FACTORS INFLUENCING ADOPTION OF MEDICAL IOT IN U.S. NURSING HOMES

by

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Abstract

The rise of the Internet of Things (IoT) gives people the ability to check the status of their home securities, start their cars, and remotely open and close their garage doors from anywhere in the world via smartphones and other applications. Industries, such as the health care sector, are also set to benefit from the unlimited potential of IoT-based technologies in the form of improved efficiency, safety, monitoring, reduction of errors, and compliance, which could ultimately provide new profit streams. Despite the opportunities that the internet of medical things (M-IoT) presents for health care organizations, such as skilled nursing homes, in many cases, the technology has not been adopted to the extent that was previously expected. This research is a quantitative investigation of the socio-organizational and individualistic factors of effort expectancy, performance, social influence, perceived risk, and how these factors may influence adoption and use of M-IoT within US-based small and medium-sized skilled nursing homes. The study used the Unified Theory of Acceptance and Use of Technology (UTAUT) combined with Perceived Risk (PR) as a means to evaluate the social factors influencing user adoption intention and behavior, with the goal to assess if these variables can be used as a predictor for M-IoT system adoption. Based on the findings, the variables in question predict over 69% of M-IoT system acceptance and use within small and medium-sized (SME) U.S. skilled nursing organizations. In general, the findings are in alignment with past studies that employed the UTAUT model. However, the study identified a significant result, which was that PR is not a significant predictor for M-IoT adoption in this population. Future adoption and implementation strategies of M-IoT could leverage this information with the goal of widespread use to increase efficiency, productivity, safety, and compliance for SME U.S. skilled nursing organizations.

Dedication

This work is dedicated to my son, father, and mother. My family supported me during the most challenging moments as I struggled to reach the acme of knowledge. My faith and trust in God sustained my inner courage, determination, hope, and strength during the most painful moments when I felt like quitting and giving up. To God be all the glory and honor forever, Amen.

Acknowledgments

I take this opportunity to thank my advisor, Dr. Dominguez, for his continuous support throughout my journey of pursuing my dissertation under his guidance. He has been an encouraging and supporting mentor who has always provided a flexible environment for me to work and explore my abilities. His immense knowledge was an asset that was always readily available for me to explore, which eventually turned out to be the best source of information.

Thank you to Capella and the dissertation support team for the availability of resources for my research work. Last but not least, thanks to all my family members and friends for their constant support and love throughout my research.

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CHAPTER 1. INTRODUCTION

Introduction

The Internet has evolved from being used for email, web browsing, and cursory research to a diverse communication medium that affords devices more autonomy and wider implementation (Voas, 2016). The resulting object-to-object paradigm, which consists of electronic elements tethered to the Internet, has become known as the *Internet of Things* (Voas, 2016). Although the creators of the Internet intended to foster chiefly human-to-human interaction, the rise in the popularity of Internet-connected objects has resulted in a significant increase in object-to-object and human-to-object communication (Sodhro, Sangaiah, & Pirphulal, 2019). The Internet is used in almost every area of human endeavor, with a forecast of 50,000,000,000 connected devices by 2020 (Asplund & Nadjm-Tehrani, 2016). Medical devices have become increasingly intelligent and informative as the IoT has developed and spread, forming an interconnection with medical servers, other devices, and medical staff (Park & Park, 2017). Because of the unlimited possibilities of the IoT in health care, the goal of the study was to evaluate variables that may have a direct effect on the adoption of The Internet of Medical Things (M-IoT) technology within the context of small and medium-sized skilled nursing homes in the United States.

Information technology (IT) based on the IoT has enabled medical devices to link sensors together with wireless communication to collect medical information via health-care IT (HIT) systems through online computer networks (Bhatt, Dey, & Ashour, 2017). M-IoT is also known as *health care IoT*. These devices link to cloud platforms where data is captured, stored, and analyzed (Park & Park, 2017). Examples of M-IoT include remote patient-monitoring systems,

systems used to dispense and track patient medication, infusion pumps that connect to analytics dashboards, hospital beds rigged with sensors that measure patients' vital signs (blood pressure, pulse, breath rate, and temperature), smart glucometers, and IoT-based environmental-monitoring systems, such as security cameras and fall-detection systems (Bhatt & Bhatt, 2017). M-IoT technology is a critical part of the digital transformation of health care because of its influence as a catalyst for new business models to emerge and is enabling changes in work processes, productivity improvements, safety, cost containment, and enhanced customer experiences (Dimitrov, 2016).

