for identifying significant factors influencing the adoption of secure EMR best practices within the broader healthcare field. Forthcoming healthcare medical practitioners and IT managers can utilize this study's results to develop strategies to collectively design more approachable secure EMR best practices, thus positively influencing practitioner adoption rates. This present study may help elucidate the association between medical practitioners' perceptions and their intent to use secure EMR best practices in medium to large Northeastern U.S. hospitals.

Section 1 began with an introduction to the problem investigated by this research through the background of the study. This section presented the problem and purpose statements, the nature of the study, research questions, hypotheses, theoretical framework, and the significance of the study. Further expansion of this study was in operation definitions, assumptions, limitations, and delimitations. As the conclusion of this section, the literature review outlined a more in-depth discussion of the theoretical framework, methods, and instruments proposed along with their applicability to the problem as stated.

Section 2 begins with a reiteration of the purpose statement to facilitate the reader's broader perspective on the proposed study. Section 2 continues with examining the researcher's role, participants, and the research method and design. Discussion of the population, sampling strategy, and ethical protections of study participants follows. Finally, Section 2 concludes with segments on data analysis and collection strategies, instrument choice, and study validity assurance.

Section 3 exhibits an overview of the study and discuss the findings resulting from data analysis via conducted surveys. Section 3 closes with the application of findings to professional practice, the implication of the study for social change, and resulting recommendations for action and further inquiry.

Section 2: The Project

In this section, I discuss my role as a researcher and follow with an overview of the participants. I also present a thorough description of both the research method and design, continuing with discussions on the chosen population and sampling, any ethical research concerns, the research instrument, data collection and analysis procedures, and the validity of the study. Section 2 closes with a transition to Section 3.

Purpose Statement

The purpose of this quantitative, correlational study was to investigate the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare environments. The independent variables were (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. The intention to use secure EMRs was the dependent variable. The target population of this study were nurses, doctors, and healthcare IT staff in the greater northeastern region of the United States. Heightened enforcement activity of HIPAA privacy violations by the Office of Civil Rights highlighted the choice of healthcare practitioners as a population to sample. Results from this study contribute to positive social change by outlining increased privacy protections for patients and could lead to the development of a transferable patient privacy-enhancing model to other healthcare settings across the United States.

Role of the Researcher

The role of the researcher is an evolving one, changing through the course of a given study, beginning with thought experiments leading to the call for proper investigation, then on through the collection of data, the analysis of this data, and finishing with the study's socialization through the broader academic community (Depaoli et al., 2018). Like prior quantitative researchers, my role as a quantitative researcher likewise shifted as this study progressed through the planning phases onto the process's final presentation stages. Explicitly put, my role encompassed topic selection, the definition of the hypotheses and research question, reviewing the pertinent literature, data collection, data analysis, and presenting any findings.

Researchers must be ever mindful of the presence of bias throughout any research process. In quantitative research studies, there is a constant possibility of introducing subjectivity when collecting data, as well as when it is time to present potential findings (Johnson & Shoulders, 2019). Bias within research can never be entirely eradicated; recognizing this possibility, I was vigilant against any undue effects my principles and tenets had on increasing my research bias.

Researchers leveraging quantitative methods must endeavor to be impersonal, neutral data collectors and analyzers for consistent bias minimization. A quantitative researcher is separate from the research, striving for an unprejudiced perspective by maintaining as much cognitive independence from the researched subject matter as possible (Bloomfield & Fisher, 2019). To minimize personal bias during this study, I curtailed direct interaction with participants, maintaining impartiality through data collection, data analysis, and presentation of any findings.

My function as a researcher was to uphold the reliability and validity of the conducted study. Any researchers seeking to employ quantitative research methods pursue result reliability and validity to produce dependable decision-making aids (Martin et al., 2019). A previously validated instrument was used with slight repurposing for contextual study alignment to study reliability and validity further. Written permission for instrument reuse is presented in Appendix C. Protecting the instrument's veracity and stringent faithfulness to the research design helped promote result validity.

I have had the privilege of working in information security for nearly 6 years, most of which has been spent in the healthcare security sector. Before beginning the information security portion of my career, I was primarily a business analyst in the financial industry; this was where my introduction to and appreciation for quantitative data analysis began. Before commencing this study, my background in healthcare information security was primarily in the realm of penetration testing, with little knowledge of EMR security awareness policies, techniques, or best practices. I also had no previous involvement with the participants regarding these matters; any incidental engagement was of a purely professional and impartial nature and free from any possibility of affecting study demographics. To minimize my bias, I maximized objectivity by maintaining cognitive and practical distance from the subject being researched. Any conclusions drawn or findings presented were the result of collected data analysis only.

Participant rights advocacy is crucial in any research. Fidelity to the provisions put forth by the Belmont Report (U.S. Department of Health and Human Services, 1979) were achieved to confirm that participant rights were not violated. The research study did not include human subjects from vulnerable groups.

Participants

I chose the eligibility criterion for this study. Participant selection is a crucial aspect of research preparation (Cook et al., 2019). Any prospect of applying results from one study to others, along with comparing and contrasting said results, is rooted in a researcher's careful implementation of cogent inclusion standards employed in choosing participants. Both inclusion and exclusion decisions were made via the leveraging of systematic criteria. Scoping of participant groups through researcher-declared characteristics is a best practice that helps study sample integrity and provides a documented reasoning for disqualifying any specific participants or groups (Cypress, 2018).

Participants for this study were EMR users in medium-to-large hospital settings in the northeast region of the United States. The participants were screened for EMR proficiency by the Centiment survey platform before engagement for participation. These users were a critical demographic consulted for workflow enhancements and continuous process improvement inputs related to EMR use and adoption. These participant demographics were also deeply involved with the eventual business cases made for technological projects spanning EMR planning, application, evolution, and development within their organization. All participants were between the ages of 18 and 79 and had worked in a healthcare setting with exposure to EMRs for at least a year, with minors excluded due to not being necessary, representative of the target population, or aligned with the overarching research question.

I used a sample panel approach that ensured a diverse selection of participants: Centiment survey panels. Centiment panels are similar to survey dashboarding software, which allows the researcher to designate parameters for the needed sample population (Holt & Loraas, 2019); using such a tool grants both reliable and generalizable data (Molnar, 2019). In this fashion, purposeful sampling enabled through the Centiment panel software via choosing medical practitioners familiar with EMR use became an easily facilitated extension of the nonprobabilistic sampling modality. Increased participation rates were also a noted benefit of leveraging Centiment panels, both with and without incentives for participation granted to survey takers (Holt & Loraas, 2019). Low response rates can hinder useful data collection for a study, and the ease of use built into the Centiment platform helped mitigate this collection rate risk (Legg et al., 2020).

Maintaining a professional air of inquisitive distance was paramount for reliable data collection. Enlisting active participation through anonymized means significantly influences the usability of any samples gained (Roulin & Levashina, 2019). Participants were kept anonymous, ensuring a consensual, transparent relationship highlighted by the researcher and collection instrument openness on research methods as well as possible risk factors inherent in the data collection process (House, 2018). The confidentiality and integrity of the data collection workflow, along with the crafting of a smoothly unobtrusive survey process, established the baselines of trust necessary to productive researcher/participant feedback in a highly scrutinized setting such as healthcare (Ryan et al., 2020). To bolster the interaction's credibility, documented informed consent tools were leveraged to clarify research aims, what the collected data would be used for, and to ensure anonymity. Enabling low-overhead data collection that was also securely gathered were primary drivers throughout the survey construction, participant interaction, and data analysis phases of this study.

Research Method and Design

Before selecting the research method for this study, I examined which research method represented the most suitable choice. Researchers gravitate toward three primary research methodologies: qualitative, quantitative, and mixed (Guetterman, 2020). Each technique was a strong candidate for steering the course of this study. Still, due to seeking potential relationships between the variables in this environment, quantitative research was best suited for selection (AlKhars, 2019).

I evaluated possible research designs to ascertain the best fitting quantitative research schema for this study. Three primary research design outlines leveraged within quantitative research were experimental, descriptive, and relational or correlational (Martin et al., 2019). Each of these individual designs has its pros and cons; the chosen model must encompass the study's context by enhancing both the hypotheses and research question. Correlational designs seek to elucidate the connections or relationships between variables (Chen et al., 2018). The quantitative, correlational method was chosen to be most suitable for this study because it facilitates the closest investigation of the relationship between medical practitioners' perceptions and their intent to use secure

EMRs in healthcare organizations. This research method and design were selected to align with the problem statement, purpose statement, research question, and hypotheses. The subsequent sections offer more specific support for the selected design and research method.

Method

In this study, I used a quantitative methodology. Researchers use quantitative research methodologies to investigate the possible associations between dependent and independent variables contained in a sample population (Bloomfield & Fisher, 2019). By evaluating a host of differing elements, quantitative researchers can begin to find indicators on how factors interact with each other, potentially extrapolate these interactions as templates for external generalization to like circumstances, produce foundations for predictive indicators, and explicate causal relationships among the factors. In this study, I investigated the relationship between medical practitioners' perceptions of four independent variables and one dependent variable: intention to use secure EMRs in healthcare organizations.

A critical element of the quantitative research methodology is the concept of testing hypotheses (Johnson & Shoulders, 2019). A null hypothesis is either accepted or rejected based on statistical investigations of the quantitative data collected during a study. I used such quantitative methods to examine if there was any relationship of statistical significance amid the medical practitioners' perceptions of their intent to use secure EMR practices. Section 1 contains both the alternate and null hypotheses.

The quantitative methodology leverages positivist underpinnings, logical rigor, and at least an attempt at maintaining an objective research viewpoint. The quantitative methodology also consists of numerical data analysis and the continual striving of research to maintain an investigative separation between themselves and any study subjects or survey participants (AlKhars, 2019).

Survey use facilitates the quantitatively encouraged researcher/subject distance aimed at promoting study finding objectivity. Likert-scale-type surveys transform participant responses into numerical measurements, which can be quantitatively analyzed. I followed the example set by previous quantitative researchers and employed a survey instrument to accumulate and statistically analyze numerical participant data in an anonymous fashion (Kerry & Huber, 2018). Thus, the quantitative methodology was appropriate for this study because the study's purpose was to statistically analyze numeric data amassed from Likert-scale survey question responses and extend possible inferences to healthcare organizations' healthcare practitioners weighing the intent to use secure EMRs.

Qualitative methods are focused more on describing a holistic phenomenon's factors. Neither numeric nor enumerative factors are the main research emphasis in qualitative methodology, with the latter instead suited more for analysis of the overall facilitating and enabling factors within a research topic (Speed-Crittle, 2019). Rather than eliciting data suitable for numerical conversion, qualitative researchers employ nonbinary, freeform questioning of the how, who, and why behind a given phenomenon. Because the objective of this study was to leverage such numerical data in a statistically analytical fashion to pinpoint possible relationships among the study variables, a qualitative method was inappropriate. Qualitative research methods are more appropriate when statistical analysis is insufficient to study specific nuances of motivational indicators of study subjects, particularly in environments where comingling between the researcher and the study subject is analytically beneficial (Cypress, 2018). In contrast, objective distance is emphasized in a quantitative research context; the research tactic of deep researcher engagement in a study's environment is emphasized in a qualitative research context. Because this study leveraged the objectivity and subject/researcher separation as primary research perspectives found in many quantitative studies, a qualitative method was not appropriate for this specific study.

Mixed-method studies pool the characteristics of both quantitative and qualitative approaches. Mixed-method studies are best suited for research environments that would benefit from a fusion of qualitative and quantitative analysis to investigate a particular phenomenon (Cook et al., 2019). By employing dual research perspectives, mixed-method researchers can conduct a broader investigation that bears a more varied array of findings than quantitative or qualitative methodologies could in isolation. Through the combination of numerical data and deeper background factors, mixed-method researchers seek a more holistic perspective on the research subjects (Poellhuber et al., 2018).

Triangulation is a critical concept for any mixed-method research approach. Mixed-method research practice facilitates result triangulation by leveraging quantitative and qualitative data (Long, 2017). This combination of data from dual sources then enables a broader investigation of prospective study subjects. A wide-ranging study can, however, be fraught with risk. Triangulation of study data is not only routinely more difficult than qualitative or quantitative data analysis on their own, but the time needed for data gathering increases significantly with a mixed-methods approach (Koorts et al., 2020). because the prospect of increasing risk and cost factors was appreciable, a mixed research methodology was not chosen for this study.

I chose a quantitative approach instead of a mixed-method or qualitative approach because my goal was to numerically analyze the relationships between medical practitioners' perceptions of the four identified independent variables and their intention to use secure EMRs as well as to test both the proposed and alternative hypotheses.

Design

The research design I select must align with and address both the research question and proposed hypotheses. Four primary quantitative research design methodologies leverage observational quantification: descriptive, correlational, quasiexperimental, and experimental (King et al., 2019). However, descriptive methodologies were not best at relationship identity among independent and dependent variables (Johnston et al., 2019). As such, I only further examined correlational, quasiexperimental, and experimental research designs. While there were benefits and deterrents to picking each of these three designs, contextual alignment with the study was the primary driver for a final choice. I elected a correlation design for this study.

The umbrella of experimental quantitative research designs contains two main research avenues: Classic (or true) experimental and quasiexperimental research designs. The former depends upon similarity among the study and control groups as well as randomness reigning in participant's assignments to either group (Smith & Hasan, 2020). Quasiexperimental research eliminates the element of random participant assignment (Nansen-McCloskey & Ziliak, 2019). Both types of experimental research design examine the manipulation of variables within an environment to produce observable interactions of effects; quasiexperimental researchers eschew classical experimental randomness in efforts to replicate an actual scenario more firmly within the confines of a study.

Examination of cause and effect poses the most efficacious experimental design utilization (Dubovicki & Topolovcan, 2020). The manipulation of both independent and dependent variables that is the hallmark of either kind of experimental design allows for investigating the effects of independent variables on the dependent variable; this aids in pinpointing potential causes of a given occurrence. Crafting these types of research designs pose more inherent complexity than both correlational and descriptive research design alternatives. Through this study, I did not seek to establish such a cause-and-effect relationship; hence both true experimental and quasiexperimental designs were not chosen.

The goal of this study was to investigate the relationship between the identified independent and dependent variables. Correlation designs focus on uncovering the underlying components of said relationship (Moeyaert, 2019; Provenzano & Baggio, 2019), namely the size and direction of this relationship among the variables. A positive correlation denotes variables that move in concert, while a negative correlation denotes variables that move in opposite directions. Consequently, no correlation denotes a lack of relationship between variables. A known characteristic of correlational designs was their inability to ascertain any causal relationships between variables in contrast to experimental designs' aims (Kerry & Huber, 2018). However, since this study investigated the relationship between practitioner perceptions and the use of secure EMR rather than determined the causes for the lack of secure EMR use, an experimental design was not employed.

Correlational designs were appropriate for those studies where the researcher either does not wish to or cannot manipulate the independent variable (Rendle-Short, 2019). This study did not involve any manipulation of the independent variable. A correlational research design was most apt for this study as it investigated the relationship between the dependent variables and the independent variables in a nonexperimental context. This study's primary purpose was to evaluate the relationship between a health organization's medical practitioners' perceptions of independent variables and their intention to use secure EMRs. Therefore, a quantitative correlation design was applied.

Population and Sampling

The initial undertaking when sampling was to define the population. Per Smith and Hasan (2020), the population of a study is the group from which a researcher would potentially draw findings and inferences. The target population for this study was healthcare practitioners working in medium to large Northeastern U.S. hospital settings. More specifically, clinical and IT practitioners that interact with EMRs as part of their daily work routines in a Northeastern US hospital environment. Much like Muir (2019) and as well as Fuad and Chien-Yeh (2018), the target population consisted of both medical personnel (registered nurses, nurse practitioners, doctors, physician's assistants, and other clinical staff) and IT representatives (system administrators, IT directors, system analysts, the security workforce, and other IT staff). To scope down the sample size, I used Centiment software to only solicit survey responses from hospital staff that met the requisite criteria. Population relevance was a function of the participants' knowledge of and level of consistent interaction with EMRs.

Sampling involves choosing representative constituents from a larger population to glean insights about that larger group. Two principal sampling methods exist that aim to facilitate sampling representational rigor: probability and nonprobability sampling (Al-Omari & Haq, 2019). Probability sampling (which is also referenced as "random sampling") is the process of sampling where every person of the population has the same chance of being selected for the sample (Ciccarelli et al., 2019; Smith & Hasan, 2020). Any participant chosen within this sampling method had the same salient characteristics as the target population being studied. Random sampling can be challenging to implement due to the need for identification of each sample member; this can, in turn, hamper efforts to investigate specific characteristics among larger population sets (Göçoğlu & Demirel, 2019).

In contrast, nonprobability (also referenced as "nonrandom sampling") is the process of sampling a population without an equal chance at election among constituents (Smith & Hasan, 2020). For specific targeting of a specific subgroup of a population, nonprobability sampling was encouraged. There are four primary nonprobability sampling methods: purposive, snowball, convenience, and respondent drive sampling

(Rivera, 2019). I chose the purposive sampling strategy to maximize sampling efficacy when targeting time-constrained or otherwise adversely motivated constituents.

Purposeful sampling is a nonprobability sampling technique utilized in quantitative research when constituent selection conditions were determined beforehand (Deslonde & Becerra, 2018). A purposeful sampling strategy was most appropriate for this study since I determined key participant eligibility based on their level of use and knowledge of EMRs. There were some drawbacks to purposeful sampling that need consideration, namely generalizability issues, the potential for improper inclusion selections, and restrictions on applicable data analysis techniques (Dapar et al., 2020; Smith & Hasan, 2020). Even with these known concerns, purposive sampling remained a suitable approach for this study. Due to the nature of some of the proposed participants' schedules, making them somewhat less than readily available, purposeful sampling enabled this researcher to gather sufficient participation that matched the determined selection criteria.

Effect size, alpha level, and power level were all factors used in calculating sample size. Researchers usually dictate effect sizes under .03 as small, rising to more than .15 as medium effect sizes, and large effect sizes clocking in at .35 or above for multiple partial as well as multiple correlations (Dapar et al., 2020). Estimates for effect sizes denote the relative strength between variables. I chose a medium effect size of (f =.15), which was similar to that used in comparable studies (Hamutoglu et al., 2020; Rahi et al., 2017; Tambe, 2020).

