QUANTITATIVE INFLUENCES OF TRUST AND UNIFIED USE AND ACCEPTANCE FACTORS ON AI ADOPTION IN HEALTHCARE

by

Sergio C. Carbone

WILLIAM J. MCKIBBIN, PhD, Faculty Mentor and Chair

CHERYL LENTZ, PhD, Committee Member

PAMELYN WITTEMAN, PhD, Committee Member

Todd C. Wilson, PhD, Dean, School of Business and Technology

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Abstract

The research topic for this study was the adoption of artificial intelligence technology in healthcare. Healthcare is at a critical turning point because of the growing costs of detection and treatment, and society needs the potential benefits of artificial intelligence healthcare technologies. The factors that affect artificial intelligence technology adoption in healthcare are not known. Society needs to identify issues blocking the adoption of artificial intelligence healthcare technologies to promote adoption. The purpose of this research was to examine what factors affect artificial intelligence technology adoption in healthcare and close this gap. This study asked the following question: To what extent, if any, do unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) influence the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals? This study was a quantitative nonexperimental correlational cross-sectional survey study that used an anonymous online survey. This research study sampled from the population of 803,090 U.S. healthcare IT professionals and collected a total sample of $N = 215$. This study conducted a hierarchical linear regression analysis. The results of the hierarchical multiple regression analysis indicate that performance expectancy, social influence, innovativeness, and trust in system influenced the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals. These findings indicate that trust had the strongest influence on artificial intelligence technology adoption among U.S. healthcare IT professionals. However, effort expectancy performed inconsistently in the model, and perceived risk did not contribute.

Dedication

First, to my loving wife, Michele, thank you for putting our family first and freeing me to achieve this life accomplishment. To my sons, Christopher and Patrick, I have illuminated the path and shown you the way. Now, it is your turn to take the torch and lead so others may see. To Dr. Celeste Schwartz, thank you for encouraging me to start and motivating me throughout this journey. Finally, to my mother, Jean; my father, Sergio; and my sisters, Kathy, Patty, and Danelle, thank you for holding a seemingly never-ending belief in me.

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Table of Contents

List of Tables

List of Figures

CHAPTER 1. INTRODUCTION

The research topic for this study is the adoption of artificial intelligence technology in healthcare. Artificial intelligence technology can automate human efforts in the detection of disease and outperform human-based methods; thus, artificial intelligence and smart technology, such as diagnostic assistants, are suitable as a solution to automate human tasks and reduce the human costs associated with this problem (Banzi & Xue, 2015; Rigla, García-Sáez, Pons, & Hernando, 2017). However, the extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare remains unknown (Keel et al., 2018). This chapter provides an introduction to this study by including discussion of the background of the research problem, identifying the research problem, communicating the purpose of this study, stating the significance of this study, identifying this study's research questions, defining study variables and important terms, describing the research design used in this study, and presenting the organization for the remainder of this study.

Background of the Problem

This section provides a background, based on the literature, that leads to and supports the need for the research problem: *the adoption of artificial intelligence technology in healthcare* (Keel et al., 2018). The background of the problem explores the significance of the research problem, research in artificial intelligence capabilities, and research in technology adoption applicable to the research problem. With an understanding of the purpose and organization of this section in place, this section proceeds with a discussion of the significance of the problem this study addresses.

Artificial intelligence technology can relieve a growing healthcare problem. The operational costs of chronic diseases, such as diabetes, remain challenging for healthcare systems to control (Lynn, Hess, Weng, Lipner, & Holmboe, 2012). The American Diabetes Association (2018) reported that the diabetes healthcare problem alone cost the United States $327 billion. Preventing disease progression requires patient education, detection, and early treatment (Gregg et al., 2014; Olesen et al., 2014). Significant quality gaps exist in healthcare, and physician training is not closing this gap (Lynn et al., 2012). Making early detection, providing treatment, and containing costs associated with advanced disease remains challenging for the healthcare sector, and this includes healthcare IT professionals (Lynn et al., 2012; U.S. Department of Health and Human Services, 2016). However, advancements in artificial intelligence technology can support the detection of disease and outperform human capabilities while offering automated solutions to reduce the costs associated with healthcare (Banzi & Xue, 2015; Rigla et al., 2017). Significant work in artificial intelligence technology anchors in computational learning (Servedio, 2002).

Artificial intelligence accomplishes disease prediction through computational learning. Thinking of machine learning started in 1959 with Samuel's (1959) *Some Studies in Machine Learning Using the Game of Checkers* (Holzinger, 2016). Valiant (1984) improved on machine learning by focusing on efficiency to form computational learning theory (Brodag, Herbold, & Waack, 2014; Servedio, 2002). Computational learning theory, and its probably approximately correct (PAC) framework, explain the moderating role of concept complexity, required accuracy, and allowable computing time between a concept class and the concept class's learnability (Brodag et al., 2014; Servedio, 2002). With the origins of machine learning communication, it is important to understand how artificial intelligence may outperform human capability.

In studies, artificial intelligence applied through computational learning has managed medical test data too subtle and complex for typical human conducted diagnosis (Banzi & Xue, 2015). Computational learning scanned human iris image data to identify diabetic symptoms through coloration changes by study-physicians during patient examinations (Banzi & Xue, 2015). Unsupervised computational learning identified brain tumors from magnetic resonance imaging time-series data (Duan & Man, 2012). Computational learning detected Parkinson's disease from subtleties in vocal measurement data beyond typical human diagnosis capability (Ozcift, 2012). Machine learning identified *activity of daily living* from the recorded accelerometer data for automated patient monitoring (Akour, 2016). Computational learning outperformed human interpretation in consistency and accuracy to diagnose Alzheimer's, vascular dementia, and Parkinson's disease in 2169 clock drawing tests created with digitizing pens (Souillard-Mandar et al., 2016). Artificial intelligence identified population rates of diabetes in the longitudinal data correctly 75% of the time (Casanova et al., 2016).

Additionally, computational learning predicted diabetes and hypertension comorbidities from the medical records of 74,134 diabetic patients, 58,745 patients with hypertension, 30,522 comorbid patients, and 106,771 healthy patients with 95.3% classification accuracy (Farran, Channanath, Behbehani, & Thanaraj, 2013). Artificial intelligence achieved more than 80% correlation in predicting high blood pressure, obesity, cardiovascular disease, and diabetes from socio-demographic data from the American Community Survey (Luo et al., 2015). Machine learning out predicted human abilities to achieve 95% accuracy in predicting surgical outcomes of temporal lobe epilepsy surgery candidates using medical records and patient family histories (Memarian, Kim, Dewar, Engel, & Staba, 2015). Computational learning with feature classification models correctly identified rheumatoid arthritis in 92.29% of 20,667 subjects (Zhou et al., 2016). Artificial intelligence with pathology image feature data correctly predicted lung cancer in 85% of study cases (Yu et al., 2016). Overall, these studies showed computational learning capable of dealing with both subtle details and complex relationships beyond typical human conducted diagnosis. With an understanding of how artificial intelligence may outperform human capability in place, it is important to understand how researchers have examined technology adoption in healthcare.

Studies have examined technology adoption in healthcare. De Camargo, Guedes, Caetano, Menezes, and Trajman (2015) explored views of patients and healthcare professionals regarding the adoption of tuberculosis diagnostic technology in Brazil. Liberati et al. (2017) explored trust obstacles to the adoption of decision support systems in hospitals and proposed a framework for implementation. Romare, Hass, and Skär (2018) observed the perceptions of healthcare professionals regarding smart-glasses technology in intensive care. Kyratsis, Ahmad, and Holmes (2012) completed a case study to understand how healthcare is managing the adoption of innovation. Heselmans et al. (2012) explored perceptions of healthcare professionals in the adoption of clinical decision support technology. Radhakrishnan, Jacelon, and Roche (2012) examined the views of nurses and patients on telehealth technology for homecare post-heart-failure. Romare et al. examined the perceptions of healthcare professionals regarding smart-glasses technology in intensive care. Hampshire (2017) studied perceptions of risk and trust in technology adoption. Hoque, Albar, and Alam (2016) and Lee and Rho (2013) studied factors influencing e-health and mobile health adoption by physicians. Hong (2015); Rouibah, Lowry, and Hwang (2016); and Roghanizad and Neufeld (2015) measured perceptions of risk and trust in technology adoption. Researchers have employed several core theories.

Adoption research focused on several core theories, such as the technology acceptance model (TAM), the theory of planned behavior, and the unified theory of acceptance and use of technology (UTAUT; Koul & Eydgahi, 2017; Lai, 2017). De Almeida, Farias, and Carvalho

(2017) used TAM to explain technology adoption in healthcare and proposed an adoption framework. Lin, Lin, and Roan (2012) conducted quantitative research with TAM and equity theory to study obstacles for healthcare professionals to adopt IT in hospitals. Sezgin, Özkan-Yildirim, and Yildirim (2018) used a modified TAM model to explain perceptions of physicians regarding mobile health applications. Thompson-Leduc, Clayman, Turcotte, and Légaré (2015) reviewed a series of studies that used the theory of planned behavior to explain behaviors in healthcare professionals. Gopalakrishna-Remani, Jones, and Wooldridge (2016) used neo-institutional theory to explain beliefs of management in healthcare analytics adoption. Vaart, Atema, and Evers (2016) used UTAUT to explain factors and obstacles for healthcare stakeholders to the adoption of web-based patient self-management technology. San Martín and Herrero (2012) studied innovativeness using UTAUT. Alaiad, Zhou, and Koru (2014) employed UTAUT to explain issues in-home healthcare robot adoption. Vanneste, Vermeulen, and Declercq (2013) used UTAUT to study the acceptance of web-based technology by healthcare professionals. Golant (2017) used UTAUT, with the addition of coping, to model the adoption of smart healthcare technology by elderly individuals. Finally, Phichitchaisopa and Naenna (2013) used UTAUT to explain issues affecting healthcare IT adoption. However, the clinical performance of artificial intelligence technology in healthcare is unknown, and the influencers affecting the rate of adoption are generally unstudied (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Rigla et al., 2017). Although risk and trust are known factors in adoption, the extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare remains unknown (Keel et al., 2018; Suki & Suki, 2017; Yang, Pang, Liu, Yen, & Tarn, 2015).

The extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare is of interest in this study. Qualitative research found that trust is important to healthcare professionals and patients (Van Velsen et al., 2016). When dealing with information technology and artificial intelligence, healthcare professionals are hesitant to trust technology that does not employ know methods (Liberati et al., 2017).

To support examining the extent that adoption factors, such as trust in artificial intelligence technology, this study needed to include a theory that includes trust as one of its constructs. This study used the extended UTAUT, visualized in Figure 1, consisting of independent variables of *performance expectancy*, *effort expectancy*, *social influence*, *innovativeness*, *perceived risk*, and *trust in system*, and the dependent variable *behavioral intention* to adopt artificial intelligence technology (Slade, Dwivedi, Piercy, & Williams, 2015). Researchers used the extended UTAUT as the theoretical framework in similar inquiries regarding trust in cross-sectional survey studies that used a quantitative research methodology with a nonexperimental correlational design (Slade et al., 2015).

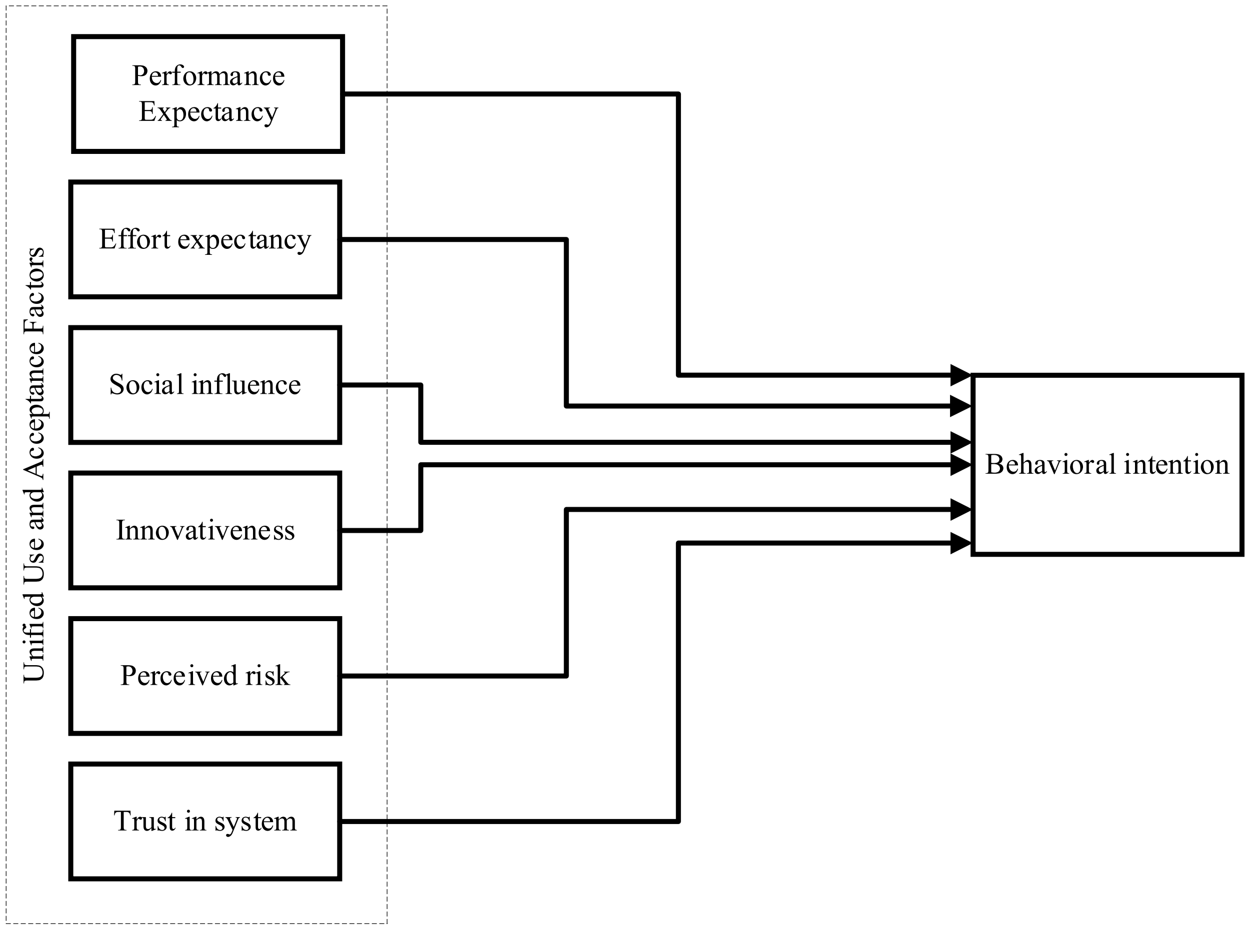

Figure 1. The extended UTAUT. Adapted from "Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust," by E. L. Slade, Y. K. Dwivedi, N. C. Piercy, and M. D. Williams, 2015, *Psychology & Marketing*, 32, 860-873. Copyright 2015 by Wiley Periodicals. Adapted with permission.

Statement of the Problem

The research literature regarding healthcare adopting artificial intelligence technologies indicated that disease detection and treatment are challenging to both healthcare technology providers and healthcare professionals (Gregg et al., 2014; Lynn et al., 2012). Healthcare technology providers and healthcare professionals are struggling to contain operational costs, and even with extensive training, significant patient-care quality gaps exist (Gregg et al., 2014; Lynn et al., 2012). Artificial intelligence can perform disease prediction, and key findings from Souillard-Mandar et al. (2016), Casanova et al. (2016), Luo et al. (2015), and Keel et al. (2018)

showed how artificial intelligence could identify conditions and predict disease from complex feature relationships. Additionally, findings by Banzi and Xue (2015), Samkange-Zeeb et al. (2015), and Souillard-Mandar et al. showed artificial intelligence could outperform human diagnosis in complex predictive relationships with high feature counts. However, the clinical performance of artificial intelligence technology remains unknown (Rigla et al., 2017). Additionally, what factors affect artificial intelligence technology adoption in healthcare remains unknown (Keel et al., 2018). This study included an examination of what factors affect artificial intelligence technology adoption in healthcare (Keel et al., 2018).

Purpose of the Study

The purpose of this quantitative nonexperimental correlational cross-sectional survey research was to examine what factors affect artificial intelligence technology adoption in healthcare. This study uses the variables of the extended UTAUT to measure and assess the effect of trust on the adoption of artificial intelligence technology. The extended UTAUT relates the independent variables of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system, as measured by the instrument, to the dependent variable of behavioral intention, as measured by the instrument, for U.S. healthcare IT participants (Slade et al., 2015). The Slade et al. (2015) instrument measured both the independent and dependent variables. By fulfilling this purpose, this study intended to attempt to confirm the extended UTAUT relative to the adoption of artificial intelligence technology. Specifically, this study measured and assessed how the levels of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system influenced the level of behavioral intention (Slade et al., 2015). Additionally, by fulfilling this purpose, this study sought to confirm the effect of trust on the intention to adopt artificial intelligence technology in U.S. healthcare IT professionals; thus, addressing an open question in the literature and informing industry of the role of trust in the adoption of artificial intelligence technology among U.S. healthcare IT professionals (Beam & Kohane, 2016; Keel et al., 2018).

Significance of the Study

This study is significant to the community of healthcare IT professionals and the field of artificial intelligence healthcare technologies because the results address an open question in the literature and informing industry of the role of trust in the adoption of artificial intelligence technology among U.S. healthcare IT professionals (Beam & Kohane, 2016; Keel et al., 2018). This study is significant within IT and the general specialization because of the ability to explain the obstacles, such as trust, affecting the adoption of artificial intelligence technology. This study is significant to the knowledge base and theory because of contributing new knowledge regarding the effect of adoption factors, such as trust, on the intention to adopt artificial intelligence healthcare technology by U.S. healthcare IT professionals.

Research Questions

RQ: To what extent, if any, do unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) influence the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals?

Definition of Terms

Behavioral Intention

The construct behavioral intention represents an individual's intention to adopt artificial intelligence technologies for use as a healthcare IT professional (Slade et al., 2015; Venkatesh, Thong, & Xu, 2012). Aligned with this construct, the outcome variable behavioral intention is a ratio composite variable measuring the level the participant indicates they would be likely to adopt artificial intelligence technologies for use as a healthcare IT professional (Slade et al., 2015; Venkatesh et al., 2012). BI operationalizes the outcome variable behavioral intention (Slade et al., 2015). BI is a composite score representing the level the participant indicates they would be likely to adopt artificial intelligence technologies for use as a healthcare IT professional (Slade et al., 2015; Venkatesh et al., 2012).

Effort Expectancy

The construct effort expectancy represents an individual's view of the extent that it would be easy to use artificial intelligence technologies (Slade et al., 2015; Venkatesh et al., 2012). Aligning with this construct, the predictor variable effort expectancy is a ratio composite variable measuring the level of ease the participant indicates they would experience in using artificial intelligence technologies (Slade et al., 2015; Venkatesh et al., 2012). EE operationalizes the predictor variable effort expectancy (Slade et al., 2015). EE is a composite score representing the level of ease the participant indicates they would experience in using artificial intelligence technologies (Slade et al., 2015; Venkatesh et al., 2012).

Frequency of Use

Frequency of use represents how often participants reported using artificial intelligence. Participants selected from never, once per year, several times per year, about once per month, several times per month, several times per week, or several times per day. USE1 operationalizes frequency of use.

Healthcare IT Professional

Healthcare IT professionals include a range of professionals that provide IT service in the healthcare sector such as actuaries, applications, computer and information research scientists, computer network architects, computer network support specialists, computer programmers, computer systems analysts, computer user support specialists, database administrators, information security analysts, mathematicians, network and computer systems administrators, operations research analysts, software developers, software developers, statisticians, and web developers (U.S. Bureau of Labor Statistics, 2018).

Healthcare Sector

The healthcare sector includes of a wide range of private and public subsectors including direct patient care, federal response and program offices, health information technology, health plans and payers, laboratories and pharmaceuticals, mass fatality management services, medical materials, and public health (U.S. Department of Health and Human Services, 2016).

IBM Watson Health

The IBM Watson Health is a recognized leading initiative in healthcare artificial intelligence (McGregor & Banifatemi, 2018). The IBM Watson Health initiative includes advancements in artificial intelligence technologies in healthcare for medical image processing, oncology screening, and genomics (International Business Machines, 2015).

Innovativeness

The construct innovativeness represents an individual's view of the extent that they embrace IT innovation (Slade et al., 2015; Thakur & Srivastava, 2014; Yang, Lu, Gupta, Cao, & Zhang, 2012). Aligned with this construct, the predictor variable innovativeness is a ratio composite variable measuring the level the participant indicates they embrace IT innovation (Slade et al., 2015; Thakur & Srivastava, 2014; Yang et al., 2012). IV operationalizes the predictor variable innovativeness (Slade et al., 2015). IV is a composite score representing the level the participant indicates they embrace IT innovation (Slade et al., 2015; Thakur & Srivastava, 2014; Yang et al., 2012).

Perceived Risk

The construct perceived risk represents an individual's view of the risk associated with using artificial intelligence technologies (Lu, Yang, Chau, & Cao, 2011; Slade et al., 2015). Aligning with this construct, the predictor variable perceived risk is a ratio composite variable measuring the level of risk the participant indicates the use of artificial intelligence technologies would introduce (Lu et al., 2011; Slade et al., 2015). PR operationalizes the predictor variable perceived risk (Slade et al., 2015). PR is a composite score representing the level of risk the participant indicates that using artificial intelligence technologies would introduce (Lu et al., 2011; Slade et al., 2015).

Performance Expectancy

The construct performance expectancy represents an individual's view of the extent that artificial intelligence technologies would improve the performance of providing healthcare (Slade et al., 2015; Venkatesh et al., 2012). Aligning with this construct, the predictor variable performance expectancy is a ratio composite variable measuring the level the participant indicates artificial intelligence technologies could improve the performance of providing healthcare (Slade et al., 2015; Venkatesh et al., 2012). PE operationalizes the predictor variable performance expectancy (Slade et al., 2015). PE is a composite score representing the level the participant indicates that artificial intelligence technologies would improve the performance of providing healthcare (Slade et al., 2015; Venkatesh et al., 2012).

Social Influence

The construct social influence represents an individual's view of the extent that the use of artificial intelligence technologies is important to influential individuals (Slade et al., 2015; Venkatesh et al., 2012). Aligning with this construct, the predictor variable social influence is a ratio composite variable measuring the level of influence to use artificial intelligence technologies the participant indicates they perceive from influential individuals (Slade et al., 2015; Venkatesh et al., 2012). SI operationalizes the predictor variable social influence (Slade et al., 2015). SI is a composite score representing the level of influence to use artificial intelligence technologies the participant indicates they perceive from influential individuals (Slade et al., 2015; Venkatesh et al., 2012).

Trust in System

The construct trust in system represents an individual's propensity to place trust in artificial intelligence technologies for use in healthcare applications (Chandra, Srivastava, & Theng, 2010; Slade et al., 2015). Aligning with this construct, the predictor variable trust in system is a ratio composite variable measuring the level the participant indicates they trust artificial intelligence technologies (Chandra et al., 2010; Slade et al., 2015). TRU operationalizes the predictor variable trust in system (Slade et al., 2015). TRU is a composite score representing the level the participant indicates they would trust artificial intelligence technologies (Chandra et al., 2010; Slade et al., 2015).

Research Design

This study is a cross-sectional survey study that used a quantitative research methodology with a nonexperimental correlational design. Researchers can use a quantitative nonexperimental survey study to collect specific population data and measure influencing cause-effect relationships to test new hypotheses (Creswell, 2014). This study's purpose and research questions necessitate measuring the influencing relationships among variables found in the extended UTAUT, visualized in Figure 1; thus, this study seeks to explain the extent, if any, that there is a statistically significant influencing relationship between performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system and behavioral intention (Slade et al., 2015). The use of statistical methods to explain the influencing relationships among the variables places this study in a quantitative methodology with a correlational design (Creswell, 2014; Field, 2013; Sekaran & Bougie, 2013). Other cross-sectional survey studies that measured similar variable relationships also used a nonexperimental correlational design (Golant, 2017; Phichitchaisopa & Naenna, 2013; Slade et al., 2015; Vaart et al., 2016). Several studies on healthcare information technology adoption used a quantitative nonexperimental survey study for their research method (Gao, Li, & Luo, 2015; Sezgin et al., 2018; Vaart et al., 2016). A quantitative nonexperimental correlational design offers the advantage of surveying a large sample to support stronger correlation coefficients and better generalizability (Creswell, 2014; Sekaran & Bougie, 2013). This study is nonexperimental because the research questions do not imply an intervention or control treatment, and there is no control or intervention group (Creswell, 2014).

Other research designs lacked suitability as a quantitative nonexperimental survey study. Several studies on healthcare information technology adoption used a qualitative case study for their research method (De Almeida et al., 2017; De Camargo et al., 2015; Liberati et al., 2017). Researchers can use case studies to analyze a case or program and identify views and events that occur as part of it (Creswell, 2014). Case studies contributed new insights regarding influences on technology adoption in healthcare; however, because of the specifics of the studied organizations, case studies may have limited generalizability (Creswell, 2014; De Almeida et al., 2017; De Camargo et al., 2015; Liberati et al., 2017). Similarly, artificial intelligence algorithm development widely used quantitative secondary data analyses; however, few studies used the method to study adoption (Akour, 2016; Carroll et al., 2017; Rigla et al., 2017; Zhang, Yang, Qiu, Bao, & Li, 2018; Zhou et al., 2016). Because secondary data analysis studies reuse existing data, the data may not fit the purpose of the secondary analysis well and may not provide sufficient reliability, validity, and generalizability (Carroll et al., 2017; Zhang et al., 2018).