The strategic acceptance and adoption of M-IoT have continued to gain prominence as a means of improving organizational efficiency, productivity, and data analytics (Alasmari & Anwar, 2016). M-IoT has been a revolutionizing force because its use has resulted in lower costs, improved service delivery, efficiency, and increased quality of patient care (Majumder et al., 2017). Despite these benefits, while some nursing home facilities have been using M-IoT systems, others have not. The adoption rate in general in the health-care industry has been extremely low (Verizon, 2018). The health care industry has been lagging far behind other major industries, and this low adoption has affected health-care organizations of all sizes, especially smaller organizations, such as nursing homes. Specifically, few nursing homes have adopted M-IoT, and adoption rates have not kept pace with other health care organizations. There has not been enough research to identify this low adoption (Irfan & Ahmad, 2018; Spinelli-Moraski & Richards, 2013).

This research considered factors described in the unified theory of acceptance and use of technology (UTAUT; Venkatesh, Morris, Davis, & Davis, 2003) with an additional variable of perceived risk (PR) to the patient (Despins, Scott-Cawiezell, & Rouder, 2010; Trevino et al., 2017). Researchers have used the UTAUT extensively in the study of adoption and acceptance of technology. However, for this research, the core variables of UTAUT were combined with perceived risk for the evaluation of M-IoT adoption (Despins et al., 2010; Trevino et al., 2017). The results highlighted areas within existing practices and procedures that could potentially lead to opportunities for future research. Analysis of the results provided paths for possible strategies and applications for current and future investigations. As a result, other health care organizations, businesses, and individuals may benefit from the findings to increase awareness of risk, improve patient safety, reduce errors, improve compliance, and benefit from improved efficiency and productivity.

In the following sections, I introduce the technical business problem and its context, expound on the importance of the research specific to the technology and population, and provide an overview of the research design. I also discuss the rationale for and the importance of the research. These introductory sections incorporate scholarly research to substantiate the need for additional research and describe the benefits derived from the study.

Later sections of the chapter provide further information regarding the theories, concepts, and variables that form the foundation for the study. These sections include the theoretical framework, providing context for the use of the instrument chosen for this study, and the variables I intend to consider. I also present the research questions and discuss the significance of this research to the body of knowledge regarding attitudes and behaviors toward the adoption and use of M-IoT technology. The final sections include definitions of relevant terms, as well as assumptions and limitations of the study and its research design.

Background

IoT has been the most impactful socio-technological trend influencing health services (Achituv & Haiman, 2016). The immense capabilities of M-IoT have the potential to drive significant changes in health-care systems in different health-care environments (Bhatt & Bhatt). The application of M-IoT in health-care environments creates business advantages that include the ability to monitor health behaviors, enable a personalized, preventative, and collaborative form of care (Pinto, Cabral, & Gomes, 2017). Quality and effectiveness of service to elderly-care patients (those with chronic conditions or requiring constant supervision) significantly improves when IoT is integrated with medical devices (Achituv & Haiman, 2016; Yang, Zheng, Guo, Liu, & Chang, 2019). The implementation of IoT in health care has improved preventive care, assisted living, personal fitness, remote clinical monitoring, and chronic disease management (Pal, Funilkul, Charoenkitkarn, & Kanthmanon, 2018). M-IoT can improve the delivery of health care and outcome quality by increasing communication and efficiency, enabling easy data retrieval and reporting, and reducing medical errors (Sun & Qu, 2014; Zakaria & Yusof, 2016).