Any Type I errors that can be avoided by researchers should be avoided by researchers. Alpha levels in quantitative studies were typically set to .05, indicating that a researcher was approximately 95% confident in the genuine estimate of a given variable (Noori et al., 2020; Paquin & Keating, 2017; Tounekti et al., 2020). Shifting to a smaller alpha value might mitigate Type I errors, but this increases the probability of Type II errors. I chose an alpha of .05 for this study. Balancing the preponderance of Type II errors with a sample size that was temporally and fiscally feasible was the primary goal of this study. Power values smaller than .80 grow the likelihood of Type II errors, but conversely, larger values create a significant uptick in requisite sample sizes (Dapar et al., 2020). I chose a statistical power of .80 for this study.

I conducted a power analysis leveraging G*Power 3.1.9.7 software to pinpoint the proper study sample size. An F-Test for multiple linear regression was run to ascertain the a priori sample size at a medium effect size ($f = 0.15$), an error probability of .05, a power of .8, and four predictors (Figure 7). A G*Power calculation showed that a power of .80 was reached at the 85-participant mark. 129 participants were needed at the .95 power level. Per the G*Power output, a floor of 85 participants and a ceiling of 129 participants were needed for this study (Figure 8).

Figure 7

*G*Power Run to Determine the Proper Study Sample Size*

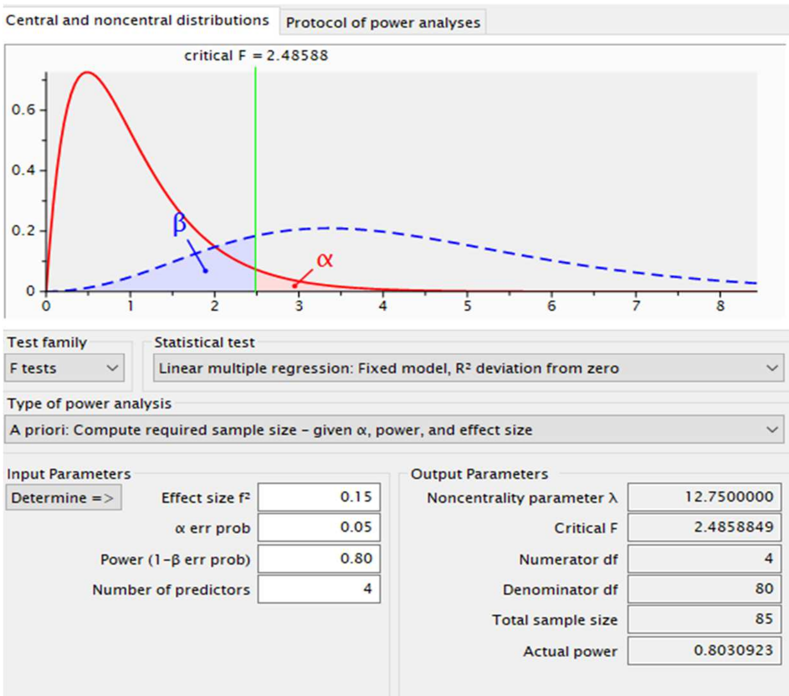
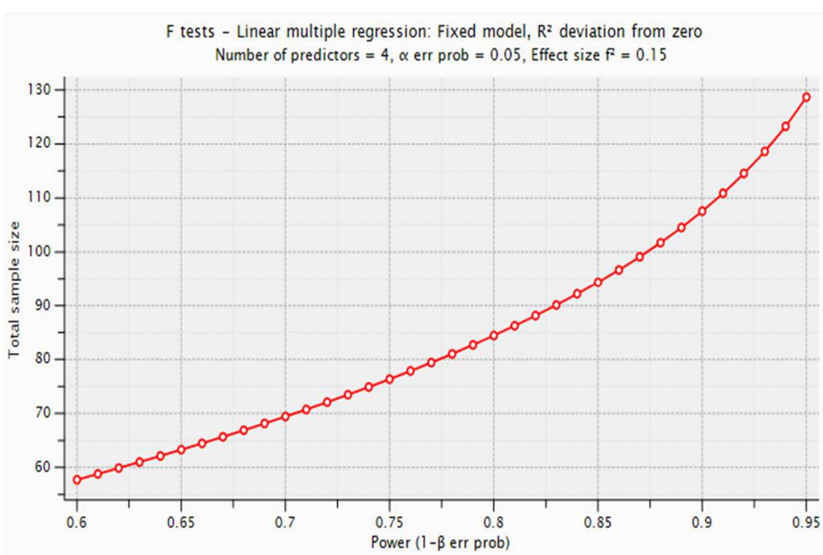


Figure 8

Power Levels for a Given Sample Size



Another way of ascertaining the proper sample size was through the formula $N \geq 50 + 8(m)$ (Green, 1991). In this formula, m is equal to the number of independent variables being analyzed, which in this study was four (effort expectancy, perceived usefulness, social influence, and facilitating conditions). Thus, the formula would then become $N \geq 50 + 8(4) = 82$. There was a range of desired sample size from 82 to 129 participants per both sample size analyses. With G*Power calculating a floor of 85 participants, I targeted a minimum sample of 85 respondents for the required power level of .80.

Study validity was directly affected by the response rate. Comparable studies presented a wide range of response rates (ranging from 22% through 84%) (Loban et al., 2017; Ryan et al., 2020; Tsai et al., 2019). Due to this variable response rate, two calendar weeks were sufficient for collecting the required number of responses. I sent out an email reminder every week to the anonymous respondents to complete the survey. The survey was closed shortly after the 85-participant response threshold was reached.

Ethical Research

Ethical issues were an ever-present concern when conducting research. Researchers leverage recommended practices, ethical guidelines, and ethical research standards to protect participant rights and safety (Martineau et al., 2020). Following ethical research, recommendations confirm that a baseline of ethical protections for participants was in place irrespective of researcher experience while ensuring high research quality. My objective was to implement ethical best practices to safeguard participant rights in this study.

Specific ethical research standards offer available direction for researchers when deciding how to protect subjects' rights best. Guidance surrounding data confidentiality, consent, as well as free and anonymous participation is of primary importance when researchers seek to uphold participant safety, self-esteem, interests, and rights (Evans, 2020). There is a moral imperative for the researcher to steward the dignity of study participants (Rothstein et al., 2020). Throughout this study, I followed the best approach recommendations by implementing ethical standards.

Consent must be a foundational aspect of any researcher-participant study relationship. Ethical guidelines for scientific research consistently state the need for a researcher to obtain informed consent from all participants (Bunnik et al., 2020). Informed consent is based upon the researcher striving to disclose study goals fully, any risks involved in the process, as well as what the process itself would look like (Head, 2018). This transparency is driven by an ethical researcher's need to limit any possibilities of coercive research practices (Rothstein et al., 2020). To ensure compliance with Walden University IRB standards, a consent form complete with opt-in acknowledgment and the consent agreement to participate was presented to all study participants.

Voluntary participation is also of primary importance to the ethically minded researcher. To facilitate such participant notification that their involvement is voluntary and a seamless process for withdrawal, they must be included in participant procedures (Adhikari et al., 2020). Embedded in the consent form is an informational section describing the voluntary nature of study participation and instructions on how a participant can withdraw from the study before survey submission. Anonymity settings built into the survey by the Centiment software employed would preclude withdrawal of survey responses post submission, a fact that was also conveyed to participants in the prestudy consent form. These anonymity settings were also set to protect the names of participating individuals and their home institutions to keep both data points confidential.

Maintaining participant anonymity and preserving their data confidentiality were also crucial issues in ethical research. Conservation of participant data confidentiality and anonymity must remain principal concerns for the ethical researcher (Huang et al., 2020). Prior to engaging in the survey, participants were advised that any data collected was wiped from the survey tool's data repositories once the study was concluded. To uphold participant data confidentiality, survey data is stored in either an encrypted Amazon S3 bucket or on an encrypted USB drive. Checksum hashes were generated (either inherently through Amazon's S3 bucket encryption process or as an add-on to the physical USB encryption procedure) for data integrity preservation. Data is to be preserved (either in a secured Amazon Web Services environment or in a physical safe should encrypted USB be employed) for a total of five years poststudy, after which all study data will be rendered commercially unrecoverable. Additionally, no participation incentives were utilized for this study. I ascribed to the standards outlined in the Belmont Report (United States Department of Health and Human Services, 1979) for the preservation of participant rights.

Data Collection

Data collection was of primary importance when addressing the research question. In quantitative research settings, researchers leverage instruments as the principal data collection constructs (Bloomfield & Fisher, 2019). To parse the data collected, quantitative researchers utilize varied techniques, including questionnaires, structured observations, data analysis methods, and surveys (Cheng et al., 2019). Finding an efficacious blend of appropriate data collection techniques and research instruments is a crucial facilitator for researchers collecting study-relevant material, which is then analyzed for insights into the research question. For this study, I used an instrument created by Kim et al. (2017) combined with the initially proposed estimators in Venkatesh et al. (2003) for measuring behavioral intention/intention to adopt, which was distributed via a link to an online survey. The subsequent subsections describe the data instrument and expound upon this quantitative research study's data collection process.

Instruments

I adapted a survey instrument crafted by researchers investigating electronic health record adoption in patient populations via a phone-administered survey. The adaptation was a shift from the original's target population of patients (Kim et al., 2017) to a target population encompassing clinical and technological medical practitioners. The study instrument is provided in Appendix A. The survey was administered via online format by leveraging the Centiment web-based survey software. An email containing the participation link was emailed to prospective participants.

The survey instrument measured four concepts associated with secure EMR best practice use, specifically investigating performance expectancy, effort expectancy, social influence, and facilitating conditions. Intent to utilize secure EMR best practices was the dependent variable as in prior UTAUT-based studies on technological adoption intention (Alam et al., 2020; Suki & Suki, 2017; Tsai et al., 2019;). The survey instrument used, which contained all the questions asked, is available in Appendix A. The concepts themselves measured by the instrument were presented in Section 1. The instrument contained the ten close-ended questions that were used in participant data collection. Leveraging close-ended questions facilitated the quantification of participant responses (House, 2018). Using Likert scales, participant sentiment was quantifiably collected and analyzed concerning the instrument's questions. This conceptual convertibility offered using the Likert scale was most appropriate when variables in a study were not themselves directly quantifiable.

The survey questions used an ordinal measurement scale through a five-point Likert schema ranging from 1 = *strongly disagree* to 5 = *strongly agree* to enable consistency with the source instrument. Question totals for the four independent concepts numbered two each for every concept. The dependent concept had two questions measured via a five-point Likert scale as well.

Integrated into the survey instrument were demographic questions on age, gender, and job title. Age was measured on a scale of years, while gender was measured on a tripartite answer set of "male," "female," and "prefer not to answer." The model instrument employed a five-point Likert scale to investigate the concepts under study

(Kim et al., 2017). Researchers have used the five-point Likert scale in a myriad of settings, including the measurement of client satisfaction of clinic flow times (Hopkins et al., 2020) as well as in wrist injury reconstruction assessment (Grunz et al., 2020). The scales and measurement factors I utilized for this study were harmonious with comparable studies in similar fields conducted by other researchers. Using a Likert scale, I was able to quantify and calculate the degree of secure EMR best practice use intention, as higher scores supported a higher level of secure EMR best practice use intent.

Other researchers have employed similar instruments to investigate the adoption of security best practices amongst varied populations. Quantitative research often leverages, either in full or through adaptation, many previously utilized instruments (Maree, 2020). Preservation of measurement validity through instrument adoption was a concern but one that prior researchers have managed to assuage (Martineau et al., 2020). Researchers have conducted comparable UTAUT investigations in the fields of mobile banking and its adoption (Raza et al., 2019) as well as public transportation adoption (Madigan et al., 2017).

This study required an instrument with requisite reliability and validity. Per researchers such as Lewis et al., concepts such as validity and reliability are foundations for credible research findings (Lewis et al., 2020). Kim et al. (2017) successfully tested the measurement instrument's content validity before conducting their survey.

The instrument model was tested for composite reliability within scale reliability. Researchers posit that results greater than .7 intimate scale reliability (Madigan et al., 2017; Sohaib et al., 2020). Kim et al.'s investigation of full samples presented values higher than .7. Also, another study by Shiferaw and Mehari (2019) used similar variables within the UTUAT framework to model the acceptance and use of an EMR system, and their reliability results also stayed above the .7 threshold (see Table 1). These results, coupled with other researcher's composite reliability tests, show that Kim et al.'s instrument upholds its reliability; therefore, it was a suitable model for this study (Kim et al., 2017; Shiferaw & Mehari, 2019). Tests for concept reliability were conducted. Construct validity is the level to which an instrument applicably measures a concept; these concepts were typically articulated as discriminant validity and convergent validity (Bloomfield & Fisher, 2019; Cheng et al., 2019; Johnson & Shoulders, 2019; Rivera, 2019).

Table 1

Cronbach's Alpha Summary of Reliability for Instrument Variables

Scale	Items	α
Performance expectancy	4	0.86
Effort expectancy	4	0.85
Social influence	3	0.81
Facilitating conditions	6	0.82
Behavioral intention	5	0.78

Note. Adapted from "Modeling predictors of acceptance and use of EMR system in a resource limited setting: Using modified UTAUT model," by K.B. Shiferaw and E.B. Mehari, 2019, *Informatics in Medicine Unlocked, 17*. Copyright 2019 by Elsevier. Adapted with permission.

Construct validity is defined as the level that an instrument actually measures the constructs themselves and is generally codified as discriminant validity and convergent validity (Bloomfield & Fisher, 2019; Cheng et al., 2019; Johnson & Shoulders, 2019; Rivera, 2019). Convergent validity substantiates the scope wherein results were aligned and congruent with conceptual or theoretical values (Kregel et al., 2018; Venter et al., 2018). The average variance extracted (AVE) values of > .5 point to convergent validity. Conversely, discriminant validity describes the amount of difference a construct presents towards other constructs and their intent to measure a given subject (McDonagh et al., 2020). Measurements of discriminant validity were customarily done via cross-loadings or Fornell-Lackner methodology. The model instrument leveraged convergent validity methodology (Kim et al., 2017). Tests for concept discriminant validity leveraging Fornell-Lackner specifications, along with cross-loadings, present each concept as independent of their measures. Reliability and validity testing for Kim et al.'s (2017) survey instrument confirmed both measures as suitable for the conducted study.

Adaption of the model instrument was necessary for this study. Wording changes and order/positioning shifts of the specific survey questions were necessary for alignment with the research question. Other researchers have likewise modified instrument wording versus the models their studies were based on to account for differences in research question scope and applicability (Grunz et al., 2020; Hopkins et al., 2020; Huang et al., 2020). Even though the changes conducted while adapting the instrument were minimal, validity and reliability scoring could have been modified. Credibility and reproducibility were fundamental concepts of quantitative studies (Moeyaert, 2019). Threats to said credibility and reproducibility can impact the generalizability of studies (Agénor, 2020). The reassertion of the study instrument validity and reliability was ensured via employing Cronbach's coefficient alpha and factor analysis.

Untouched initial survey data will be kept on either an encrypted Amazon Web Services S3 bucket or a physically secure, encrypted USB drive for at least five years. Centiment hosting data was purged to mitigate the risk of unauthorized leakage. Raw data will be available upon request inside of the five-year purge period.

Data Collection Techniques

Surveys sent via electronic means present a straightforward medium for participant data collection. Quantitative researchers can use such close-ended questionnaires to collect participant data (Nansen-McCloskey & Ziliak, 2019). Sending the survey links through emails facilitates a more considerable potential participant base while simultaneously keeping their participation anonymous. Closed-ended questions give quantitative researchers the means to convert participant responses into quantitative data points (House, 2018). This study used an online survey that leverages closed-ended questions with Likert-scale responses to amass participant data. There were various examples in the literature of both similar survey construction and delivery methodologies (Gesser-Edelsburg et al., 2019).

As with any data collection technique, online surveys had both pros and cons associated with their use. By far, the most significant advantage of this method is the ability for quick dissemination of the survey to a higher number of people (Smith & Hasan, 2020). This permeation into the higher participant population can ultimately lead to a higher chance of generalizing study findings. Conversely, question context is somewhat lost through the online survey method: Researchers cannot ensure that participants fully parsed what the questions were asking, thereby possibly marring the accuracy of responses (Smith & Hasan, 2020). Online surveys can simultaneously increase participant response rates while also lessening the researcher's logistical load by reducing the time necessary for entering data (Dubovicki & Topolovcan, 2020). The latter is accomplished by the very nature of online survey data collection; for this study specifically, Centiment allowed for the seamless importing of respondent data into easily configurable .csv format (Legg et al., 2020). Even with these convenience advantages, there were still low response rates when using online surveys (Otuyama et al., 2020). Low response rates can be somewhat mitigated by targeting a population interested (not just knowledgeable) in the topic studied and keeping the survey to as short a length as the research question allows (Michaels et al., 2019). To spur participation, I kept the length of survey completion to between twelve and fifteen minutes.

This study used an online survey to collect participant data. I created a web-based series of questions through the Centiment web-based data collection tool and circulated the survey by embedding a link inside an invitation email. I collected data for approximately two calendar weeks to ensure that enough participants were reached.

Pilot studies help verify and hone the specifics of a given data collection technique (Juul et al., 2020). Although a pilot study can improve overall instrument characteristics, I did not conduct a pilot study after gaining IRB endorsement. All survey questions used in this study were placed in Appendix A.