This study used a stepwise hierarchical linear regression, as its statistical method, to complete the quantitative analysis of the cross-sectional survey responses. By using a hierarchical linear regression statistical analysis, this study measures the influences of each of the independent variables on the dependent variable for comparative strength of statistically significant predictive power (Field, 2013; Leech, Gliner, Morgan, Harmon, & Harmon, 2003; Mertler & Reinhart, 2017; Uyanık & Güler, 2013).

Assumptions and Limitations

This research design makes several assumptions and has some limitations. This section presents these assumptions and limitations. This section starts with a discussion of the assumptions taken by this research design. After reviewing the assumptions, this section concludes with a discussion of the limitations of this research design. With the purpose and organization of this section presented, this section moves forward with assumptions take by this research design.

Assumptions

This research makes several assumptions, and this subsection provides a discussion of the assumptions applicable to this study. This subsection accomplishes this by including discussion of general methodological assumptions, explaining theoretical assumptions, reviewing topic-specific assumptions, and explaining assumptions about measures. With the purpose and organization of this subsection communicated, this section moves forward with general methodological assumptions.

General methodological assumptions. A study with a quantitative research methodology and a nonexperimental correlational design should support the basic tenets and assumptions of postpositivism (Creswell, 2014). In postpositivism, knowledge exists, and researchers make theory-based claims as the starting point of research to discover this knowledge (Creswell, 2014). Postpositivists view knowledge as not an absolute truth, and researchers cannot prove a claim is always true (Creswell, 2014). Postpositivists can disprove a claim or cannot disprove the claim but cannot prove a claim true (Creswell, 2014). Postpositivist researchers use measured evidence to advance knowledge (Creswell, 2014; Zyphur & Pierides, 2019). The postpositivist view is deterministic, and researchers focus on identifying and observing the causes of an outcome (Creswell, 2014). Postpositivist researchers develop new questions and hypotheses to explain cause-effect phenomena and reject or support these hypotheses through evidence (Creswell, 2014; Sekaran & Bougie, 2013). Postpositivist research uses scientific methods to collect and measure numeric evidence of the extent that a cause influences the outcome (Creswell, 2014; Zyphur & Pierides, 2019). In survey studies, postpositivist researchers collect and measure data from a population unobtrusively and use valid and reliable survey instruments (Sekaran & Bougie, 2013). Postpositivist researchers use statistical methods to explain the significance of the observed influence (Creswell, 2014; Zyphur & Pierides, 2019). Postpositivists are objective and use valid and reliable methods that manage bias and ethical issues (Creswell, 2014; Field, 2013; Zyphur & Pierides, 2019).

Theoretical assumptions. The research literature recognized assumptions and supports several implications regarding the technology acceptance model. Because Venkatesh based the UTAUT on the theory of planned behavior and the technology acceptance model, the UTAUT shares assumptions associated with those theories (Lai, 2017; Venkatesh, Morris, Davis, & Davis, 2003). An assumption associated with the UTAUT is that performance expectancy combined with effort expectancy predicts behavior intention stronger than facilitating conditions (Venkatesh et al., 2003). An additional assumption associated with the UTAUT that is applicable to research in artificial intelligence technology adoption in healthcare is that risk and trust are constructs that could further moderate the influences on behavioral intention (Keel et al., 2018; Lin et al., 2012).

Topic-specific assumptions. This study makes assumptions regarding the adoption of artificial intelligence technology in healthcare. This study sampled from the population of U.S. healthcare IT professionals. This study assumes that the adoption of artificial intelligence technology in healthcare interests the participants, and the participants completed the survey without an alternative motive. Additionally, this study assumes that the participants have an awareness of artificial intelligence healthcare technologies to support them in completing the survey.

Assumptions about measures. This study makes assumptions about measures. The seven-point Likert scale responses collected through the survey instrument are ordinal data, and ordinal data is not consumable by parametric statistical methods (Norman, 2010; Wu & Leung, 2017). Ordinal data does not guarantee an equal distribution among the ordinal values (Fleiss & Cohen, 1973; Norman, 2010). Likert scale responses have an implied distribution with an implied weighting found in the defined responses (Fleiss & Cohen, 1973). Weighted Likert scale values are representative of interval values, and a larger number of Likert value options produce better accuracy (Fleiss & Cohen, 1973; Wu & Leung, 2017). This study assumes that seven-point Likert scale responses are accurate when used as interval values in parametric statistical analysis (Fleiss & Cohen, 1973; Norman, 2010; Wu & Leung, 2017).

Limitations

This research has limitations, and this subsection provides a discussion of these limitations. This subsection accomplishes this by including discussion of the known design limitations and explaining the delimitations that this research did not investigate. With the purpose and organization of this subsection communicated, this section moves forward with the known design limitations.

Design limitations. This study has limitations because of its design. A design limitation of this cross-sectional survey study is that it cannot identify views and events that occur in healthcare IT organizations attempting to adopt artificial intelligence technologies (Creswell, 2014). These views and events may be discoverable with qualitative case studies research designs that would focus on analyzing a case or program (Creswell, 2014). Such case studies contributed new insights regarding influences on technology adoption in healthcare (De Almeida et al., 2017; De Camargo et al., 2015; Liberati et al., 2017). An additional design limitation of this cross-sectional survey study is that it collected data at only a single point in time and cannot make any measurement of longitudinal effects from exposure or attempts to adopt artificial intelligence technologies (Creswell, 2014). A design limitation because of this study's use of existing theory is that it focused on extended UTAUT constructs and did not evaluate additional factors through structural equation modeling (Mertler & Reinhart, 2017).

Delimitations. This research intentionally did not investigate several areas. This study's population included healthcare IT professionals and did not include other populations, such as healthcare practitioners or patients. The study findings from healthcare IT professionals may not be generalizable to other populations, such as healthcare practitioners or patients. Future studies should focus on differences with these populations. Additionally, this study did not collect participant location data and cannot identify if there is any regional effect in the data. This study did not evaluate enhancing the extended UTAUT to improve model efficiency.

Organization of the Remainder of the Study

This introduction has presented the topic of this cross-sectional survey study that used a quantitative research methodology with a nonexperimental correlational design. This section discussed the background of the problem. This introduction identified a gap in the literature that the factors affecting artificial intelligence technology adoption in healthcare are not known. This introduction described the research design and presented the research questions. This study is significant because of its confirmation of the effect of trust on the intention of healthcare IT professionals to adopt artificial intelligence technology. This study addresses an open question in the literature regarding the role that adoption factors, such as trust, have in the adoption of artificial intelligence technology among U.S. healthcare IT professionals (Beam & Kohane, 2016; Keel et al., 2018). The remainder of this study provides a review of recent literature, describes the details of the research methods, presents the results of the research and statistical analysis, and concludes with a discussion of the results, implications, and recommendations for future research.

CHAPTER 2. LITERATURE REVIEW

This literature review seeks to build a basis of understanding of the contributions and issues in recent research regarding this research topic: The adoption of artificial intelligence technology in healthcare. This review discusses the methods of searching the literature for recent research related to the adoption of artificial intelligence technology in healthcare, explain the theoretical orientation used in this study, provide an extensive review of the recent literature regarding artificial intelligence adoption technology in healthcare, synthesize the finding of the review of the literature, and provide a critique of previous research. With an understanding of the organization and strategy of this literature review communicated, this chapter moves forward with the methods used for searching the literature for recent research related to the adoption of artificial intelligence technology in healthcare.

Methods of Searching

This study conducted an extensive search of the literature regarding this topic, and this subsection describes the methods used to search the literature. This subsection accomplishes this by including a discussion of search terms and databases and explaining the search methods used to search the literature. With the purpose and organization of this subsection communicated, this section moves forward with the search terms and databases.

Search Terms and Databases

The keywords used to search the literature included *acceptance*, *adopt*, *adoption*, *AI*, *Alzheimer's*, *analytics*, *app*, *artificial intelligence*, *assistants*, *barriers*, *behavior*, *cancer*, *case-study*, *classification*, *clinical*, *computational learning*, *computational*, *correlation*, *diabetes*, *diagnose*, *diagnosis*, *diagnostic*, *disease*, *doctor*, *e-health*, *factors*, *fear*, *feature selection*, *health*, *healthcare IT*, *healthcare practitioner*, *healthcare*, *innovation*, *intelligence*, *learning*, *literature* *review*, *machine learning*, *medical*, *medicine*, *mobile*, *nurses*, *obstacles*, *outcomes*, *patient*, *pattern recognition*, *perceptions*, *performance*, *physician*, *population health*, *population*, *predict*, *predictive*, *qualitative*, *quantitative*, *recognition*, *research*, *resistance*, *risk*, *smart technology*, *smart*, *supervised learning*, *symptom detection*, *TAM*, *technology*, *telehealth*, *theories*, *theory of planned behavior*, *theory*, *treatment*, *trust*, *unsupervised learning*, *unsupervised*, *UTAUT*, *Watson*, and *Watson Health*. Key databases used to search the literature included ABI/INFORM Global, Academic Search Premier, ACM Digital Library, Business Source Complete, CINAHL Complete, Computers & Applied Sciences Complete, Directory of Open Access Journals, Education Database, Education Research Complete, InfoSci-Journals, JAMA Network, Medical Database, ProQuest Central, PsycARTICLES, Psychology Database, PubMed Central, SAGE Complete, SAGE Premier 2020, ScienceDirect Journals, SocINDEX, and Wiley Online Library (American Medical Association, 2020; Association for Computing Machinery, 2020; Directory of Open Access Journals, 2020; EBSCO Industries, 2020; Elsevier, 2020; IGI Global, 2020; National Center for Biotechnology Information, n.d.; ProQuest, 2020; Springer Nature, 2020).

Search Methods

The search strategy was to find articles that built research support around artificial intelligence, technology adoption, and healthcare. The tactical search moved from generic concepts to specific and focused terms. This method indicated AI concepts important to information technology and healthcare. Combining and truncating keywords in numerous ways with Boolean operators gave an initial indication of relevance when searching article bodies and produced concrete search results when targeting abstracts and titles. A combination of searching keywords as literal phrases and truncation proved useful to find articles that used various forms or tenses of the search terms. Other than establishing merit for search keywords in the field of information technology, the search methods used only peer-reviewed journal articles or government sources.

Theoretical Orientation for the Study

This research includes an extended UTAUT as its theoretical orientation in the study of artificial intelligence technology adoption in healthcare. This study's research question includes trust and risk as constructs. The extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare remains unknown (Keel et al., 2018). Additionally, perceptions of trust influence perceptions of risk; thus, risk and trust are important variables a suitable theoretical model must consider (Slade et al., 2015; Van Velsen et al., 2016). The extended UTAUT, as visualized in Figure 1, consists of the predictor variables of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system, and the outcome variable of individuals' behavioral intention to adopt artificial intelligence technology (Slade et al., 2015). The UTAUT has an extensive history in research.

Venkatesh (2000) developed UTAUT, and researchers have extended UTAUT to include specific variables (Nysveen & Pedersen, 2016; Venkatesh et al., 2012; Wu, Huang, & Hsu, 2014). This study used the extended UTAUT consisting of the independent variables of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system, and the dependent variable of individuals' behavioral intention to adopt artificial intelligence technology (Slade et al., 2015). With an understanding of the history of the UTAUT in place, it is to understand its adaptability.

Recent literature adapted the UTAUT to include constructs, such as risk and trust, that are important to healthcare information technology adoption (Keel et al., 2018; Lin et al., 2012; Slade et al., 2015). The UTAUT specifically addresses social influence, gender, age, and experience (Davis, Bagozzi, & Warshaw, 1989; Venkatesh et al., 2003). Previous research validated the performance of the UTAUT applied to the needs of specific contexts, topics, and populations (Kohnke, Cole, & Bush, 2014; Slade et al., 2015; Wu et al., 2014). Finally, Slade et al. (2015) adapted the UTAUT for risk and trust, and by selecting this version of the UTAUT, this research utilized an existing theory that meets the specific needs of research on artificial intelligence technology adoption in healthcare (Keel et al., 2018; Lin et al., 2012).

Research that focused on the topic of adoption has employed several theories that consider human behavior (Koul & Eydgahi, 2017; Lai, 2017). Several research studies have examined adoption through the lens of TAM; however, the base TAM did not consider trust (De Almeida et al., 2017; Lin et al., 2012; Sezgin et al., 2018). Researchers used diffusion of innovation theory (DOI) to examine adoption; however, DOI did not consider trust (Cranfield et al., 2015; Johnson, Kiser, Washington, & Torres, 2018; Mohammadi, Poursaberi, & Salahshoor, 2018). Some studies have employed behavioral decision theory to behavioral adoption intentions and technology adoption in healthcare; however, behavioral decision theory did not consider trust (Einhorn & Hogarth, 1981; Rosoff, Cui, & John, 2013; Yu-Hsi et al., 2017). Researchers employed the theory of planned behavior to study technology adoption; however, the theory of planned behavior did not consider trust (Gao et al., 2015; Ifinedo, 2018; Yang, Lee, & Zo, 2017). Several research studies have used UTAUT to study technology adoption and have extended UTAUT to include risk and trust (Bhatiasevi, 2016; Kohnke et al., 2014; Rempel & Mellinger, 2015; Slade et al., 2015). This proven extended UTAUT is the best theoretical orientation for this research.

Review of the Literature

This review of the literature seeks to build a basis of understanding of the contributions and issues in recent research regarding artificial intelligence adoption technology in healthcare. This review provides an overview of the need for artificial intelligence technology in healthcare, build a basis of understanding of artificial intelligence technology, review recent research regarding technology adoption, review research approaches taken in recent research, and discuss common theories applied in technology adoption research. Through this evaluation of recent literature, this review raises questions for further research regarding motivators and perceived barriers to the adoption of artificial intelligence technology in healthcare. Finally, based on the literature, this review proposes topics for further research. With an understanding of the organization and strategy of this review of the literature communicated, this chapter moves forward with the need for artificial intelligence technology in healthcare.

The Need for Artificial Intelligence Technology in Healthcare

Artificial intelligence technology can relieve a growing healthcare problem. The operational costs of chronic diseases, such as diabetes, are challenging for healthcare systems to control (Lynn et al., 2012). As reported in Chapter 1, the American Diabetes Association (2018) reported that the U.S. diabetes healthcare problem costs are high. Preventing disease progression requires patient education, detection, and early treatment (Gregg et al., 2014; Olesen et al., 2014). Significant quality gaps exist in healthcare, and physician training is not closing these gaps (Lynn et al., 2012). Making early detection, providing treatment, and containing the costs associated with advanced disease is challenging for the healthcare sector, and this includes healthcare information technology professionals (Gregg et al., 2014; Lynn et al., 2012; U.S. Department of Health and Human Services, 2016). Advancements in artificial intelligence technology can support the detection of disease and outperform human capabilities while offering automated solutions to reduce the costs associated with healthcare (Banzi & Xue, 2015; Rigla et al., 2017). Having discussed how artificial intelligence technology can relieve a growing healthcare problem, this review proceeds to discuss the background of artificial intelligence technology.

Artificial Intelligence Technology Background

Understanding a background of how artificial intelligence technology works is essential to this study because the methods that artificial intelligence solutions work may be different from established workflows and may affect adoption (De Camargo et al., 2015). Artificial intelligence often accomplishes disease prediction through machine learning (Akour, 2016; Rigla et al., 2017; Zhou et al., 2016). Thinking of machine learning started in 1959 with Samuel's (1959) *Some Studies in Machine Learning Using the Game of Checkers* (Holzinger, 2016). Valiant (1984) improved on machine learning by focusing on efficiency to form computational learning theory (Brodag et al., 2014; Servedio, 2002). Computational learning theory and its PAC framework explain the moderating role of concept complexity, required accuracy, and allowable computing time between a concept class and the concept class's learnability (Brodag et al., 2014; Servedio, 2002). With a discussion of the origins of machine learning completed, this study proceeds to examine machine learning in more detail.

Researchers accomplished machine learning through pattern identification and prediction algorithms (Brodag et al., 2014; Servedio, 2002; Valiant, 1984). In recent literature regarding artificial intelligence, researchers used a variety of efficient pattern identification algorithms such as support vector machine, k-nearest neighbor, feature classification, and artificial neural networks as a basis for machine learning (Akour, 2016; Rigla et al., 2017; Zhou et al., 2016).

The pattern identification algorithms computationally examine learning data such as test results, images, surveys, medical records, and medical samples (Akour, 2016; Memarian et al., 2015; Souillard-Mandar et al., 2016; Yu et al., 2016). In supervised machine learning, the learning dataset contains an indicator indicating if a record fits the concept class pattern (Brodag et al., 2014; Rigla et al., 2017; Servedio, 2002). The algorithm builds a model to identify the pattern from correct and incorrect guesses regarding the learning dataset (Brodag et al., 2014; Servedio, 2002). Researchers test the model by applying it to predict from a new dataset and then validating the prediction results (Brodag et al., 2014; Servedio, 2002). The algorithm and pattern-based methods can differ from established workflows used in healthcare, and this difference may affect adoption (Brodag et al., 2014; De Camargo et al., 2015; Souillard-Mandar et al., 2016; Van Velsen et al., 2016). With an understanding of how machine learning works, it is important to this study to examine the risk of artificial intelligence producing errors.

Artificial intelligence has the risk of making inaccurate predictions and returning false-positive and false-negative results, and it is vital to technology adoption that healthcare professionals can trust the performance of artificial intelligence (Brodag et al., 2014; Servedio, 2002; Van Velsen et al., 2016). Artificial intelligence results fall into four categories true-positive, false-positive, true-negative, and false-negative (Brodag et al., 2014; Servedio, 2002). True-positive and true-negative results are correct predictions where positive means a match for the medical condition and negative means no match for the medical condition (Brodag et al., 2014; Servedio, 2002). A false-positive result incorrectly indicates a match for the medical condition (Brodag et al., 2014; Servedio, 2002). A false-negative result incorrectly indicates no match for the medical condition (Brodag et al., 2014; Servedio, 2002). In the case of disease prediction, a false-positive could indicate a person had a disease they did not have, and a false-negative could indicate a person did not have a disease they had (Servedio, 2002; Yu et al., 2016). Similar issues are associated with using artificial intelligence to predict the risk of undergoing a medical procedure or the anticipated outcome of a medical procedure (Memarian et al., 2015; Servedio, 2002). Artificial intelligence has the risk of making either false-positive or false-negative predictions, and it is vital to technology adoption that healthcare professionals can trust the performance of artificial intelligence will exceed human performance (Brodag et al., 2014; Servedio, 2002; Van Velsen et al., 2016). With a discussion of the risk of artificial intelligence errors complete, it is critical to this study to examine if artificial intelligence, applied through machine learning, outperforms human capability.

It is vital to technology adoption that healthcare professionals can trust the performance of artificial intelligence will exceed human performance in efficiency and accuracy (De Camargo et al., 2015; Van Velsen et al., 2016). Artificial intelligence outperforms human conducted diagnosis. In studies, artificial intelligence identified relationships too complex for efficient human conducted diagnosis and demonstrated methods of artificial intelligence that could help manage healthcare costs (Luo et al., 2015). Artificial intelligence identified diabetes through coloration in iris images collected during patient examinations (Banzi & Xue, 2015). Artificial intelligence identified *activity of daily living* from accelerometer data to provide automated patient monitoring (Akour, 2016). Artificial intelligence diagnosed Alzheimer's disease, vascular dementia, and Parkinson's disease in 2169 clock drawing tests and outperformed human interpretation in consistency and accuracy (Souillard-Mandar et al., 2016). Artificial intelligence correctly identified population rates of diabetes, 75% of the time from longitudinal medical records data (Casanova et al., 2016).

Additionally, artificial intelligence achieved more than 80% accuracy in predicting high blood pressure, obesity, cardiovascular disease, and diabetes from socio-demographic data from the American Community Survey (Luo et al., 2015). Artificial intelligence out predicted human abilities and achieved 95% accuracy in predicting surgical outcomes of temporal lobe epilepsy surgery candidates using medical records data and patient family histories (Memarian et al., 2015). Artificial intelligence identified rheumatoid arthritis in 92.29% of 20,667 subjects (Zhou et al., 2016). Artificial intelligence interpreted pathology image data and predicted lung cancer in 85% of study cases (Yu et al., 2016). Healthcare professionals placed a high value on a technology's efficiency, accuracy, and usability, and artificial intelligence can offer the performance and safety needed to be part of the diagnosis and treatment workflow (De Camargo et al., 2015; Memarian et al., 2015; Souillard-Mandar et al., 2016; Van Velsen et al., 2016; Zhou et al., 2016). Even with these study results, the clinical performance of artificial intelligence technology in healthcare is unknown, and the influences affecting the rate of adoption are generally unstudied; therefore, understanding technology adoption in healthcare is essential. (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Rigla et al., 2017).

Research Regarding Technology Adoption

Researchers have focused on the influences of healthcare technology adoption by both healthcare professionals and patients that offer insight regarding performance and effort expectancy (De Camargo et al., 2015; Vaart et al., 2016). In a qualitative study of two Brazilian medical sites, De Camargo et al. (2015) explored views of patients and healthcare professionals regarding the adoption of tuberculosis diagnostic computer technology in Brazil. The tuberculosis diagnostic computer technology automated familiar testing procedures to remove human error and improve the time needed to generate test results (De Camargo et al., 2015).

Healthcare professionals found the technology difficult to use but still supported using the technology (De Camargo et al., 2015). Healthcare professionals placed a high value on the technology's efficiency and accuracy and coped with usage difficulties by assigning administrative staff to interact with the system (De Camargo et al., 2015). Advancements in artificial intelligence technology can support the detection of disease and function within trusted and familiar testing procedures to automated solutions and outperform human capabilities (Banzi & Xue, 2015; De Camargo et al., 2015; Rigla et al., 2017). Patients did not focus on technology and instead focused on their diagnosis (De Camargo et al., 2015). Study results indicated that the technology outperformed traditional testing, and the accuracy and speed were crucial factors in technology acceptance (De Camargo et al., 2015). The De Camargo et al. study included technology that functioned like proven testing methods, and the healthcare professionals used the technology as part of an established workflow (De Camargo et al., 2015). Even with trusted testing methods, performance expectancy was a crucial factor in adoption (De Camargo et al., 2015; Vaart et al., 2016). The use of trusted and familiar testing methods combined with pattern identification and prediction algorithms offered by artificial intelligence may have allowed healthcare professionals to focus on how well the technology helped them perform their job and choose to cope with the difficulties of using the technology (Brodag et al., 2014; De Camargo et al., 2015; Vaart et al., 2016). Other researchers found similar results in mental healthcare.

Performance expectancy and facilitating conditions may influence the intention to use technology in mental healthcare (Vaart et al., 2016). Vaart et al. (2016) conducted a quantitative cross-sectional survey study of 481 mental healthcare practitioners and 290 psychologists to examine factors influencing the adoption of online self-management computer technology. Vaart et al. utilized the UTAUT to examine factors influencing adoption. Performance expectancy and facilitating conditions statistically significantly predicted the behavioral intention of mental healthcare practitioners and psychologists to use online self-management computer technology with patients (Vaart et al., 2016). Effort expectancy had a weak correlation with behavioral intention in mental healthcare practitioners but was not statistically significant in psychologists (Vaart et al., 2016). Healthcare professionals are willing to adopt technology solutions that require more effort when they trust the technology's efficiency and accuracy performance (De Camargo et al., 2015; Vaart et al., 2016). The Vaart et al. study leaves an open question.

An open question exists regarding the results of the Vaart et al. (2016) study. Vaart et al. used the same instrument for both mental healthcare practitioners and psychologists; however, the instrument contained questions that were not appropriate for psychologists (Vaart et al., 2016). This issue raises a question regarding bias in the Vaart et al. study and the quality of the conclusions regarding psychologists (Vaart et al., 2016). Although Vaart et al. collected data on age, experience, and gender, they did not include these in their analysis. Vaart et al. did not fully explain the extent these measures moderated the influences of the other constructs, and this leaves an open question of what are the moderating influences of age, sex, experience, and voluntariness of use on physician adoption of e-health technology. In some cases, performance may not be the strongest influencing factor.

The effort required to use technology and the surrounding social influences may outweigh technology performance (Hoque et al., 2016). Hoque et al. (2016) conducted a quantitative cross-sectional survey study of Bangladesh physicians and utilized the UTAUT to examine factors influencing e-health and mobile health adoption. Hoque et al. added personal innovativeness to the UTAUT to represent a physician's level of accepting technology innovation. Although performance expectancy, effort expectancy, social influence, and personal innovativeness had strong correlations with behavioral intention, facilitating conditions did not (Hoque et al., 2016). In the sample of 203 Bangladesh physicians, effort expectancy, and social influence were more predictive of behavioral intention than performance expectancy or personal innovativeness (Hoque et al., 2016). Effort expectancy is known to affect the adoption of healthcare technology; however, social influence, such as the views of managers or peers, may improve adoption (Hoque et al., 2016; Vaart et al., 2016). The Hoque et al. study leaves an open question.

An open question exists regarding the results of the Hoque et al. (2016) study. Hoque et al. did not describe how they selected the study sample, and there is no clarity on how they avoided sample bias. Hoque et al. did not include any moderating constructs in their analysis, and this omission may have hidden possible sample bias (Trochim, 2006). Hoque et al. reported results that were different from Vaart et al. (2016). The context of the use of these technologies was different, and one of the technologies provided mental health self-management (Hoque et al., 2016; Vaart et al., 2016). This issue leaves the further question of does a technology's purpose and context of usage present differences in the obstacles to the adoption of healthcare technology. Other researchers found effort expectancy important to adoption.