Aruba (2017) has claimed that the real-world benefits gained from the use of IoT in the health-care industry have exceeded original expectations in two critical areas of business: efficiency and profitability. Aruba explains that only 16% of health-care executives interviewed projected a substantial profit increase because of their IoT investment, yet, after adoption, 32% realized profit increases. Aruba concludes that only 29% of executives expected that their IoT strategies would result in improvements to business efficiency. However, results demonstrated that 46% experienced efficiency gains (Aruba, 2017). The competitive advantages provided by M-IoT are especially compelling for small and medium-sized skilled nursing homes in the

United States, which could expect to receive a wide range of benefits by adopting this technology (Bhatt & Bhatt, 2017).

Leaders of health-care organizations have recognized the strategic advantages provided by M-IoT, especially in meeting the needs of a rapidly growing and aging U.S. population (Alexander & Madsen, 2018). According to Ortman, Velkoff, and Hogan (2014), the population of people aged 65 years and over was on pace to increase by 20,000,000 from 2015 to 2025. The increasing numbers of older adults may result in many Americans needing nursing care rising from 1,300,000 in 2013 to 2,300,000 in 2030 (Mather, Jacobsen, & Pollard, 2015). A significant and steady rise in this segment of the population would place considerable pressure on skilled nursing homes to provide essential, affordable, unobtrusive, and easy-to-use health solutions to its customers, while maintaining safety and complying with regulations (Majumder et al., 2017).

Because of the phenomenon of the increasing numbers of older adults, skilled nursing homes providing long-term care services have been facing unprecedented challenges addressing resident acuity while providing assistance with daily activities and personal care (Grossman & Valiga, 2016). According to the Bureau of Labor Statistics (2018) and the Centers for Medicare and Medicaid Services (2018), there has been a nationwide shortage of skilled nurses, and skilled nursing positions have been linked with low wages, which could result in approximately 400,000 fewer nurses providing care by 2020. Nurses work in environments where they have to monitor the change in a patient's condition and make fast decisions that can either help or harm the patient (Keers, Williams, Cooke, & Ashcroft, 2013; Trevino et al., 2017). Nurses have often found that they are the final link in the patient treatment chain and traditionally bear the blame for errors that affect the patient (Bowblis & Roberts, 2018). These scenarios can have adverse effects on the employment or career of nurse practitioners and technicians.

Bowblis and Roberts (2018) believe solutions to these challenges will require new approaches to services for older adults in skilled nursing homes. Service providers, government policymakers, manufacturers, and researchers have asserted that technology-based interventions have the potential to control these pressures, revolutionize care for older persons, and improve the quality of life for residents in nursing home environments (MacTaggart & Thorpe, 2013; Ortman & Velkoff, 2014). Innovative and cost-effective solutions will be necessary to keep health-care expenditures within bounds while providing a wide range of health services. These attributes are why M-IoT is poised to have a significant influence on the health-care industry (Alexander, Madsen, Miller, & Wise, 2016). M-IoT technology has revolutionized the delivery of health care services to older adults in ways that provide more efficiency, productivity, and safety (Xu, He, & Li, 2014).

Despite the potential benefits and innovations that IoT adoption could bring to the health-care industry (Achituv & Haiman, 2016), the anticipated adoption (Achituv & Haiman, 2016; Alexander et al., 2016), has not materialized. The findings of surveys suggest low adoption of IoT-based medical devices in small health care organizations compared to previously expected intensity of adoption. (Alexander et al., 2016; Broughton, Lashlee, Marcum, & Wilson, 2013). According to Verizon (2017), many long-term care organizations, such as skilled nursing homes, have not adopted M-IoT at the previously expected rates (Alexander & Madsen, 2018). Verizon reports that the entire health-care industry experienced only an 11% increase in IoT network connections between 2016 and 2017, ranking last behind four other industries: manufacturing

(84%), energy/utilities (41%), transportation/distribution (40%), and smart cities/communities (19%).