Data Analysis

This research study attempted to examine the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, and the intention to use secure EMRs. The null and alternative hypotheses were:

H_0: There is no statistically significant relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

H_a: There is a statistically significant relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

Various tests can investigate the relationships between variables. Simple tests include analysis of variance (ANOVA), t-test, regression testing, and Pearson product-moment correlation (Seeram, 2019). Study design alignment should be a significant deciding factor when choosing which correlational test should be the foundation of inferential statistical investigations. For example, ANOVA and t-tests were more closely aligned with research investigating possible relationships among means scores across multiple participant groups (Chirume & Dick, 2019; Seeram, 2019). Since this study did not investigate causal effects nor variable relationships among multiple participant groups and instead seeks to investigate the intent to adopt within a single participant group, ANOVA and t-tests would not be sufficiently aligned. Conversely, multiple regression analysis enhances simple linear regression to investigate any possible relationships between multiple independent variables and a single dependent variable (Jain, 2017). I used multiple regression analysis to measure if the four independent variables had a statistically significant relationship with the intent to use secure EMRs.

Before engaging in data analysis, researchers should seek to eliminate invalid responses that might introduce research errors. Incomplete (either wholly blank or partially filled) surveys are removed for the sake of enhanced result quality (Macinnis et al., 2018; Otuyama et al., 2020). Data scrubbing to remove incomplete surveys was conducted before SPSS data importing. Following the import, data validation was undertaken by comparing both data sets and correcting or excising any incorrectly coded, transcribed, or missing data.

Data scrubbing must also include the removal of outliers. Outliers represent data points that sharply diverge from other data in the sample set and should be expunged prior to analyzing the data (O'Brien et al., 2018). Outliers can negatively affect correlational study findings and should, therefore, be expurgated before data analysis. Visual analysis of results by leveraging scatter plots and boxplots can detect outliers (Xia et al., 2018). I perused the results from a scatter plot of the data to pinpoint and subsequently excised any outliers detected.

Descriptive Statistics

The survey instrument includes three demographic questions on age, gender, and job title. I did not use job titles for analytical purposes aside from aligning participants with demographic participant requirements on knowledge and familiarity with secure EMR use. I did use gender and age to uncover possible insights into any relationship between the dependent and independent variables. I leveraged SPSS software to quantify descriptive statistical measures such as mean, percentage, frequencies, standard deviations, and total numbers of participants in the study.

Inferential Statistics

I conducted this research to investigate the existence of any relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMR in healthcare organizations. Multiple regression analysis was most appropriate in this instance since the hypothesis contained more than two independent variables. I used SPSS software to examine two hypotheses via multiple regression analytic methodology to measure any significance within the variables' relationships.

SPSS is a popular data analysis tool used by researchers. Even though inferential data analysis is practically possible in more straightforward spreadsheet software (such as LibreOffice, Excel, or Google Sheets), SPSS and other equally robust software packages enable researchers to directly import collected data, creating an environment more conducive to the advanced analysis required for studies such as the one proposed (Hamutoglu et al., 2020). Several quantitative study researchers have utilized SPSS for their data analysis (Z. X. Huang, 2018; Najafi Ghezeljeh et al., 2019; Noori et al., 2020). Researchers have also leveraged SPSS to produce descriptive statistics for data analysis (Najafi Ghezeljeh et al., 2019; Noori et al., 2020). SPSS has also been useful for examining the validity and reliability of any proposed research instruments (Z. X. Huang, 2018; Najafi Ghezeljeh et al., 2019). I used the Windows native SPSS version 25 for descriptive statistics generation, validity evaluation, reliability assessment, and correlational analysis of the data. The study results are made available in Section 3.

Study Validity

This study contained the investigation of four threats to validity: construct and reliability, statistical conclusion, internal, and external. To craft a reliable study, researchers employ these four validity tests to examine the appropriateness of research tools, the data collected, and the collection process itself (Jordan, 2018). Researchers pursuing quantitative research goals pursue valid and reliable results to generate accurate and dependable data to support future decision-making. The next sections recount the process I followed to safeguard the reliability and validity of the study.

Threats to External Validity

This study addressed the issue of garnering sufficient generalizability. To this end, using a convenience sample was discounted as it presented a possible threat to external validity. Convenience sampling would have facilitated faster data gathering, but the threat of generalizability loss was too high (Hoevenaar-Blom et al., 2017). To maintain this study's external validity, I distributed the survey instrument to medical practitioners throughout the target setting regardless of department, specialty, or clinical/nonclinical designation. This distribution choice enhanced study generalizability to both larger hospital and mixed medical populations.

Two conventional methods researchers use to dampen any negative impact to study external validity were reducing any undue influence on participants and managing sufficient statistical power throughout datasets. Leveraging an online survey actively curtails any researcher/subject contact, minimizing researcher influence on collected responses (Loban et al., 2017). Additionally, study power can be a mitigating factor against external validity loss through enhanced significance recognition. By adjusting the statistical power setting for this study to .95, there was a 95% likelihood of detecting any statistically significant events. Through online survey use lessening the effects of researcher influence on participant responses, in concert with the power setting, external validity maintenance was more likely. Pretest and posttest design factor relevance were negated through the study's nonexperimental modeling and further preserved its external validity.

Threats to Internal Validity

Threats to external validity were not significant risks to the proposed study. Quasiexperimental and experimental designs were prone to various threats concerning internal validity, including instrumentation, maturation, testing, history, statistical regression, selection, and selection by maturation (Flannelly et al., 2018). Studies that seek to examine or uncover causal relationships were more vulnerable to internal validity threats. Since this study leveraged a nonexperimental design to examine possible correlational relationships between independent and dependent variables, internal validity was a significantly reduced risk factor to consider. Additionally, the absence of study variable manipulation also contributed to reductions of threats to internal validity.

Threats to Construct Validity

The degree that an instrument truthfully gauges any concept or construct is customarily known as construct validity (Zakariya, 2020). Construct validity is customarily denoted as either discriminant or convergent validity (Ford & Scandura, 2018). Discriminant validity is a measure of the degree that one construct differs from another construct and how well that construct measures what it was meant to calculate (Joshanloo, 2019). Both cross-loadings, along with Fornell-Larkcer criteria, were leveraged to tabulate the presence and level of discriminant validity. Convergent validity designates the level at which the results attune and support conceptual values (Kregel et al., 2018). Satisfactory levels of convergent validity were indicated with outer loadings of greater than .7, in addition to average variance extracted (AVE) values of .5. This study adapted an instrument employed by Kim et al. (2017) that accounted for discriminant as well as convergent validity levels that confirmed study validity and reliability. To measure construct validity, I assessed both portions of the multiple regression analytics and the correlation matrix.

Threats to Statistical Conclusion Validity

One of a researcher's ultimate objectives is to generate accurate results that support and enable future decision-making on the research topic. The measure of this trustworthiness is known to researchers as statistical conclusion validity (Grigsby & McLawhorn, 2019; Kenny, 2019; Lachmann et al., 2017). Type I and Type II errors are the main threats that can arise within threats to statistical conclusion validity (Kenny, 2019; Lachmann et al., 2017). With both types of errors, the fundamental veracity of study conclusions is malleable, leading to potentially misguided decision-making regarding acceptance or rejection of the null hypothesis. Such threats to statistical conclusion validity can emerge from missteps in statistical analysis, statistical power measurements, and a faulty sampling procedure (Grigsby & McLawhorn, 2019; Kenny, 2019). The following sections present the deliberate decision made regarding instrument reliability, data assumptions, and sample size that sufficiently mitigated any risk factors influencing statistical conclusion validity.

Reliability of the Instrument

Producing a consistent and reproducible study is an essential goal for the quantitative researcher; this is a crucial aspect of what is meant when discussing instrument reliability (Svendsen et al., 2020). For this study, I used an instrument that has been previously validated (Kim et al., 2017). The instrument authors leveraged composite reliability for scale vetting, falling comfortably in the higher than .7 range (Kim et al., 2017). Per previous researchers, values at or beyond the .7 mark for measurements of composite reliability, as well as for internal consistency through Cronbach's alpha, indicated appropriate levels of an instrument's internal reliability (Jordan, 2018; Kim et al., 2020; Svendsen et al., 2020). The original instrument employed by Kim et al. (2017) was reliable. However, due to slight alterations of question-wording made to support the EMR context and practitioner (versus patient) respondent perspective, instrument reliability could have been justifiably called into question. To alleviate such concerns, the ultimate reliability for the adapted instrument was related. I used the SPSS software package to reverify instrument internal reliability through both Cronbach's coefficient alpha, and factor analyses for scale validation on each variable tested.

Data Assumptions

A researcher must always endeavor to note any necessary data assumptions that can correspond with the statistical analysis chosen for a study. Because I used multiple regression, examined assumptions included homoscedasticity, linearity, and multicollinearity (Moeyaert, 2019; Talukder et al., 2020). Should any of the named assumptions not have held, then any data from the regression analysis could have been deemed inaccurate. Conversely, the dearth of any assumption violations substantiated choosing multiple regression testing for this study.

Assessing normality was critical for confirming that the proper statistical test for a study was being utilized. Assumed normality in a multiple regression analysis context posits normality amongst dependent and independent variables (King et al., 2019). I checked for normality by SPSS-enabled residual plotting. Researchers were customarily able to plot the normal distribution against the error distribution to assess nonnormality (King et al., 2019).

Assumptions of linearity involve supposing a linear relationship between model coefficients and the dependent variable (Jain, 2017). Akin to the proposed normality testing, I evaluated nonlinearity through SPSS-enabled residual plotting: A diagonal data point distribution denotes linearity.

Assuming homoscedasticity entails presuming random errors of constant variance (Talukder et al., 2020). Conversely, heteroscedasticity indicates the lack of constant variances pointing to statistical influences aside from randomness (Wilcox, 2019). Homoscedasticity is one conventional marker of uniformity. Outliers were one primary distortion that makes collected datasets heteroscedastic (Wilcox, 2019). Visual data representations such as scatter plots assist in the detection of heteroscedasticity. On the other hand, checking for homoscedasticity is accomplished via Levene, Durbin-Watson, and Brown-Forsythe testing (Talukder et al., 2020; Tambe, 2020). I used an SPSS-enabled Durbin-Watson test, in addition to visual markers, to test assumed homoscedasticity. Residual plots alongside scatter plots were leveraged for visual heteroscedasticity checking.

Multicollinearity is defined as a state of increased or high intercorrelations among independent variables being used to measure the same entities (Lachmann et al., 2017). Assumed collinearity is based upon the presumption that each forecasted variable is independent of any other variables (Wilcox, 2019). Left unmitigated, multicollinearity could cloud interpretations of findings, leading to a potential uptick in Type 1 errors; these errors, in turn, could influence a researcher to reject the null hypothesis incorrectly. Tests such as condition number and variance inflation factor (VIF) can help researchers test for multicollinearity (Salmerón et al., 2018). VIF measures higher than ten denote a high level of multicollinearity (Kim, 2019), while variance inflation factors within three to ten signal potential multicollinearity issues (Bager et al., 2017; Kim, 2019). Researchers utilize the Durbin-Watson statistical test for multicollinearity correction (Naghawi et al., 2019). Through SPSS-enabled VIF testing, I checked for any indications of multicollinearity.

Researchers must plan to address any violations that occur within their research appropriately. Bootstrapping is a technique that allows for augmenting analytical accuracy in the face of assumption violations by way of data resampling (Talloen et al., 2019). Bootstrapping allows random sampling methods to be leveraged should assumption violations occur. With no such violations, bootstrapping would not need to be used.

Sample Size

The generalizability and significance of research results were shaped by sample size. Estimates on effect size signify the strength of relationships among variables (Schawo et al., 2019). Smaller sample sizes open the door for Type II errors, results with low power, and potentially overstated effect sizes (Erev et al., 2019). Smaller sample sizes also introduced a higher possibility of negating test significance, as well as delivering false positives. I ran a power analysis prior to collecting the data for sample size determination with a medium effect size ($f = 0.15$) and a .95 power. This sample size analysis determined a suitable sample size range from between 85 and 129 participants.

Transition and Summary

The purpose of this quantitative correlational study was to examine the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and intention to use secure EMR in healthcare organizations. Section 2 consisted of considerations on the role of the researcher, research methods and design, study participants, sampling and population approaches, protection of participants, and other ethical research concerns. Section 2 also encompassed deliberations on data collection and analysis schemas, instrument choice, and plans to safeguard study validity. Section 3 consists of a complete study synopsis, along with a presentation of the findings from collected survey data analysis. Section 3 closes with a discussion on applying the findings to professional practice, any implications for social change, and recommendations for action and further study.

Section 3: Application to Professional Practice and Implications for Change

For this study, I leveraged a quantitative, correlational research methodology to investigate the relationships between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations. In this section, I display the gathered data analysis findings from the completed study participant online surveys.

Overview of the Study

The purpose of this correlational, quantitative research study was to examine the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations. I assembled data from 126 medical practitioners through Centiment panels. One hundred twenty-six participants reached a power of .944; the participant response rate logged at 43%. Evaluation of any relationship between the dependent and independent variables was conducted through multiple linear regression analysis.

The multiple regression analysis results were significant, $F(2,123) = 26.13$, $p < .001$, $R2 = 0.30$, denoting that approximately 30% of the variance in the intention to use secure EMRs could be explained by performance expectancy and effort expectancy. Performance expectancy ($\beta = .20$, $p < .00$) and effort expectancy ($\beta = .38$, $p < .02$) were significant at the .05 level of prediction for medical practitioners' intent to use secure EMRs. These two independent variables were the most significant predictors of the intention to use secure EMRs. Thus, I rejected the null hypothesis because the study results verified a relationship between the independent variables and medical practitioners' intention to use secure EMR.

Presentation of the Findings

Inferential and descriptive statistics were used to elucidate findings from the collected sample data. Multiple regression analysis was used to assess both the hypotheses and the research question. The research question was:

RQ: What is the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations?

The null and alternative hypotheses posited in the study were:

H_0: There is no statistically significant relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

H_a: There is a statistically significant relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

Before analyzing the data, I appraised the data for missing data points, multicollinearity, linearity, normality, outliers, and homoscedasticity. Afterward, I ran a multiple regression analysis to ascertain any possible relationships of significance among the variables. The analysis results are presented in the following sections.

Descriptive Statistics

Data were gathered from a sample of 126 medical practitioners in a medium to large hospital setting within the northeastern United States (N = 126). Table 2 shows the percent statistics and frequency of participants' age and gender. The most frequently observed category of gender was female (n = 97, 77%), with men representing 23% (n = 29). Participants range in age from 18 to 79. The most frequently observed age category was 34–49 (n = 49, 38.9%). A total of 95.2 % of participants were between the ages of 18 and 64.

Table 2

Frequency and Percent Statistics of Participants' Age and Gender

Demographic	Frequency (n)	Percent
Age		
18-34	47	37.3
34-49	49	38.9
50-64	24	19.0
65-79	6	4.8
Total	126	100.0
Gender		
Female	97	77.0
Male	29	23.0
Total	126	100

Note. Total N = 126

Table 3 displays the frequency of distribution of demographic job roles in the collected sample. There were 126 valid participants' responses with roles varying from aides and therapists to the executive level. Descriptive statistics analysis conducted on the job roles displayed that the highest percentage of participants held the title of nurse (34.1%).

Table 3

Frequency and Percent Statistics of Participants' Job Role

Demographics	Frequency (n)	Percent
Job title		
Aide	6	4.8
Behavioral therapist	1	0.8
Executive level	6	4.8
Case manager	1	0.8
CMA	2	1.6
CNA	5	4
Certified recovery specialist	1	0.8
Clinical psychologist	1	0.8
Consultant	1	0.8
Dental	5	4
Director	4	3.2
Doctor	10	7.9
EMT	1	0.8
Lab personnel	2	1.6
Nurse	43	34.1
Manager/supervisor	8	6.3
Medical assistant	5	4
Admin	3	2.4
Medical technologist	4	3.2
MRI technologist	1	0.8
Occupational therapist	4	3.2
Pharmacy	2	1.6
Physical therapist	6	4.8
Respiratory therapist	1	0.8
Social worker	1	0.8
Therapist	2	1.6
Total	126	100

Note. Total N = 126

Table 4 shows the frequency distribution of participants' intention to use secure EMRs in healthcare organizations. The most frequently observed behavioral intention category was *agree* (n = 47, 37.3%).

Table 4

Frequency and Percent Statistics of Participants' Behavioral Intention to Adopt Secure EMR

Variable		
Behavioral intention	Frequency (n)	Percent
Strongly disagree/disagree	1	0.8
Disagree	1	0.8
Disagree/neither agree nor disagree	5	4
Neither agree nor disagree	10	7.9
Neither agree nor disagree/ agree	17	13.5
Agree	47	37.3
Agree/strongly agree	19	15.1
Strongly agree	26	20.6
Total	126	100

Note. Total N = 126

Testing of Hypotheses

The hypotheses testing consisted of multiple regression analysis to ascertain any significant relationships between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations. Independent and dependent composite score variables were computed via averaging pertinent construct case scores.

Data Cleaning

Prior to evaluating the research question, data were screened for univariate outliers as well as missing values. Frequency count was leveraged to evaluate any potential missing data, with no cases skipping or missing any survey items. Per Cohen et al. (2002), outliers are defined as any values outside of +/– 3 standard deviations from the mean (Cohen et al., 2002). No univariate outliers were found nor removed; thus, all variables included all cases (n = 126). Presented in Table 5 are the descriptive statistics of all covariates used to investigate the research question. The negative skewness results for all variables indicated varying levels of distribution shapes: effort expectancy, social influences, and facilitating conditions indicating fairly symmetrical skewness (values approximately between –.5 and .5), behavioral intention evidencing moderate skewness (values approximately between –1 and .5 or .5 and 1), and performance expectancy indicating a highly skewed distribution (values approximately less than –1 or greater than 1). The varying levels for kurtosis across all variables make indications against concluding that the data set was normally distributed.

Table 5

Descriptive Statistics of Dependent and Independent Variables

Variable	M	SD	N	SEM	Skewness	Kurtosis
Performance expectancy	4.119	0.8401	126	0.0748	-1.093	1.421
Effort expectancy	3.925	0.7296	126	0.065	-0.534	0.484
Social influences	3.869	0.7488	126	0.0667	-0.006	-0.987
Facilitating conditions	4.091	0.6047	126	0.0539	-0.22	-0.133
Behavioral intention	4.04	0.7283	126	0.0649	-0.677	0.599

Validity and Reliability Assessment

Per the Section 2 discussion on validity, the instrument I used was a validated scale from a prior research study. Kim et al. (2017) had tested and validated the constructs I used, but I chose to test the instrument scales' reliability and validity due in part to my adaptation of the scales for study context alignment. This alignment included replacing the study patient perspective and question focus with an emphasis on the medical practitioner context.