The effort required to use technology may outweigh technology performance (Sezgin et al., 2018). Sezgin et al. (2018) conducted a quantitative cross-sectional survey study of 122 Turkish physicians and proposed a modified technology acceptance model (TAM) to explain perceptions regarding mobile health application adoption. Sezgin et al. supplemented TAM to include constructs for social influence, compatibility, technical support and training, perceived service availability, result demonstrability, personal innovativeness, mobile anxiety, mobile self-efficacy, and habit. Results indicated that perceived service availability, effort expectancy, mobile anxiety, and technical training and support had the strongest direct influences on behavioral intention (Sezgin et al., 2018). Performance expectancy was not a statistically significant influence on behavioral intention with $p = 0.697$ (Sezgin et al., 2018). The lack of statistical significance of performance expectancy conflicts with other studies on adoption in healthcare (Hoque et al., 2016; Sezgin et al., 2018; Vaart et al., 2016). Physicians have avoided adopting technology because of the effort expectancy; however, technical training, support, and trust, based on an understanding of how the technology functions, may improve adoption (De Camargo et al., 2015; Hoque et al., 2016; Sezgin et al., 2018; Vaart et al., 2016). Other than compatibility, no other constructs were a statistically significant influence on performance expectancy and personal innovativeness was not a statistically significant influence on any model construct (Sezgin et al., 2018). The Sezgin et al. study leaves an open question.

An open question exists regarding the results of the Sezgin et al. (2018) study. Sezgin et al. stated that they created a custom survey instrument and validated it with a pilot study; however, they did not disclose any details about the performance of the instrument. The performance of the Sezgin et al. model's constructs raises questions regarding the model and requires further testing to clarify the model's validity, and this leaves an open question of does the Sezgin et al. model explain mobile health application adoption in a different population, such as patients. Other researchers found that adoption influences may be different among different types of healthcare technology.

Influences on adoption may be different based on the type of healthcare information technology (Gao et al., 2015). Gao et al. (2015) conducted a quantitative cross-sectional survey study of 462 total consumers to examine the adoption of a selection of wearable medical device technology and wearable fitness technology. Gao et al. combined the unified theory of acceptance and use of technology 2 (UTAUT2) with protection motivation theory and privacy calculus theory to focus on risks to patient health and privacy. Gao et al. defined the model constructs as performance expectancy, hedonic motivation, effort expectancy, functional congruence, self-efficacy, social influence, perceived vulnerability to health risk, perceived severity of health risk, and perceived privacy risk as influencers, moderated by product type, on the intention to adopt healthcare wearable devices. In the context of wearable medical device technology, perceived severity of health risk, healthcare self-efficacy, perceived privacy risk, and performance expectancy had a strong influence on the intention to adopt healthcare technology in 297 medical device participants (Gao et al., 2015).

Additionally, in the context of wearable fitness technology, functional congruence, and hedonic motivation had a strong influence on the intention to adopt healthcare technology in 341 fitness device participants (Gao et al., 2015). Consumers have different priorities when adopting medical device technology than fitness technology (Gao et al., 2015). When consumers are considering adopting medical device healthcare technology, perceptions of performance and risk have a more substantial influence on adoption (Gao et al., 2015). The context of medical technology solutions introduces additional consideration regarding performance and risk, a critical obstacle for artificial intelligence healthcare technology adoption is user trust in the performance and safety of the technology solution (De Camargo et al., 2015; Gao et al., 2015; Liberati et al., 2017). Other studies examined risk and trust in information technology adoption.

Risk and trust are factors in information technology adoption in healthcare (Liberati et al., 2017). Liberati et al. (2017) conducted a grounded theory qualitative study to explored trust obstacles to the adoption of decision support computing technology. Liberati et al. conducted qualitative interviews with 30 healthcare professionals at two hospitals to identify adoption barriers experienced during the implementation of a decision support computing system. Based on interview findings, Liberati et al. identified six positions defined by the combination of perceived familiarity with technology and perceived trust in the function of technology. The six positions represented individuals' sentiment toward adopting healthcare computing technology (Liberati et al., 2017). The six-position indicated medical professionals had no trust in the healthcare computing technology, felt a risk of losing control in providing healthcare, had no trust in the managers of the technology, believed the technology was valuable to others but inapplicable to themselves, believed the technology may be useful, or believed the technology represented true innovation and benefit for the practice (Liberati et al., 2017). Liberati et al. defined a framework that addresses the actions needed to address the obstacles represented by each of the six positions and increase the chance of healthcare technology adoption.

Liberati et al. (2017) found that trust and risk are key obstacles to the adoption of healthcare information technology in the context of technology efficacy, safety, and practitioner self-autonomy. Participants had lower trust and felt higher risk when they did not see scientific evidence of results or were unfamiliar with the technology (Liberati et al., 2017). The assumption of the Liberati et al. model aligns with other studies that indicated familiarity with the solution influenced adoption (De Camargo et al., 2015). Trust in artificial intelligence healthcare technology may increase with education regarding artificial intelligence methods and prediction algorithms (Brodag et al., 2014; De Camargo et al., 2015; Liberati et al., 2017; Vaart et al., 2016). The Liberati et al. study leaves an open question.

An open question exists regarding the results of the Liberati et al. (2017) study. A limitation of the Hoque et al. study is that the researchers developed the model based on two hospital sites but did not confirm the model in the study (Liberati et al., 2017). Although Liberati et al. included actions needed to address the obstacles represented in each of the six positions, there is no further evidence to support the model, and this leaves an open question of does the transparency of how healthcare information technology achieves results affect healthcare practitioners' perceptions of trust and risk. Other studies found trust important to healthcare professionals and patients using healthcare technology.

Trust is a factor for healthcare professionals and patients adopting healthcare information technology (Van Velsen et al., 2016). Van Velsen et al. (2016) conducted qualitative focus groups to explore perceptions regarding the importance of trust in their use of a rehabilitation portal and treatment involving a remote sensor technology. Patients used the rehabilitation portal to interact with their healthcare professional (Van Velsen et al., 2016). The portal informed the patient of their treatment plan and guided patients to complete their treatment (Van Velsen et al., 2016). The remote sensor technology tracked patient treatments and informed the healthcare professional (Van Velsen et al., 2016). This implementation made the patient and healthcare professional interaction with the healthcare information technology part of the treatment (Van Velsen et al., 2016). Results indicated that trust was important to all users.

Van Velsen et al. (2016) found that trust is important to healthcare professionals and patients. In focus groups with 15 total patients, patients were concerned for their ability to control their healthcare, privacy, data availability, and usability while using the rehabilitation portal and remote sensor technology (Van Velsen et al., 2016). In focus groups with 13 healthcare professionals, healthcare professionals were concerned for technical reliability, usability, and the information protection of the rehabilitation portal (Van Velsen et al., 2016). Healthcare professionals were also concerned with the functional accuracy of the remote sensor technology as part of treatment and did not trust the technology (Van Velsen et al., 2016). Information privacy, reliability, and accuracy are important to users (Gao et al., 2015; Johnson et al., 2018; Liberati et al., 2017; Van Velsen et al., 2016). Artificial intelligence healthcare technology uses predictive methods with user data, and this introduces information privacy considerations that may affect user perceptions of trust and risk regarding when adopting artificial intelligence healthcare solutions (Brodag et al., 2014; Gao et al., 2015; Johnson et al., 2018; Liberati et al., 2017; Servedio, 2002; Van Velsen et al., 2016). The Van Velsen et al. study leaves an open question.

An open question exists regarding the results of the Van Velsen et al. (2016) study. The patients selected for this study had prior trust issues developed because of the complexity in their healthcare treatments, and this could have introduced sample bias (Van Velsen et al., 2016). Because of the limited number of studies examining the effects of trust in the adoption of healthcare information technology, the findings of this study raise a further question of what is the statistical significance of trust in the adoption of healthcare information technology (Keel et al., 2018; Van Velsen et al., 2016). Studies examined risk and trust in other areas of information technology adoption.

Although not healthcare technology, researchers examined the influences of risk and trust in other technology adoption solutions that have parallels with artificial intelligence healthcare technology regarding perceptions of performance, risk, and trust, and these findings may apply to artificial intelligence technology adoption in healthcare (Brodag et al., 2014; Johnson et al., 2018; Servedio, 2002; Slade et al., 2015; Van Velsen et al., 2016). Slade et al. (2015) conducted a quantitative cross-sectional survey study of 268 UK consumers and studied perceptions of innovativeness, risk, and trust in technology adoption. Slade et al. utilized the UTAUT and extended the theory with innovativeness, perceived risk, and trust in system constructs. Slade et al. collected knowledge of mobile payments, as a measure of experience, and included it in their analysis. Slade et al. reported findings useful to the adoption of healthcare information technology.

Slade et al. (2015) reported that performance expectancy, social influence, and innovativeness were statistically significant positive influences on behavioral intention. Perceived risk negatively influenced behavioral intention, and increased levels of trust in system negatively influenced levels of perceived risk (Slade et al., 2015). Analyzing all of the participants, trust in system was not a statistically significant direct influence on behavioral intention (Slade et al., 2015). In only participants with knowledge of mobile payments, increased levels of trust in system positively influenced behavioral intention (Slade et al., 2015). In only participants with no knowledge of mobile payments, increased levels of trust in system were not a statistically significant direct influence on behavioral intention (Slade et al., 2015). Effort expectancy was not a statistically significant influence on behavioral intention (Slade et al., 2015). When users have awareness and understanding of a technology solution, they may perceive the less risk regarding the use of the technology solution, and this may allow them to focus on focus on how well the technology performs (De Camargo et al., 2015; Van Velsen et al., 2016; Slade et al., 2015). Establishing trust influences technology adoption by influencing a reduction of perceived risk (De Camargo et al., 2015; Van Velsen et al., Slade et al., 2015).

Johnson et al. (2018) conducted a quantitative cross-sectional survey study of rapid mobile payment technology adoption. Johnson et al. surveyed 270 internet users living in the United States to examine obstacles to mobile payment adoption. Johnson et al. developed a model based on diffusion of innovation theory to explain the influences of privacy risk, ubiquity, and trialability, perceived security, ease of use, relative advantage, and visibility on usage intention. Perceived security and relative advantage had the strongest influence on usage intention (Johnson et al., 2018). Privacy risk had a negative influence on perceived security, and ubiquity and trialability had a positive influence on perceived security (Johnson et al., 2018). A reduction of privacy risk is associated with perceived security, and high levels of privacy risk could result in lower perceived security and lower usage intention (Johnson et al., 2018; Slade et al., 2015; Van Velsen et al., 2016). When users believe a technology solution uses their private information, information privacy becomes a perceived risk (Johnson et al., 2018; Van Velsen et al., 2016). Because artificial intelligence healthcare technology leverages a healthcare data, information privacy is an area that may affect trust (Brodag et al., 2014; Johnson et al., 2018; Servedio, 2002; Slade et al., 2015; Van Velsen et al., 2016). The Johnson et al. study leaves an open question.

An open question exists regarding the results of the Johnson et al. (2018) study. The statistical significance in efforted expectancy's influence on usage intention was contrary to the findings of a similar study (Johnson et al., 2018; Slade et al., 2015). Johnson et al. sampled from a population consisting of mostly 25 to 44-year-old internet users living in the United States. Although Johnson et al. claimed the sample was more representative of the actual userbase for mobile payments technology, this age bias may have affected the study results (Trochim, 2006). Slade et al. (2015) sampled from consumers with no clear age majority living in the UK. Both Slade et al. and Johnson et al. collected age but did not include it in their analyses. The difference in the populations of these studies and missing analysis raises a question of age or nationality affects the influence of efforted expectancy and trust in system on behavioral intention. The findings of Slade et al. (2015) and Johnson et al. have parallels with artificial intelligence healthcare technology regarding perceptions of performance, risk, and trust, and these findings may apply to artificial intelligence technology adoption in healthcare (Brodag et al., 2014; Johnson et al., 2018; Servedio, 2002; Slade et al., 2015; Van Velsen et al., 2016).

Although artificial intelligence technology offers a possible valuable contribution in healthcare, the clinical performance of artificial intelligence technology in healthcare is unknown, and the influences affecting the rate of adoption are generally unstudied (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Rigla et al., 2017). Results of recent research indicated that differences in the type of healthcare information technology and its context of use might cause differences in the adoption of healthcare information technology by healthcare professionals and patients (Gao et al., 2015). Healthcare professionals do not entirely understand artificial intelligence technology, and research has indicated that perceived familiarity with technology influences risk and trust (Liberati et al., 2017; Rigla et al., 2017). Although risk and trust are known factors in adoption, the extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare remains unknown (Johnson et al., 2018; Keel et al., 2018; Slade et al., 2015; Van Velsen et al., 2016).

Research Approaches Taken in Technology Adoption Research

Studies have used qualitative, quantitative, and mixed method approaches to examine technology adoption in healthcare. De Camargo et al. (2015) used a qualitative approach to explore views of patients and practitioners regarding the adoption of tuberculosis diagnostic technology in Brazil. Liberati et al. (2017) used a qualitative approach to understand trust obstacles to the adoption of decision support systems in hospitals and proposed a framework for implementation. Romare et al. (2018) used a qualitative study to understand the perceptions of healthcare practitioners regarding smart-glasses technology in intensive care. Kyratsis et al.

(2012) completed a qualitative case-study to understand how healthcare is managing the adoption of innovation.

Heselmans et al. (2012) conducted a mixed methods approach to explore perceptions of healthcare practitioners in the adoption of clinical decision support technology. Radhakrishnan et al. (2012) used a mixed methods approach to understand the views of nurses and patients on telehealth technology for homecare post heart-failure. Hampshire (2017) employed mixed methods to study perceptions of risk and trust in technology adoption. San Martín and Herrero (2012) applied a mixed methods approach to study innovativeness using UTAUT.

Mosweu, Bwalya, and Mutshewa (2016) used a quantitative approach using UTAUT to study technology adoption. Hoque et al. (2016) and Lee and Rho (2013) used a quantitative approach using UTAUT to study factors influencing e-health and mobile health adoption by healthcare practitioners. Hong (2015), Rouibah et al. (2016), and Roghanizad and Neufeld (2015) applied quantitative methods to study perceptions of risk and trust in technology adoption. With an understanding of research approaches taken in technology adoption research in place, it is essential to this literature review to review the core theories researchers used in quantitative studies.

Common Theories Applied in Technology Adoption Research

The research focused on the topic of adoption has employed several theories that consider human behavior (Koul & Eydgahi, 2017; Lai, 2017). Gopalakrishna-Remani et al. (2016) used neo-institutional theory to explain the beliefs of management in healthcare analytics adoption. Research has used diffusion of innovation theory (DOI) to examine technology adoption (Cranfield et al., 2015; Johnson et al., 2018; Mohammadi et al., 2018). Some studies have employed behavioral decision theory to behavioral adoption intentions and technology adoption in healthcare (Einhorn & Hogarth, 1981; Rosoff et al., 2013; Yu-Hsi et al., 2017). In quantitative technology adoption literature, researchers commonly leverage the technology acceptance model (TAM), the theory of planned behavior, and UTAUT (Koul & Eydgahi, 2017; Lai, 2017).

Technology acceptance model. Fred Davis based the technology acceptance model on the theory of reasoned action (Davis et al., 1989). Fred Davis modified the theory of reasoned action to develop the technology acceptance model with a focus on factors that influence intentions to accept software and other computer technologies (Davis et al., 1989; Lai, 2017). Davis et al. (1989) defined the model constructs as *external variables*, *perceived usefulness*, *perceived ease of use*, *attitude toward using*, *behavioral intention to use*, and *actual system use*. The technology acceptance model differs from the theory of reasoned action because the technology acceptance model explains that perceived usefulness and perceived ease of use are the key influences on behavioral intention to use software and computer technologies (Davis et al., 1989; Lai, 2017; Venkatesh & Davis, 1996). This perspective was a shift from the theory of reasoned action and its focus on *attitude toward behavior* and *subjective norms* as the influence on behavioral intention (Davis et al., 1989; Venkatesh & Davis, 1996). Davis et al. defined a direct relationship between perceived usefulness and perceived ease of use to behavioral intention. Venkatesh and Davis (1996) refined the technology acceptance model to remove the construct attitude toward using. Understanding the theory's constructs is important.

Venkatesh and Davis (1996) defined the technology acceptance model constructs as external variables, perceived usefulness, perceived ease of use, behavioral intention, and actual system use. External variables are variables that may influence perceived usefulness or perceived ease of use (Davis et al., 1989; Venkatesh & Davis, 1996). To identify external variables, researchers select external variables based on expectations associated with the study topic (Davis et al., 1989; Venkatesh & Davis, 1996). Perceived usefulness is a participant's view of the utility of the proposed computer technology (Davis et al., 1989; Venkatesh & Davis, 1996). Perceived ease of use is a participant's view of how easy the proposed computer technology is to use, and perceived ease of use influences perceived usefulness (Davis et al., 1989; Venkatesh & Davis, 1996). Behavioral intention is a participant's view of the level of intention the participant has in accepting the proposed computer technology (Davis et al., 1989; Venkatesh & Davis, 1996). Actual system use indicates whether the participant used the proposed computer technology (Davis et al., 1989; Venkatesh & Davis, 1996). The technology acceptance model is adaptable.

The technology acceptance model is a popular and adaptable model used in recent research. Researchers used the technology acceptance model widely in recent literature in both its traditional form and as a basis for highly modified forms (De Almeida et al., 2017; Lin & Kim, 2016; Sezgin et al., 2018; Shropshire, Warkentin, & Sharma, 2015). De Almeida et al. (2017) used TAM to explain technology adoption in healthcare and proposed an adoption framework. Lin et al. (2012) conducted quantitative research with TAM and equity theory to study obstacles for healthcare professionals to adopt IT in hospitals. Sezgin et al. (2018) used a modified TAM model to explain perceptions of physicians regarding mobile health applications. A conclusion supported by recent literature is that the technology acceptance model continues to perform satisfactorily with extensive adaptation because of the opportunity offered by the external variables construct (Lin & Kim, 2016; Sezgin et al., 2018; Shropshire et al., 2015). A further conclusion supported by recent literature is that by allowing the inclusion of external variables, unique to concerns of healthcare information technology, the adaptability of the technology acceptance model supports the needs of research on artificial intelligence technology adoption in healthcare (Lin et al., 2012; Venkatesh & Davis, 1996). The theory also informs research regarding computer technology acceptance.

Theory of planned behavior. Ajzen (1991) based the theory of planned behavior on the theory of reasoned action. Ajzen modified the theory of reasoned action to develop the theory of planned behavior to emphasize an individual's view of the availability of the prerequisites needed to carry out a given behavior (Ajzen, 2011; Madden, Ellen, & Ajzen, 1992). Ajzen defined the model constructs as attitude toward the behavior, subjective norm, *perceived behavioral control*, *intention*, and *behavior*. The theory of planned behavior differs from the theory of reasoned action because the theory of planned behavior explains that an individual's perceived behavioral control influences the individual's intention to perform the behavior and influences the individual's actual behavior (Ajzen, 1991; Madden et al., 1992). This difference supplemented the theory of reasoned action's attitude toward behavior and subjective norms constructs, as the sole influences on behavioral intention, with perceived behavioral control (Ajzen, 1991; Madden et al., 1992). In the theory of planned behavior, Ajzen defined a direct relationship from perceived behavioral control to behavioral intention and behavior. Understanding the theory's constructs is important.

Ajzen (1991) defined the theory of planned behavior constructs as attitude toward the behavior, subjective norm, perceived behavioral control, intention, and behavior. Attitude toward the behavior is a participant's view reflecting positive or negative sentiment toward the behavior (Ajzen, 1991; Lai, 2017). The participant forms positive or negative sentiment from a combination of the participant's impressions and beliefs regarding the behavior combined with the participant's evaluation of the outcome associated with performing the behavior (Ajzen, 1991; Lai, 2017). Subjective norm is a participant's positive or negative sentiment reflecting the participant's view of the social norms and expectations associated with complying with the behavior (Ajzen, 1991; Lai, 2017). Perceived behavioral control is a participant's view of the availability of the prerequisites to complete the behavior (Ajzen, 1991; Lai, 2017). Intention is a participant's view of the level of intention the participant has in performing the proposed behavior (Ajzen, 1991; Lai, 2017). Behavior indicates whether the participant performed the proposed behavior (Ajzen, 1991; Lai, 2017). The theory of planned behavior is a flexible model.

The theory of planned behavior is a popular and flexible model used in recent research. Researchers used the theory of planned behavior widely in recent literature in both studies on computer technology adoption and information technology management studies of human behavior (Ferri, Ginesti, Spanò, & Zampella, 2018; Hau, Kim, & Lee, 2016; Safa & Solms, 2016). Thompson-Leduc et al. (2015) reviewed a series of studies that used the theory of planned behavior to explain behaviors in healthcare professionals. Researchers have employed the theory of planned behavior to study technology adoption; however, the theory of planned behavior does not consider trust (Gao et al., 2015; Ifinedo, 2018; Yang et al., 2017). To adapt the theory to the needs of specific research topics, researchers add variables expected to influence attitude toward the behavior, subjective norm, or perceived behavioral control (Ajzen, 2011). A conclusion supported by recent literature is that the theory of planned behavior is flexible and continues to perform as expected when extended with new constructs or combined with other theoretical models (Ferri et al., 2018; Hau et al., 2016; Safa & Solms, 2016). A further conclusion supported by recent literature is that the constructs of the theory of planned behavior offer the flexibility to support research on healthcare information technology behaviors such as artificial intelligence technology adoption in healthcare (Ifinedo, 2018; Thompson-Leduc et al., 2015). The theory informs the research of influences on behavior.

Unified theory of acceptance and use of technology. Researchers used the UTAUT to study many phenomena associated with technology adoption in healthcare. Vaart et al. (2016) used UTAUT to explain factors and obstacles for healthcare stakeholders to the adoption of web-based patient self-management technology. San Martín and Herrero (2012) studied innovativeness using UTAUT. Alaiad et al. (2014) employed UTAUT to explain issues in home healthcare robot adoption. Vanneste et al. (2013) used UTAUT to study the acceptance of web-based technology by healthcare professionals. Golant (2017) used UTAUT with the addition of coping to model the adoption of smart healthcare technology by elderly individuals. Finally, Phichitchaisopa and Naenna (2013) used UTAUT to explain issues affecting healthcare IT adoption. The UTAUT is related to the theory of planned behavior.

Venkatesh based the UTAUT on the technology acceptance model and the theory of planned behavior (Venkatesh et al., 2003). Venkatesh et al. (2003) combined the technology acceptance model with the theory of planned behavior and added additional moderating constructs to develop the UTAUT. Venkatesh et al. defined the model constructs as *performance expectancy*, *effort expectancy*, *social influence*, *facilitating conditions*, *gender*, *age*, *experience*, *voluntariness of use*, *behavior intention*, and *use behavior*. The UTAUT differs from the technology acceptance model and the theory of planned behavior because the UTAUT explains that additional factors moderate the influences of performance expectancy, effort expectancy, social influence, and facilitating conditions (Lai, 2017; Venkatesh et al., 2003; Venkatesh et al., 2012). The UTAUT introduces gender, age, experience, and voluntariness of use into the model with constructs from the technology acceptance model and the theory of planned behavior (Lai, 2017; Venkatesh et al., 2003). Understanding the theory's constructs is important.

It is important to review the constructs of the UTAUT. The UTAUT model constructs are performance expectancy, effort expectancy, social influence, facilitating conditions, gender, age, experience, voluntariness of use, behavior intention, and use behavior (Venkatesh et al., 2003). Performance expectancy is the level of the participant's positive or negative sentiment regarding the usefulness of the behavior's anticipated result in the context of the participant's job (Venkatesh et al., 2003). Effort expectancy is the level of the participant's positive or negative sentiment regarding how much effort performing the behavior will take (Venkatesh et al., 2003). Social influence is the level of the participant's positive or negative sentiment regarding the social norms, cultural influence, and image associated with complying with the behavior (Venkatesh et al., 2003). Facilitating conditions is the participant's view of if the participant has the requirements to easily complete the behavior available to them (Venkatesh et al., 2003). Gender and age are data about the participant (Venkatesh et al., 2003). Experience is the participant's experience, often represented by years or job level, in a relevant area (Venkatesh et al., 2003). Voluntariness of use is the participant's view of the extent that performing the behavior is voluntary (Venkatesh et al., 2012). Behavior intention is the participant's level of intention in performing the proposed behavior (Venkatesh et al., 2003). Use behavior indicates whether the participant performed the proposed behavior (Venkatesh et al., 2003). The relationship among the constructs is intricate.

The UTAUT constructs form an intricate set of relationships. The constructs, performance expectancy, social influence, and effort expectancy, influence behavior intention (Venkatesh et al., 2003). Facilitating conditions influences use behavior directly without influencing behavior intention (Venkatesh et al., 2003). Behavior intention influences use behavior directly (Venkatesh et al., 2003). Gender and age moderate the influence of performance expectancy (Venkatesh et al., 2003). Gender, age, and experience moderate the influence of effort expectancy (Venkatesh et al., 2003). Gender, age, experience, and voluntariness of use moderate the influence of social influence (Venkatesh et al., 2003). Age and experience moderate the influence of facilitating conditions (Venkatesh et al., 2003). The UTAUT is an extensible model.

The UTAUT is an extensible and popular model used in recent research. Researchers used the UTAUT widely in recent literature and frequently supplemented the model to consider topic-specific constructs (Bhatiasevi, 2016; Nysveen & Pedersen, 2016; Rempel & Mellinger, 2015). Recent research showed that the constructs and moderators of the UTAUT influence behavior intention and use behavior as expected but context, topic, and population-specific constructs such as innovativeness, risk, and trust have shown to be factors (Kohnke et al., 2014; Slade et al., 2015; Wu et al., 2014). A conclusion supported by recent literature is that the UTAUT provides a proven model that researchers can enrich to address the specific needs of specific contexts, topics, and populations (Kohnke et al., 2014; Slade et al., 2015; Wu et al., 2014). A further conclusion supported by recent literature is that the UTAUT supports the needs of healthcare information technology through its extensibility to include constructs, such as risk and trust, needed for research on artificial intelligence technology adoption in healthcare (Keel et al., 2018; Lin et al., 2012; Slade et al., 2015). The theory also informs research on the acceptance and use of technology.