Users often trade safety for convenience (Bojanova, Hurlburt, & Voas, 2014; Martins, Oliveira, & Popovic, 2014). The significance of PR in existing research justifies why PR is appropriate for this study because it provides the core variables necessary to measure the importance of risk when adopting M-IoT. Researchers have shown that PR to the patient is a critical factor in explaining user acceptance of technology in e-business environments (Bowblis & Roberts, 2018; Keers et al., 2013; Trevino et al., 2017). The purpose of their research has been to discover how important PR is to the decision to adopt e-services. However, past attempts to integrate trust and PR into the UTAUT have been limited to conceptual frameworks (Cody-Allen & Kishore, 2006; Lee & Song, 2013) or validation of certain aspects of their causal relationships (Chen, 2019; Lee & Song, 2013; Monilakshmane & Rajeswari, 2018), rather than empirical testing in field studies.

There is a lack of research on how the variables under investigation influence decisions to adopt and use M-IoT in small and medium-sized skilled nursing homes. This gap in research represents the very reason the impact of these variables merits additional investigation. The study into how these variables affect adoption could provide a better understanding of when these variables are most likely to influence individual behavior and identify which approaches or strategies support successful adoption and use of M-IoT in small and medium-sized skilled nursing homes (Venkatesh et al., 2003). By combining PR with the UTAUT, I included the constructs that related to users' risk perceptions and addressed the core factors identified by other researchers, which are relevant to the adoption by users of Internet-based technologies.

Business Technical Problem

The specific technical problem addressed in the study is the low adoption of M-IoT in skilled nursing homes in the United States. Skilled nursing homes have not been adopting IoT at the feverish pace that manufacturers initially expected. To address this problem of low adoption, nursing practitioners, technicians, and other decision-makers in skilled nursing homes and other long-term care facilities need to understand the challenges and primary factors that affect the successful adoption of M-IoT. The technical and logistical challenges involved in acceptance, implementation, and maintenance, along with PR, to patients and consumers' and administrators' concerns about the security and privacy of digital health information have posed significant barriers to the adoption and use of these types of devices (Alexander & Madsen, 2016; Chiuchisan, Costin, & Geman, 2014; Mieronkoski et al., 2017; Trevino et al., 2017). Before industry stakeholders can begin to address these issues, they will need to understand the social and behavioral factors that influence decisions to adopt M-IoT solutions among nurse practitioners, technicians, managers, and other decision-makers within skilled nursing homes in the United States.

Long-term care organizations, such as skilled nursing homes, have lagged behind the health-care industry with respect to the adoption of M-IoT. According to Rayes and Salam (2017), who has investigated global IoT adoption, the adoption rate within health care has been only 7%. This adoption rate trails behind the industrial, automotive, high-technology, and retail industries, which have adoption rates of 25%, 13%, 23%, and 8%, respectively (Rayes & Salam, 2017). Unique challenges in the health-care industry have prevented it from adopting and benefiting from IoT implementation. Only 30% of nursing homes in the United States have adopted complex systems, such as IoT-based patient and medication tracking (Zhang et al., 2013). Additionally, only 20%–30% of nursing homes in California, Minnesota, and New York have implemented electronic medical records, which indicates a lack of existing M-IoT infrastructure (Irfan & Ahmed, 2018; Zhang et al., 2013). As a result of this phenomenon, these facilities have been struggling to store, access, and share data needed for them to reduce costs and improve efficiency, performance, and patient care (Alexander & Madsen, 2016). They have not been able to take full advantage of enhanced communication, information exchange between entities, and regulatory compliance that M-IoT provides.

Numerous researchers have evaluated HIT adoption in different health-care environments (Bowles, Dykes, & Demiris, 2015; Gregory & Madsen, 2018). However, I could find no comprehensive investigation of the social aspects of the adoption of M-IoT in long-term care settings, such as skilled nursing homes. Understanding the primary social factors affecting adoption from the perspectives of nurse practitioners, technicians, and other decision-makers within these nursing homes would help to increase awareness of strategies that could lead to acceptance of M-IoT and contribute to increased adoption in the future.

Research Purpose

The purpose of this causal-comparative study was to evaluate variables in UTAUT, along with PR, which may have a direct effect on the adoption of M-IoT technology within the context of small and medium-sized skilled nursing homes in the United States. The independent variables are performance expectancy (PE), effort expectancy (EE), and social influence (SI) from the UTAUT, along with PR from Trevino et al. (2017) and Despins et al. (2010). I assessed five constructs to determine their impact on behavioral intention (BI) to use the technology. The study clarified which factors are most negatively or positively influential in affecting an employee's decision to use M-IoT-based technology.