Reliability Analysis

The Cronbach's alpha measurement was analyzed for both the dependent and independent variables. Analyzing measurement scales along with their constituent properties is conducted under the purview of reliability analysis (Cohen et al., 2002). A scale is considered sufficiently reliable if the coefficient is ≥ .70. Cronbach's alpha was calculated leveraging the guidance in Jordan (2018): > .9 excellent, > .8 good, > .7 acceptable, > .6 questionable, > .5 poor, and ≤ .5 unacceptable. Per the results in Table 6, performance expectancy showed good reliability; behavioral intention, effort expectancy, and social influence indicated acceptable reliability; and facilitating conditions indicated unacceptable reliability. Therefore, barring facilitating conditions, both classifications of variables were considered satisfactorily reliable.

Table 6

Cronbach's Alpha Analysis of Reliability for the Dependent and Independent Variables

Scale	No. of Items	α
Behavioral intention	2	0.73
Performance expectancy	2	0.84
Effort expectancy	2	0.73
Social influence	2	0.75
Facilitating conditions	2	0.60

Validity Analysis

Various authors presented differing baselines for determining sufficient sample size when considering Confirmatory Factor Analysis (CFA). A group of authors use baselines predicated on the total size of the sample. A general baseline of 300 is commonly fixed as a marker for sufficient sample size (Cohen et al., 2002). Different authors prefer the (*N:q*) ratio of a full sample size to the number of free parameter estimates (regression approximations, latent variables, variances, covariances, indicators) incorporated into the model. Brown (2015) recommends an *N:q* ratio of approximately 20:1. Byrne (2011) advocates for an *N:q* ratio threshold of half that, at 10 to 1. Even lower, Bentler and Chou (1987) proposed that an adequate ratio was in the 5:1 range. The *N:q* ratio in this analysis was approximately 12 to 1, with a sample size of 126; according to the generalized benchmark, the sample size was insufficient for CFA. Additionally, CFA is not accurate at less than three observed variables due to the resultant negative degrees of freedom calculation (Brown, 2015). To confirm the validity of the constructs, I began with a Spearman's rank-order correlation to analyze the strength and direction of any association between the independent variables and behavior intention to adopt secure EMRs, if any.

Spearman's correlation coefficient can calculate values in the ± 1range, which can signal either a perfect positive (when + 1) or a perfect negative (- 1) association among the variables tested. A zero (0) correlation coefficient signals no association between tested variables. When p values in a Spearman's correlation are below .05, the correlation coefficients are held to be statistically significant. As shown in Table 7, there is a statistically significant positive correlation between each of the independent variables and behavioral intention to adopt, with performance expectancy expressing the strongest correlation out of all variables tested.

Table 7

Spearman's Rho Correlation Between Dependent Variables and Behavioral Intention

Variable	Correlation coefficient	N	p
Performance expectancy	0.507	126	.00
Effort expectancy	0.486	126	.00
Social influence	0.399	126	.00
Facilitating conditions	0.422	126	.00

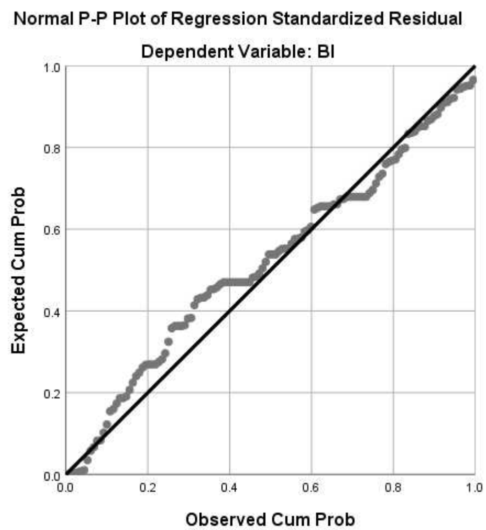
Evaluation of Statistical Assumptions

Assumptions of residual normality, residual homoscedasticity, multicollinearity, and the presence of outliers were tested. I assessed homoscedasticity, independence, and linearity via scatterplots; there were no observable violations. The following sections present the findings from these assumption analyses.

Normality was investigated leveraging a P-P scatterplot (Moeyaert, 2019). An approximately straight line is an indicator in a P-P scatter plot of normality. Deviations from normality were observed (see Figure 9).

Figure 9

P=P Scatterplot of Regression Standardized Residual Testing Normality

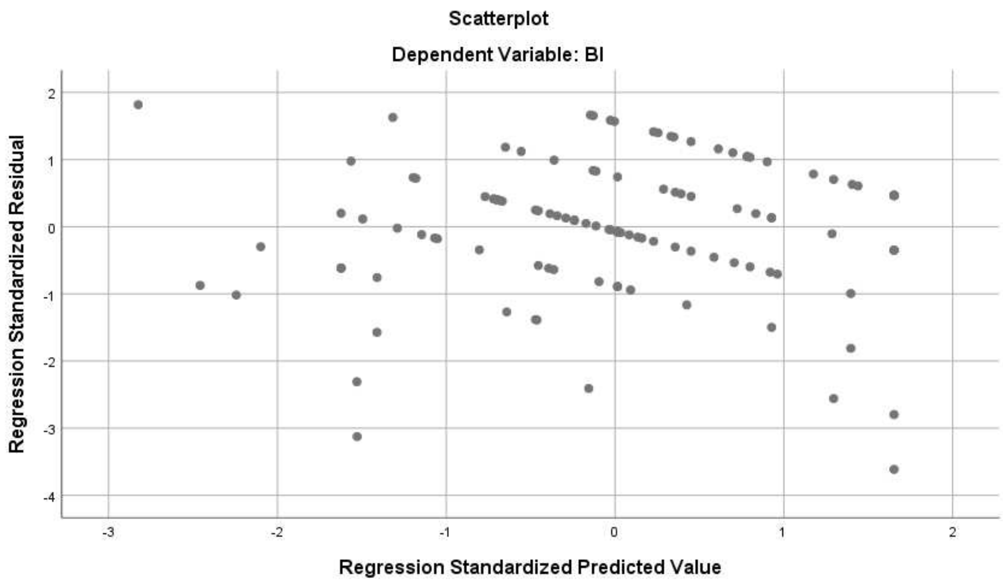


Homoscedasticity

Homoscedasticity was investigated by comparing the residuals against predicted values in the form of a scatterplot (Talukder et al., 2020). Homoscedasticity is upheld as a valid assumption if the points in the scatterplot evidence a random distribution and a mean of zero, lacking any readily apparent curvature. This assumption was encountered (Figure 10). Additionally, to further validate homoscedasticity, I leveraged the Durbin-Watson test. The data output was a Durbin-Watson $d = 2.012$, falling within the critical values of $1.5 < d < 2.5$. There was also no first-order linear auto-correlation in this multiple linear regression dataset.

Figure 10

Standardized Residuals Predicted Value for Observing Homoscedasticity



Multicollinearity

To examine multicollinearity, variance inflation factor (VIF) was analyzed to verify the absence of multicollinearity amongst predicting variables. Every value examined was below a threshold of ten, with a tolerance score of less than three, which indicates multicollinearity as not a significant concern in this study. Table 8 displays the calculated VIF for every independent variable.

Table 8

Variance Inflation Factor for Independent Variables

Variable	VIF
Performance expectancy	1.535
Effort expectancy	1.973
Social influence	1.604
Facilitating conditions	2.07

Outliers

For outlier identification, I investigated the scatterplot of residuals, Figure 10, for any data points that fell outside of three standard variations. While there was one residual that approached this threshold, no significant violations of assumptions were observed.

All examinations for assumptions of multiple linear regression except normality indicated no significant violations. The data was nonnormal.

Inferential Results

Multiple linear regression analysis was run to address the research question, namely investigating the prediction of intention to use secure EMRs from (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. I chose the “Enter” variable selection method that encompassed all the chosen forecasters for the linear regression modeling.

RQ: What is the relationship between medical practitioners’ perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations?

H_0: There is no statistically significant relationship between medical practitioners’ perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

H_a: There is a statistically significant relationship between medical practitioners’ perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions and the intention to use secure EMRs in healthcare organizations.

The results of the initial linear regression model were significant, F(4,121) = 13.87, p < .001, R2 = 0.31, demonstrating that approximately 31% of the variance in the intention to use secure EMR in healthcare organizations could be explained by (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions. The observed results of the multiple linear regression analysis indicated social influence and facilitating conditions not to be statistically significant predictors to the model (p > .05). Conversely, the observed results of the multiple linear regression indicated a statistically significant association between performance expectancy (B = .17, p < .03) and effort expectancy (B = .29, p < .01) as statistically significant predictors (p < .05) of medical practitioners' intent to adopt secure EMR (Table 9).

Table 9

Multiple Regression Analysis Among Study Predictors

Variable	B	SE	95% CI	β	t	p
(Intercept)	1.37	0.39	[0.59, 2.15]	0.00	3.48	0.01
Performance expectancy	0.17	0.08	[0.01, .33]	0.201	2.16	0.03
Effort expectancy	0.29	0.11	[0.08, .50]	0.293	2.77	0.01
Social influence	0.11	0.09	[-0.079, .29]	0.108	1.13	0.26
Facilitating conditions	0.98	0.13	[-0.16, .36]	0.081	0.75	0.46

Note. $F(4,121) = 13.87$, $p < .001$, $R^2 = 0.31$. Dependent Variable: Behavioral Intention to Adopt Secure EMR

The results of the best-fit linear regression model were also significant, F(2,123) = 26.13, p < .001, R2 = 0.30, demonstrating that approximately 30% of the variance in the intention to use secure EMR in healthcare organizations could be explained by (a) performance expectancy and (b) effort expectancy. The observed results of the initial multiple linear regression analysis indicated social influence and facilitating conditions not to be statistically significant predictors to the model (p > .05), leading to a rerunning of the analysis with only performance expectancy and effort expectancy as independent variables. Conversely, the observed results of the multiple linear regression indicated a statistically significant association between performance expectancy (B = .20, p < .02) and effort expectancy (B = .38, p < .01) as statistically significant predictors (p < .05) of medical practitioners' intent to adopt secure EMR (Table 10). I rejected the null hypothesis.

Table 10

Best-Fit Multiple Regression Analysis Among Study Predictors

Variable	B	SE	95% CI	β	t	p
(Intercept)	1.71	0.33	[1.06, 2.36]	0.00	5.23	0.00
Performance expectancy	0.20	0.08	[0.05, .36]	0.233	2.58	0.01
Effort expectancy	0.38	0.90	[0.20, .56]	0.382	4.22	0.00

Note. $F(2,123) = 26.13$, $p < .001$, $R^2 = 0.30$. Dependent Variable: Behavioral Intention to Adopt Secure EMR

Analysis Summary

In this study, I investigated the relationship between medical practitioner's perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions, and the intention to use secure EMR in healthcare organizations. I ran a multiple linear regression analysis to evaluate the said relationship; there were no violations of any assumptions. Cronbach's Alpha was computed to assess instrument reliability. All UTAUT survey instrument variables were calculated at .7 save for facilitating conditions, signaling the other indicators were reliable for measurement. Generally, the four constructs of this UTAUT model predicted medical practitioners' intention to use secure EMR in healthcare organizations $F(4,121) = 13.87$, $p < .001$, $R2 = 0.31$. Specifically, a best-fit model was run excluding nonsignificant factors (social influence and facilitating conditions) that resulted in $F(2,123) = 26.13$, $p < .001$, $R2 = 0.30$. By assessing the beta (β), performance expectancy and effort expectancy were the most influential factors in medical practitioners' intention to use secure EMR.

Theoretical Conversation on Findings

There was evidence of a gap between knowledge of secure EMR best practices and the adoption of secure EMRs by medical practitioners in healthcare organizations within the literature review. Leveraging the UTAUT theoretical framework, I employed a quantitative survey instrument to query medical practitioners from medium to large New York City hospital settings for background on their perspectives of crucial factors that influence the intent to use secure EMRs. The utilized constructs were cataloged as performance characteristics, social context, and organizational context.

Empirical evidence collected in this study supported acceptance of the alternative hypothesis. The results for the research question showed that approximately 30% of the variance in the intent to use secure EMR could be explained by (a) performance expectancy and (b) effort expectancy ($R^2 = 0.30$). I rejected the null hypothesis.

The findings denoted that neither the social nor organizational characteristics are significant, while the performance characteristics were significant. A possible reason for these findings is the proposed continued expansion of UTAUT to capture more granular characteristics at the social and organizational levels to close any predictive gaps that the original UTAUT might express (Zwain, 2019).

Performance Characteristics

Two variables were utilized to describe performance characteristics (performance expectancy and effort expectancy) as well as assess the hypothesis. The findings gleaned from this study indicated that both performance characteristics were significant factors for predicting medical practitioners' intention to use secure EMR. The findings align with Venkatesh et al. (2003), who posited that performance characteristics were among the direct determinants of intention to use technology.

Performance Expectancy

One result from the data investigation was that performance expectancy had a significant relationship with the intention to use secure EMR in US hospitals. The results confirmed Venkatesh et al. (2003), as well as the results in similar healthcare settings that examined performance expectancy as part of a UTAUT-centric inquiry (Alam et al., 2020; Brandsma et al., 2020; Kapser & Abdelrahman, 2020). Some UTAUT studies added additional moderating elements on performance characteristics, but this did not wholly remove the relationship significance of performance characteristic variables on the dependent variables in each study (Baishya & Samalia, 2020; Harlie et al., 2019; Marinković et al., 2020; Suki & Suki, 2017). One possible explanation for the consistency of findings in the literature, reinforced by this data investigation, is the principal connection that study participants make between technology and its purpose to enhance performance in given tasks. Such constant observable results regarding performance expectancy, even in studies where moderating factors were introduced to uncover possibly nascent underlying relationships among performance characteristics, reinforce conclusions surrounding performance characteristics' primacy (and particularly performance expectancy) as predictor elements.

Effort Expectancy

An added outcome of the data analysis was that effort expectancy, in line with the results for performance characteristics as a whole, has a significant relationship with the intention to use secure EMR in a hospital setting. The results also confirmed Venkatesh et al.'s (2003) exposition on UTAUT, as well as aligning with further literature examining the nature of any relationship between effort expectancy and the respective dependent variables (Almetere et al., 2020; Kaye et al., 2020; Magsamen-Conrad et al., 2019; Zwain, 2019). The results for effort expectancy are not mixed in relation to earlier studies. However, there would be a call for further research surrounding the effects of moderating factors on effort expectancy, which are more pronounced for this variable than for the other performance characteristic, performance expectancy (Arif et al., 2018; Gupta et al., 2020; Madigan et al., 2017; Mansoori et al., 2018).

Social Context

The social context describes aspects of an organization or group that enhance or detract from cohesion among individuals, both to each other as separate entities and to a group as a whole (Patel & Patel, 2018). The study results observed that social context did not have a significant relationship with the intention to use secure EMR. The previous scholarship did find a significant relationship between social context/social influence and the intention to adopt new technology (El-Masri & Tarhini, 2017; Rakhmawati et al., 2020; Vermaut, 2017; Zhou et al., 2018). However, many of the later examples determined that there were other moderating factors (some demographic with others being more a result of more extensive social context variables) that could contribute to social influence expressing this predictive relationship (Alam et al., 2020; Rakhmawati et al., 2020; Zhou et al., 2018). Previous studies have been mixed in their findings of social influence as a primary predictor for technological adoption. Therefore, further research is needed before making more definitive conclusions.

Organizational Context

In this study, the variable of facilitating conditions described the organizational context aspects of technology adoption influences. The study results showed that facilitating conditions did not have a significant relationship with intent to use secure EMRs by medical practitioners. Previous studies were mixed regarding the significance of facilitating conditions in general, what specific factors to consider when crafting the facilitating conditions construct in particular, as well as how strong of a relationship existed if there was one found (Baishya & Samalia, 2020; Kapser & Abdelrahman, 2020; Panhwer et al., 2020; Raza et al., 2019; Sobti, 2019). When extending the breadth of compositional factors, the relationship significance between facilitating conditions and the given dependent variable(s) typically increases, but this then creates discursive space for academic objection from scholars positing that too much of an extension brings the conceptual framework for a study into the realm of UTAUT2 (Chipeva et al., 2018; Farooq et al., 2017; Mansoori et al., 2018). Therefore, concerning prior scholarship, the results for facilitating conditions are not completely clear. Thus, further research is necessary before attaining more definitive findings.

Applications to Professional Practice

The multiple regression analysis findings in conjunction with a correlational, quantitative research study design assisted in measuring the levels of significance in the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions, and the intention to use secure EMR in healthcare organizations. For this research study, the UTAUT framework assisted in adapting a research paradigm to assess the factors that influence the intent to use secure EMRs. Only a smaller number of studies were detected in the literature that examined the relationships between working in the medical field, knowledge of secure EMR best practices, and the intent to use secure EMR best practices in the said field. This study is significant to IT practice because it might facilitate awareness around what influences the actual intent to use secure EMRs in populations with a working knowledge of the technology. Future practitioners can implement the survey instrument and research model for use in subsequent secure EMR studies.

Within this study, the factors with the most influence on intention to use secure EMR by medical practitioners in healthcare organizations were performance characteristics in the form of performance expectancy and effort expectancy. Kim et al. (2017) first presented the employed theoretical model's validity and reliability; confirmation for this study was achieved through regression analysis. Based on the research, there are multiple implications for prospective practitioners in the medical field.

Performance expectancy was the primary influence on intention to use secure EMR. Medical practitioners, particularly the technologists designing security solutions regarding EMRs, should seek to spearhead initiatives that are both secure and as easy to use as possible. Security implementation without proper training of personal on specific use cases or security initiatives that do not make usability and workflow enhancements a notable design concerns are less likely to see continued rates of adoption beyond any initial user interest (Tavares & Oliveira, 2018). Any group that focuses on either or both performance expectancy and effort expectancy observe higher rates of technological adoption across new and existing technologies (Feldman et al., 2018; Khan et al., 2020).