In application to the information technology general specialization, the UTAUT informs research of the acceptance and use of technology. The UTAUT informs research that changes in the levels of performance expectancy, social influence, and effort expectancy influence the level of behavioral intention of performing the proposed behavior, and changes in the levels of facilitating conditions and behavioral intention influence the level of use behavior (Lai, 2017; Venkatesh et al., 2003). The UTAUT informs research that a participant's gender, age, experience, and voluntariness of use affects the influences of performance expectancy, social influence, effort expectancy, and facilitating conditions on behavioral intention and use behavior (Lai, 2017; Venkatesh et al., 2003). To apply the UTAUT, researchers must identify context-specific measures that represent performance expectancy, social influence, effort expectancy, facilitating conditions, experience, and voluntariness of use (Lai, 2017; Venkatesh et al., 2003). A conclusion supported by literature is that to apply the theory to research on artificial intelligence technology adoption in healthcare, this research employed variables unique to the concerns of healthcare information technology to influence the theory's constructs (Keel et al., 2018; Lin et al., 2012; Slade et al., 2015). This research measured and analyzed the variables to understand the extent the variables affect the overall influence on the intention to adopt artificial intelligence technology in healthcare (Lai, 2017; Venkatesh et al., 2003). Assumptions and theoretical implications are associated with this theory.

The research literature recognized assumptions and supports several implications regarding the technology acceptance model. Because Venkatesh based the UTAUT on the theory of planned behavior and the technology acceptance model, the UTAUT shares assumptions associated with those theories (Lai, 2017; Venkatesh et al., 2003). An assumption associated with the UTAUT is that performance expectancy combined with effort expectancy predicts behavior intention stronger than facilitating conditions (Venkatesh et al., 2003). An additional assumption associated with the UTAUT that is applicable to research in artificial intelligence technology adoption in healthcare is that risk and trust are constructs that could further moderate the influences on behavioral intention (Keel et al., 2018; Lin et al., 2012). Theoretical implications are associated with this theory.

Several theoretical implications are associated with the UTAUT. A theoretical implication for information technology and the general specialization is that the UTAUT explains that performance expectancy, social influence, and effort expectancy predict behavioral intention, and behavioral intention and facilitating conditions predict use behavior (Lai, 2017; Venkatesh et al., 2003). A theoretical implication applicable to artificial intelligence technology adoption in healthcare is that the UTAUT can measure information technology adoption topics when extended with constructs such as risk, trust, perceived threat, and perceived inequity (Kohnke et al., 2014; Lin et al., 2012; Slade et al., 2015; Wu et al., 2014). Although the UTAUT, the theory of planned behavior, and the technology acceptance model have similarities, one of the theories is best for this research.

Comparison of theory. The technology acceptance model, the theory of planned behavior, and the UTAUT are comparable theories. The three theories share the basic principle that participants have perceptions regarding the use of computer technology or performing a behavior (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). These perceptions influence participants' intentions regarding the computer technology or the behavior (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). The participants' intentions, along with their perceptions, influence participants' actual use and behavior (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). Although the theory of planned behavior and UTAUT provide more specific constructs than the technology acceptance model, the three theories examine perception, intention, and behavior (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). Although the theory of planned behavior and UTAUT provide more specific constructs than the technology acceptance model, the constructs are still categorical, and the three theories offer researchers similar adaptability (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). To adapt the theories to the needs of specific research topics, researchers add variables expected to influence or moderate the participants' perceptions regarding the model constructs (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). Differences exist between the theories.

Differences exist among the technology acceptance model, the theory of planned behavior, and UTAUT. The theory of planned behavior explains behavior and does not focus on a specific type of behavior (Ajzen, 2011). Although the acceptance and use of computer technology is fundamentally a behavior, the technology acceptance model and UTAUT specifically explain acceptance and use of computer technology (Davis et al., 1989; Venkatesh et al., 2003). The theory of planned behavior constructs supports a generic view of behavior by focusing on attitude, subjective norms, and perceived behavioral control (Ajzen, 2011). In contrast, the technology acceptance model places focus on perceived usefulness and perceived ease of use, and researchers provide external variables that influence these constructs (Davis et al., 1989). The core UTAUT constructs focus on performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Both the technology acceptance model and the UTAUT have constructs that emphasize the utility and ease of using a technology (Davis et al., 1989; Venkatesh et al., 2003). Foundational work for the technology acceptance model and the UTAUT indicated that the context of performing a job or function affect the utility and ease of using technology (Davis et al., 1989; Venkatesh et al., 2003). Of the three theories, the UTAUT is the most specific because it includes constructs focused on performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Additionally, the UTAUT recognizes gender, age, experience, and voluntariness of use as moderators of influences on behavioral intention or use behavior (Venkatesh et al., 2003). One of the three theories is most suitable for this research.

The research topic of artificial intelligence technology adoption in healthcare is a technology acceptance and use problem. The theory of planned behavior explains behavior and does not focus on a specific type of behavior (Ajzen, 2011). Although researchers have used the theory of planned behavior to examine technology adoption, it does not offer the specialized focus that the technology acceptance model and UTAUT provide (Ajzen, 2011; Davis et al., 1989; Ifinedo, 2018; Thompson-Leduc et al., 2015; Venkatesh et al., 2003). As a result, this study did not use the theory of planned behavior. The technology acceptance model has core constructs that focus on perceived usefulness and perceived ease of use; however, healthcare information technology is a specialized field that is known to emphasize influences outside usefulness and ease of use (Davis et al., 1989; Keel et al., 2018; Lin et al., 2012). Although the external variables construct of the technology acceptance model supports wide options for accommodating the needs of healthcare information technology, the UTAUT is more specific (Davis et al., 1989; Venkatesh et al., 2003). The UTAUT is the best fit for this research.

Additional Topics for Further Research

The influence of *context of use* on artificial intelligence technology adoption in healthcare is a topic for further research. This topic would examine obstacles to artificial intelligence technology adoption in healthcare based on the technology's purpose and context of use. Recent literature on healthcare information technology adoption produced inconsistent results in the factors influencing adoption by healthcare professionals from different fields of practice (Hoque et al., 2016; Vaart et al., 2016). Recent literature indicated inconsistent views on the adoption of healthcare information technology between fitness management technology, health information management technology, and medical device treatment technology (De Camargo et al., 2015; Gao et al., 2015; Liberati et al., 2017). These differences are in the context of use in different healthcare disciplines and for different solution purposes such as information management, health management, and treatment (Gao et al., 2015; Hoque et al., 2016; Vaart et al., 2016). Context of use may be influential in artificial intelligence technology adoption in healthcare by healthcare professionals and patients. Further research on the influences of the context of use on artificial intelligence technology adoption in healthcare would further this scholarly dialog and may close this gap. Another topic for further research involves transparency.

The effect of functional transparency in artificial intelligence technology adoption in healthcare is a topic for further research. This topic would examine obstacles to the adoption of healthcare artificial intelligence technology based on the transparency of how artificial intelligence technology achieves results. Recent literature on the adoption of healthcare information technology found that solution familiarity reduced risk and positively influenced the adoption of healthcare information technology by healthcare professionals (De Camargo et al., 2015; Liberati et al., 2017). Healthcare professionals do not completely understand artificial intelligence technology, and a lack of familiarity may make healthcare professionals perceive a loss of control (Liberati et al., 2017; Rigla et al., 2017). Research indicated that perceived familiarity with technology and control influences risk and trust in healthcare professionals (De Camargo et al., 2015; Liberati et al., 2017). Healthcare professionals placed a high value on tuberculosis diagnostic technology that automated familiar testing procedures to remove human error and reduce the time needed to generate test results (De Camargo et al., 2015). Transparency in how artificial intelligence technology functionally solves a problem may be influential in reducing risk and increasing trust in artificial intelligence technology in healthcare professionals. Further research on the influences of functional transparency on artificial intelligence technology adoption in healthcare would further this scholarly dialog and may close this gap.

Synthesis of the Research Findings

The healthcare sector needs artificial intelligence technology to help address the growing healthcare problem that is evident in growing operational costs of chronic diseases, such as diabetes (American Diabetes Association, 2018; Banzi & Xue, 2015; Lynn et al., 2012; Rigla et al., 2017). Finding new solutions to close the gaps in making early detection, providing treatment, and containing the costs associated with advanced disease involves all area of the healthcare sector including healthcare information technology professionals (Gregg et al., 2014; Lynn et al., 2012; Olesen et al., 2014; U.S. Department of Health and Human Services, 2016). Machine learning is a core artificial intelligence technology that can address the growing healthcare problem.

Artificial intelligence accomplishes disease prediction through machine learning that accomplishes efficient pattern identification and prediction using proven algorithms such as support vector machine, *k*-nearest neighbor, feature classification, and artificial neural networks as a basis for machine learning (Akour, 2016; Rigla et al., 2017; Zhou et al., 2016). In healthcare applications, supervised machine learning uses pattern identification algorithms to build a model that identifies the pattern of traits indicating the presence of a disease or condition (Akour, 2016; Brodag et al., 2014; Memarian et al., 2015; Servedio, 2002; Souillard-Mandar et al., 2016; Yu et al., 2016). Researchers test the model and measure its accuracy by applying the model to new datasets and measuring the true-positive, false-positive, true-negative, and false-negative predictions (Brodag et al., 2014; Servedio, 2002). Understanding the accuracy of artificial intelligence is critical because incorrect prediction could result in providers treating patients for a disease they do not have or incorrectly predicting the outcome of a medical procedure (Memarian et al., 2015; Servedio, 2002; Yu et al., 2016). Including the risk of incorrect identification, artificial intelligence, applied through machine learning, outperforms human capability (Banzi & Xue, 2015; Casanova et al., 2016; Luo et al., 2015; Memarian et al., 2015; Souillard-Mandar et al., 2016; Yu et al., 2016; Zhou et al., 2016). Even with the high performance in study results, the clinical performance of artificial intelligence technology in healthcare is unknown, and the influences affecting the rate of adoption are generally unstudied (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Rigla et al., 2017). Many factors affect technology adoption in healthcare.

Understanding artificial intelligence technology adoption in healthcare involves examining a complex network of factors. Healthcare professionals place a high value on the performance, efficiency, and accuracy of healthcare technology, and these are factors affecting adoption (De Camargo et al., 2015; Vaart et al., 2016). When healthcare technology has strong performance, and the facilitating conditions support the use of the technology, the complexity and effort involved in the new technology is less of a concern for healthcare professionals (De Camargo et al., 2015; Vaart et al., 2016). However, some physicians are affected more strongly by effort expectancy (Hoque et al., 2016; Sezgin et al., 2018). The context of healthcare technology influences the factors affecting adoption; for example, performance and risk have a stronger influence on the adoption of medical devices than fitness technology (Gao et al., 2015). Context affects adoption factors, and populations respond differently to adoption factors (Gao et al., 2015; Hoque et al., 2016; Sezgin et al., 2018). Risk and trust affect adoption, and these are adoption obstacles that are affected by familiarity with the solution (De Camargo et al., 2015;

Liberati et al., 2017; Van Velsen et al., 2016). In industries outside of healthcare, previous research found that risk and trust are statistically significant obstacles for technology adoption (Johnson et al., 2018; Slade et al., 2015). Because of the limited number of studies examining the effects of trust in the adoption of healthcare information technology, the statistical significance of trust in the adoption of healthcare technology remains unknown (Keel et al., 2018; Van Velsen et al., 2016). These results may apply to artificial intelligence technology adoption in healthcare.

Although artificial intelligence technology offers a possible valuable contribution in healthcare, the clinical performance of artificial intelligence technology in healthcare is unknown, and the influences affecting the rate of adoption are generally unstudied (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Rigla et al., 2017). Although risk and trust are known factors in adoption, the extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare remains unknown (Johnson et al., 2018; Keel et al., 2018; Slade et al., 2015; Van Velsen et al., 2016). Studies have used qualitative, quantitative, and mixed method approaches.

Studies have used qualitative, quantitative, and mixed method approaches to examine technology adoption in healthcare. Qualitative approaches explored the adoption of diagnostic technology, trust obstacles to adoption, smart-glasses technology adoption, and adoption of innovation (De Camargo et al., 2015; Liberati et al., 2017; Romare et al., 2018). Mixed method approaches explored adoption decision support technology, views of telehealth technology, perceptions of risk and trust in technology adoption, study innovativeness (Hampshire, 2017; Heselmans et al., 2012; Radhakrishnan et al., 2012; San Martín & Herrero, 2012). Qualitative approaches examined technology adoption, e-health and mobile health adoption, and perceptions of risk and trust in technology adoption (Hong, 2015; Hoque et al., 2016; Lee & Rho, 2013; Mosweu et al., 2016; Roghanizad & Neufeld, 2015; Rouibah et al., 2016). None of the quantitative studies examined the effects of trust in the adoption of healthcare information technology (Hong, 2015; Hoque et al., 2016; Lee & Rho, 2013; Mosweu et al., 2016; Roghanizad & Neufeld, 2015; Rouibah et al., 2016). The statistical significance of trust in the adoption of healthcare technology remains unknown (Keel et al., 2018; Van Velsen et al., 2016). Among the quantitative studies, researchers employed several core theories.

In quantitative technology adoption literature, researchers commonly leveraged the technology acceptance model (TAM), the theory of planned behavior, and UTAUT (Koul & Eydgahi, 2017; Lai, 2017). The three theories share the basic principle that participants have perceptions regarding the use of computer technology or performing a behavior (Ajzen, 2011; Davis et al., 1989; Venkatesh et al., 2003). Of the three theories, the UTAUT is the most specific because it includes constructs focused on performance expectancy, effort expectancy, social influence, and facilitating conditions; additionally, the UTAUT recognizes gender, age, experience, and voluntariness of use as moderators of influences on behavioral intention or use behavior (Venkatesh et al., 2003). Previous research offers room for critique.

Critique of Previous Research Methods

Recent research contained several flaws regarding bias because of instrument fit or sample selection. In their quantitative cross-sectional survey study of mental healthcare practitioners and psychologists to examine factors influencing the adoption of online self-management computer technology, Vaart et al. (2016) used the same instrument for both mental healthcare practitioners and psychologists. The instrument was completely not appropriate for psychologists (Vaart et al., 2016). The problem with the instrument introduces possible bias and questions the quality of the conclusions regarding psychologists (Vaart et al., 2016). In their quantitative cross-sectional survey study of Bangladesh physicians to examine factors influencing e-health and mobile health adoption, Hoque et al. (2016) did not describe how they selected the study sample, and there is no clarity on how they avoided sample bias.

Additionally, Hoque et al. (2016) and Vaart et al. (2016) did not include any moderating constructs in their analysis, and this omission may have hidden possible sample bias (Trochim, 2006). Although examining similar constructs, Hoque et al. reported results that were different from Vaart et al. The context of the use of these technologies was different. One of the technologies provided mental health self-management, and this opens a question regarding the differences in the obstacles to the adoption of healthcare technology based on the technology's purpose and context of use (Hoque et al., 2016; Vaart et al., 2016). Other studies had undisclosed instrument validity.

Some researchers, who created instruments, had possible flaws regarding validity. In their quantitative cross-sectional survey study of Turkish physicians to explain perceptions regarding mobile health application adoption, Sezgin et al. (2018) stated that they created a custom survey instrument and validated it with a pilot study. Sezgin et al. did not disclose the details about the performance of the instrument or its validity and reliability. This flaw raises questions regarding the model and requires further testing to clarify the model's validity. Other studies had incomplete research.

Some researchers did not include enough in their research scope to allow for a concrete conclusion. In their grounded theory qualitative study to explored trust obstacles to adoption of decision support computing technology, Liberati et al. (2017) defined a framework that addresses actions needed to address the obstacles represented in healthcare technology adoption. Although

Liberati et al. developed the model based on two hospital sites and included actions needed to address the obstacles, they did not confirm the model in the study. Liberati et al. did not provide further evidence to test or support the model. The gap, introduced by a lack of testing, leaves the model as only a proposal. Other studies had bias because of sample selection.

Some researchers had sample selection flaws that introduced bias. In their qualitative focus groups to explore perceptions regarding the importance of trust in the use of a rehabilitation portal and treatment, Van Velsen et al. (2016) selected patients for this study that had developed known trust issues because of the complexity of their prior healthcare treatments. The sample had a bias regarding trust, and a one-sided perspective could have compromised the study conclusions (Van Velsen et al., 2016). Other studies had similar sample bias.

Other researchers had sample selection problems. In their quantitative cross-sectional survey study of rapid mobile payment technology adoption, Johnson et al. (2018) sampled from a population consisting of mostly 25 to 44-year-old internet users living in the United States. Although Johnson et al. claimed the sample was more representative of the actual userbase for mobile payments technology, this age bias may have affected the study results (Trochim, 2006). In a similar study examining the influence of risk and trust on mobile payments adoption, Slade et al. (2015) sampled from consumers with no clear age majority living in the UK. The statistical significance in efforted expectancy's influence on usage intention, found by Johnson et al., was contrary to the findings of Slade et al.

None of the recent research thoroughly examined the influence of trust on artificial intelligence adoption in healthcare. The clinical performance of artificial intelligence technology in healthcare is unknown, and the influences affecting the rate of adoption of artificial intelligence technology in healthcare are generally unstudied (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Rigla et al., 2017). Although risk and trust are known factors in adoption, the extent that trust in artificial intelligence technology affects the adoption of artificial intelligence technology in healthcare remains unknown (Johnson et al., 2018; Keel et al., 2018; Slade et al., 2015; Van Velsen et al., 2016). This research addresses this gap.

Summary

This literature review has built a basis of understanding of the contributions and issues in recent research regarding this research topic: The adoption of artificial intelligence technology in healthcare. The healthcare sector needs artificial intelligence technology to help address the growing healthcare problem that is evident in growing operational costs of chronic diseases, such as diabetes (American Diabetes Association, 2018; Banzi & Xue, 2015; Lynn et al., 2012; Rigla et al., 2017). Finding new solutions to close the gaps in making early detection, providing treatment, and containing the costs associated with advanced disease involves all area of the healthcare sector including healthcare information technology professionals (Gregg et al., 2014; Lynn et al., 2012; Olesen et al., 2014; U.S. Department of Health and Human Services, 2016). Artificial intelligence technology offers a possible valuable contribution in healthcare that could help manage healthcare costs; however, the influences affecting the rate of adoption are generally unstudied (Beam & Kohane, 2016; Golden, 2017; Keel et al., 2018; Luo et al., 2015; Rigla et al., 2017). Studies have used qualitative, quantitative, and mixed method approaches to examine technology adoption in healthcare (De Camargo et al., 2015; Hong, 2015; Hoque et al., 2016). None of the recent quantitative studies examined the effects of trust in the adoption of artificial intelligence technology in healthcare (Hong, 2015; Hoque et al., 2016; Lee & Rho, 2013; Mosweu et al., 2016; Roghanizad & Neufeld, 2015; Rouibah et al., 2016). The statistical significance of trust in the adoption of healthcare technology remains unknown (Keel et al., 2018; Van Velsen et al., 2016). This research closes this gap. With this literature review complete, this study moves forward to explain this study's research methodology.

CHAPTER 3. METHODOLOGY

This quantitative study used a nonexperimental correlational design. This chapter explains this study's methodology and reviews all aspects of the research design. This chapter presents the purpose of this study, reviews the research questions and hypotheses, explains the research design, provides a discussion of the target population and sample, explains the procedures, presents the instrument, provides a discussion of ethical considerations, and provides a summary of this chapter. With the purpose and organization of this chapter reviewed, this chapter moves forward to present the purpose of this study.

Purpose of the Study

The purpose of this quantitative nonexperimental correlational cross-sectional survey research was to examine what factors affect artificial intelligence technology adoption in healthcare. This study used the variables of the extended UTAUT to measure and assess the effect of trust on the adoption of artificial intelligence technology. The extended UTAUT relates the independent variables of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system, as measured by the instrument, to the dependent variable of behavioral intention, as measured by the instrument, for U.S. healthcare IT participants (Slade et al., 2015). The Slade et al. (2015) instrument measured both the independent and dependent variables. By fulfilling this purpose, this study confirms the extended UTAUT relative to the adoption of artificial intelligence technology. Specifically, this study measures and assess how the levels of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system influence the level of behavioral intention (Slade et al., 2015). Additionally, by fulfilling this purpose, this study assesses the effect of adoption factors, such as trust, on the intention to adopt artificial intelligence technology by healthcare IT professionals, thus, addressing an open question in the literature and informing industry of the role of trust in the adoption of artificial intelligence technology among U.S. healthcare IT professionals (Beam & Kohane, 2016; Keel et al., 2018).

Research Questions and Hypotheses

RQ: To what extent, if any, do unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) influence the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals?

H_0: Unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) do not have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence indicated by a statistically significant *F*-score for any given model using a significance of $p = 0.05$.

H_a: One or more combination of unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence indicated by a statistically significant *F*-score for any given model using a significance of $p = 0.05$.

Research Design

This study is a cross-sectional survey study that used a quantitative research methodology with a nonexperimental correlational design. Researchers can use a quantitative nonexperimental survey study to collect specific population data and measure influencing cause-effect relationships to test new hypotheses (Creswell, 2014). This study's purpose and research questions necessitate measuring the influencing relationships among variables found in the extended UTAUT, visualized in Figure 1; thus, this study seeks to explain the extent that there is a statistically significant influencing relationship between performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system and behavioral intention (Slade et al., 2015). The use of statistical methods to explain the influencing relationships among the variables places this study in a quantitative methodology with a correlational design (Creswell, 2014; Field, 2013; Sekaran & Bougie, 2013). This study is nonexperimental because the research questions do not imply an intervention or control treatment, and there is no control or intervention group (Creswell, 2014). This study included a hierarchical linear regression analysis.

This study used a stepwise hierarchical linear regression analysis for its statistical method to analyze the survey responses. By using a hierarchical linear regression statistical analyses, this study measures the influences of each of the independent variables on the dependent variable for comparative strength of statistically significant predictive power (Field, 2013; Leech et al., 2003; Mertler & Reinhart, 2017; Uyanık & Güler, 2013). This study included a cross-sectional survey.

This study used an anonymous cross-sectional survey to collect perspectives of healthcare IT professionals at a single point in time (Levin, 2006). This study used the Slade et al. (2015) survey instrument to collect cross-sectional data from participants (Creswell, 2014; Levin, 2006). This study used simple random sampling, a basic probability sampling method, to randomly select participants without weighting or deterministic controls (Bondesson & Traat, 2013; Trochim, 2006). This design aligns with similar previously published research.

Previously published cross-sectional survey studies, that measured similar variable relationships, also used a nonexperimental correlational design (Golant, 2017; Phichitchaisopa & Naenna, 2013; Slade et al., 2015; Vaart et al., 2016). Several previously published studies on healthcare information technology adoption used a quantitative nonexperimental survey study for their research method (Gao et al., 2015; Sezgin et al., 2018; Vaart et al., 2016). A quantitative nonexperimental correlational design offers the advantage of surveying a large sample to support stronger correlation coefficients and better generalizability (Creswell, 2014; Sekaran & Bougie, 2013). Other research designs were not suited for this study.

Other research designs were not as suitable as a quantitative nonexperimental survey study. Several studies on healthcare information technology adoption used a qualitative case study for their research method (De Almeida et al., 2017; De Camargo et al., 2015; Liberati et al., 2017). Researchers can use case studies to analyze a case or program and identify views and events that occur as part of it (Creswell, 2014). Case studies contributed new insights regarding influences on technology adoption in healthcare; however, because of the specifics of the studied organizations, case studies may have limited generalizability (Creswell, 2014; De Almeida et al., 2017; De Camargo et al., 2015; Liberati et al., 2017). Similarly, artificial intelligence algorithm development has widely used quantitative secondary data; however, few studies used the method to study adoption (Akour, 2016; Carroll et al., 2017; Rigla et al., 2017; Zhang et al., 2018; Zhou et al., 2016). Because secondary data analysis studies reuse existing data, the data may not fit the purpose of the secondary analysis well and may not provide sufficient reliability, validity, and generalizability (Carroll et al., 2017; Zhang et al., 2018).

Target Population and Sample

This study includes a cross-sectional survey that requires a population sample. In a cross-sectional survey study, researchers measure and collect data from a population sample using a survey instrument (Sekaran & Bougie, 2013). A practical challenge of this research methodology is that this study needed to recruit and qualify a population sample, and this may be difficult and expensive (Sekaran & Bougie, 2013). This study managed the difficulty and expense by recruiting the sample by using an online survey service. To explain this process, this chapter examines the nature of the population, the sample, and the power analysis.

Population

This research study sampled from the population of 803,090 U.S. healthcare IT professionals (U.S. Bureau of Labor Statistics, 2018). Healthcare IT professionals include a range of professionals that provide IT service in the healthcare sector such as actuaries, applications, computer and information research scientists, computer network architects, computer network support specialists, computer programmers, computer systems analysts, computer user support specialists, database administrators, information security analysts, mathematicians, network and computer systems administrators, operations research analysts, software developers, software developers, statisticians, and web developers (U.S. Bureau of Labor Statistics, 2018). The healthcare sector includes of a wide range of private and public subsectors including direct patient care, federal response and program offices, health information technology, health plans and payers, laboratories and pharmaceuticals, mass fatality management services, medical materials, and public health (U.S. Department of Health and Human Services, 2016). Healthcare IT professionals may have different views on artificial intelligence technology adoption than other populations because healthcare IT professionals view patient safety, risk management, information privacy, and software validation as control processes that are required for software medical device development and managing healthcare information (International Organization for Standardization, 2016; U.S. Department of Health and Human Services, 1996).

Sample

The sample frame included persons in the Qualtrics (2018) U.S. participant panel who are aware of artificial intelligence capabilities in healthcare from healthcare IT professionals. Inclusion was determined by asking if participants know of the advances of the IBM Watson Health initiative (International Business Machines, 2015). Data collection included participants answering yes. The IBM Watson Health initiative has made recognized advancements in artificial intelligence technologies in healthcare for medical image processing, oncology screening, and genomics (International Business Machines, 2015). Additionally, the IBM Watson Health initiative is a recognized leader in healthcare artificial intelligence (McGregor & Banifatemi, 2018).