Demographic factors are also considered when crafting a holistic secure EMR technology deployment strategy (Alam et al., 2020). The difficulty in application to professional practice is determining exactly where and how said factors are to be considered when planning both training and adoption approaches (Brandsma et al., 2020). Medical practitioners should be cognizant of the observably mixed effect of demographic moderators, as well as the need for further investigation of both social influence and facilitating conditions before launching any major new technological initiatives dealing with secure EMR (Magsamen-Conrad et al., 2019).

Information security professionals, risk managers, and healthcare IT specialists can leverage these study’s findings to develop secure EMR best practices that more closely align with medical practitioners’ inherent competencies and motivations, thereby expanding secure EMR usage. Opportunities exist for all three stakeholder groups (information security professionals, risk managers, and healthcare IT specialists) to spur secure EMR use by simplifying the implementation of secure EMRs and improving training on their usage.

Implications for Social Change

I investigated the relationship between the four independent variables of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions, and the dependent variable of the intention to use secure EMR in healthcare organizations. Study results showed the independent variables performance expectancy and effort expectancy having a significant relationship with the intent to use secure EMRs in medium to large NYC hospitals. These insights can be leveraged to hone organizational strategies for the proliferation of secure EMR use.

Social change implications from this study can be viewed concerning both the base increased adoption of secure EMRs and the enhanced efficacy of the training associated with their secure use. When practitioners craft better, more individualized training programs for medical personnel surrounding secure EMR, overall implementation costs for this technology will decrease. This decrease in overhead would, in turn, remove financial barriers to secure EMR adoption in underserved patient care demographics, allowing for the health benefits care efficiencies associated with digitized medical care to reach previously isolated societal sectors.

Recommendations for Action

I investigated the relationship between the four independent variables of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions, and the dependent variable of the intention to use secure EMR in healthcare organizations. Study results expressed that two of the independent variables (social influence and facilitating conditions) had little to no significant observable relationship with the intent to use secure EMRs in healthcare organizations. By winnowing out such variables without significance, models for predicting intention to use secure EMRs can be improved and enhanced throughout the healthcare field.

While the mandate for and practical use of secure EMRs in the medical sector is not altogether new, it is there where the call for action would be most beneficial: Even after decades of increasing adoption, there are still too many gaps between theory and application regarding secure EMR best practices. It is recommended that more studies be conducted, both within the UTAUT framework and through other framework perspectives, to investigate the barriers to the alignment of medical practitioner actions with known best practices for secure EMRs. Also, broadening the scope of future studies beyond the New York City or even the U.S. east coast region would provide opportunities for hypothesis validation and comparison of findings.

Recommendations for Further Study

Multiple limitations were identified within this study. Firstly, the participant pool was restricted to medical practitioners in medium to large NYC hospital settings. As Tarabasz and Poddar (2019) posit, varying demographics and market sectors have varying factors that influence the intention to use technology. A future study could focus on expanding the sample population by either broadening the scope of inquiry outside of medical practitioners’ use of secure EMR or querying the same medical practitioner sample population on their secure EMR use in other industry sectors as geographical footprints.

Participant surveys were all gathered through Centiment panels. The study population was not incentivized to take the survey; future studies may seek to incentivize respondents to elicit more meaningful results or open the possibilities of longer inquiries. Additionally, results can only indeed be generalized to medical practitioners with comparable demographic qualities as this study's participants. Future studies should seek to broaden both the collection tools utilized as well as the audience studies for broader applicability of findings.

Another limitation of the study was the lack of moderating factors examined, especially when considering the lack of observed significance for two primary factors in customary UTAUT models: social influence and facilitating conditions. The reintroduction of gender, age, occupation, race, and hedonic motivations, while usually reserved for studies conducted through the UTAUT2 framework, could identify existing predictive forces within the social influence and facilitating conditions constructs that this study did not find (Almaiah et al., 2019; Nghi et al., 2020). Such moderating factors would not need to be limited in application just to the independent variables that showed no significant relationship in this study; performance expectancy and effort expectancy could also provide more in-depth insights overall to both researchers and field participants if considered with a mix of moderating factors as well (Angeli et al., 2020; Merhi et al., 2019). There is the possibility that by leveraging additional factors in an integrated model, greater predictive significance could be observed on what influences the intention to use secure EMR in a healthcare organization.

Prospective researchers could leverage this work to investigate the adoption intention of other secure technologies aside from EMRs, both within the healthcare space and without. Additionally, researchers could utilize this study's proposed model to analyze secure EMR use intention in other industries that touch and interact with EMRs and other parts of the world where secure EMRs are in heavy or mandatory rotation.

Reflections

Nothing worth doing is easy. To that notion, my time at Walden University has been a profoundly worthwhile endeavor. From the time I started, I have steadily refined my academic research abilities, specifically within the quantitative realm, as well as designing research studies overall. This expanded toolkit will allow me to continue my research within the medical IT and security fields.

When starting my doctoral study journey, I was not overly familiar with the inner technical workings of EMRs themselves, much less what research frameworks or intellectual constructs were best suited to their study. This unfamiliarity changed as my research began to focus on EMRs in general and the motivations behind their use. Through the applied study of plentiful peer-reviewed articles, my grasp on the chosen UTAUT framework became firmer, as did my ability to relate this theoretical structure to studying practitioners' intentions to use secure EMRs.

There were no previously existing biases when I started researching the relationship between (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions, and the dependent variable of the intention to use secure EMR in healthcare organizations. Findings denote a significant relationship between (a) performance expectancy and (b) effort expectancy and medical practitioners' intention to use secure EMRs. This study's results offer insights to medical IT decision-makers on which factors have the most influence on medical practitioners' intention to use secure EMRs in medium to large hospital settings.

Summary and Study Conclusions

I ran a correlational, quantitative study to investigate the relationship between medical practitioners' perceptions of (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, and the intention to use secure EMR in healthcare organizations. I solicited responses from 126 medical practitioners through Centiment panels; this quantity of respondents met the required sample size. The response rate was 43%. Through the SPSS software package, I conducted instrument validity and reliability analyses, descriptive statistics measurements, and standard multiple regression analysis to examine the hypothesis posed by the research question.

Statistical results analysis supported the alternative hypothesis. Two of the four independent variables (performance expectancy and effort expectancy) assisted in predicting the intention to use secure EMRs. Even with some of the study's limitations, medical practitioners in medium to large healthcare organizations can utilize the findings to guide decision-making surround which factors influence the use of secure EMRs the most. Thus, this study represents a significant impact on the existing library of research involving the intention to use secure EMRs.

References

Abouelmehdi, K., Beni-Hssane, A., Khaloufi, H., & Saadi, M. (2017). Big data security and privacy in healthcare: A review. *Procedia Computer Science*, *113*, 73–80. https://doi.org/10.1016/j.procs.2017.08.292

Abrar, M., Bashir, M., Shabbir, R., & Saqib, S. (2019). Adoption of mobile banking services in emerging market: An investigation from the perspective of UTAUT2 theory. *Dialogue (1819-6462)*, *14*(3), 150–160.

Adhikari, B., Pell, C., & Cheah, P. Y. (2020). Community engagement and ethical global health research. *Global Bioethics, 31*(1), 1–12. https://doi.org/10.1080/11287462.2019.1703504

Agénor, M. (2020). Future directions for incorporating intersectionality into quantitative population health research. *American Journal of Public Health, 110(*6), 803–806. https://doi.org/10.2105/ajph.2020.305610

Akinsanya, O. O., Papadaki, M., & Sun, L. (2019). Factors limiting the adoption of cloud computing in teleradiology. *International Journal for Information Security Research, 9*(2), 854–861. https://doi.org/10.20533/IJISR.2042.4639.2019.0098

Alalwan, A. A. (2020). Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. *International Journal of Information Management, 50*, 28–44. https://doi.org/10.1016/j.ijinfomgt.2019.04.008

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., & Algharabat, R. (2018). Examining factors influencing Jordanian customers' intentions and adoption of internet banking:

Extending UTAUT2 with risk. *Journal of Retailing and Consumer Services, 40,* 125–138. https://doi.org/10.1016/j.jretconser.2017.08.026

Alam, M. Z., Hoque, M. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International Journal of Information Management, 50*(October 2018), 128–143. https://doi.org/10.1016/j.ijinfomgt.2019.04.016

Alblooshi, S., Aziati, N., & Abdul, B. (2019). An empirical investigation of the unified theory of acceptance and use of technology in e-learning adoption in higher education institutions in the UAE. *International Journal of Research and Review, 6*, 133–147.

Al-Issa, Y., Ashraf Ottom, M., & Tamrawi, T. (2018). eHealth cloud security challenges: A survey. *Journal of Healthcare Engineering, 13*(1), 15. https://doi.org/10.1155/2019/7516035

AlKhars, M. A. (2019). Survey and analysis of the quantitative methods used in electricity research on GCC countries: 1983–2018. *Heliyon, 5*(10). https://doi.org/10.1016/j.heliyon.2019.e02634

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of a mobile learning system in higher education. IEEE Access, 7, 174673–174686. https://doi.org/10.1109/ACCESS.2019.2957206

Almalki, S. (2016). Integrating quantitative and qualitative data in mixed methods research—challenges and benefits. *Journal of Education and Learning, 5*(3), 288. https://doi.org/10.5539/jel.v5n3p288

Almetere, E. S., Kelana, B. W. Y., & Mansor, N. N. A. (2020). Using UTAUT model to determine factors affecting internet of things acceptance in public universities. *International Journal of Academic Research in Business and Social Sciences, 10*(2), 141–150. https://doi.org/10.6007/IJARBSS/v10-i2/6915

Al-Omari, A. I., & Haq, A. (2019). A new sampling method for estimating the population mean. *Journal of Statistical Computation and Simulation, 89*(11), 1973–1985. https://doi.org/10.1080/00949655.2019.1604710

Alqahtani, A., Crowder, R., & Wills, G. (2017). Barriers to the adoption of EHR systems in the Kingdom of Saudi Arabia: An exploratory study using a systematic literature review. *Journal of Health Informatics in Developing Countries, 11*(2), 1–23.

Alwahaishi, S., & Snášel, V. (2013). Consumers' acceptance and use of information and communications technology: A UTAUT and flow-based theoretical model. *Journal of Technology Management and Innovation, 8*(2), 61–73. https://doi.org/10.4067/s0718-27242013000200005

Angeli, A., Mcneill, A., & Coventry, L. (2020). Desires for active aging technology. *International Journal of Human-Computer Studies, 138*. https://doi.org/10.1016/j.ijhcs.2020.102412

Angst, C. M., Block, E. S., D'arcy, J., & Kelley, K. (2017). When do IT security investments matter? Accounting for the influence of institutional factors in the context of healthcare data breaches. *MIS Quarterly, 41*, 893–925. https://doi.org/10.25300/MISQ/2017/41.3.10

Arain, M. A., Tarraf, R., & Ahmad, A. (2019). Assessing staff awareness and effectiveness of educational training on IT security and privacy in a large healthcare organization. *Journal of Multidisciplinary Healthcare, 12*, 73–81. https://doi.org/10.2147/JMDH.S183275

Arif, M., Ameen, K., & Rafiq, M. (2018). Factors affecting student use of Web-based services: Application of UTAUT in the Pakistani context. Electronic Library, 36(3), 518–534. https://doi.org/10.1108/EL-06-2016-0129

Bager, A., Roman, M., Algelidh, M., & Mohammed, B. (2017). Addressing multicollinearity in regression models - A ridge regression application. *Journal of Social and Economic Statistics, 6*(1), 30–45.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 244–254. https://doi.org/10.17705/1jais.00122

Bailey, A. A., Pentina, I., Mishra, A. S., & Ben Mimoun, M. S. (2017). Mobile payments adoption by US consumers: an extended TAM. *International Journal of Retail and Distribution Management, 45*(6), 626–640. https://doi.org/10.1108/IJRDM-08-2016-0144

Baird, S., & Boak, G. (2016). Leading change: Introducing an electronic medical record system to a paramedic service. *Leadership in Health Services, 29*(2), 136–150. https://doi.org/10.1108/LHS-04-2015-0012

Baishya, K., & Samalia, H. V. (2020). Extending the unified theory of acceptance and use of technology with perceived monetary value for smartphone adoption at the bottom of the pyramid. *International Journal of Information Management, 51*. https://doi.org/10.1016/j.ijinfomgt.2019.11.004

Baki, R., Birgoren, B., & Aktepe, A. (2018). A meta-analysis of factors affecting perceived usefulness and perceived ease of use in the adoption of E-Learning systems. *Turkish Online Journal of Distance Education, 19*(4), 4–42. https://doi.org/10.17718/tojde.471649

Barr, N. G., & Randall, G. E. (2019). Protection of digital health information: Examining guidance from the physician regulatory colleges in Canada. *Health Information Management Journal*. https://doi.org/10.1177/1833358319873968

Beglaryan, M., Petrosyan, V., & Bunker, E. (2017). Development of a tripolar model of technology acceptance: Hospital-based physicians' perspective on EHR. *International Journal of Medical Informatics, 102*, 50–61. https://doi.org/10.1016/j.ijmedinf.2017.02.013

Bentler, P. M., & Chou, C. P. (1987). Practical issues in structural modeling. *Sociological Methods & Research, 16*(1), 78-117

Bervell, B., & Al-Samarraie, H. (2019). A comparative review of mobile health and electronic health utilization in sub-Saharan African countries. *Social Science and Medicine, 232*(April), 1–16. https://doi.org/10.1016/j.socscimed.2019.04.024

Bloomfield, J., & Fisher, M. (2019). Quantitative research design. *Journal of the Australasian Rehabilitation Nurses' Association, 22*(2), 27–30. https://doi.org/10.33235/jarna.22.2.27-30

Boehmke, F. J., Rury, A. M., Desmarais, B. A., & Harden, J. J. (2017). The seeds of policy change: Leveraging diffusion to disseminate policy innovations. Journal of *Health Politics, Policy, and Law, 42*(2), 285–307. https://doi.org/10.1215/03616878-3766728

Brandsma, T., Stoffers, J., & Schrijver, I. (2020). Advanced technology use by care professionals. *International Journal of Environmental Research and Public Health, 17*, 1–16. https://doi.org/10.3390/ijerph17030742

Brown, T. (2015). Confirmatory factor analysis for applied research (2nd Editio). The Guilford Press

Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning: A combination of the theory of reasoned action and technology acceptance model. *Journal of Research in Innovative Teaching & Learning, 11*(2), 178–191. https://doi.org/10.1108/jrit-03-2017-0004

Bunnik, E. M., Timmers, M., & Bolt, I. L. L. E. (2020). Ethical issues in research and development of epigenome-wide technologies. *Epigenetics Insights, 13*, 1–7. https://doi.org/10.1177/2516865720913253

Busdicker, M., & Upendra, P. (2017). The role of healthcare technology management in facilitating medical device cybersecurity. *Biomedical Instrumentation & Technology, 51*(s6), 19–25. https://doi.org/10.2345/0899-8205-51.s6.19

Byrne, B. (2011). Structural equation modeling with Mplus: Basic concepts, applications, and programming. Routledge

Calderón-Mora, J., Byrd, T. L., Alomari, A., Salaiz, R., Dwivedi, A., Mallawaarachchi, I., & Shokar, N. (2020). Group versus individual culturally tailored and theory-based education to promote cervical cancer screening among the underserved Hispanics: A cluster randomized trial. *American Journal of Health Promotion, 34*(1), 15–24. https://doi.org/10.1177/0890117119871004

Canova, L., Bobbio, A., & Manganelli, A. M. (2020). Predicting fruit consumption: A multi-group application of the theory of planned behavior. *Appetite, 145*. https://doi.org/10.1016/j.appet.2019.104490

Cassia de Moura, A., Gosling, M. D. S., Christino, J. M. M., & Macedo, S. B. (2017). Acceptance and use of technology by older adults for choosing a tourism destination: A study using UTAUT2. *Revista Brasileira de Pesquisa Em Turismo, 11*(2), 239–269. https://doi.org/10.7784/rbtur.v11i2.1277

Celik, H. (2016). Customer online shopping anxiety within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. *Asia Pacific Journal of Marketing and Logistics, 28*(2), 278–307.

Chen, X., Liu, Z., Wei, L., Yan, J., Hao, T., & Ding, R. (2018). A comparative quantitative study of utilizing artificial intelligence on electronic health records in the USA and China during 2008-2017. *BMC Medical Informatics & Decision Making, 18*(117), 15. https://doi.org/10.1186/s12911-018-0692-9

Cheng, C. C., Chang, Y. Y., Tsai, M. C., Chen, C. T., & Tseng, Y. C. (2019). An evaluation instrument and strategy implications of service attributes in LOHAS restaurants. *International Journal of Contemporary Hospitality Management, 31*(1), 194–216. https://doi.org/10.1108/IJCHM-06-2017-0361

Chi, T. (2018). Understanding Chinese consumer adoption of apparel mobile commerce:

An extended TAM approach. *Journal of Retailing and Consumer Services, 44*(April), 274–284. https://doi.org/10.1016/j.jretconser.2018.07.019

Chipeva, P., Cruz-Jesus, F., Oliveira, T., & Irani, Z. (2018). Digital divide at individual level: Evidence for Eastern and Western European countries. *Government Information Quarterly, 35*(3), 460–479. https://doi.org/10.1016/j.giq.2018.06.003

Chirume, S., & Dick, M. T. (2019). The quality of orientation in ODL: A correlational and content analysis of ZOU sessions held in Midlands Regional Campus. *Asian Association of Open Universities Journal, 14*(1), 50–63. https://doi.org/10.1108/aaouj-02-2019-0012

Cho, Y. (2017). A consumer satisfaction model based on the integration of EDT and TAM: Comparative study of Korean and US consumers. *Asia Pacific Journal of Marketing and Logistics, 29*(5), 978–993. https://doi.org/10.1108/APJML-07-2016-0127

Ciccarelli, C., Leinoudi, M., Semeraro, A. M., Di Trani, V., Angelozzi, G., Ciccarelli, E., & Corti, I. (2019). Assessment of sampling methods about the level of mercury in fish. *Italian Journal of Food Safety, 8*(3), 153–157. https://doi.org/10.4081/ijfs.2019.7593

Cohen, J., Cohen, P., West, S., & Aiken, L. (2002). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Routledge.