This study used a probability sampling design. Because this study attempted to contact highly paid workers that may have proven to be difficult to reach, there was a concern that further clustering may result in a very low response rate. As a result, this study used a basic probability sampling method known as simple random sampling (Bondesson & Traat, 2013; Trochim, 2006). However, the study survey collected data on age, gender, and years of education to support stratified random sampling and relieve issues because of having a particular demographic over-represented (Trochim, 2006). If needed, stratified random sampling allows a study to examine the performance of each stratification in the results (Bondesson & Traat, 2013; Trochim, 2006).

This study addresses practical and ethical challenges introduced by sampling design. In a cross-sectional survey study, researchers use methods that are free from bias (Creswell, 2014). A practical and ethical challenge is to prevent forms of sample bias because of having a particular demographic over-represented (Sekaran & Bougie, 2013; Trochim, 2006). In a cross-sectional survey study, researchers want a random representation of the population for the study sample (Creswell, 2014; Trochim, 2006). This study used a basic probability sampling method known as simple random sampling to address this challenge (Bondesson & Traat, 2013; Trochim, 2006). Simple random sampling does not prevent issues because of having a particular demographic over-represented (Trochim, 2006). Because this study attempted to contact highly paid workers that may have proven to be difficult to reach, there was a concern that further clustering may result in a very low response rate (Trochim, 2006). The study survey collected data on age, gender, and years of education to support stratified random sampling and relieve issues because of having a particular demographic over-represented (Trochim, 2006). If needed, stratified random sampling allows a study to examine the performance of each stratification in the results (Bondesson & Traat, 2013; Trochim, 2006).

Power Analysis

Researchers need to understand the relationship of a sample size to type-I and type-II error. Researchers generate a type-I error when their analysis indicates they should reject the null hypothesis when they should not (Schönbrodt, Wagenmakers, Zehetleitner, & Perugini, 2017; Sedgwick, 2014; Sekaran & Bougie, 2013). In the case of a type-I error, researchers are erroneously indicating the cause-effect phenomena under study is not false when it is (Schönbrodt et al., 2017; Sedgwick, 2014; Sekaran & Bougie, 2013). In a survey study with a nonexperimental correlational design, researchers control a type-I error through the significance level they use in the analysis (Schönbrodt et al., 2017). Researchers generate a type-II error when their analysis indicates they should not reject the null hypothesis when they should (Schönbrodt et al., 2017; Sedgwick, 2014; Sekaran & Bougie, 2013). In the case of a type-II error, researchers are erroneously indicating the cause-effect phenomena under study is false when it is not false (Schönbrodt et al., 2017; Sedgwick, 2014; Sekaran & Bougie, 2013). A type-II error can occur when the realized effect size is smaller than the researcher expected, and the sample is not large enough to account for the smaller effect size (Schönbrodt et al., 2017). To avoid type-I and type-II, researchers must understand the sample size requirements for the analysis methods, standard error, and statistical power they expect (Field, 2013; Schönbrodt et al., 2017). This study manages the risk of type-I and type-II error through sample size.

This study addresses this challenge and manages type-I, and type-II error through standard error, effect size, statistical power, and by calculating the minimum sample size using the G*Power (Version 3.1.9.4) software package. The analysis calculated two sample sizes using the G*Power software package. Initially, G*Power calculated a minimum sample size based on the planned use of a hierarchical linear regression statistical analyses and a conventional statistical power of .80 (Sekaran & Bougie, 2013). The parameters for the G*Power required sample size calculation selected were "Linear multiple regression: Fixed model, R^2 deviation from zero", 5% standard error, .15 effect size, .80 power, and six predictors. Based on the required sample size calculation results, this study required a minimum sample size of 98 participants to achieve a conventional statistical power of .80. This study managed type-I error by using a commonly accepted 5% standard error and small .15 effect size (Schönbrodt et al., 2017; Sedgwick, 2014; Sekaran & Bougie, 2013).

To further control type-I and type-II error, this study sought to achieve a statistical power of .95 and needed more than a minimum of 98 participants (Schönbrodt et al., 2017; Sedgwick, 2014). The advantage of using a statistical power of 0.95 is that the statistical power of 0.95 reduces the chances of a type-II error (Sekaran & Bougie, 2013). To determine the larger sample size, the G*Power (Version 3.1.9.4) software package recalculated the required sample size based on an analysis requiring, 5% standard error, 0.15 effect size, 0.95 power, and six predictors. Based on the adjusted power calculation results, this study required an adjusted sample size of 146 participants for a statistical power of 0.95. To help account for unusable responses and incomplete surveys and assure the minimum valid responses, this study planned to recruit 200 participants online anonymously.

Setting

The setting for this study is virtual because this research study planned to anonymously recruit participants using the Qualtrics (2018) online respondent recruitment service. Online recruitment offers lower costs than postal mail and can access participants over a wide geographic area (Dworkin, Hessel, Gliske, & Rudi, 2016; Lefever, Dal, & Matthíasdóttir, 2007). Although online recruitment may be discarded or ignored by some potential participants, compared to traditional interviews or postal mail, recruiting participants online is faster and allows a larger volume of recruitment attempts (Dworkin et al., 2016; Heiervang & Goodman, 2011; Weigl et al., 2019). Because the research did not take place on a physical site, and this study recruited the healthcare IT professionals anonymously in their privacy, site permission is not applicable.

A virtual research setting addresses several practical and ethical challenges. An ethical challenge of conducting research is that the study must protect the identity of participants and, if conducting research at a site, gain permission to conduct research at the site (Creswell, 2014). A practical and ethical challenge of conducting a survey at a physical setting is that the physical setting exposes the study to unpredictability and exposes participants to physical, privacy, and social risks (Sekaran & Bougie, 2013). This study addresses most site related and human ethical challenges by requiring that the survey service administer only anonymous online recruitment and issue an anonymous online survey (Dworkin et al., 2016; Qualtrics, 2018). Participants selected a time and location of their choosing to complete the survey online, so this study did not require site permission (Dworkin et al., 2016; Qualtrics, 2018). The use of an online survey allowed the participants to complete their survey in private by using mobile devices or other computers (Dworkin et al., 2016; Qualtrics, 2018). The survey service recruited participants throughout the United States to eliminate inadvertent participant identification or a loss of privacy, and survey participants are unlikely to become vulnerable in their workplace (Dworkin et al., 2016; Lefever et al., 2007). Online surveys have some weaknesses.

Online surveys have several weaknesses. Online surveys require comfort with technology (Lefever et al., 2007). This study addresses this challenge by sampling from members of information technology teams who are comfortable with technology. Another weakness is that research has shown that participants may not stay engaged with online surveys as compared with traditional interviews that have human interaction (Heiervang & Goodman, 2011; Lefever et al., 2007). Although participants may lose interest in completing surveys when compared with traditional interviews, sending participants reminders improves response completion (Dworkin et al., 2016; Weigl et al., 2019). Another weakness is that online surveys may be discarded or ignored by some potential participants; however, the low cost of online surveys allows for a larger volume of survey attempts (Dworkin et al., 2016). The sample size affects statistical power and the chance of a type-I and type-II error.

Procedures

This study followed specific procedures for participant selection, protection of the participants, data collection, and data analysis. This section explains this study's procedures and reviews all the steps needed to complete the procedures. This section accomplishes this by including discussion of the participant selection, explaining the protection of participants, reviewing the data collection, and explaining the data analysis. With the purpose and organization of this section communicated, this section moves forward with the participant selection.

Participant Selection

This research study planned to recruit participants using an online respondent recruitment service anonymously. The Qualtrics (2018) online recruitment service recruited anonymous participants using their private email from Qualtrics's repository. Online recruitment can access participants over a wide geographic area for lower costs than postal mail (Dworkin et al., 2016; Lefever et al., 2007). Recruiting participants online is faster than traditional interviews or postal mail (Heiervang & Goodman, 2011; Weigl et al., 2019). Online recruitment is cost-effective and is less expensive than traditional interviews or surveys conducted through postal mail (Dworkin et al., 2016; Heiervang & Goodman, 2011; Weigl et al., 2019). Although online recruitment may be discarded or ignored by some potential participants, compared to traditional interviews or postal mail, recruiting participants online is faster and allows a larger volume of recruitment attempts (Dworkin et al., 2016; Heiervang & Goodman, 2011; Weigl et al., 2019). As part of recruitment, participants must complete the inclusion criteria.

Participants needed to complete inclusion criteria before participating in this study. This study did not collect data from any participant before collecting an agreement to informed consent. The first step for a participant was to review and agreed to the informed consent agreement before proceeding with the survey. After agreeing to the informed consent, the study determined the inclusion of each participant by asking if participants are Healthcare IT professionals and if they know of the advances of the IBM Watson Health initiative (International Business Machines, 2015). Participants answering yes to both questions were included for participation and proceeded with the survey questions. Participants rejecting the informed consent or answering no to either inclusion question were thanked for their time and excluded from the study. Online recruitment helps protect participants.

Protection of Participants

This study addressed the practical and ethical challenges associated with protecting participants. An ethical challenge of conducting this study's research methodology is that this study must protect the identity of participants, and if conducting research at a site, gain permission to conduct research at the site (Creswell, 2014). A practical and ethical challenge of conducting a survey at a physical setting is that the physical setting exposes the study to unpredictability and exposes participants to physical, privacy, and social risks (Sekaran & Bougie, 2013). This study protected participants and addresses most site related and human ethical challenges by requiring that the survey service administer only anonymous online recruitment and issue an anonymous online survey (Dworkin et al., 2016; Qualtrics, 2018). Participants selected the time and location of their choosing to complete the survey online, so this study does not require site permission (Dworkin et al., 2016; Qualtrics, 2018). The use of an online survey allowed the participants to complete their survey in private by using mobile devices or other computers (Dworkin et al., 2016; Qualtrics, 2018). The survey service recruited participants throughout the United States to eliminate inadvertent participant identification or a loss of privacy, and survey participants are unlikely to become vulnerable in their workplace (Dworkin et al., 2016; Lefever et al., 2007). The study must also protect the participants from psychological harm (Sekaran & Bougie, 2013). This study addressed this challenge by collecting survey responses anonymously, and this allowed the participant to end the survey at any time (Qualtrics, 2018).

Data Collection

As a data collection mechanism, this study used an anonymous online survey to collect the views of healthcare organization IT staff. A practical challenge of conducting this study's research methodology is that this study must securely and accurately collect and retain the data for analysis and records (Creswell, 2014). This study addresses this challenge by including the Qualtrics (2018) online recruitment and survey service. The Qualtrics service collected and maintained the accurate records of participant responses in a secure repository and provide the status of survey progress. The survey data is available for secure download from the Qualtrics service for data analysis without the need for rekeying. When downloaded for analysis, an encrypted hard drive and encrypted external storage drive stored and protected all response data. The use of an online survey is secure, cost-effective, and less error-prone than methods involving manual rekeying or postal mail data collection (Dworkin et al., 2016; Qualtrics, 2018). The study's data analysis methods introduce practical and ethical challenges. The sampling procedures followed the following steps.

1. As part of the study approval, a Capella University internal review board reviewed and approved the survey procedures, instructions, informed consent

form, screening questions, and the survey adapted from the Slade et al. (2015) instrument.

2. The study utilized Qualtrics to implement the approved survey procedures, instructions, informed consent form, screening questions, and the approved instrument as an online survey.

3. The study defined a recruitment size of n = 200 to exceed the sample size requirement discussed earlier in this study.

4. The study defined a distribution population with Qualtrics that recruited U.S. healthcare IT professionals.

5. The Qualtrics service emailed possible participants from its recruitment database; however, the study did not receive any email addresses or personally identifiable information of any participants.

6. Participants received survey instructions for all official communications regarding the study in the survey instructions and the informed consent form.

7. The Qualtrics recruitment service requested participants to review the survey instructions and informed consent form. Only participants that agreed to the informed consent form were permitted to continue.

8. To ensure all participants were U.S. healthcare IT professionals, the Qualtrics recruitment service asked participants if they were U.S. healthcare IT professionals as recognized by the U.S. Bureau of Labor Statistics. Healthcare IT professionals include a range of professionals that provide IT service in the healthcare sector such as actuaries, applications, computer and information research scientists, computer network architects, computer network support

specialists, computer programmers, computer systems analysts, computer user support specialists, database administrators, information security analysts, mathematicians, network and computer systems administrators, operations research analysts, software developers, software developers, statisticians, and web developers (U.S. Bureau of Labor Statistics, 2018). The healthcare sector includes of a wide range of private and public subsectors including direct patient care, federal response and program offices, health information technology, health plans and payers, laboratories and pharmaceuticals, mass fatality management services, medical materials, and public health (U.S. Department of Health and Human Services, 2016).

9. The Qualtrics recruitment service disqualified any participants who are not U.S. healthcare IT professionals by thanking them and ending the survey.

10. To screen for awareness of artificial intelligence, the Qualtrics recruitment service asked participants if they are aware of the IBM Watson Health initiative (International Business Machines, 2015). The IBM Watson Health initiative has made recognized advancements in artificial intelligence technologies in healthcare for medical image processing, oncology screening, and genomics (International Business Machines, 2015). Additionally, the IBM Watson Health initiative is a recognized leader in healthcare artificial intelligence (McGregor & Banifatemi, 2018).

11. The Qualtrics recruitment service disqualified participants who are not aware of the IBM Watson Health initiative by thanking them and ending the survey.

12. The study allowed participants that the inclusion criteria did not disqualify to complete the survey as part of the data collection procedures.
13. If any participant elects to end the survey, the survey thanked them and end.
14. A participant may stop the survey and continue at a later time (Qualtrics, 2018).
15. The study used the Qualtrics recruitment service to remind participants to respond to the survey if they have not responded.
16. The study used the Qualtrics recruitment service to remind participants to complete partially completed surveys.
17. As participants complete the survey, the Qualtrics recruitment service validated the responses for completeness and store them for data analysis.
18. Once the target number of complete survey responses was collected, the data was formatted into a comma-separated values file and transferred to secure storage for data analysis.

Data Analysis

This study planned a hierarchical linear regression analysis as the data analysis technique to use on the survey responses and answer the research question. A practical and ethical challenge of a quantitative research methodology is that it must use valid and reliable statistical methods to explain the significance of the observed cause-effect influence that manages bias and ethical issues (Creswell, 2014; Field, 2013; Zyphur & Pierides, 2019). A hierarchical linear regression provided a statistical explanation to measure the extent that the predictor variables predict the levels of the outcome variable (Field, 2013; Leech et al., 2003; Uyanık & Güler, 2013). Similar published studies based on the UTAUT used a hierarchical linear regression analysis (Alaiad et al., 2014; Kohnke et al., 2014). This study completed the data analysis using the recognized SPSS Statistical 24 software package as the analysis tool (Field, 2013; International Business Machines, n.d.). By using an existing theory and methods recognized by similar studies, this study should provide good transferability and dependability (Alaiad et al., 2014; Creswell, 2014; Field, 2013; Kohnke et al., 2014; Slade et al., 2015).

Descriptive statistics. To prepare for computing the descriptive statistics, the survey responses were counted, encoded, and stored. The data should not be missing values for any record, and the analysis must correctly code all data for its type (Field, 2013). The survey service screened the responses for completeness and valid 7-point Likert scale values then stored them for download (Qualtrics, 2018). The analysis downloaded and formatted the data into a comma-separated values file for import into SPSS Statistics 24 (International Business Machines, n.d.). Once imported into SPSS, the analysis added field names, set raw field types to scale, and saved the data as an SPSS dataset.

Multiple survey instrument questions represented each composite variable, and the SPSS calculated the question responses into composite values. The adapted instrument contains four questions pertaining to trust in system, three questions pertaining to performance expectancy, four questions pertaining to effort expectancy, three questions pertaining to social influence, three questions pertaining to innovativeness, three questions pertaining to perceived risk, and three questions pertaining to behavioral intention. The survey instrument collected 7-point Likert scale values for all questions pertaining to trust in system, performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and behavioral intention and fixed a lower bound of *strongly disagree* and an upper bound of *strongly agree*. Weighted Likert scale values are representative of interval values are accurate when used as interval values in parametric statistical analysis (Fleiss & Cohen, 1973; Wu & Leung, 2017). Because trust in system, performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and behavioral intention are composite values of multiple weighted Likert scale values, the analysis treated all variables as ratio variables (Field, 2013; Fleiss & Cohen, 1973; Norman, 2010; Wu & Leung, 2017). Ratio variables align with a regression analysis method because a regression analysis requires the data to represent a level, rather than a nominal value, and has an assumption of linearity (Field, 2013). To calculate composite vales, SPSS calculated the Z-score for each question response and averaged the Z-scores of the questions that represent each variable (Lund Research, 2018; Song, Lin, Ward, & Fine, 2013). SPSS accomplishes this in two steps. First, SPSS calculates the Z-score as an added field during a descriptive statistics command. Second, SPSS adds a new composite score field that is the average of the Z-scores by using the SPSS compute variable command.

Hypothesis testing. This study conducted a hierarchical linear regression analysis to complete the hypothesis testing. This subsection explains the steps the analysis included. This subsection discusses the verification of assumptions required by the hierarchical linear regression analysis, discuss the methods of the hierarchical linear regression analysis, and describe the posthoc analysis. With the purpose and organization of this subsection communicated, this subsection moves forward with the verification of assumptions required by the hierarchical linear regression analysis.

Verification of assumptions. A hierarchical linear regression analysis requires upholding additional assumptions to produce valid and reliable results. This study must test for the assumptions needed for hierarchical linear regression including completeness, treating outliers and high leverage/influential points, independence of observations, linear model fit, homoscedasticity of residuals, low multicollinearity, and normality of residuals using results calculated during the regression (Field, 2013; International Business Machines, n.d.; Lund Research, 2018). This study used SPSS to calculate descriptive statistics and screen data for normality, completeness, and linear model fit to address these challenges (Field, 2013; International Business Machines, n.d.). SPSS calculated the data needed to test for outliers and evaluate the assumptions of independence of observations, linear model fit, homoscedasticity of residuals, low multicollinearity, and normality of residuals multicollinearity as part of calculating the hierarchical regression (Field, 2013; Lund Research, 2018). This study must evaluate and report any violation of assumptions because a violation may affect the validity and reliability of the results (Field, 2013; Sekaran & Bougie, 2013). As part of the hierarchical regression calculation, SPSS generated the specific data needed to evaluate each assumption. The analysis used Cook's distance, studentized deleted residuals, leverage values, and casewise diagnostics standardized residuals to test for outliers, high leverage points, and highly influential points (Field, 2013; Lund Research, 2018; Song et al., 2013).

Outliers, high leverage points, and highly influential points. Data rows that appear in the casewise diagnostics with standardized residuals greater than three indicate outliers (Field, 2013; Lund Research, 2018). Data rows with a studentized deleted residuals greater than three or less than negative three indicate outliers (Field, 2013; Lund Research, 2018). Data rows with leverage values greater than 0.200 indicate high leverage points (Field, 2013; Lund Research, 2018). Data rows with Cook's distances greater than one indicate influential points (Field, 2013; Lund Research, 2018).

Independence of observations. The analysis used the Durbin-Watson statistic to evaluate the independence of observations (Field, 2013; Lund Research, 2018). A Durbin-Watson statistic that is approximately two indicates independence of observations (Field, 2013; Lund Research, 2018).

Linear model fit. The analysis used a scatterplot formed from studentized residuals and unstandardized predicted values, and individual scatterplots of each predictor variable with the outcome variable to evaluate the linear model fit (Field, 2013; Lund Research, 2018). The presence of a rectangular non-U shaped scatterplot formed from studentized residuals and unstandardized predicted values partially indicates the linear model fit (Field, 2013; Lund Research, 2018). When combined with the suggestion of a linear collection of plots in the individual scatterplots of each predictor variable with the outcome variables, the data has a good linear model fit (Field, 2013; Lund Research, 2018).

Homoscedasticity of residuals. The analysis used a scatterplot formed from studentized residuals and unstandardized predicted values to evaluate the homoscedasticity of residuals (Field, 2013; Lund Research, 2018). The presence of a rectangular non-cone shaped scatterplot formed from studentized residuals and unstandardized predicted values indicates homoscedasticity of residuals (Field, 2013; Lund Research, 2018).

Low multicollinearity. The analysis interpreted correlation coefficients, specifically collinearity statistics tolerance values, to evaluate low multicollinearity (Field, 2013; Lund Research, 2018). Predictor variables with collinearity statistics tolerance values above .1 indicate acceptable multicollinearity (Lund Research, 2018).

Normality of residuals. The analysis used a histogram formed from frequencies of standardized residuals, a P-P plot of standardized residuals, and a Q-Q plot of studentized residuals to evaluate the normality of residuals (Field, 2013; Lund Research, 2018). The presence of a typical bell-shaped normal curve histogram, as well as Q-Q and P-P plot that are close to linear, indicate normality of residuals (Field, 2013; Lund Research, 2018).

Regression analysis. The analysis included a hierarchical linear regression test in calculating influences on behavioral intention. The analysis introduced each of the six predictors separately for better control of the introduction order than simple stepwise entry. The final model included trust in system, performance expectancy, effort expectancy, social influence, innovativeness, and perceived risk. The final model regression formula was

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_5 X_{i5} + \beta_6 X_{i6} + \varepsilon_i$$

where X_{i1} was trust in system, X_{i2} was performance expectancy, X_{i3} was effort expectancy, X_{i4} was social influence, X_{i5} was innovativeness, and X_{i6} was perceived risk.

The interpretation of the statistical analysis indicated the extent of the cause-effect relationships described by the theory, the answers to the research question, and when to reject the null hypothesis (Cohen, Cohen, West, & Aiken, 2013; Connelly, 2015; Farrugia, Petrisor, Farrokhyar, & Bhandari, 2010). The analysis identified models showing statistically significant correlations and evaluated significant models to determine the advantage in R^2 over the mean as a predictor or other models. After calculating the hierarchical regression results, SPSS outputs the ANOVA and the model summary table (Cohen et al., 2013; Field, 2013; Lund Research, 2018). The ANOVA indicates the statistical significance of each model with a model F-score significance value of $p < .050$ (Cohen et al., 2013; Field, 2013; Lund Research, 2018). A statistically significant F-score for model six indicated to reject the null hypothesis and accept the alternate hypothesis (Cohen et al., 2013; Field, 2013). A statistically significant F-score for model six protects the findings from a larger type-I error (Cohen et al., 2013). With a statistically significant F-score for any given model, the analysis interpreted the individual variable contributions based on the variable's coefficient *t*-test having a significance of $p < .050$ (Cohen et al., 2013).

The predictive improvements identified each predictor variable's contribution and provided a deeper explanation of the answer to the research question. The adjusted R^2 indicates the percentage of variation explained based on adding a variable and the significance of the variable's contribution in the hierarchical regression (Cohen et al., 2013; Field, 2013; Lund Research, 2018). With each variable added, the new model should remain significant at $p = .050$ and have stronger predictive power as indicated by a larger adjusted R^2 (Cohen et al., 2013; Field, 2013; Lund Research, 2018).

Posthoc analysis. This study confirmed achieved performance through posthoc testing (Field, 2013). G*Power (Version 3.1.9.4) calculated the posthoc effect size based on R^2 (Field, 2013). G*Power calculated the achieved power using a posthoc achieved power calculation for the statistical test "Linear multiple regression: Fixed model, R^2 deviation from zero" (Field, 2013). After all computations, this study must report the results of the data analysis and posthoc testing (Field, 2013; Sekaran & Bougie, 2013). With an understanding of the posthoc analysis in place, the study moves forward to discuss the research instrument.

Instruments

This study included a proven survey instrument. This section presents this research instrument. This section starts by reviewing the details regarding the instrument then presents support for the instrument's validity and reliability. With the purpose and organization of this section communicated, this section moves forward to review the details regarding the instrument.

The Slade et al. Survey Instrument

This study used a proven survey instrument published by Slade et al. (2015) to investigate all variables. The instrument is an existing cross-sectional survey instrument published in the peer-reviewed journal, *Psychology & Marketing*, and copyrighted in 2015 by Wiley Periodicals, Inc. (Slade et al., 2015). Dr. Emma Louise Slade provided written permission for this study to use the survey instrument for this research. This study adapted the instrument, made up of twenty-three Likert scale questions, by replacing some nouns in the questions to reflect the population and research topic. This study recreated the instrument, plus two inclusion questions and four demographic questions as an online survey.

The instrument specifies a 7-point Likert scale for all questions pertaining to trust in system, performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and behavioral intention and fixed a lower bound of *strongly disagree* and an upper bound of *strongly agree* (Slade et al., 2015). The adapted instrument contains four questions pertaining to trust in system, three questions pertaining to performance expectancy, four questions pertaining to effort expectancy, three questions pertaining to social influence, three questions pertaining to innovativeness, three questions pertaining to perceived risk, and three questions pertaining to behavioral intention. Likert scale responses have an implied distribution with an implied weighting found in the defined responses (Fleiss & Cohen, 1973). Weighted Likert scale values are representative of interval values, and a greater number of Likert value options produce greater accuracy (Fleiss & Cohen, 1973; Wu & Leung, 2017). This study assumes that seven-point Likert scale responses are accurate when used as interval values in parametric statistical analysis (Fleiss & Cohen, 1973; Norman, 2010; Wu & Leung, 2017). Because trust in system, performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and behavioral intention are composite values of multiple weighted Likert scale values, the analysis treated all variables as ratio variables (Field, 2013; Fleiss & Cohen, 1973; Norman, 2010; Wu & Leung, 2017). Ratio variables align with a regression analysis method because a regression analysis requires the data to represent a level, rather than a nominal value, and has an assumption of linearity (Field, 2013). The survey instrument offers good validity and reliability.

Validity. The survey instrument offers good validity. A practical challenge of the quantitative research methodology is that this study must address the assumption that researchers are objective and use valid methods that manage bias and ethical issues (Creswell, 2014; Field, 2013; Zyphur & Pierides, 2019). This study addresses this challenge by including a survey instrument with published validity (Slade et al., 2015). A variable's average variance extracted (AVE) indicates discriminant validity if the square root of AVE exceeded the variable's correlations to the other predictors (Fornell & Larcker, 1981). As displayed in Table 1, the survey instrument indicated good discriminant validity with the √AVE for all variables exceeding their correlations to the other predictors (Slade et al., 2015).