Colicchio, T., Cimino, J., & Del Fiol, G. (2019). Unintended consequences of nationwide EHR adoption: challenges and opportunities in the post-Meaningful Use era. (Preprint). Journal of Medical Internet Research. https://doi.org/10.2196/13313

Cook, L. D., Moore, S., Haynes, T., Mccalla, R., & Thwaites, K. (2019). A methodological review of mixed methods research studies from selected journals in the Caribbean. *International Journal of Multiple Research Approaches, 11*(3), 277–297. https://doi.org/10.29034/ijmra.vlln3a3

Crameri, K. A., Maher, L., Van Dam, P., & Prior, S. (2020). Personal electronic healthcare records: What influences consumers to engage with their clinical data online? A literature review. *Health Information Management Journal*, 1–7. https://doi.org/10.1177/1833358319895369

Cresswell, K., McKinstry, B., Wolters, M., Shah, A., & Sheikh, A. (2019). Five key strategic priorities of integrating patient-generated health data into United Kingdom electronic health records. *Journal of Innovation in Health Informatics, 25*(4), 6. https://doi.org/10.14236/jhi.v25i4.1068

Curtis, M. B., & Payne, E. A. (2008). An examination of contextual factors and individual characteristics affecting technology implementation decisions in auditing. *International Journal of Accounting Information Systems, 9*(2), 104–121. https://doi.org/10.1016/j.accinf.2007.10.002

Cypress, B. (2018). Qualitative research methods: A Phenomenological focus. *Dimensions of Critical Care Nursing, 37*(6), 302–309. https://doi.org/10.1097/DCC.0000000000000322

Dapar, M. L. G., Alejandro, G. J. D., Meve, U., & Liede-Schumann, S. (2020). Quantitative ethnopharmacological documentation and molecular confirmation of medicinal plants used by the Manobo tribe of Agusan del Sur, Philippines.

Journal of Ethnobiology and Ethnomedicine, 16(1), 1–61. https://doi.org/10.1186/s13002-020-00363-7

Davis, F. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results. https://dspace.mit.edu/handle/1721.1/7582

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

Dendere, R., Slade, C., Burton-Jones, A., Sullivan, C., Staib, A., & Janda, M. (2019). Patient portals facilitating engagement with inpatient electronic medical records: A systematic review (Preprint). *Journal of Medical Internet Research, 21*, 1–13. https://doi.org/10.2196/12779

Depaoli, S., Agtarap, S., Choi, A. Y., Coburn, K. M., & Yu, J. (2018). Advances in quantitative research within the psychological sciences. *Translational Issues in Psychological Science, 4*(4), 335–339. https://doi.org/10.1037/tps0000183

Deslonde, V., & Becerra, M. (2018). The technology acceptance model (TAM): Exploring school counselors' acceptance and use of Naviance. *The Professional Counselor, 8*(4), 369–382. https://doi.org/10.15241/vd.8.4.369

Dippel, E. A., Hanson, J. D., McMahon, T. R., Griese, E. R., & Kenyon, D. Y. B. (2017). Applying the theory of reasoned action to understanding teen pregnancy with American Indian communities. *Maternal and Child Health Journal, 21*(7), 1449–1456. https://doi.org/10.1007/s10995-017-2262-7

Dubovicki, S., & Topolovcan, T. (2020). Through the looking glass: Methodological features of research of alternative schools. *Journal of Elementary Education, 13*(1), 55–71. https://doi.org/10.18690/rei.13.1.55-71.2020

Dulle, F. W., & Minishi-Majanja, M. K. (2011). The suitability of the unified theory of acceptance and use of technology (UTAUT) model in open access adoption studies. *Information Development, 27*(1), 32–45. https://doi.org/10.1177/0266666910385375

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA - Extending the unified theory of acceptance and use of technology 2 (UTAUT2). *Educational Technology Research and Development, 65*(3), 743–763. https://doi.org/10.1007/s11423-016-9508-8

Eneizan, B., Mohammed, A. G., Alnoor, A., Alabboodi, A. S., & Enaizan, O. (2019). Customer acceptance of mobile marketing in Jordan: An extended UTAUT2 model with trust and risk factors. *International Journal of Engineering Business Management, 11*, 1–10. https://doi.org/10.1177/1847979019889484

Erev, I., Gilboa-Freedman, G., & Roth, Y. (2019). The impact of rewarding medium effort and the role of sample size. *Journal of Behavioral Decision Making, 32*(5), 507–520. https://doi.org/10.1002/bdm.2125

Erratum to: Diffusing software product and process innovations. (2017). In M. A. Ardis & B. L. Marcolin (Eds.), Diffusing Software Product and Process Innovations (Vol. 59). IFIP - The International Federation for Information Processing. https://doi.org/10.1007/978-0-387-35404-0_19

Evans, B. J. (2020). The perils of parity: Should citizen science and traditional research follow the same ethical and privacy principles? *The Journal of Law, Medicine & Ethics, 48*(1), 74–81. https://doi.org/10.1177/1073110520917031

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. Interactive Technology and Smart Education, 14(4), 329–348. https://doi.org/10.1108/ITSE-06-2016-0015

Feldman, S., Bhavsar, G., & Schooley, B. (2018). Consumer perceptions of health IT utilization and benefits. JAMIA Open, 00(0). https://doi.org/10.1093/jamiaopen/ooy049

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Addison-Wesley.

Flannelly, K. J., Flannelly, L. T., & Jankowski, K. R. B. (2018). Threats to the internal validity of experimental and quasi-experimental research in healthcare. *Journal of Health Care Chaplaincy, 24*(3), 107–130. https://doi.org/10.1080/08854726.2017.1421019

Florenthal, B. (2019). Young consumers' motivational drivers of brand engagement behavior on social media sites: A synthesized U&G and TAM framework. *Journal of Research in Interactive Marketing, 13*(3), 351–391. https://doi.org/10.1108/JRIM-05-2018-0064

Ford, L. R., & Scandura, T. A. (2018). A typology of threats to construct validity in item generation. *American Journal of Management, 18*(2), 132–142.

https://doi.org/10.33423/ajm.v18i2.298

Fuad, A., & Chien-Yeh, H. (2018). UTAUT for HSS: Initial framework to study health IT adoption in developing countries. *F1000 Research, 7*. https://doi.org/10.12688/f1000research.13798.1

Gesser-Edelsburg, A., Shahbari, N. A. E., Cohen, R., Halavi, A. M., Hijazi, R., Paz-Yaakobovitch, G., & Birman, Y. (2019). Differences in perceptions of health information between the public and health care professionals: Nonprobability sampling questionnaire survey. *Journal of Medical Internet Research, 21*(7). https://doi.org/10.2196/14105

Göçoğlu, A., & Demirel, N. (2019). Estimating the population proportion in modified ranked set sampling methods. *Journal of Statistical Computation and Simulation, 89*(14), 2694–2710. https://doi.org/10.1080/00949655.2019.1631315

Gordon, W. J., Bates, D. W., Fuchs, D., Pappas, J., Silacci, S., & Landman, A. (2019). Comparing characteristics of patients who connect their iPhones to an electronic health records system versus patients who connect without personal devices: Cohort study. *Journal of Medical Internet Research, 21*(8). https://doi.org/10.2196/14871

Green, S. B. (1991). How many subjects does it take to do a regression analysis? *Multivariate Behavioral Research, 26*(3), 499–510. https://doi.org/10.1207/s15327906mbr2603_7

Gregorio-Pascual, P., & Mahler, H. I. M. (2020). Effects of interventions based on the theory of planned behavior on sugar-sweetened beverage consumption intentions and behavior. *Appetite, 145*, 104491. https://doi.org/10.1016/j.appet.2019.104491

Grigsby, T. J., & McLawhorn, J. (2019). Missing data techniques and the statistical conclusion validity of the survey-based alcohol and drug use research studies: A review and comment on reproducibility. *Journal of Drug Issues, 49*(1), 44–56. https://doi.org/10.1177/0022042618795878

Grunz, J. P., Gietzen, C. H., Luetkens, K., Wagner, M., Kalb, K., Bley, T. A., Lehmkuhl, L., van Schoonhoven, J., Gassenmaier, T., & Schmitt, R. (2020). The importance of radial multiplanar reconstructions for assessment of triangular fibrocartilage complex injury in CT arthrography of the wrist. *BMC Musculoskeletal Disorders, 21*(1), 286. https://doi.org/10.1186/s12891-020-03321-2

Guetterman, T. C. (2020). Qualitative, Quantitative, and Mixed Methods Research Sampling Strategies. Oxford University Press.

Gupta, A., Yousaf, A., & Mishra, A. (2020). How pre-adoption expectancies shape post-adoption continuance intentions: An extended expectation-confirmation model. International Journal of Information Management, 52. https://doi.org/10.1016/j.ijinfomgt.2020.102094

Gyamfi, A., Mensah, K. A., Oduro, G., Donkor, P., & Mock, C. N. (2017). Barriers and facilitators to electronic medical records usage in the emergency centre at Komfo Anokye Teaching Hospital, Kumasi-Ghana. *African Journal of Emergency Medicine, 77*, 177–182. https://doi.org/10.1016/j.afjem.2017.05.002

Ha, N., Nguyen, T. L., Nguyen, T. P., & Nguyen, T. D. (2019). The effect of trust on consumers' online purchase intention: An integration of TAM and TPB.

Management Science Letters, 9(9), 1451–1460. https://doi.org/10.5267/j.msl.2019.5.006

Hamutoglu, N. B., Topal, M., & Gezgin, D. M. (2020). Investigating direct and indirect effects of social media addiction, social media usage, and personality traits on FOMO. *International Journal of Progressive Education, 16*(2), 248–261. https://doi.org/10.29329/ijpe.2020.241.17

Harandi, T. F., Taghinasab, M. M., & Nayeri, T. D. (2017). Development of the UTAUT2 model to measure the acceptance of medical laboratory portals by patients in Shiraz. *Electronic Physician, 2,* 1–17. https://doi.org/10.19082/5212

Harlie, M., Hairul, R. I., & Abbas, E. W. (2019). Managing information systems by integrating the information systems success model and the unified theory of acceptance and usage of technology. *Polish Journal of Management Studies, 20*(1), 192–201. https://doi.org/10.17512/pjms.2019.20.1.17

He, K., Zhang, J., & Zeng, Y. (2020). Households' willingness to pay for energy utilization of crop straw in rural China: Based on an improved UTAUT model. *Energy Policy, 140*(January). https://doi.org/10.1016/j.enpol.2020.111373

Head, G. (2018). Ethics in educational research: Review boards, ethical issues, and researcher development. *European Educational Research Journal, 19*(1), 72–83. https://doi.org/10.1177/1474904118796315

Herrero, Á., San Martín, H., & Garcia-De los Salmones, M. (2017). Explaining the adoption of social networks sites for sharing user-generated content: A revision of the UTAUT2. Computers in Human Behavior, 71, 209–217.

https://doi.org/10.1016/j.chb.2017.02.007

Hoevenaar-Blom, M. P., Guillemont, J., Ngandu, T., Beishuizen, C. R. L., Coley, N., Van Charante, E. P. M., Andrieu, S., Kivipelto, M., Soininen, H., Brayne, C., Meiller, Y., & Richard, E. (2017). Improving data sharing in research with context-free encoded missing data. *PLoS ONE, 12*(9), 1–7. https://doi.org/10.1371/journal.pone.0182362

Holt, T. P., & Loraas, T. M. (2019). Using Qualtrics panels to source external auditors: A replication study. *Journal of Information Systems, 33*(1), 29–41. https://doi.org/10.2308/isys-51986

Hopkins, K. L., Hlongwane, K. E., Otwombe, K., Dietrich, J., Cheyip, M., Khanyile, N., Doherty, T., & Gray, G. E. (2020). Level of adult client satisfaction with clinic flow time and services of an integrated non-communicable disease-HIV testing services clinic in Soweto, South Africa: A cross-sectional study. *BMC Health Services Research, 20*(1), 404. https://doi.org/10.1186/s12913-020-05256-9

House, J. (2018). Authentic vs. elicited data and qualitative vs. quantitative research methods in pragmatics: Overcoming two non-fruitful dichotomies. *System, 75*, 4–12. https://doi.org/10.1016/j.system.2018.03.014

Huang, J., Zhou, Y., & Sheeran, T. (2020). Educational researchers' ethical responsibilities and human subjects' ethical awareness: Implications for research ethics education in China. *Ethics and Behavior*, 1–14. https://doi.org/10.1080/10508422.2020.1740885

Huang, Z. X. (2018). Application of statistical inference in education and teaching.

Educational Sciences: Theory & Practice, 18(6), 2782–2793. https://doi.org/10.12738/estp.2018.6.179

Hui-Lung, H., Yu-Ming, K., Shiang-Ru, W., Bi-Kun, C., & Chung-Hung, T. (2016). A study of personal health record user's behavioral model based on the PMT and UTAUT integrative perspective. *International Journal of Environmental Research and Public Health, 14*(1), 8–22. https://doi.org/10.3390/ijerph14010008

Hung, S. Y., Nakayama, M., Chen, C. C., & Tsai, F.-L. (2019). Physician perceptions of electronic medical records: The impact of system service quality, and generation/experience gaps. *International Journal of Healthcare Technology and Management, 17*(4), 229–253. https://doi.org/10.1504/IJHTM.2019.10026703

Jain, S. (2017). Regression modeling of different proteins using linear and multiple analyses. *Network Biology, 7*(4), 80–93. http://www.iaees.org/publications/journals/nb/articles/2017-7(4)/regression-modeling-of-different-proteins.pdf

Johnson, D., & Shoulders, C. (2019). Beyond magic words and symbols: Rethinking common practices in quantitative research. *Journal of Agricultural Education, 60*(3), 291–303. https://doi.org/10.5032/jae.2019.03291

Johnson, S. L. (2019). Impact, growth, capacity-building of mixed methods research in the health sciences. *American Journal of Pharmaceutical Education, 83*(2), 136–139. https://doi.org/10.5688/ajpe7403

Johnston, R., Harris, R., Jones, K., Manley, D., Wang, W. W., & Wolf, L. (2019). Quantitative methods I: The world we have lost – or where we started from.

Progress in Human Geography, 43(6), 1133–1142. https://doi.org/10.1177/0309132518774967

Jordan, K. (2018). Validity, reliability, and the case for participant-centered research: Reflections on a multi-platform social media study. *International Journal of Human-Computer Interaction, 34*(10), 913–921. https://doi.org/10.1080/10447318.2018.1471570

Joshanloo, M. (2019). Structural and discriminant validity of the tripartite model of mental well-being: Differential relationships with the big five traits. *Journal of Mental Health, 28*(2), 168–174. https://doi.org/10.1080/09638237.2017.1370633

Joshi, M., Joshi, K. P., & Finin, T. (2019). Delegated Authorization Framework for EHR Services using Attribute Based Encryption. 1–12.

Juul, L., Pallesen, K. J., Bjerggaard, M., Nielsen, C., & Fjorback, L. O. (2020). A pilot randomised trial comparing a mindfulness-based stress reduction course, a locally-developed stress reduction intervention, and a waiting list control group in a real-life municipal health care setting. *BMC Public Health, 20*(1), 1–17. https://doi.org/10.1186/s12889-020-08470-6

Kalambe, K. B., & Apte, S. M. (2017). An exhaustive survey on security solutions in Healthcare 4.0. *Computer Communications, 153*(5), 311–335. https://doi.org/10.1016/j.comcom.2020.02.018

Kalinić, Z., Marinković, V., Djordjevic, A., & Liebana-Cabanillas, F. (2020). What drives customer satisfaction and word of mouth in mobile commerce services? A UTAUT2-based analytical approach. *Journal of Enterprise Information*

Management, 33(1), 71–94. https://doi.org/10.1108/JEIM-05-2019-0136

Kamerer, J. L., & Mcdermott, D. (2019). Cybersecurity: Nurses on the front line of prevention and education. *Journal of Nursing Regulation, 10*(4), 48–53. https://doi.org/10.1016/S2155-8256(20)30014-4

Kapser, S., & Abdelrahman, M. (2020). Acceptance of autonomous delivery vehicles for last-mile delivery in Germany – extending UTAUT2 with risk perceptions. Transportation Research Part C: Emerging Technologies, 111, 210–225. https://doi.org/10.1016/j.trc.2019.12.016

Kaye, S. A., Lewis, I., Forward, S., & Delhomme, P. (2020). A priori acceptance of highly automated cars in Australia, France, and Sweden: A theoretically-informed investigation guided by the TPB and UTAUT. *Accident Analysis and Prevention, 137*(May 2019). https://doi.org/10.1016/j.aap.2020.105441

Kenny, D. A. (2019). Enhancing validity in psychological research. *American Psychologist, 74*(9), 1018–1028. https://doi.org/10.1037/amp0000531

Kerry, M. J., & Huber, M. (2018). Quantitative methods in interprofessional education research: Some critical reflections and ideas to improving rigor. *Journal of Interprofessional Care, 32*(3), 254–256. https://doi.org/10.1080/13561820.2018.1426267

Khan, S., Zairah, N., Rahim, A., & Maarop, N. (2020). A systematic literature review and a proposed model on antecedents of trust to use social media for e-government services. *International Journal of Advanced and Applied Sciences, 7*(2), 44–56. https://doi.org/10.21833/ijaas.2020.02.007

Kim, J. H. (2019). Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology, 72*(6), 558–569. https://doi.org/10.4097/kja.19087

Kim, K. K., Sankar, P., Wilson, M. D., & Haynes, S. C. (2017). Factors affecting willingness to share electronic health data among California consumers. *BMC Medical Ethics, 18*(1), 1–11. https://doi.org/10.1186/s12910-017-0185-x

Kim, M. J., & Hall, C. M. (2020). What drives visitor economy crowdfunding? The effect of digital storytelling on the unified theory of acceptance and use of technology. *Tourism Management Perspectives, 34*. https://doi.org/10.1016/j.tmp.2020.100638