Table 1

Validity and Reliability

Variable	*CR*	√*AVE*	Strongest *r*	*N*
Performance expectancy	0.949	0.928	0.717	268
Effort expectancy	0.955	0.936	0.705	268
Social influence	0.989	0.983	0.538	268
Innovativeness	0.910	0.879	0.697	268
Perceived risk	0.972	0.879	(0.214)	268
Trust in system	0.975	0.952	0.500	268
Behavioral intention	0.975	0.976	0.717	268

Note. A variable's average variance extracted (AVE) indicates discriminant validity if the square root of AVE exceeded the variable's correlations to the other predictors (Fornell & Larcker, 1981).

Reliability. The survey instrument offers good reliability. A practical challenge of the quantitative research methodology is that this study must address the assumption that researchers are objective and reliable methods that manage bias and ethical issues (Creswell, 2014; Field, 2013; Zyphur & Pierides, 2019). This study addresses this challenge by including a survey instrument with published reliability (Slade et al., 2015). As displayed in Table 1, the survey instrument achieved composite reliability ranging from 0.879 to 0.989 with $n = 268$ (Slade et al., 2015). These results exceeded recognized values of 0.7 for composite reliability and maintained strong discriminant validity (Field, 2013; Slade et al., 2015). By using a previously proven survey instrument that matches the theory variables and is known to have strong validity and reliability, this study should offer strong validity, reliability, credibility, and trustworthiness (Creswell, 2014; Field, 2013; Sekaran & Bougie, 2013; Slade et al., 2015). The study's data collection methods introduce practical and ethical challenges.

Ethical Considerations

Although this study addresses numerous ethical considerations throughout this chapter, this section highlights some important ethical considerations. Osei (2013) stated that conducting a risk assessment is an important starting point for understanding a study's ethical considerations. Osei identified informed consent, privacy and confidentiality, data handling and reporting, and mistakes and negligence as critical ethical considerations. This study method addresses the ethical risk by applying the risk assessment to the design. Osei stated that informed consent is a critical requirement before collecting data from any participant. This study required participants to agree to an IRB approved informed consent agreement before allowing them to proceed with the survey. This study addressed privacy and confidentiality by using an anonymous online survey, and participants controlled the survey location; thus, most privacy and confidentiality risks are unlikely.

Additionally, this study protected vulnerable participants by not using vulnerable populations or conducting research on an especially sensitive topic. This study addressed data handling by compiling survey results in a private, secure home office. Additionally, the Qualtrics (2018) survey service, used by this study, provided security and data integrity while collecting survey responses. This study addressed ethical issues with reporting and mistakes and negligence by working closely with an experienced mentor and committee.

Summary

The purpose of this quantitative nonexperimental correlational cross-sectional survey research was to examine what factors affect artificial intelligence technology adoption in healthcare. This study is a cross-sectional survey study that used a quantitative research methodology with a nonexperimental correlational design. This study uses the variables of the extended UTAUT to measure and assess the effect of trust on the adoption of artificial intelligence technology. The extended UTAUT relates the independent variables of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system to the dependent variable of behavioral intention (Slade et al., 2015). This research study sampled from the population of 803,090 U.S. healthcare IT professionals (U.S. Bureau of Labor Statistics, 2018). As a data collection mechanism, this study used an anonymous online survey to collect the views of healthcare organization IT staff. The analysis included a hierarchical linear regression test in calculating influences on behavioral intention. This study used a proven survey instrument, published by Slade et al. (2015), to investigate all variables using a 7-point Likert scale. By including a survey instrument with published reliability, this study offers good validity and reliability (Slade et al., 2015). Because this study collected data used an anonymous online survey and participants controlled the survey location, most ethical risks are unlikely (Osei, 2013). This study moves forward to report the results produced by this methodology.

CHAPTER 4. RESULTS

The purpose of this chapter is to report this study's results. This chapter presents a chapter background, a description of the sample, hypothesis testing, posthoc analyses, and summary. With the organization of this chapter established, this study moves forward to report the study results.

Background

This study conducted a hierarchical linear regression analysis as the data analysis technique to use on the survey responses and answer the research question. This section presents the results of this analysis. The content of this section reports a description of the sample, the results of descriptive statistics, the results of regression analysis, a summary of the hypothesis testing, posthoc analyses, and provides a summary of the answers to the research questions and results of the hypothesis testing. With a background of this section presented, this study moves forward to report a description of the sample.

Description of the Sample

This study planned to collect a sample of 200 participants, and this study collected an actual total sample of $N = 215$. Table 2 displays the sample's descriptive statistics. The Qualtrics (2018) recruitment service ran an initial soft launch to collect data from $n = 20$ participants and paused data collect so this study could gauge initial data quality. The soft launch data quality met expectations for completeness and valid values. Participants had a median time to completion of four minutes. For the full launch of data collection, the Qualtrics recruitment service added a speeding check of one-half the median time to completion. Adding the speeding check reduced the chances of participant straight-lining or not responding thoughtfully by discarding participants found speeding. All the responses were complete and had valid values for all questions. A preliminary achieved power calculation indicated an achieved power of $1 - \beta = .995$, based on an analysis with $SE = .050$, $f^2 = 0.15$ effect size, $N = 215$ sample size, and six predictors.

Table 2

Descriptive Statistics

Variable	*N*	*M*	Minimum	Maximum	*SD*	Skewness (*SE*)	Kurtosis (*SE*)
Behavioral intention	215	0.000	-0.82	3.92	.870	1.603 (.166)	3.239 (.330)
Effort expectancy	215	0.000	-0.91	2.94	.809	1.033 (.166)	0.909 (.330)
Innovativeness	215	0.000	-0.87	2.99	.795	0.941 (.166)	0.563 (.330)
Performance expectancy	215	0.000	-0.83	4.81	.825	1.686 (.166)	5.481 (.330)
Perceived risk	215	0.000	-1.04	2.10	.923	0.843 (.166)	-0.363 (.330)
Social influence	215	0.000	-0.93	3.62	.865	1.332 (.166)	2.164 (.330)
Trust in system	215	0.000	-0.84	4.01	.847	1.280 (.166)	2.074 (.330)

Note. The descriptive statistics, indicating the *N*, minimum, maximum, *SD*, skewness, and kurtosis of the sample data. All variables were slightly positively skewed.

Hypothesis Testing

This study conducted a hierarchical linear regression analysis. As previously described, this study completed the data analysis using the SPSS Statistical 24 software package as the analysis tool. This section reports the descriptive statistics, reports the results of the regression analysis, and reports the results of the hypothesis test.

Descriptive Statistics

The survey responses were counted, encoded, and stored. The data was complete and valid for all variables, and as planned, SPSS calculated Z-scores for all 7-point Likert scale values. The analysis preparation process calculated the composite values from the Z-scores as outcome variable behavioral intention – composite (BI), predictor variable trust in system – composite (TRU), predictor variable perceived risk – composite (PR), predictor variable performance expectancy – composite (PE), predictor variable effort expectancy – composite

(EE), predictor variable social influence – composite (SI), and predictor variable innovativeness – composite (IV). Because the composite variables are Z-scores, the mean for all variables is μ = 0.000 (Lund Research, 2018; Song et al., 2013). As displayed in Table 2, the means and standard deviations were BI μ = 0.000 (.870), TRU μ = 0.000 (.847), PR μ = 0.000 (.923), PE μ = 0.000 (.825), EE μ = 0.000 (.809), SI μ = 0.000 (.865), and IV μ = 0.000 (.795).

Regression Analysis

This subsection reports the results of the regression analysis. This subsection starts by reporting on the verification of the assumptions. After reporting on the verification of the assumptions, this subsection reports the regression analysis results. With an understanding of the organization of this subsection established, this study moves forward to report on the verification of the assumptions.

Verification of assumptions. A hierarchical linear regression analysis requires upholding additional assumptions to produce valid and reliable results. Thise study validated these assumptions are after regression analysis. As part of the hierarchical regression calculation, SPSS generated the specific data needed to evaluate each assumption. This subsection reports the verification of the assumptions needed for hierarchical linear regression, including outliers, high leverage points, highly influential points, independence of observations, linear model fit, homoscedasticity of residuals, low multicollinearity, and normality of residuals.

Outliers, high leverage points, and highly influential points. Data rows 10, 112, and 152 appeared in the casewise diagnostics with standardized residuals 6.043, 4.105, and 3.154. These three standardized residuals were greater than three and indicated outliers. These outliers are visually confirmed in Figure 2 that includes the visualization of studentized deleted residuals as a Q-Q plot. Two data rows had leverage values of .252 and .233, indicating two high leverage points. No data rows had a Cook's distances of greater than one; thus, there were no highly influential points and no need to treat the two high leverage points (Lund Research, 2018). Overall, these values do not violate the assumptions regarding outliers, high leverage points, and highly influential points (Field, 2013; Lund Research, 2018).

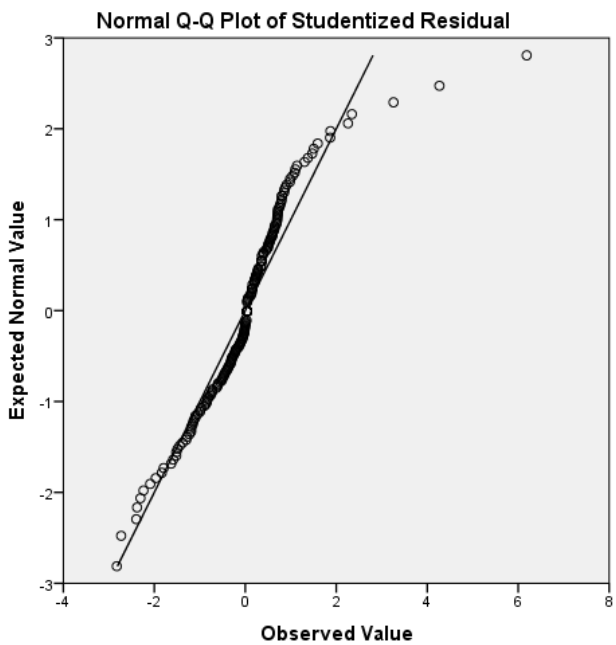

Figure 2. The Q-Q plot of studentized residuals. This Q-Q plot shows a linear plot with three outlier rows.

Independence of observations. The analysis indicated a Durbin-Watson statistic of 1.815. The Durbin-Watson statistic value is close to 2. A value is close to 2 indicates that there was not a violation of the assumption of independence of observations (Field, 2013; Lund Research, 2018).

Linear model fit. The analysis used a scatterplot formed from studentized residuals and unstandardized predicted values, and individual scatterplots of each predictor variable with the outcome variable to evaluate the linear model fit. Figure 3 that includes the visualization of a rectangular non-U shaped scatterplot formed from studentized residuals and unstandardized predicted values and partially indicates a good linear model fit. Figure 4, Figure 6, Figure 7, Figure 8, and Figure 9 visualize a linear collection of plots in the individual scatterplots of each predictor variable TRU, PE, EE, SI, and IV with the outcome variable BI, and individually indicate good linear model fit. Figure 5 includes the visualization of a marginally linear collection of plots for the predictor variable PR with the outcome variable BI and indicates a marginal linear model fit. Overall, the combination of these figures indicates that there was not a violation of the assumption of linear model fit.

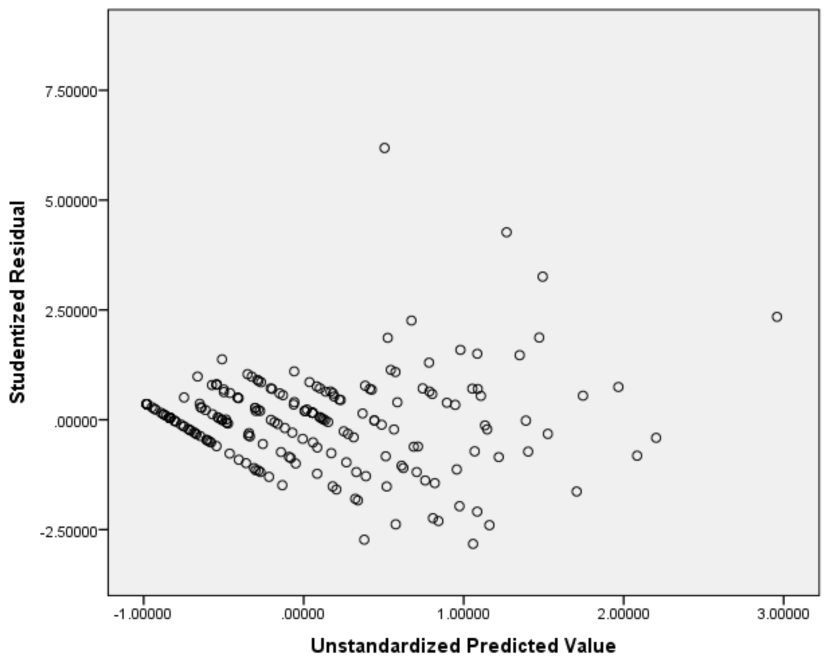

Figure 3. The scatterplot of studentized residuals. This scatterplot is formed from studentized residuals and unstandardized predicted values.

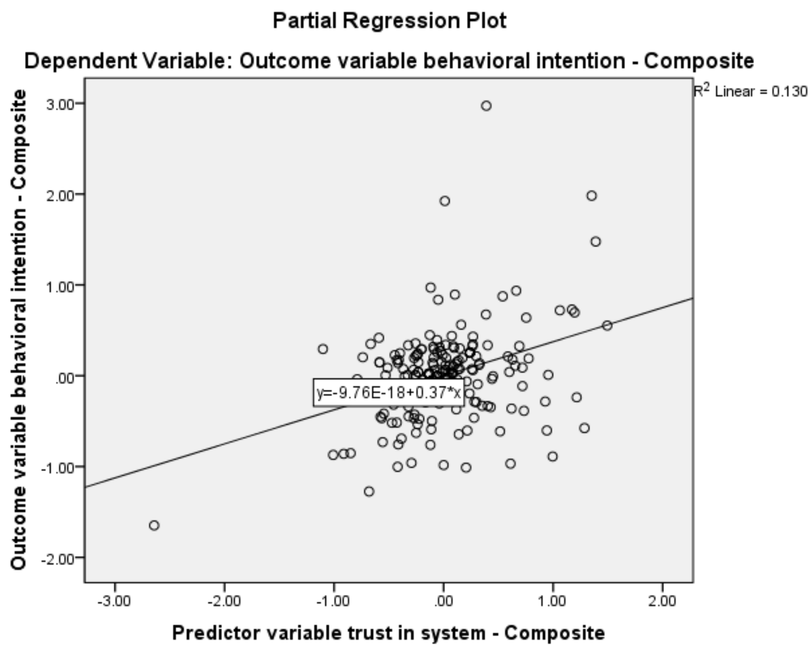

Figure 4. The partial regression plot of TRU. This individual scatterplot formed from TRU and BI indicates a good linear model fit.

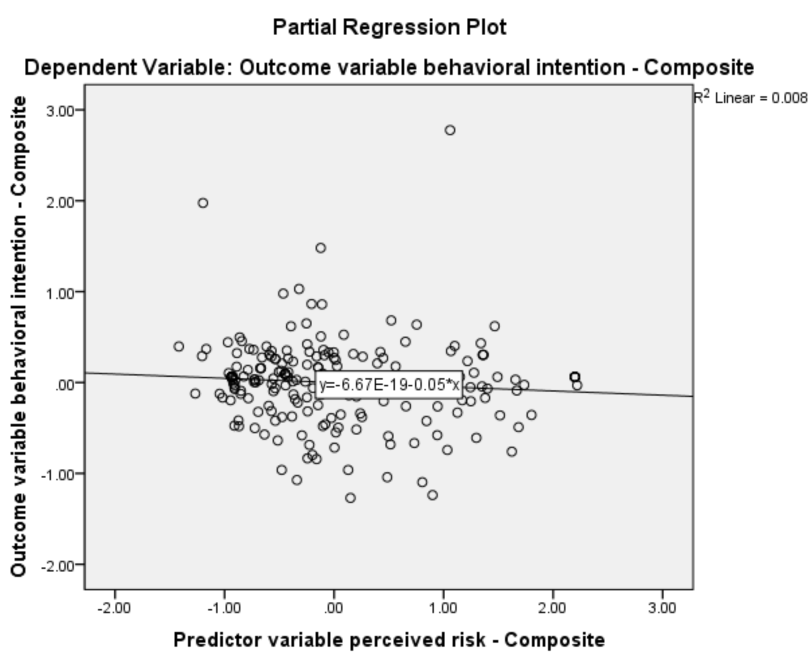

Figure 5. The partial regression plot of PR. This individual scatterplot formed from PR and BI indicates a marginal linear model fit.

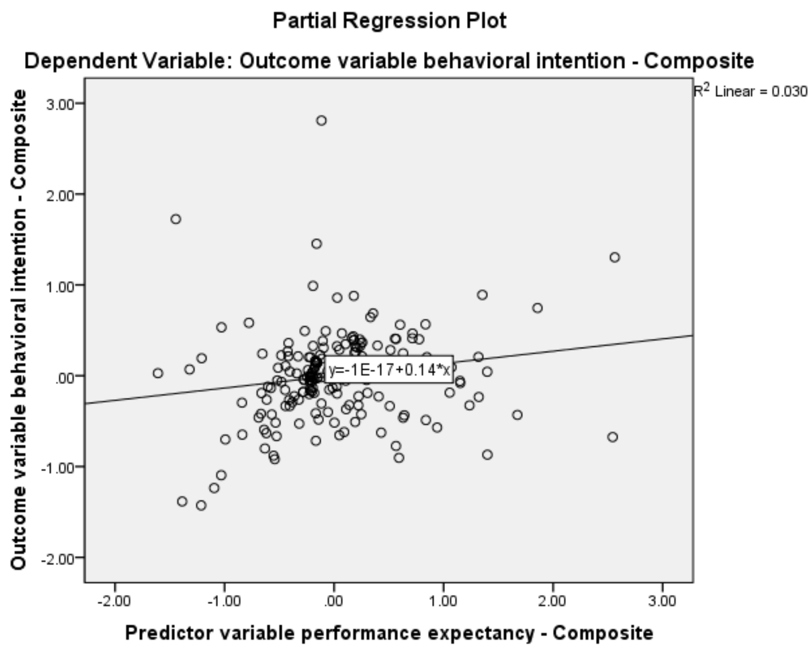

Figure 6. The partial regression plot of PE. This individual scatterplot formed from PE and BI indicates a good linear model fit.

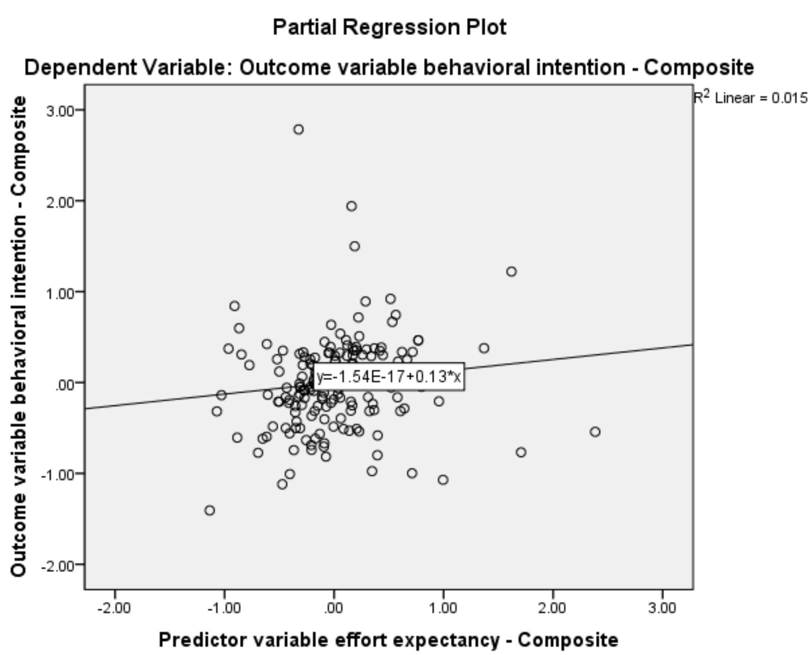

Figure 7. The partial regression plot of EE. This individual scatterplot formed from EE and BI indicates a good linear model fit.

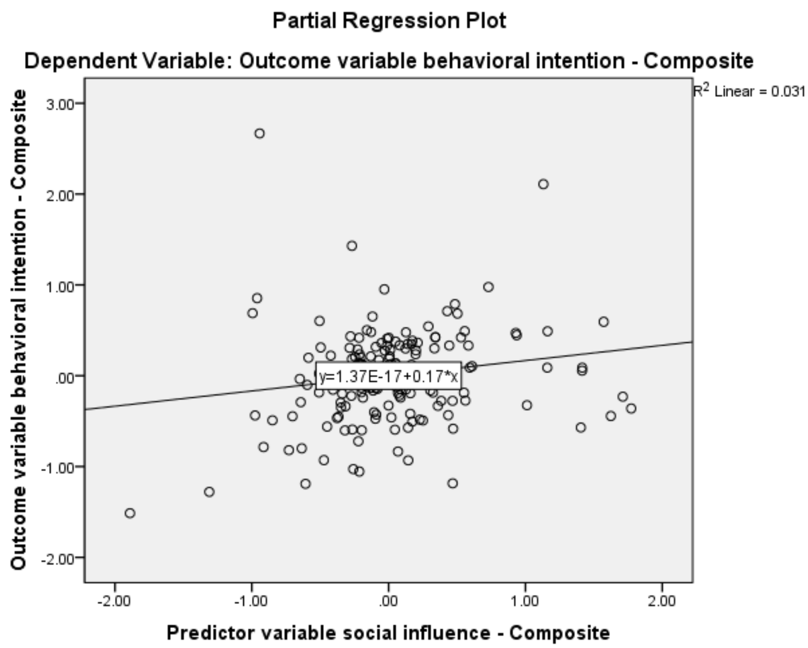

Figure 8. The partial regression plot of SI. This individual scatterplot formed from SI and BI indicates a good linear model fit.

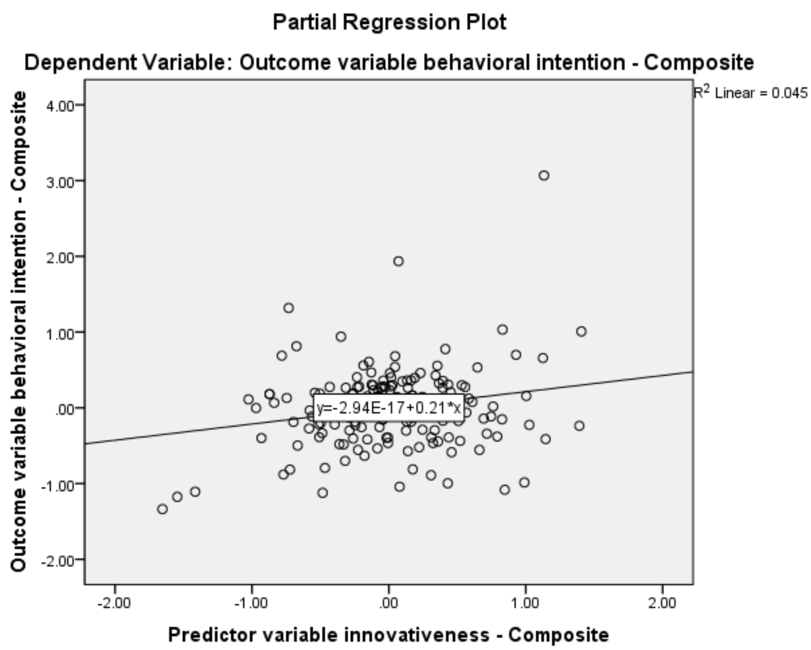

Figure 9. The partial regression plot of IV. This individual scatterplot formed from IV and BI indicates a good linear model fit.

Homoscedasticity of residuals. Figure 3 includes the visualization of a scatterplot formed from studentized residuals and unstandardized predicted values to evaluate the homoscedasticity of residuals. Although heavier with plot points to the left portion of the scatterplot, Figure 3 indicates a rectangular non-cone shaped scatterplot. There was not a violation of the assumption of homoscedasticity of residuals.

Low multicollinearity. The analysis interpreted correlation coefficients, specifically collinearity statistics tolerance values, to evaluate low multicollinearity. Some predictor variables had a Pearson correlations that required further analysis TRU and EE with $r(213) = .729$, $p < .001$; TRU and SI with $r(213) = .724$, $p < .001$; EE and SI $r(213) = .736$, $p < .001$; EE and IV $r(213) = .764$, $p < .001$; and SI and IV $r(213) = .726$, $p < .001$. The analysis inspected the correlation coefficients, specifically collinearity statistics tolerance values, to further evaluate low multicollinearity. All predictor variables had a collinearity statistics tolerance value above .1 with TRU *Tolerance* = .315, *VIF* = 3.174; PR *Tolerance* = .903, *VIF* = 1.107; PE *Tolerance* = .520, *VIF* = 1.924; EE *Tolerance* = .304, *VIF* = 3.288; SI *Tolerance* = .323, *VIF* = 3.096; and IV *Tolerance* = .345, *VIF* = 2.896. Overall, these results indicate acceptable multicollinearity and no violation of the assumption of low multicollinearity.

Normality of residuals. The analysis used a histogram formed from frequencies of standardized residuals, a P-P plot of standardized residuals, and a Q-Q plot of studentized residuals to evaluate the normality of residuals. Figure 10 that includes the visualization of a histogram formed from frequencies of standardized residuals. The histogram indicates the presence of a typical bell-shaped normal curve. Figure 11 that includes the visualization of a P-P plot of standardized residuals. Although the P-P plot has a slight S-shaped bow, the plot indicates a linear plot of standardized residuals with expected cumulative probabilities. As displayed previously in Figure 2, other than the three outlier rows, the Q-Q plot indicates a tight linear plot of studentized residuals. The presence of a typical bell-shaped normal curve histogram, as well as Q-Q and P-P plot that are close to linear, indicate normality of residuals; thus, no violation of the assumption of normality of residuals.