Kim, M. J., McKenna, H., Park, C. G., Ketefian, S., Park, S. H., Galvin, K., & Burke, L. (2020). Global assessment instrument for quality of nursing doctoral education with a research focus: Validity and reliability study. *Nurse Education Today, 91*. https://doi.org/10.1016/j.nedt.2020.104475

Kim, S., Lee, K. H., & Yoo, S. (2016). Analysis of the factors influencing healthcare professionals’ adoption of mobile electronic medical record (EMR) using the unified theory of acceptance and use of technology (UTAUT) in a tertiary hospital. *BMC Medical Informatics and Decision Making, 16*. https://doi.org/10.1186/s12911-016-0249-8

King, K. M., Pullmann, M. D., Lyon, A. R., Dorsey, S., & Lewis, C. C. (2019). Using implementation science to close the gap between the optimal and typical practice of quantitative methods in clinical science. *Journal of Abnormal Psychology, 128*(6), 547–562. https://doi.org/10.1037/abn0000417

Koorts, H., Naylor, P. J., Laws, R., Love, P., Maple, J. L., & van Nassau, F. (2020). What hinders and helps academics to conduct dissemination and implementation (D&I) research in the field of nutrition and physical activity? An international perspective. *The International Journal of Behavioral Nutrition and Physical Activity, 17*(1), 7. https://doi.org/10.1186/s12966-020-0909-z

Kregel, J., Schumacher, C., Dolphens, M., Malfliet, A., Goubert, D., Lenoir, D., Cagnie, B., Meeus, M., & Coppieters, I. (2018). Convergent validity of the Dutch Central Sensitization Inventory: Associations with psychophysical pain measures, quality of life, disability, and pain cognitions in patients with chronic spinal pain. *Pain Practice, 18*(6), 777–787. https://doi.org/10.1111/papr.12672

Kuchta, S. R., Brown, A. D., Converse, P. E., & Highton, R. (2016). Multilocus phylogeography and species delimitation in the Cumberland plateau salamander, plethodon kentucki: Incongruence among data sets and methods. *PLoS ONE, 11*(3), 1–26. https://doi.org/10.1371/journal.pone.0150022

Kurilovas, E., & Kubilinskiene, S. (2020). Lithuanian case study on evaluating suitability, acceptance, and use of IT tools by students - An example of applying technology-enhanced learning research methods in higher education. *Computers in Human Behavior, 107*. https://doi.org/10.1016/j.chb.2020.106274

Lachmann, M., Trapp, I., & Trapp, R. (2017). Diversity and validity in positivist management accounting research—A longitudinal perspective over four decades. *Management Accounting Research, 34*, 42–58. https://doi.org/10.1016/j.mar.2016.07.002

Lee, S. H. N., & Chow, P. S. (2020). Investigating consumer attitudes and intentions toward online fashion renting retailing. *Journal of Retailing and Consumer Services, 52*(October 2018), 101892. https://doi.org/10.1016/j.jretconser.2019.101892

Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: Extending UTAUT2 with information quality. *Sustainability (Switzerland), 11*. https://doi.org/10.3390/su11113141

Legg, K., Gee, E., Bolwell, C., Bridges, J., & Rogers, C. W. (2020). A cross-sectional survey of training and management of a cohort of 2-year-old standardbred racehorses in New Zealand. Journal of Equine *Veterinary Science, 87*, 102936. https://doi.org/10.1016/j.jevs.2020.102936

Leslie, H. H., Doubova, S. V., & Pérez-Cuevas, R. (2019). Assessing health system performance: Effective coverage at the Mexican Institute of Social Security. *Health Policy and Planning, 34*(2), ii67–ii76. https://doi.org/10.1093/heapol/czz105

Lewis, C. C., Boyd, M. R., Walsh-Bailey, C., Lyon, A. R., Beidas, R., Mittman, B., Aarons, G. A., Weiner, B. J., & Chambers, D. A. (2020). A systematic review of empirical studies examining mechanisms of implementation in health. *Implementation Science: IS, 15*(1), 1–25. https://doi.org/10.1186/s13012-020-00983-3

Liu, Y., Segev, S., & Villar, M. E. (2017). Comparing two mechanisms for green consumption: cognitive-affect behavior vs. theory of reasoned action. *Journal of*

Consumer Marketing, 34(5), 442–454. https://doi.org/10.1108/JCM-01-2016-1688

Loban, A., Mandefield, L., Hind, D., & Bradburn, M. (2017). A randomized trial found online questionnaires supplemented by postal reminders generated a cost-effective and generalizable sample, but don't forget the reminders. *Journal of Clinical Epidemiology, 92*, 116–125. https://doi.org/10.1016/j.jclinepi.2017.08.003

Long, H. (2017). Validity in mixed methods research in education: The application of Habermas' critical theory. *International Journal of Research & Method in Education, 40*(2), 201–213. https://doi.org/10.1080/1743727X.2015.1088518

Macinnis, B., Krosnick, J. A., Ho, A. S., & Cho, M. J. (2018). The accuracy of measurements with probability and nonprobability survey samples: Replication and extension. *Public Opinion Quarterly, 82*(4), 707–744. https://doi.org/10.1093/poq/nfy038

Madigan, R., Louw, T., Wilbrink, M., Schieben, A., & Merat, N. (2017). What influences the decision to use automated public transport? Using UTAUT to understand public acceptance of automated road transport systems. *Transportation Research Part F: Traffic Psychology and Behaviour, 50*, 55–64. https://doi.org/10.1016/j.trf.2017.07.007

Magsamen-Conrad, K., Wang, F., Tetteh, D., & Lee, Y.-I. (2019). Using technology adoption theory and a lifespan approach to develop a theoretical framework for eHealth literacy: Extending UTAUT. *Health Communication, 34*(19). https://doi.org/10.1080/10410236.2019.1641395

Manias, E., Bucknall, T., Wickramasinghe, N., Gray, K., Schaffer, J., & Rosenfeld, E. (2020). Patient and family engagement in communicating with electronic medical records in hospitals: A systematic review. *International Journal of Medical Informatics, 134*(November 2019), 104036. https://doi.org/10.1016/j.ijmedinf.2019.104036

Mansoori, K. A. A., Sarabdeen, J., & Tchantchane, A. L. (2018). Investigating Emirati citizens' adoption of e-government services in Abu Dhabi using a modified UTAUT model. *Information Technology and People, 31*(2), 455–481. https://doi.org/10.1108/ITP-12-2016-0290

Maree, J. G. (2020). Innovative career construction counselling for a creative adolescent. *British Journal of Guidance and Counselling, 48*(1), 98–113. https://doi.org/10.1080/03069885.2018.1504202

Marinković, V., Đorđević, A., & Kalinić, Z. (2020). The moderating effects of gender on customer satisfaction and continuance intention in mobile commerce: a UTAUT-based perspective. *Technology Analysis and Strategic Management, 32*(3), 306–318. https://doi.org/10.1080/09537325.2019.1655537

Martin, A. J., Collie, R. J., Durksen, T. L., Burns, E. C., Bostwick, K. C. P., & Tarbetsky, A. L. (2019). Growth goals and growth mindset from a methodological-synergistic perspective: Lessons learned from a quantitative correlational research program. *International Journal of Research and Method in Education, 42*(2), 204–219. https://doi.org/10.1080/1743727X.2018.1481938

Martineau, J. T., Minyaoui, A., & Boivin, A. (2020). Partnering with patients in healthcare research: A scoping review of ethical issues, challenges, and recommendations for practice. *BMC Medical Ethics, 21*(1), 1–20. https://doi.org/10.1186/s12910-020-0460-0

Martins, C., Duarte, J., Portela, C., & Santos, M. (2019). Improving the use of the electronic health record using an online documentation manual and its acceptance through the technology acceptance model. *Proceedings of the 5th International Conference on Information and Communication Technologies for Ageing Well and E-Health*, 346–351. https://doi.org/10.5220/0007878103460351

Mathai, N., McGill T., Toohey D. (2020). Factors influencing health hare consumer adoption of electronic health records: An empirical investigation. *Journal of Computer Information Systems*. https://doi.org/10.1080/08874417.2020.1802788

Mbonihankuye, S., Nkunzimana, A., & Ndagijimana, A. (2019). Healthcare data security technology: HIPAA compliance. *Wireless Communications and Mobile Computing*, 2019, 1–7. https://doi.org/10.1155/2019/1927495

McDonagh, J., Salamonson, Y., Ferguson, C., Prichard, R., Jha, S. R., Macdonald, P. S., Davidson, P. M., & Newton, P. J. (2020). Evaluating the convergent and discriminant validity of three versions of the frailty phenotype in heart failure: Results from the FRAME-HF study. *European Journal of Cardiovascular Nursing, 19*(1), 55–63. https://doi.org/10.1177/1474515119865150

McEnroe-Petitte, D., & Farris, C. (2020). Using gaming as an active teaching strategy in nursing education. *Teaching and Learning in Nursing, 15*(1), 61–65. https://doi.org/10.1016/j.teln.2019.09.002

Mehta, S., Jamieson, T., & Ackery, A. D. (2019). Helping clinicians and patients navigate electronic patient portals: Ethical and legal principles. *Canadian Medical Association Journal, 191*(40), E1100–E1104. https://doi.org/10.1503/cmaj.190413

Merhi, M., Hone, K., & Tarhini, A. (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy, and trust. *Technology in Society, 59*, 101151. https://doi.org/10.1016/j.techsoc.2019.101151

Mi, C., Chang, F. K., Lin, C. T., & Chang, Y. H. (2018). The theory of reasoned action to CSR behavioral intentions: The role of CSR expected benefit, CSR expected effort, and stakeholders. *Sustainability (Switzerland), 10*(12), 1–17. https://doi.org/10.3390/su10124462

Michaels, S., Pineau, V., Reimer, B., Ganesh, N., & Dennis, J. M. (2019). Test of a hybrid method of sampling the LGBT population: Web respondent-driven sampling with seeds from a probability sample. *Journal of Official Statistics, 35*(4), 731–752. https://doi.org/10.2478/jos-2019-0031

Mijin, N., Jang, H., Choi, B., & Khongorzul, G. (2019). Attitude toward the use of electronic medical record systems: Exploring moderating effects of self-image. *Information Development, 35*(1), 67–79. https://doi.org/10.1177/0266666917729730

Moeyaert, M. (2019). Quantitative synthesis of research evidence: Multilevel meta-analysis. *Behavioral Disorders, 44*(4), 241–256.

https://doi.org/10.1177/0198742918806926

Molnar, A. (2019). SMARTRIQS: A simple method allowing real-time respondent interaction in qualtrics surveys. *Journal of Behavioral and Experimental Finance, 22*, 161–169. https://doi.org/10.1016/j.jbef.2019.03.005

Muir, K. J. (2019). Historical perspectives informing modern-day nursing innovation and economics. *Nursing Economics, 37*(6), 284.

Munthe-Kaas, H. M., Glenton, C., Booth, A., Noyes, J., & Lewin, S. (2019). Systematic mapping of existing tools to appraise methodological strengths and limitations of qualitative research: First stage in the development of the CAMELOT tool. BMC *Medical Research Methodology, 19*(1), 1–14. https://doi.org/10.1186/s12874-019-0728-6

Munyoka, W., & Maharaj, M. (2017). The effect of UTAUT2 moderator factors on citizens' intention to adopt e-government: The case of two SADC countries. *Problems and Perspectives in Management, 15*(1), 115–123. https://doi.org/10.21511/ppm.15(1).2017.12

Naghawi, H., Alobeidyeen, A., & Abdel-Jaber, M. (2019). Econometric modeling for international passenger air travel demand in Jordan. *Jordan Journal of Civil Engineering, 13*(3), 377–385.

Najafi Ghezeljeh, T., Mohammad Aliha, J., Haghani, H., & Javadi, N. (2019). Effect of education using the virtual social network on the knowledge and attitude of emergency nurses of disaster preparedness: A quasi-experiment study. *Nurse Education Today, 73*(August 2018), 88–93.

https://doi.org/10.1016/j.nedt.2018.12.001

Nansen-McCloskey, D., & Ziliak, S. T. (2019). What quantitative methods should we teach to graduate students? A comment on Swann's "Is precise econometrics an illusion?" *Journal of Economic Education, 50*(4), 356–361. https://doi.org/10.1080/00220485.2019.1654957

Narattharaksa, K., Speece, M., Newton, C., & Bulyalert, D. (2016). Key success factors behind electronic record adoption in Thailand. *Journal of Health Organization & Management, 30*(6), 985–1008. https://doi.org/10.1108/JHOM-10-2014-0180

Nghi, H., Dung, M., Hoang, V. H., & Dung, T. (2020). Determinants influencing customers' decision to use mobile payment services: The case of Vietnam. Management Science Letters, 11, 2635–2646. https://doi.org/10.5267/j.msl.2020.3.029

Noori, J., Nejat, H., Nameni, E., & Fariborzi, E. (2020). Comparison of the effectiveness of the treatment of a monotheistic integrated and the objective relationship on self-differentiation and marital intimacy. *American Journal of Family Therapy, 48*(1), 70–86. https://doi.org/10.1080/01926187.2019.1679052

O'Brien, T., Russell, C. L., Tan, A., Washington, M., & Hathaway, D. (2018). An exploratory correlational study in the use of mobile technology among adult kidney transplant recipients. *Progress in Transplantation, 28*(4), 368–375. https://doi.org/10.1177/1526924818800051

Otuyama, L. J., de Carvalho Moraes, B. D. G., Mariano, L., & Rocha, V. (2020). SWOT analysis of a tool for data management in hematopoietic stem cell transplantation.

Biology of Blood and Marrow Transplantation, 26(3). https://doi.org/10.1016/j.bbmt.2019.12.460

Panhwer, P., Pitafi, A., Memon, M. S., & Memon, A. (2020). Awareness and reason towards slow adoption of e-payment system: Study of Hyderabad. *Annals of Contemporary Developments in Management & HR, 2*(1), 6–21. https://doi.org/10.33166/ACDMHR.2020.01.002

Paquin, R. S., & Keating, D. M. (2017). Fitting identity in the reasoned action framework: A meta-analysis and model comparison. *Journal of Social Psychology, 157*(1), 47–63. https://doi.org/10.1080/00224545.2016.1152217

Park, J. S., Sharma, R. A., Poulis, B., & Noble, J. (2017). Barriers to electronic medical record implementation: A comparison between ophthalmology and other surgical specialties in Canada. *Canadian Journal of Ophthalmology, 52*, 503–507. https://doi.org/10.1016/j.jcjo.2017.02.018

Patel, K. J., & Patel, H. J. (2018). Adoption of internet banking services in Gujarat: An extension of TAM with perceived security and social influence. International Journal of Bank Marketing, 36(1), 147–169. https://doi.org/10.1108/IJBM-08-2016-0104

Poellhuber, B., St-Laurent, S. F., & Roy, N. (2018). Using the TAM and functional analysis to predict the most used functions of an active learning classroom (ALC). *Frontiers in ICT, 5*(MAY), 1–11. https://doi.org/10.3389/fict.2018.00008

Provenzano, D., & Baggio, R. (2019). Quantitative methods in tourism and hospitality: A perspective article. *Tourism Review, 75*(1), 24–28. https://doi.org/10.1108/TR-07-

2019-0281

Rahi, S., & Abd. Ghani, M. (2018). The role of UTAUT, DOI, perceived technology security, and game elements in internet banking adoption. *World Journal of Science, Technology and Sustainable Development, 15*(4), 338–356. https://doi.org/10.1108/wjstsd-05-2018-0040

Rahi, S., Ghani, M. A., & Alnaser, F. M. I. (2017). Predicting customer's intentions to use internet banking: The role of technology acceptance model (TAM) in e-banking. *Management Science Letters, 7*(11), 513–524. https://doi.org/10.5267/j.msl.2017.8.004

Rakhmawati, H., T, S., & Rusydi, M. (2020). Influence of TAM and UTAUT models of the use of e-filing on tax compliance. *International Journal of Research in Business and Social Science, 9*(1), 106–111. https://doi.org/10.20525/ijrbs.v9i1.576

Ramírez-Correa, P., Rondán-Cataluña, F. J., Arenas-Gaitán, J., & Martín-Velicia, F. (2019). Analyzing the acceptation of online games in mobile devices: An application of UTAUT2. *Journal of Retailing and Consumer Services, 50(May)*, 85–93. https://doi.org/10.1016/j.jretconser.2019.04.018

Ravert, P., Whipple, K., & Hunsaker, S. (2020). Academic electronic health record implementation: Tips for success. *Clinical Simulation in Nursing, 41*, 9–13. https://doi.org/10.1016/j.ecns.2019.12.008

Raza, S. A., Shah, N., & Ali, M. (2019). Acceptance of mobile banking in Islamic banks: Evidence from modified UTAUT model. *Journal of Islamic Marketing, 10*(1), 357–376. https://doi.org/10.1108/JIMA-04-2017-0038

Razaque, A., Amsaad, F., Jaro Khan, M., Hariri, S., Chen, S., Siting, C., & Ji, X. (2019). Survey: Cybersecurity vulnerabilities, attacks, and solutions in the medical domain. *IEEE Access, 7*, 168774–168797. https://doi.org/10.1109/ACCESS.2019.2950849

Rendle-Short, J. (2019). Analysing atypical interaction: Reflections on the intersection between quantitative and qualitative research. *Journal of Pragmatics, 143*, 267–278. https://doi.org/10.1016/j.pragma.2018.04.009

Rezaei, R., Safa, L., & Ganjkhanlo, M. M. (2020). Understanding farmers' ecological conservation behavior regarding the use of integrated pest management- an application of the technology acceptance model. *Global Ecology and Conservation*. https://doi.org/10.1016/j.gecco.2020.e00941

Rivera, J. D. (2019). When attaining the best sample is out of reach: Nonprobability alternatives when engaging in public administration research. *Journal of Public Affairs Education, 25*(3), 314–342. https://doi.org/10.1080/15236803.2018.1429821

Rogers, E. M. (2003). Diffusion of Innovations (5th ed.). Free Press.

Roth, C. P., Coulter, I. D., Kraus, L. S., Ryan, G. W., Jacob, G., Marks, J. S., Hurwitz, E. L., Vernon, H., Shekelle, P. G., & Herman, P. M. (2019). Researching the appropriateness of care in the complementary and integrative health professions part 5: Using patient records: Selection, protection, and abstraction. *Journal of Manipulative and Physiological Therapeutics, 42*(5), 327–334.

https://doi.org/10.1016/j.jmpt.2019.02.008

Rothstein, M. A., Wilbanks, J. T., Beskow, L. M., Brelsford, K. M., Brothers, K. B., Doerr, M., Evans, B. J., Hammack-Aviran, C. M., McGowan, M. L., & Tovino, S. A. (2020). Unregulated health research using mobile devices: Ethical considerations and policy recommendations. *Journal of Law, Medicine & Ethics, 48*(Supp.1), in production. https://doi.org/10.1177/1073110520917047

Roulin, N., & Levashina, J. (2019). LinkedIn as a new selection method: Psychometric properties and assessment approach. *Personnel Psychology, 72*(2), 187–211. https://doi.org/10.1111/peps.12296

Ryan, E. C., Dubrow, R., & Sherman, J. D. (2020). Medical, nursing, and physician assistant student knowledge and attitudes toward climate change, pollution, and resource conservation in health care. *BMC Medical Education, 20*(1), 200. https://doi.org/10.1186/s12909-020-02099-0

Salameh, B., Eddy, L. L., Batran, A., Hijaz, A., & Jaser, S. (2019). Nurses' attitudes toward the use of an electronic health information system in a developing country. *SAGE Open Nursing, 5*. https://doi.org/10.1177/2377960819843711

Salmerón, R., García, C. B., & García, J. (2018). Variance inflation factor and condition number in multiple linear regression. *Journal of Statistical Computation and Simulation, 88*(12), 2365–2384. https://doi.org/10.1080/00949655.2018.1463376

Sangkaew, P., Jago, L., & Gkritzali, A. (2019). Adapting the technology acceptance model (TAM) for business events: The event organizer perspectives. *Event Management, 23*, 773–788. https://doi.org/10.3727/152599519x15506259855832

Schawo, S. J., Carlier, I. V. E., van Hemert, A. M., & de Beurs, E. (2019). Measuring treatment outcome in patients with anxiety disorders: A comparison of the responsiveness of generic and disorder-specific instruments. *Journal of Anxiety Disorders, 64*(March), 55–63. https://doi.org/10.1016/j.janxdis.2019.04.001

Seeram, E. (2019). An overview of correlational research. *Radiologic Technology, 91*(2), 176–179.

Shaw, N., & Sergueeva, K. (2019). The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International Journal of Information Management, 45*, 44–55. https://doi.org/10.1016/j.ijinfomgt.2018.10.024

Shiferaw, K. B., & Mehari, E. A. (2019). Modeling predictors of acceptance and use of electronic medical record system in a resource limited setting: *Using modified UTAUT model. Informatics in Medicine Unlocked, 17*(April), 100182. https://doi.org/10.1016/j.imu.2019.100182

Simpson, G., & Clifton, J. (2017). Testing the diffusion of innovations theory with data: Financial incentives, early adopters, and distributed solar energy in Australia. *Energy Research & Social Science, 29*, 12–22. https://doi.org/10.1016/j.erss.2017.04.005

Singh, V., & Dhiman, S. (2019). Shielding the confidentiality, privacy, and data security of bio-medical information in India: Legal edifice. In B. Singh, B. Saini, D. Singh, & A. Pandey (Eds.), Medical Data Security for Bioengineers. IGI Global. https://doi.org/10.4018/978-1-5225-7952-6.ch004

Smith, J. D., & Hasan, M. (2020). Quantitative approaches for the evaluation of implementation research studies. *Psychiatry Research, 283*(March 2019), 112521. https://doi.org/10.1016/j.psychres.2019.112521

Sobti, N. (2019). Impact of demonetization on diffusion of mobile payment service in India: Antecedents of behavioral intention and adoption using extended UTAUT model. *Journal of Advances in Management Research, 16*(4), 472–497. https://doi.org/10.1108/JAMR-09-2018-0086

Sohaib, O., Hussain, W., Asif, M., Ahmad, M., & Mazzara, M. (2020). A PLS-SEM neural network approach for understanding cryptocurrency adoption. *IEEE Access, 8*, 13138–13150. https://doi.org/10.1109/ACCESS.2019.2960083

Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. *Telematics and Informatics, 47*(December 2019), 1–14. https://doi.org/10.1016/j.tele.2019.101324

Solheim, E., Plathe, H. S., & Eide, H. (2017). Nursing students' evaluation of a new feedback and reflection tool for use in high-fidelity simulation – Formative assessment of clinical skills. A descriptive quantitative research design. *Nurse Education in Practice, 27*, 114–120. https://doi.org/10.1016/j.nepr.2017.08.021

Soltis-Jarrett, V., Shea, J., Ragaisis, K. M., Shell, L. P., & Newton, M. (2017). Integrated behavioral healthcare: Assumptions, definition and roles: Position paper from the International Society of Psychiatric-Mental Health Nurses. *Archives of Psychiatric Nursing, 31*(5), 433–439. https://doi.org/10.1016/j.apnu.2017.06.002

Sorace, J., Wong, H. H., DeLeire, T., Xu, D., Handler, S., Garcia, B., & MaCurdy, T. (2020). Quantifying the competitiveness of the electronic health record market and its implications for interoperability. *International Journal of Medical Informatics, 136*. https://doi.org/10.1016/j.ijmedinf.2019.104037

Speed-Crittle, S. D. (2019). *Healthcare Organization Change Management Strategies to Guide Information Technology for Information Technology Change Initiatives*. [Unpublished doctoral dissertation]. Walden University.

Suki, N. M., & Suki, N. M. (2017). Determining students' behavioural intention to use animation and storytelling applying the UTAUT model: The moderating roles of gender and experience level. *International Journal of Management Education, 15*(3), 528–538. https://doi.org/10.1016/j.ijme.2017.10.002

Sukno, R., & Pascual, I. (2019). E-commerce C2C en Chile: Incorporación de la reputación y de la confianza en el TAM. *Journal of Technology Management & Innovation, 14*(3), 72–82/ https://scielo.conicyt.cl/scielo.php?script=sci_arttext&pid=S0718-27242019000300072

Svendsen, M. J., Hendriksen, P. F., Schmidt, K. G., Stochkendahl, M. J., Rasmussen, C. N., & Holtermann, A. (2020). Inter-rater reliability of ergonomic work demands for childcare workers using the observation instrument TRACK. *International Journal of Environmental Research and Public Health, 17*(5), 1607–1629. https://doi.org/10.3390/ijerph17051607

Talloen, W., Loeys, T., & Moerkerke, B. (2019). A bootstrap version of the Hausman test to assess the impact of cluster-level endogeneity beyond the random intercept model. *Multivariate Behavioral Research, 54*(1), 1–14.

https://doi.org/10.1080/00273171.2018.1482192

Talukder, M. S., Sorwar, G., Bao, Y., Ahmed, J. U., & Palash, M. A. S. (2020). Predicting antecedents of wearable healthcare technology acceptance by elderly: A combined SEM-neural network approach. *Technological Forecasting and Social Change, 150*(June 2019). https://doi.org/10.1016/j.techfore.2019.119793

Tambe, M. N. (2020). *Factors influencing cloud computing adoption by small firms in the payment card industry* [Unpublished doctoral dissertation].Walden University.

Tamilmani, K., Rana, N. P., Prakasam, N., & Dwivedi, Y. K. (2019). The battle of brain vs. heart: A literature review and meta-analysis of "hedonic motivation" use in UTAUT2. *International Journal of Information Management, 46*, 222–235. https://doi.org/10.1016/j.ijinfomgt.2019.01.008

Tarabasz, A., & Poddar, G. (2019). Factors influencing adoption of wearable devices in Dubai. Journal of Economics and Management, 36(2), 123–143. https://doi.org/10.22367/jem.2019.36.07

Tavares, J., Goulão, A., & Oliveira, T. (2018). Electronic health record portals adoption: Empirical model based on UTAUT2. *Informatics for Health and Social Care, 43*(2), 109–125. https://doi.org/10.1080/17538157.2017.1363759

Tavares, J., & Oliveira, T. (2018). New integrated model approach to understand the factors that drive electronic health record portal adoption: Cross-sectional national survey. *Journal of Medical Internet Research, 20*(11). https://doi.org/10.2196/11032

Terry, N. P. (2017). Regulatory disruption and arbitrage in health-care data protection.

Yale Journal of Health Policy, Law, and Ethics, 17(1), 143–207.

Thomas, M. A. (2019). *Evaluating electronic health records interoperability symbiotic relationship to information management governance security risks* (13808526) [Doctoral dissertation, Northcentral University]. ProQuest.

Tounekti, O., Ruiz-Martinez, A., & Skarmeta Gomez, A. F. (2020). Users supporting multiple (mobile) electronic payment systems in online purchases: An empirical study of their payment transaction preferences. *IEEE Access, 8*, 735–766. https://doi.org/10.1109/ACCESS.2019.2961785

Tripopsakul, S. (2018). Social media adoption as a business platform: An integrated TAM-TOE framework. *Polish Journal of Management Studies, 18*(2), 350–362. https://doi.org/10.17512/pjms.2018.18.2.28

Tsai, M. F., Hung, S. Y., Yu, W. J., Chen, C. C., & Yen, D. C. (2019). Understanding physicians' adoption of electronic medical records: Healthcare technology self-efficacy, service level, and risk perspectives. *Computer Standards & Interfaces, March*. https://doi.org/10.1016/j.csi.2019.04.001

Tsai, T. H., Lin, W. Y., Chang, Y. S., Chang, P. C., & Lee, M. Y. (2020). Technology anxiety and resistance to change behavioral study of a wearable cardiac warming system using an extended TAM for older adults. *PloS ONE, 15*(1), 1–24. https://doi.org/10.1371/journal.pone.0227270

Turner, B., & Hasford, J. (2016). Planned to miss: The use of two-method measurement design in experimental marketing research. *Advances in Consumer Research, 44*, 655–658.

United States Department of Health and Human Services. (1979). The Belmont Report. https://doi.org/10.1021/bi00780a005

U.S. Department of Health and Human Services Office of Civil Rights. (2019). Annual report to Congress on breaches of unsecured protected health information for calendar years 2015, 2016, and 2017. U.S. Department of Health and Human Services.

Venkatesh, V., & Davis, F. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal studies. *Management Science, 46*(2), 186–204. http://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. M. G., Davis, G. G. B., & Davis, F. D. F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly, 36*(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management, 13*(1), 5–27. https://doi.org/10.1080/1097198X.2010.10856507

Venter, L., Richmond, J., & Taylor, M. F. (2018). Convergent validity of the Richmond Reversal Rating in relation to visual-spatial perception as measured by the SASP. *South African Journal of Occupational Therapy, 48*(3), 24–30. https://doi.org/10.17159/2310-3833/2017/vol48n3a5

Venugopal, P., Jinka, S., & Aswini Priya, S. (2016). User acceptance of electronic health records: Cross validation of the UTAUT model. *Sona Global Management Review, 10*(3), 42–54. https://www.sonamgmt.org/journal/previous-issues/may-2016/electronic-health.pdf

Vermaut, G. (2017). *Performance expectancy, effort expectancy, and social influence as factors predicting the acceptance of (non-) fluoroscopy-guided positioning for radiographs, and the relationship with leadership* (01006199) [Master's Thesis, Universiteit Gent Masterproef]. Universiteits Bibliotheek Gent.

Wang, Xingyuan, Liu, Y., & Liu, H. (2020a). Examining users' adoption of precision medicine: The moderating role of medical technical knowledge. *International Journal of Environmental Research and Public Health, 17*(3), 1113. https://doi.org/10.3390/ijerph17031113

Wang, Xue, Li, B., & Yin, S. (2020b). The convergence management of strategic emerging industries: Sustainable design analysis for facilitating the improvement of innovation networks. *Sustainability, 12*. https://doi.org/10.3390/su12030900

Wang, Y. Y., Wang, Y. S., & Jian, S. E. (2020c). Investigating the determinants of students' intention to use business simulation games. *Journal of Educational Computing Research, 58*(2), 433–458. https://doi.org/10.1177/0735633119865047

Wilcox, R. R. (2019). Robust regression: Testing global hypotheses about the slopes when there is multicollinearity or heteroscedasticity. *British Journal of Mathematical and Statistical Psychology, 72*(2), 355–369.

https://doi.org/10.1111/bmsp.12152

Wolgemuth, J. R., Hicks, T., & Agosto, V. (2017). Unpacking assumptions in research synthesis: A critical construct synthesis approach. *Educational Researcher, 46*(3), 131–139. https://doi.org/10.3102/0013189x17703946

Wong, S. H., & Chow, A. Y. M. (2017). An exploratory study on university students' perceptions of posthumous organ donation base on the theory of reasoned action. *Omega (United States), 75*(3), 284–299. https://doi.org/10.1177/0030222816633241

Xia, J., Gao, L., Kong, K., Zhao, Y., Chen, Y., Kui, X., & Liang, Y. (2018). Exploring linear projections for revealing clusters, outliers, and trends in subsets of multi-dimensional datasets. *Journal of Visual Languages and Computing, 48*(July), 52–60. https://doi.org/10.1016/j.jvlc.2018.08.003

Yoon, C. (2018). Extending the TAM for green IT: A normative perspective. *Computers in Human Behavior, 83*, 129–139. https://doi.org/10.1016/j.chb.2018.01.032

Yoon, C., Lim, D., & Park, C. (2020). Factors affecting adoption of smart farms: The case of Korea. *Computers in Human Behavior, 108*(May 2019), 106309. https://doi.org/10.1016/J.CHB.2020.106309

Zaini, W. H. A., Hamad, M. K., & Najim, A. S. (2020). Factors affecting the adoption of an accounting information system based on UTAUT2 and its implementation in a tourism corporation. *African Journal of Hospitality, Tourism and Leisure, 9*(1).

Zakariya, Y. F. (2020). Investigating some construct validity threats to TALIS 2018 teacher job satisfaction scale: Implications for social science researchers and practitioners. *Social Sciences, 9*(4). https://doi.org/10.3390/SOCSCI9040038

Zanaboni, P., Kummervold, P. E., Sørensen, T., & Johansen, M. A. (2019). Patients' use and experiences with online access to electronic health records in Norway: Results from an online survey. *Journal of Medical Internet Research, 22*. https://doi.org/10.2196/16144

Zhou, X., Liu, J., Wu, Q., & Zhang, Z. (2018). Privacy preservation for outsourced medical data with flexible access control. *IEEE Access*. https://doi.org/10.1109/ACCESS.2018.2810243

Zwain, A. A. A. (2019). Technological innovativeness and information quality as neoteric predictors of users' acceptance of learning management system: An expansion of UTAUT2. *Interactive Technology and Smart Education, 16*(3), 239–254. https://doi.org/10.1108/ITSE-09-2018-0065

Appendix A: Intent to Use Secure EMR for Medical Practitioners Survey Instrument

This survey will examine the level to which medical practitioner's perception of a) performance expectancy, b) effort expectancy, c) social influence, and d) facilitating conditions influence the intention to use secure EMR in healthcare organizations. The analysis of data will facilitate gaging the strength of this relationship. This survey has X sections that each sync with their respective variables. For each section, please respond on a scale of 1 to 5, as follows: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree. All items will be based on this 5-point scale unless otherwise noted with an *.

Demographic

What is your age? * (values between 18-100)

What is your gender? * ("Male," Female," "Prefer not to Answer")

What is your job title? * (Freeform)

Performance Expectancy

PE1 – Using secure EMRs will enhance the quality of my work

PE2 – The advantages of EMRs outweigh the disadvantages

Effort Expectancy

EE1 – I find secure EMRs easy to use

EE2 – Learning to use secure EMRs does not require much effort

Social Influence

SI1 – People who are important to me think I should use secure EMRs

SI2 – People whose opinions I value would like me to use secure EMRs

Facilitating Conditions

FC1 – I always have the resources I need to use secure EMRs

FC2 – I have the knowledge necessary to use secure EMRs

Behavioral Intentions

BI1 – Assuming I had the access or need to use EMRs in the future, I predict I would opt to use secure EMRs

BI2 – Given the opportunity, I would use secure EMRs even when not required

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Title, description or numeric reference of the portion(s)	Figure 1. Research Model: UTAUT	**Title of the article/chapter the portion is from**	Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology
Editor of portion(s)	Peter Seddon	**Author of portion(s)**	Society for Information Management (U.S.); University of Minnesota. Management Information Systems Research Center
Volume of serial or monograph	N/A	**Issue, if republishing an article from a serial**	MIS Quarterly Vol. 36 No. 1/March 2012
Page or page range of portion	160	**Publication date of portion**	2012-03-01

Appendix C: Instrument Adaptation Permission

From: Katherine Kim <kathykim@UCDAVIS.EDU>
Sent: Monday, November 16, 2020 6:41 PM
To: Omar Sangurima <omar.sangurima@waldenu.edu>
Subject: RE: Request for Permission to Use Your Instrument

Hello Omar. I'm happy to collaborate with you to adapt the survey instrument used in that study. Please cite me for the survey instrument and let me know if I can help in any way.

In addition, I have an adaption of the UTAUT for patients which I'm submitting for publication now.

From: Omar Sangurima <omar.sangurima@waldenu.edu>
Sent: Monday, November 16, 2020 3:11 PM
To: Katherine Kim <kathykim@UCDAVIS.EDU>
Subject: Request for Permission to Use Your Instrument

Good Evening Dr. Kim

I hope this missive finds you well! I am writing to ask if it would be acceptable to adapt the instrument you used in "Factors affecting willingness to share electronic health data among California consumers" for my own upcoming Doctoral Study Capstone? You set up a great series of questions that I think my own line of inquiry (with a shift in participants to medical practitioners) would benefit from (seeing as how I too wish to utilize a survey, grounded in UTAUT, to gain insights regarding intention to adopt secure EMRs).

Should you have any questions or need further background, please just let me know!

Best,
-Omar Sangurima-