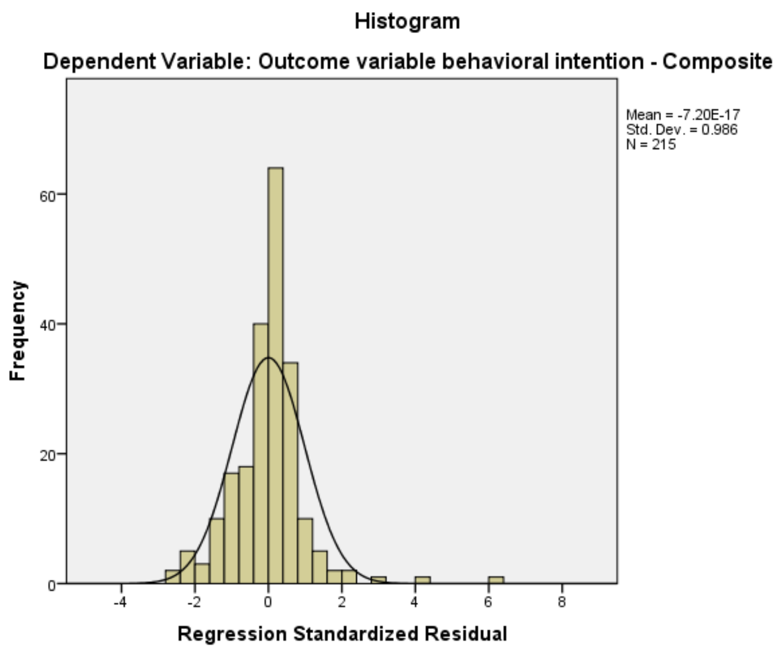

Figure 10. The histogram of standardized residuals. This histogram indicates a typical bell-shaped normal curve.

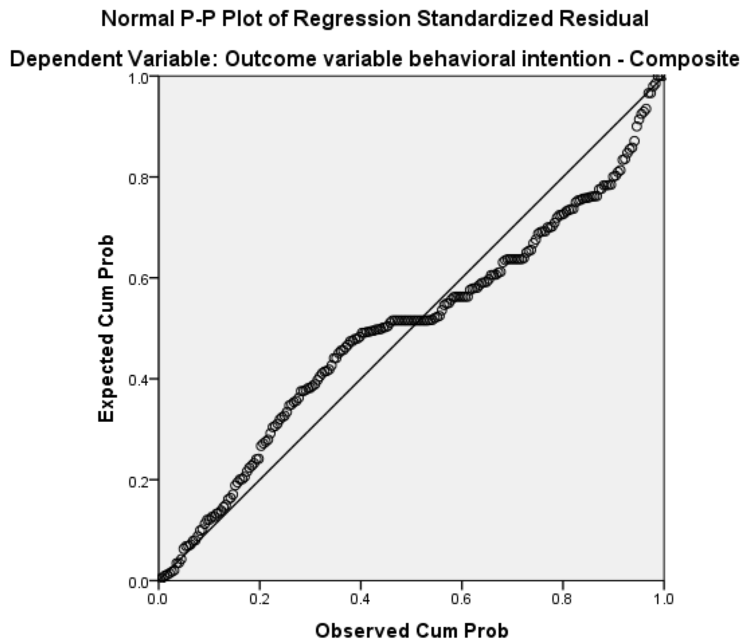

Figure 11. The P-P plot of standardized residuals. This P-P plot indicates a linear plot.

Regression analysis results. The analysis conducted a hierarchical linear regression test to calculate the influences of the predictor variables TRU, PE, EE, SI, IV, and PR to predict BI. Table 3 displays the model summary for each of the six models. All six models were significant to predict BI with Model 1 having $F(1, 213) = 363.157$, $p < .001$ with an adjusted $R^2 = .629$; Model 2 having $F(2, 212) = 180.807$, $p < .001$ with an adjusted $R^2 = .627$; Model 3 having $F(3, 211) = 131.691$, $p < .001$ with an adjusted $R^2 = .647$; Model 4 having $F(4, 210) = 116.337$, $p < .001$ with an adjusted $R^2 = .683$; Model 5 having $F(5, 209) = 100.637$, $p < .001$ with an adjusted $R^2 = .700$; and Model 6 having $F(6, 208) = 89.008$, $p < .001$ with an adjusted $R^2 = .712$. The analysis included an examination of the predictive performance of each of the predictor variables.

The analysis included data indicating the predictive performance of each of the predictor variables. As displayed in Table 3, Model 2 show that adding PR did not produce a statistically significantly increase in predicting BI over TRU alone. Coefficients results in Table 4 indicate that PR was not statistically significantly predictive of BI in any of the models it appeared in with PR performance in Model 2 as $b = .010$, $t(212) = .244$, $p = .807$; Model 3 as $b = .009$, $t(211) = .237$, $p = .813$; Model 4 as $b = -.011$, $t(210) = -0.300$, $p = .764$; Model 5 as $b = -.049$, $t(209) = -1.322$, $p = .188$; and Model 6 as $b = -.046$, $t(208) = -1.276$, $p = .203$. Coefficients results in Table 4 indicate that EE was statistically significantly predictive of BI in Model 4 with EE performance as $b = .314$, $t(210) = 5.012$, $p < .001$ and Model 5 with EE performance as $b = .216$, $t(209) = 3.213$, $p = .002$; however, EE was not statistically significantly predictive of BI in Model 6 with EE performance as $b = .127$, $t(208) = 1.773$, $p = .078$. Coefficients results in Table 4 indicate that TRU, PE, SI, and IV were statistically significantly predictive of BI in all the models they appeared in, and in Model 6, TRU, PE, SI, and IV were statistically significantly predictive of BI with TRU performance as $b = .375$, $t(208) = 5.581$, $p < .001$; PE performance as $b = .135$, $t(208) = 2.516$, $p = .013$; SI performance as $b = .167$, $t(208) = 2.577$, $p = .011$; and IV performance as $b = .214$, $t(208) = 3.125$, $p = .002$. The performance of the Models 1 through 6, displayed in Table 3 and Table 4, indicate TRU, PE, SI, and IV were statistically significantly predictive of BI in all the models they appeared. EE was statistically significantly predictive of BI in Models 4 and 5, and PR was not statistically significantly predictive of BI.

Table 3

Model Summary

Model	R	R^2	Adjusted R^2	*SE* of the Estimate	Change Statistics: R^2 Change	F Change	*df*1	*df*2	α F Change	Durbin-Watson
1	.794	.630	.629	.53071	.630	363.157	1	213	.000	
2	.794	.630	.627	.53189	.000	.060	1	212	.807	
3	.807	.652	.647	.51745	.021	12.997	1	211	.000	
4	.830	.689	.683	.49019	.037	25.118	1	210	.000	
5	.841	.707	.700	.47735	.017	12.454	1	209	.001	
6	.848	.720	.712	.46764	.013	9.764	1	208	.002	1.815

Note. The model summary indicates an improvement in model explanation in all models except model two with a significant F change of $p < .05$. Model two included perceived risk and did not have a significant F change.

Table 4

Coefficients

Model		Unstandardized Coefficients: b	*SE*	Standardized Coefficients: b^*	t	α	Collinearity Statistics: *Tolerance*	*VIF*
1	(Constant)	4.858E-16	.036		.000	1.000		
	TRU	.816	.043	.794	19.057	.000	1.000	1.000
2	(Constant)	4.870E-16	.036		.000	1.000		
	TRU	.816	.043	.794	19.016	.000	1.000	1.000
	PR	.010	.039	.010	.244	.807	1.000	1.000
3	(Constant)	3.163E-16	.035		.000	1.000		
	TRU	.680	.056	.662	12.112	.000	.552	1.812
	PR	.009	.038	.010	.237	.813	1.000	1.000
	PE	.208	.058	.197	3.605	.000	.552	1.811
4	(Constant)	-1.810E-16	.033		.000	1.000		
	TRU	.505	.064	.492	7.945	.000	.386	2.590
	PR	-.011	.037	-.012	-.300	.764	.988	1.013
	PE	.140	.056	.133	2.485	.014	.520	1.923
	EE	.314	.063	.292	5.012	.000	.436	2.292
5	(Constant)	3.908E-16	.033		.000	1.000		
	TRU	.410	.068	.399	6.058	.000	.324	3.087
	PR	-.049	.037	-.052	-1.322	.188	.904	1.106
	PE	.136	.055	.129	2.475	.014	.520	1.924
	EE	.216	.067	.200	3.213	.002	.361	2.771
	SI	.225	.064	.223	3.529	.001	.351	2.851
6	(Constant)	2.293E-16	.032		.000	1.000		
	TRU	.375	.067	.365	5.581	.000	.315	3.174
	PR	-.046	.036	-.049	-1.276	.203	.903	1.107
	PE	.135	.054	.128	2.516	.013	.520	1.924
	EE	.127	.072	.118	1.773	.078	.304	3.288
	SI	.167	.065	.166	2.577	.011	.323	3.096
	IV	.214	.068	.195	3.125	.002	.345	2.896

Note. The coefficients indicate that, in model six, trust in system, performance expectancy, social influence, and innovativeness all had significant t-tests with $p < .05$.

Summary of Hypothesis Testing

H_0: Unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) do not have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence indicated by a statistically significant *F*-score for any given model indicated by a statistically significant *F*-score for any given model using a significance of $p = 0.05$.

H_a: One or more combination of unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence indicated by a statistically significant *F*-score for any given model indicated by a statistically significant *F*-score for any given model using a significance of $p = 0.05$.

The results of the analysis indicate this study reject H_0 and accept H_a. As displayed in Table 3, the performance of Model 6 indicates to reject the null hypothesis. In the final model, Model 6, the levels of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence indicated by a statistically significant *F*-score having $F(6, 208) = 89.008$, $p < .001$ with an adjusted $R^2 = .712$.

Posthoc Analyses

This study confirmed achieved statistical power through posthoc testing. G*Power (Version 3.1.9.4) calculated a posthoc effect size of $f^2 = 2.571$ based on $R^2 = .720$ achieved in

Model 6. Using the posthoc effect size, G*Power calculated an achieved power of $1 - \beta = 1.000$ using a posthoc achieved power calculation for the statistical test. The parameters selected for the posthoc achieved power calculation were "Linear multiple regression: Fixed model, R^2 deviation from zero", and used the values achieved in Model 6, with an effect size of $f^2 = 2.571$, $p < .001$, $N = 215$, and six predictors.

Summary

The results indicate that TRU, PE, SI, and IV were statistically significantly predictive of BI in all the models in which they appeared. EE was statistically significantly predictive of BI in Models 4 and 5, and PR was not statistically significantly predictive of BI. The performance of Model 6, as displayed in Table 3 and Table 4, indicate that the levels of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence using a significance of $p = 0.05$. Based on this finding, the null hypothesis, H_0, is rejected, and that alternate, H_a, is accepted. Model 6 resulted in an achieved power of $1 - \beta = 1.000$. These findings offer important observations and implications.

CHAPTER 5. DISCUSSION, IMPLICATIONS, AND RECOMMENDATIONS

This chapter provides a discussion of the study results, a discussion of the implications of this study's findings, and presents recommendations for future research. This chapter's organization presents a summary of the results, provides a discussion of the results, draws conclusions based on the results, explains limitations of this study, discusses implications for practice, makes recommendations for further research, and provides a conclusion for this dissertation. With the purpose and organization of this chapter reviewed, this chapter moves forward to present a summary of the results.

Summary of the Results

The factors that affect artificial intelligence technology adoption in healthcare are not known (Keel et al., 2018). The purpose of this quantitative nonexperimental correlational cross-sectional survey research was to examine what factors affect artificial intelligence technology adoption in healthcare and close this gap. This purpose makes this study a significant study.

This study is significant to the community of healthcare IT professionals and the field of artificial intelligence healthcare technologies because the results address an open question in the literature and informing industry of the role of trust in the adoption of artificial intelligence technology among U.S. healthcare IT professionals. This study is significant within IT and the general specialization because of its explanation of the trust obstacles affecting the adoption of artificial intelligence technology. This study is significant to the knowledge base and theory because of its contribution to new knowledge regarding the effect of trust on the intention to adopt artificial intelligence healthcare technology by U.S. healthcare IT professionals. Recent literature has an interest in artificial intelligence healthcare technologies.

The adoption of artificial intelligence healthcare technologies is an important topic in literature. Healthcare is at a critical turning point, and society needs the potential benefits of artificial intelligence healthcare technologies (Matheny, Whicher, & Israni, 2019). Society needs to resolve issues blocking the adoption of artificial intelligence healthcare technologies (Matheny et al., 2019). As previously discussed, recent literature explored issues regarding the adoption of artificial intelligence healthcare technologies. Since this study start, researchers published the results of new studies (Cheung et al., 2019; Laï, Brian, & Mamzer, 2020; Ye et al., 2019). Laï et al. (2020) conducted qualitative interviews of French health professionals and uncovered open questions and perceptions blocking the adoption of artificial intelligence healthcare technologies. Cheung et al. (2019) developed a theoretical model based on TAM to understand the lagging adoption problem with consumer wearable healthcare technologies in China. Ye et al. (2019) used structural equation modeling to develop a theoretical model based on TAM, TPB, and the health belief model to explain socialist adoption factors with artificial intelligence healthcare technologies in Chinese mobile phone users. This study included an examination of factors that affect artificial intelligence technology adoption in healthcare to close this gap.

This study is a quantitative nonexperimental correlational cross-sectional survey study that used a quantitative research methodology with a nonexperimental correlational design. The results of a hierarchical multiple regression analysis, displayed in Table 3 and Table 4, indicate that in Models 1 through 6, performance expectancy, social influence, innovativeness, and trust in system statistically significantly influenced the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals. In the final model, Model 6, the levels of performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system have a statistically significant relationship with the level of behavioral intention to adopt artificial intelligence above that of the mean behavioral intention to adopt artificial intelligence using a significance of $p = 0.05$. G*Power (Version 3.1.9.4) calculated an achieved power of $1 - \beta = 1.000$.

Discussion of the Results

RQ: To what extent, if any, do unified use and acceptance factors (performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system) influence the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals?

The results indicate the answer to the research question RQ. As indicated in Table 3 and Table 4, performance expectancy, social influence, innovativeness, and trust in system statistically significantly influenced the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals in all the models they appeared. Effort expectancy statistically significantly influenced the level of behavioral intention in Models 4 and 5, and perceived risk was not a statistically significant influence on the level of behavioral intention.

As displayed in Table 3 and Table 4, Models 1 through 6 indicate the extent performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system influence the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals. In all models TRU had the strongest influence on BI with influence ranging from $b = .375$, $t(213) = 19.057$, $p < .001$ to $b = .816$, $t(208) = 5.581$, $p < .001$. These results differed from the model devised by Ye et al. (2019) that viewed trust only as a moderating variable on performance expectation's influence on intention to use. These results indicate that trust in system is important as a direct influence on behavioral intention to adopt artificial intelligence technology. Trust in system's influence exceeded performance expectation's influence. These findings are different from other studies that focused on performance expectancy as the strongest direct influence on behavioral intention (Ye et al., 2019). However, this study's observation of trust in system aligns with results from qualitative studies (Laï et al., 2020). Perceived risk had the weakest performance.

The results indicate that PR had the weakest performance and was not a statistically significant influence on BI in any model. The weak performance of perceived risk aligned with study results that also measured perceived risk's influence on intention to use (Ye et al., 2019). This study and Ye et al. (2019) used different populations with different cultural influences, and this raises a question regarding the importance of perceived risk in the adoption of artificial intelligence technology. Effort expectancy performed inconsistently.

The results indicate that EE had inconsistent performance and was a statistically significant influence on BI in two of the three models in which it appeared. Effort expectancy was an influence on behavioral intention until innovativeness appeared in the full model. Once innovativeness appeared in the full model, effort expectancy was not a statistically significant influence on behavioral intention. In the full model, innovativeness was stronger than performance expectancy.

The results indicate that IV had a statistically significant stronger influence on BI than performance expectancy. In the full model, Model 6, IV's influence was $b = .214$, $t(208) = 3.125$, $p = .002$ and PE's influence was $b = .135$, $t(208) = 2.516$, $p = .013$. These results differed from the model devised by Cheung et al. (2019), who reported that performance expectancy's influence on adoption intention was stronger than innovativeness's influence on adoption intention. This difference could be because of differences between the populations of this study and the Chinese consumer population Cheung et al. sampled.

Conclusions Based on the Results

This study offers several conclusions based on the results. First, this section presents a comparison of the findings with the theoretical framework and previous literature. Second, this section provides an interpretation of this study's findings. With an understanding of this section's organization established, this section moves forward to present a comparison of the findings with the theoretical framework and previous literature.

Comparison of the Findings With the Theoretical Framework and Previous Literature

The results indicate that the theoretical framework, based on the extended UTAUT, is effective when applied to artificial intelligence technology adoption among U.S. healthcare IT professionals. The model performed as expect and explained 72% of the influences on behavioral intention. Performance expectancy, social influence, innovativeness, and trust in system were statistically significant in influencing behavioral intention. Effort expectancy was not consistent in its performance in the model, and perceived risk did not contribute. These results had alignment and differences from similar published research.

The performance of perceived risk aligned with other studies that measured perceived risk's influence on behavioral intention (Ye et al., 2019). As stated previously, this study and Ye et al. (2019) used different populations with different cultural influences, and this raises a question regarding the importance of perceived risk in the adoption of artificial intelligence technology. However, the strong influence of trust in system on behavioral intention is a difference from other studies that focused on performance expectancy as the strongest direct influence on behavioral intention (Ye et al., 2019). As stated previously, this indicates that trust in system is important as a direct influence on behavioral intention to adopt artificial intelligence technology. Lastly, the performance of innovativeness differed from the model devised by Cheung et al. (2019). Cheung et al. reported that performance expectancy's influence on adoption intention was stronger than innovativeness's influence on adoption intention.

Interpretation of the Findings

This study's findings are significant to the community of healthcare IT professionals and the field of artificial intelligence healthcare technologies because the results address an open question in the literature. These findings inform practice of the role of trust, innovativeness, social influence, and performance expectancy in the adoption of artificial intelligence technology among U.S. healthcare IT professionals. These findings are significant within IT and the general specialization because they explain the strength of trust affecting the adoption of artificial intelligence technology. This study's findings are significant to the knowledge base and theory because they contributed new knowledge regarding trust in system, innovativeness, social influence, and performance expectancy, effort expectancy, and perceived risk on the behavioral intention to adopt artificial intelligence healthcare technology. Importantly, these findings raise questions regarding the influence of effort expectancy and perceived risk on the behavioral intention to adopt artificial intelligence healthcare technology.

Limitations

This study has several limitations. These limitations come from the study design and the study delimitations. First, this section identifies the limitations associated with the study design. Second, this section identifies the limitations based on the study's delimitations. With an understanding of this section's organization established, this section moves forward to identify the limitations associated with the study design.

Design Limitations

This study has limitations because of its design. A design limitation of this cross-sectional survey study is that it cannot identify views and events that occur in healthcare IT organizations attempting to adopt artificial intelligence technologies (Creswell, 2014). These views and events may be discoverable with qualitative case studies research designs that would focus on analyzing a case or program (Creswell, 2014). Such case studies contributed new insights regarding influences on technology adoption in healthcare (De Almeida et al., 2017; De Camargo et al., 2015; Liberati et al., 2017). An additional design limitation of this cross-sectional survey study is that it collected data at only a single point in time and cannot make any measurement of longitudinal effects from exposure or attempts to adopt artificial intelligence technologies (Creswell, 2014). A design limitation because of this study's use of existing theory is that it focused on extended UTAUT constructs and did not evaluate additional factors through structural equation modeling (Mertler & Reinhart, 2017).

Delimitations

This study has limitations because of delimitation. This study's population included healthcare IT professionals and did not include other populations, such as healthcare practitioners or patients. The study findings from healthcare IT professionals may not be generalizable to other populations, such as healthcare practitioners or patients. Additionally, the study did not collect participant location data and cannot identify if there is any regional effect in the data. Although the extended UTAUT explained 72% of the influences on behavioral intention, effort expectancy and perceived risk did not contribute; however, this study did not evaluate enhancing the extended UTAUT to improve model efficiency.

Implications for Practice

This study confirmed the effect of the factors performance expectancy, effort expectancy, social influence, innovativeness, perceived risk, and trust in system on the behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals. These results inform practice of the role of these factors in artificial intelligence technology adoption. With these findings, artificial intelligence application developers should focus on building applications that maximize the promoting influencers of artificial intelligence technology adoption among healthcare IT professionals, namely trust in system, innovativeness, social influence, and performance expectancy. Specifically, artificial intelligence application developers should consider the strength of trust in system to influence artificial intelligence technology adoption.

Recommendations for Further Research

This study offers several recommendations for further research. These recommendations come from the data and the study delimitations. First, this section provides recommendations for further research that the study developed directly from the data. Second, this section offers recommendations for further research based on the study's delimitations. With an understanding of this section's organization established, this section moves forward to present recommendations for further research that the study developed directly from the data.

Recommendations Developed Directly From the Data

Future studies should examine the role of perceived risk in artificial intelligence technology adoption. The expectation of this study and the study by Ye et al. (2019) was that perceived risk would influence artificial intelligence technology adoption. In both studies, perceived risk did not statistically significantly influence artificial intelligence technology adoption. Further opportunities for future research involve effort expectancy.

Future studies should examine the role of effort expectancy in artificial intelligence technology adoption and specifically examine effort expectancy's relationship with innovativeness. The expectation of this study and the study by Cheung et al. (2019) was that effort expectancy would influence artificial intelligence technology adoption. In this study's findings, effort expectancy did not perform consistently and was not statistically significant after innovativeness appeared in the model. However, Cheung et al. found that effort expectancy was not statistically significant in their model. Understanding the relationship between effort expectancy and innovativeness and how they jointly influence artificial intelligence technology adoption may be critical knowledge for artificial intelligence technology developers, product managers, and executives. Additional opportunities for further research focus on innovativeness.

Future studies should examine the role of innovativeness and performance expectancy in artificial intelligence technology adoption under different populations. As previously stated, this study's findings indicated innovativeness was a stronger influence on artificial intelligence technology adoption than performance expectancy. These findings are different from some similar studies that included consumer populations (Ye et al., 2019).

Recommendations Based on Delimitations

Future studies should focus on differences with practitioners or patient populations. The study findings from healthcare IT professionals may not be generalizable to other populations. Future research should focus on healthcare practitioners or patients. The previously stated recommendations for further research are from the data and the study delimitations and offer research opportunities for further study.

Conclusion

Healthcare is at a critical turning point, and society needs the potential benefits of artificial intelligence healthcare technologies (Matheny et al., 2019). The adoption of artificial intelligence healthcare technologies is an important topic, and society needs to resolve issues blocking the adoption of artificial intelligence healthcare technologies (Matheny et al., 2019). This quantitative nonexperimental correlational cross-sectional survey research examined what factors affect artificial intelligence technology adoption U.S. healthcare IT professionals. The results of the hierarchical multiple regression analysis indicate that performance expectancy, social influence, innovativeness, and trust in system influenced the level of behavioral intention to adopt artificial intelligence technology among U.S. healthcare IT professionals. The model explained 72% of the influences on behavioral intention. These findings indicate that trust has the strongest influence on artificial intelligence technology adoption among U.S. healthcare IT professionals. However, effort expectancy was not consistent in its performance in the model, and perceived risk did not contribute. These findings inform artificial intelligence application developers that they should focus on building applications that maximize the promoting influencers of artificial intelligence technology adoption among healthcare IT professionals, namely, trust in system, innovativeness, social influence, and performance expectancy. Specifically, artificial intelligence applications developers should consider the strength of trust in system to influence artificial intelligence technology adoption.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*, 179-211. doi:10.1016/0749-5978(91)90020-T

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology & Health, 26*, 1113-1127. doi:10.1080/08870446.2011.613995

Akour, I. (2016). Daily activity prediction using base learner and ensemble method classifiers: A comparative study. *International Journal of Computer Science and Information Security, 14*(12), 20-24. Retrieved from http://ijcsns.org

Alaiad, A., Zhou, L., & Koru, G. (2014). An exploratory study of home healthcare robots adoption applying the UTAUT model. *International Journal of Healthcare Information Systems and Informatics, 9*(4), 44-59. doi:10.4018/ijhisi.2014100104

American Diabetes Association. (2018). Economic costs of diabetes in the U.S. in 2017. *Diabetes Care, 41, 917-928*. doi:10.2337/dci18-0007

American Medical Association. (2020). JAMA network. Retrieved from https://jamanetwork.com/

Association for Computing Machinery. (2020). ACM digital library. Retrieved from https://dl.acm.org/

Banzi, J. F., & Xue, Z. (2015). An automated tool for non-contact, real time early detection of diabetes by computer vision. *International Journal of Machine Learning and Computing, 5*, 225-229. doi:10.7763/IJMLC.2015.V5.511

Beam, A. L., & Kohane, I. S. (2016). Translating artificial intelligence into clinical care. *JAMA, 316*, 2368-2369. doi:10.1001/jama.2016.17217

Bhatiasevi, V. (2016). An extended UTAUT model to explain the adoption of mobile banking. *Information Development, 32*, 799-814. doi:10.1177/0266666915570764

Bondesson, L., & Traat, I. (2013). On sampling designs with ordered conditional inclusion probabilities. *Scandinavian Journal of Statistics, 40*, 724-733. doi:10.1111/sjos.12024

Brodag, T., Herbold, S., & Waack, S. (2014). A generalized model of PAC learning and its applicability. *Theoretical Informatics and Applications, 48*, 209-245. doi:10.1051/ita/2014005

Carroll, J. K., Moorhead, A., Bond, R., LeBlanc, W. G., Petrella, R. J., & Fiscella, K. (2017). Who uses mobile phone health apps and does use matter? A secondary data analytics approach. *Journal of Medical Internet Research, 19*(4), 1-9. doi:10.2196/jmir.5604

Casanova, R., Saldana, S., Simpson, S. L., Lacy, M. E., Subauste, A. R., Blackshear, C., . . . Bertoni, A. G. (2016). Prediction of incident diabetes in the Jackson Heart Study using high-dimensional machine learning. *PLoS One, 11*(10), 1-12. doi:10.1371/journal.pone.0163942

Chandra, S., Srivastava, S. C., & Theng, Y. (2010). Evaluating the role of trust in consumer adoption of mobile payment systems: An empirical analysis. *Communications of the Association for Information Systems, 27*, 561-588. Retrieved from http://aisel.aisnet.org

Cheung, M. L., Chau, K. Y., Lam, M. H. S., Tse, G., Ho, K. Y., Flint, S. W., . . . Lee, K. Y. (2019). Examining consumers' adoption of wearable healthcare technology: The role of health attributes. *International Journal of Environmental Research and Public Health, 16*, 2257-2273. doi:10.3390/ijerph16132257

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Mahwah, NJ: L. Erlbaum Associates.

Connelly, L. M. (2015). Research questions and hypotheses. *Medsurg Nursing, 24*, 435-436. Retrieved from http://www.medsurgnursing.net

Cranfield, S., Hendy, J., Reeves, B., Hutchings, A., Collin, S., & Fulop, N. (2015). Investigating healthcare IT innovations: A "conceptual blending" approach. *Journal of Health Organization and Management, 29*, 1131-1148. doi:10.1108/JHOM-08-2015-0121

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Thousand Oaks, CA: Sage Publications.

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

De Almeida, J. P. L., Farias, J. S., & Carvalho, H. S. (2017). Drivers of the technology adoption in healthcare. *Brazilian Business Review, 14*, 336-351. doi:10.15728/bbr.2017.14.3.5

De Camargo, K. R., Guedes, C. R., Caetano, R., Menezes, A., & Trajman, A. (2015). The adoption of a new diagnostic technology for tuberculosis in two Brazilian cities from the perspective of patients and healthcare workers: A qualitative study. *BMC Health Services Research, 15*, 1-14. doi:10.1186/s12913-015-0941-x

Directory of Open Access Journals. (2020). Directory of open access journals. Retrieved from https://doaj.org/

Duan, R., & Man, H. (2012). Activation detection on fMRI time series using hidden Markov model. *Advances in Artificial Neural Systems, 2012*, 1-12. doi:10.1155/2012/190359

Dworkin, J., Hessel, H., Gliske, K., & Rudi, J. H. (2016). A comparison of three online recruitment strategies for engaging parents. *Family Relations, 65*, 550-561. doi:10.1111/fare.12206

EBSCO Industries. (2020). EBSCO information services. Retrieved from https://www.ebsco.com/

Einhorn, H. J., & Hogarth, R. M. (1981). Behavioral decision theory: Processes of judgement and choice. *Annual Review of Psychology, 32*, 53-88. doi:10.1146/annurev.ps.32.020181.000413

Elsevier. (2020). Elsevier. Retrieved from https://www.elsevier.com/

Farran, B., Channanath, A. M., Behbehani, K., & Thanaraj, T. A. (2013). Predictive models to assess risk of type 2 diabetes, hypertension and comorbidity: Machine-learning algorithms and validation using national health data from Kuwait—a cohort study. *BMJ Open, 3*(5), 1-11. doi:10.1136/bmjopen-2012-002457

Farrugia, P., Petrisor, B., Farrokhyar, F., & Bhandari, M. (2010). Research questions, hypotheses and objectives. *Canadian Journal of Surgery, 53*, 278-281. Retrieved from https://canjsurg.ca/

Ferri, L., Ginesti, G., Spanò, R., & Zampella, A. (2018). Exploring the entrepreneurial intention of female students in Italy. *Journal of Open Innovation, 4*(3), 1-10. doi:10.3390/joitmc4030027

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th Ed.). Thousand Oaks, CA: Sage Publications.

Fleiss, J. L., & Cohen, J. (1973). The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability. *Educational and Psychological Measurement, 33*, 613-619. doi:10.1177/001316447303300309

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*, 39-50. doi:10.1002/mar

G*Power. (Version 3.1.9.4) [Computer software]. Retrieved from http://www.gpower.hhu.de/

Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management & Data Systems, 115*, 1704-1723. doi:10.1108/IMDS-03-2015-0087

Golant, S. M. (2017). A theoretical model to explain the smart technology adoption behaviors of elder consumers (elderadopt). *Journal of Aging Studies, 42*, 56-73. doi:10.1016/j.jaging.2017.07.003

Golden, J. A. (2017). Deep learning algorithms for detection of lymph node metastases from breast cancer: Helping artificial intelligence be seen. *JAMA, 318*, 2184-2186. doi:10.1001/jama.2017.14580

Gopalakrishna-Remani, V., Jones, R. P., & Wooldridge, B. R. (2016). Influence of institutional forces on managerial beliefs and healthcare analytics adoption. *Journal of Managerial Issues, 28*(3), 191-209. Retrieved from https://www.jstor.org/journal/jmanaissues

Gregg, E. W., Li, Y., Wang, J., Burrows, N. R., Ali, M. K., Rolka, D., . . . Geiss, L. (2014). Changes in diabetes-related complications in the United States, 1990-2010. *The New England Journal of Medicine, 370*, 1514-1523. doi:10.1056/NEJMoa1310799

Hampshire, C. (2017). A mixed methods empirical exploration of UK consumer perceptions of trust, risk and usefulness of mobile payments. *The International Journal of Bank Marketing, 35*, 354-369. doi:10.1108/IJBM-08-2016-0105

Hau, Y. S., Kim, B., & Lee, H. (2016). What drives employees to share their tacit knowledge in practice? *Knowledge Management Research & Practice, 14*, 295-308. doi:10.1057/kmrp.2014.32

Heiervang, E., & Goodman, R. (2011). Advantages and limitations of web-based surveys: Evidence from a child mental health survey. *Social Psychiatry and Psychiatric Epidemiology, 46*, 69-76. doi:10.1007/s00127-009-0171-9

Heselmans, A., Aertgeerts, B., Donceel, P., Geens, S., Van de Velde, S., & Ramaekers, D. (2012). Family physicians' perceptions and use of electronic clinical decision support during the first year of implementation. *Journal of Medical Systems, 36*(6), 3677-84. doi:10.1007/s10916-012-9841-3

Holzinger, A. (2016). Interactive machine learning for health informatics: When do we need the human-in-the-loop? *Brain Informatics, 3*(2), 119-131. doi:10.1007/s40708-016-0042-6

Hong, I. B. (2015). Understanding the consumer's online merchant selection process: The roles of product involvement, perceived risk, and trust expectation. *International Journal of Information Management, 35*, 322-336. doi:10.1016/j.ijinfomgt.2015.01.003

Hoque, M. R., Albar, A., & Alam, J. (2016). Factors influencing physicians' acceptance of e-health in developing country: An empirical study. *International Journal of Healthcare Information Systems and Informatics, 11*, 58-70. doi:10.4018/IJHISI.2016010104

Ifinedo, P. (2018). Empirical study of Nova Scotia nurses' adoption of healthcare information systems: Implications for management and policy-making. *International Journal of Health Policy and Management, 7*, 317-327. doi:10.15171/ijhpm.2017.96

IGI Global. (2020). *InfoSci-databases*. Retrieved from https://www.igi-global.com

International Business Machines. (n.d.). *IBM SPSS Software*. Retrieved from https://www.ibm.com/analytics/data-science/predictive-analytics/spss-statistical-software

International Business Machines. (2015). *IBM Watson Health*. Retrieved from https://www.ibm.com/watson/health/

International Organization for Standardization. (2016). *ISO 13485:2016*. International Organization for Standardization. Retrieved from https://www.iso.org/

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

Keel, S., Lee, P. Y., Scheetz, J., Li, Z., Kotowicz, M. A., MacIsaac, R. J., & He, M. (2018). Feasibility and patient acceptability of a novel artificial intelligence-based screening model for diabetic retinopathy at endocrinology outpatient services: A pilot study. *Scientific Reports, 8*, 1-6. doi:10.1038/s41598-018-22612-2

Kohnke, A., Cole, M. L., & Bush, R. G. (2014). Incorporating UTAUT predictors for understanding home care patients' and clinician's acceptance of healthcare telemedicine equipment. *Journal of Technology Management & Innovation, 9*(2), 29-41. doi:10.4067/S0718-27242014000200003

Koul, S., & Eydgahi, A. (2017). A systematic review of technology adoption frameworks and their applications. *Journal of Technology Management & Innovation, 12*, 106-113. doi:10.4067/S0718-27242017000400011

Kyratsis, Y., Ahmad, R., & Holmes, A. (2012). Making sense of evidence in management decisions: The role of research-based knowledge on innovation adoption and implementation in healthcare. study protocol. *Implementation Science, 7*, 1-7. doi:10.1186/1748-5908-7-22

Laï, M., Brian, M., & Mamzer, M. (2020). Perceptions of artificial intelligence in healthcare: Findings from a qualitative survey study among actors in France. *Journal of Translational Medicine, 18*, 1-13. doi:10.1186/s12967-019-02204-y

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management, 14*, 21-38. doi:10.4301/S1807-17752017000100002

Lee, J., & Rho, M. J. (2013). Perception of influencing factors on acceptance of mobile health monitoring service: A comparison between users and non-users. *Healthcare Informatics Research, 19*, 167-176. doi:10.4258/hir.2013.19.3.167

Leech, N. L., Gliner, J. A., Morgan, G. A., Harmon, R. J., & Harmon, R. J. (2003). Use and interpretation of multiple regression. *Journal of the American Academy of Child & Adolescent Psychiatry, 42*, 738-740. doi:10.1097/01.CHI.0000046845.56865.22

Lefever, S., Dal, M., & Matthíasdóttir, Á. (2007). Online data collection in academic research: Advantages and limitations. *British Journal of Educational Technology, 38*, 574-582. doi:10.1111/j.1467-8535.2006.00638.x

Levin, K. A. (2006). Study design III: Cross-sectional studies. *Evidence-Based Dentistry, 7*, 24-25. doi:10.1038/sj.ebd.6400375

Liberati, E. G., Ruggiero, F., Galuppo, L., Gorli, M., Gonzalez-Lorenzo, M., Maraldi, M., . . . Moja, L. (2017). What hinders the uptake of computerized decision support systems in hospitals? A qualitative study and framework for implementation. *Implementation Science, 12*, 1-13. doi:10.1186/s13012-017-0644-2

Lin, C., Lin, I., & Roan, J. (2012). Barriers to physicians' adoption of healthcare information technology: An empirical study on multiple hospitals. *Journal of Medical Systems, 36*, 1965-1977. doi:10.1007/s10916-011-9656-7

Lin, C. A., & Kim, T. (2016). Predicting user response to sponsored advertising on social media via the technology acceptance model. *Computers in Human Behavior, 64*, 710-718. doi:10.1016/j.chb.2016.07.027

Lu, Y., Yang, S., Chau, P. Y. K., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management, 48*, 393-403. doi:10.1016/j.im.2011.09.006

Lund Research. (2018). *Hierarchical multiple regression SPSS statistics*. Retrieved from https://statistics.laerd.com

Luo, W., Nguyen, T., Nichols, M., Tran, T., Rana, S., Gupta, S., . . . Allender, S. (2015). Is demography destiny? Application of machine learning techniques to accurately predict population health outcomes from a minimal demographic dataset. *PLoS One, 10*(5), 1-13. doi:10.1371/journal.pone.0125602

Lynn, L., Hess, B. J., Weng, W., Lipner, R. S., & Holmboe, E. S. (2012). Gaps in quality of diabetes care in internal medicine residency clinics suggest the need for better ambulatory care training. *Health Affairs, 31*, 150-158. doi:10.1377/hlthaff.2011.0907

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality and Social Psychology Bulletin, 18*, 3-9. doi:10.1177/0146167292181001

Matheny, M. E., Whicher, D., & Israni, S. T. (2019). Artificial intelligence in health care: A report from the national academy of medicine. *JAMA, 323*, 509-510. doi:10.1001/jama.2019.21579

McGregor, S., & Banifatemi, A. (2018). Year one of the IBM watson AI XPRIZE: Case studies in "AI for good." *AI Magazine, 39*(3), 27-39. Retrieved from http://www.aaai.org/

Memarian, N., Kim, S., Dewar, S., Engel, J., & Staba, R. J. (2015). Multimodal data and machine learning for surgery outcome prediction in complicated cases of mesial temporal lobe epilepsy. *Computers in Biology and Medicine, 64*, 67-78. doi: 10.1016/j.compbiomed.2015.06.008

Mertler, C. A., & Reinhart, R. V. (2017). *Advanced and multivariate statistical methods* (6th ed.). New York, NY: Routledge.

Mohammadi, M. M., Poursaberi, R., & Salahshoor, M. R. (2018). Evaluating the adoption of evidence-based practice using Rogers's diffusion of innovation theory: A model testing study. *Health Promotion Perspectives, 8*, 25-32. doi:10.15171/hpp.2018.03

Mosweu, O., Bwalya, K., & Mutshewa, A. (2016). Examining factors affecting the adoption and usage of document workflow management system (DWMS) using the UTAUT model. *Records Management Journal, 26*, 38-67. doi:10.1108/RMJ-03-2015-0012

National Center for Biotechnology Information. (n.d.). *PubMed Central*. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education, 15*, 625-632. doi:10.1007/s10459-010-9222-y

Nysveen, H., & Pedersen, P. E. (2016). Consumer adoption of RFID-enabled services. Applying an extended UTAUT model. *Information Systems Frontiers, 18*, 293-314. doi:10.1007/s10796-014-9531-4

Olesen, C. R., Nielsen, J. H., Mortensen, R. N., Bøggild, H., Torp-Pedersen, C., & Overgaard, C. (2014). Associations between follow-up screening after gestational diabetes and early detection of diabetes—a register based study. *BMC Public Health, 14*, 1-10. doi:10.1186/1471-2458-14-841

Osei, E. (2013). The dissertation process in obtaining philosopher doctorate in business administration. *American International Journal of Contemporary Research, 3*(10), 106-112. Retrieved from http://www.aijcrnet.com

Ozcift, A. (2012). SVM feature selection based rotation forest ensemble classifiers to improve computer-aided diagnosis of Parkinson disease. *Journal of Medical Systems, 36*, 2141-2147. doi:10.1007/s10916-011-9678-1

Phichitchaisopa, N., & Naenna, T. (2013). Factors affecting the adoption of healthcare information technology. *EXCLI Journal, 12*, 413-436. doi:10.17877/DE290R-5602

ProQuest. (2020). ProQuest. Retrieved from https://search.proquest.com/

Qualtrics. (2018). *Qualtrics online sample*. Retrieved from https://www.qualtrics.com/online-sample/

Radhakrishnan, K., Jacelon, C., & Roche, J. (2012). Perceptions on the use of telehealth by homecare nurses and patients with heart failure: A mixed method study. *Home Health Care Management & Practice, 24*, 175-181. doi:10.1177/1084822311428335

Rempel, H. G., & Mellinger, M. (2015). Bibliographic management tool adoption and use: A qualitative research study using the UTAUT model. *Reference & User Services Quarterly, 54*(4), 43-53. doi:10.1300/J502v1n03-08

Rigla, M., García-Sáez, G., Pons, B., & Hernando, M. E. (2017). Artificial intelligence methodologies and their application to diabetes. *Journal of Diabetes Science and Technology, 12*, 303-310. doi:10.1177/1932296817710475

Roghanizad, M. M., & Neufeld, D. J. (2015). Intuition, risk, and the formation of online trust. *Computers in Human Behavior, 50*, 489-498. doi:10.1016/j.chb.2015.04.025

Romare, C., Hass, U., & Skär, L. (2018). Healthcare professionals' views of smart glasses in intensive care: A qualitative study. *Intensive and Critical Care Nursing, 45*, 66-71. doi:10.1016/j.iccn.2017.11.006

Rosoff, H., Cui, J., & John, R. S. (2013). Heuristics and biases in cyber security dilemmas. *Environment Systems and Decisions, 33*, 517-529. doi:10.1007/s10669-013-9473-2

Rouibah, K., Lowry, P. B., & Hwang, Y. (2016). The effects of perceived enjoyment and perceived risks on trust formation and intentions to use online payment systems: New perspectives from an Arab country. *Electronic Commerce Research and Applications, 19*, 33-43. doi:10.1016/j.elerap.2016.07.001

Safa, N. S., & Solms, R. (2016). An information security knowledge sharing model in organizations. *Computers in Human Behavior, 57*, 442-451. doi:10.1016/j.chb.2015.12.037

Samkange-Zeeb, F., Ernst, S. A., Klein-Ellinghaus, F., Brand, T., Reeske-Behrens, A., Plumbaum, T., & Zeeb, H. (2015). Assessing the acceptability and usability of an internet-based intelligent health assistant developed for use among Turkish migrants: Results of a study conducted in Bremen, Germany. *International Journal of Environmental Research and Public Health, 12*, 15339-15351. doi:10.3390/ijerph121214987

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. *IBM Journal of Research and Development, 3*, 210-229. doi:10.1147/rd.33.0210

San Martín, H., & Herrero, Á. (2012). Influence of the user's psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. *Tourism Management, 33*, 341-350. doi:10.1016/j.tourman.2011.04.003

Schönbrodt, F. D., Wagenmakers, E., Zehetleitner, M., & Perugini, M. (2017). Sequential hypothesis testing with Bayes factors: Efficiently testing mean differences. *Psychological Methods, 22*, 322-339. doi:10.1037/met0000061

Sedgwick, P. (2014). Pitfalls of statistical hypothesis testing: Type I and type II errors. *British Medical Journal (Online), 349*, 1-2. doi:10.1136/bmj.g4287

Sekaran, U., & Bougie, R. (2013). *Research methods for business: A skill-building approach* (6th ed.). West Sussex, UK: John Wiley & Sons Ltd.

Servedio, R. A. (2002). Perceptron, winnow, and PAC learning. *SIAM Journal on Computing, 31*, 1358-1369. doi:10.1137/S0097539798340928

Sezgin, E., Özkan-Yildirim, S., & Yildirim, S. (2018). Understanding the perception towards using mHealth applications in practice: Physicians' perspective. *Information Development, 34*, 182-200. doi:10.1177/0266666916684180

Shropshire, J., Warkentin, M., & Sharma, S. (2015). Personality, attitudes, and intentions: Predicting initial adoption of information security behavior. *Computers & Security, 49*, 177-191. doi:10.1016/j.cose.2015.01.002

Slade, E. L., Dwivedi, Y. K., Piercy, N. C., & Williams, M. D. (2015). Modeling consumers' adoption intentions of remote mobile payments in the United Kingdom: Extending UTAUT with innovativeness, risk, and trust. *Psychology & Marketing, 32*, 860-873. doi:10.1002/mar.20823

Song, M. K., Lin, F. C., Ward, S. E., & Fine, J. P. (2013). Composite variables: When and how. *Nursing Research, 62*, 45-49. doi:10.1097/NNR.0b013e3182741948

Souillard-Mandar, W., Davis, R., Rudin, C., Au, R., Libon, D. J., Swenson, R., . . . Penney, D. L. (2016). Learning classification models of cognitive conditions from subtle behaviors in the digital clock drawing test. *Machine Learning, 102*, 393-441. doi: 10.1007/s10994-015-5529-5

Springer Nature. (2020). *Springer*. Retrieved from https://www.springer.com/

Suki, N. M., & Suki, N. M. (2017). Modeling the determinants of consumers' attitudes toward online group buying: Do risks and trusts matters? *Journal of Retailing and Consumer Services, 36*, 180-188. doi:10.1016/j.jretconser.2017.02.002

Thakur, R., & Srivastava, M. (2014). Adoption readiness, personal innovativeness, perceived risk and usage intention across customer groups for mobile payment services in India. *Internet Research, 24*, 369-392. doi:10.1108/IntR-12-2012-0244

Thompson-Leduc, P., Clayman, M. L., Turcotte, S., & Légaré, F. (2015). Shared decision-making behaviours in health professionals: A systematic review of studies based on the theory of planned behaviour. *Health Expectations, 18*, 754-774. doi:10.1111/hex.12176

Trochim, W. M. K. (2006). *Probability sampling*. Retrieved from the Research Methods website: http://www.socialresearchmethods.net/kb/sampprob.php

U.S. Bureau of Labor Statistics. (2018). *Occupational Employment and Wages, May 2018*. Retrieved from https://www.bls.gov/

U.S. Department of Health and Human Services. (1996). *Health Insurance Portability and Accountability Act of 1996*. Retrieved from https://aspe.hhs.gov

U.S. Department of Health and Human Services. (2016). *Healthcare and public health sector-specific plan*. Retrieved from https://www.dhs.gov/sites/default/files/publications/nipp-ssp-healthcare-public-health-2015-508.pdf

Uyanık, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia - Social and Behavioral Sciences, 106*, 234-240. doi:10.1016/j.sbspro.2013.12.027

Vaart, R., Atema, V., & Evers, A. W. M. (2016). Guided online self-management interventions in primary care: A survey on use, facilitators, and barriers. *BMC Family Practice, 17*, 1-9. doi:10.1186/s12875-016-0424-0

Valiant, L. (1984). A theory of the learnable. *Communications of the ACM, 27*, 1134-1142. doi:10.1145/1968.1972

Vanneste, D., Vermeulen, B., & Declercq, A. (2013). Healthcare professionals' acceptance of BelRAI, a web-based system enabling person-centred recording and data sharing across care settings with interRAI instruments: A UTAUT analysis. *BMC Medical Informatics & Decision Making, 13*, 1-27. doi:10.1186/1472-6947-13-129

Van Velsen, L., Wildevuur, S., Flierman, I., Van Schooten, B., Tabak, M., & Hermens, H. (2016). Trust in telemedicine portals for rehabilitation care: An exploratory focus group study with patients and healthcare professionals. *BMC Medical Informatics and Decision Making, 16*, 1-12. doi:10.1186/s12911-016-0250-2

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research, 11*, 342-365. doi:10.1287/isre.11.4.342.11872

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*, 451-481. doi:10.1111/j.1540-5915.1996.tb00860.x|

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*, 425-478. Retrieved from https://www.misq.org/

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*, 157-178. doi:10.2307/41410412

Weigl, K., Tikk, K., Hoffmeister, M., De Toni, E. N., Hampe, J., Kolligs, F., . . . Brenner, H. (2019). A web-based survey among adults aged 40-54 years was time effective and yielded stable response patterns. *Journal of Clinical Epidemiology, 105*, 10-18. doi:10.1016/j.jclinepi.2018.08.021

Wu, C., Huang, Y., & Hsu, C. (2014). Benevolence trust: A key determinant of user continuance use of online social networks. *Information Systems and eBusiness Management, 12*, 189-211. doi:10.1007/s10257-013-0216-1

Wu, H., & Leung, S. (2017). Can Likert scales be treated as interval scales?—A simulation study. *Journal of Social Service Research, 43*, 527-532. doi:10.1080/01488376.2017.132977

Yang, H., Lee, H., & Zo, H. (2017). User acceptance of smart home services: An extension of the theory of planned behavior. *Industrial Management & Data Systems, 117*, 68-89. doi:10.1108/IMDS-01-2016-0017

Yang, Q., Pang, C., Liu, L., Yen, D. C., & Tarn, M. J. (2015). Exploring consumer perceived risk and trust for online payments: An empirical study in China's younger generation. *Computers in Human Behavior, 50*, 9-24. doi:10.1016/j.chb.2015.03.058

Yang, S., Lu, Y., Gupta, S., Cao, Y., & Zhang, R. (2012). Mobile payment services adoption across time: An empirical study of the effects of behavioral beliefs, social influences, and personal traits. *Computers in Human Behavior, 28*, 129-142. doi:10.1016/j.chb.2011.08.019

Ye, T., Xue, J., He, M., Gu, J., Lin, H., Xu, B., & Cheng, Y. (2019). Psychosocial factors affecting artificial intelligence adoption in health care in china: Cross-sectional study. *Journal of Medical Internet Research, 21*(10), 1-22. doi:10.2196/14316

Yu, K., Zhang, C., Berry, G. J., Altman, R. B., Ré, C., Rubin, D. L., & Snyder, M. (2016). Predicting non-small cell lung cancer prognosis by fully automated microscopic pathology image features. *Nature Communications, 7*, 1-10. doi:10.1038/ncomms12474

Yu-Hsi, Y., Sang-Bing, T., Chien-Yun, D., Hsiao-Ming, C., Wan-Fei, C., Wu, C., . . . Wang, J. (2017). An empirical research on relationships between subjective judgement, technology acceptance tendency and knowledge transfer. *PLoS One, 12*(9), 1-22. doi:10.1371/journal.pone.0183994

Zhang, S., Yang, D., Qiu, S., Bao, X., & Li, J. (2018). Open innovation and firm performance: Evidence from the Chinese mechanical manufacturing industry. *Journal of Engineering and Technology Management, 48*, 76-86. doi:10.1016/j.jengtecman.2018.04.004

Zhou, S., Fernandez-Gutierrez, F., Kennedy, J., Cooksey, R., Atkinson, M., Denaxas, S., . . . Brophy, S. (2016). Defining disease phenotypes in primary care electronic health records by a machine learning approach: A case study in identifying rheumatoid arthritis. *PloS One, 11*(5), 1-14. doi:10.1371/journal.pone.0154515

Zyphur, M. J., & Pierides, D. C. (2019). Statistics and probability have always been value-laden: An historical ontology of quantitative research methods. *Journal of Business Ethics,* 1-18. doi:10.1007/s10551-019-04187-8