M-IoT improves the quality, efficiency, and effectiveness of health-care services, which magnifies the importance of understanding what leads individuals to adopt this type of technology that can enhance the daily functions of nurses and improve the quality of care delivered to patients in these environments (Hassanalieragh et al., 2015). Although many have studied technology adoption in general, few have explored the adoption and use of M-IoT (Alansari, Anuar, & Kamsin, 2017; Canhoto & Arp, 2017; Sun & Qu, 2015). Of those who have addressed potential determinants of adoption and use of M-IoT, few have discussed factors of adoption within U.S. long-term care organizations, such as skilled nursing homes, which have formed an important sector of the economy and that could benefit tremendously from the capabilities of M-IoT. This lack of clarity regarding antecedents of adoption and the use of M-IoT within skilled nursing homes in the United States warrants additional study.

Research Questions

Derived from the literature review, and further refined through an understanding of the concepts presented, the main research question RQ 1 asks what the relationship is between the variables of PE, EE, SI, and PR and the variable of BI to use M-IoT among nursing home practitioners and technicians in small and medium-sized nursing homes in the United States.

The subquestions of the research were

RQ 2: What is the strength of the relationship, if any, between PE and BI to adopt M-IoT technology?

RQ 3: What is the strength of the relationship, if any, between EE and BI to adopt M-IoT technology?

RQ 4: What is the strength of the relationship, if any, between SI and BI to adopt M-IoT technology?

RQ 5: What is the strength of the relationship, if any, between PR and BI to adopt M-IoT technology?

The aforementioned research questions resulted in the following hypotheses:

$H_0$1: PE, EE, SI, and PR are not statistically significant predictors of BI to adopt M-IoT devices in nursing home environments.

H_a1: PE, EE, SI, and PR are statistically significant predictors of BI to adopt M-IoT devices in nursing home environments.

$H_0$2: PE does not significantly influence BI to adopt M-IoT.

H_a2: PE significantly influences BI to adopt M-IoT.

$H_0$3: EE does not significantly influence BI to adopt M-IoT.

H_a3: EE significantly influences BI to adopt M-IoT.

$H_0$4: SI does not significantly influence BI to adopt M-IoT.

H_a4: SI significantly influences BI to adopt M-IoT.

$H_0$5: PR does not significantly influence BI to adopt M-IoT.

H_a5: PR significantly influence BI to adopt M-IoT.

Rationale

The main rationale for the study was the lack of existing research evaluating specific social factors in M-IoT adoption in skilled nursing homes. It was necessary to examine the perspectives of nursing home decision-makers in their adoption of M-IoT, due to the slower than expected adoption of these technologies (Hung, 2016; Ismael, Abdullah, & Shamsuddin, 2015; Zakaria & Yusof, 2016). The present study specifically investigated how the core variables of UTAUT, along with perceived risk, influenced decision-makers in nursing homes when adopting M-IoT.

Despite the acceptance and increasing popularity of IoT in various industries (Xu et al., 2014), researchers have not sufficiently explored the potential social factors influencing adoption, including those presented in the UTAUT (Venkatesh et al., 2003) and PR in long-term care environments or health care environments (Achituv & Haiman, 2016). Because M-IoT has been an essential tool in the long-term care industry, the study attempted to understand the underlying motivating factors that lead individuals and organizations to adopt and use this type of technology. Moreover, the study sought to advance academic research in the field to help decision-makers understand the factors that affect the adoption of this type of technology in health-care environments. The study may also be of value to decision-makers in nursing homes (directors, managers, and administrators) so that they may gain a better understanding of risk perceptions, which could form the foundation to plan trust-building mechanisms, formulate risk-reduction strategies, and encourage other applications of IoT throughout the industry (Pirbhulal, Samuel, Wu, Sangaiah, & Li, 2019; Xu et al., 2014). The study serves to enlighten those in academia, the long-term health-care industry, IT, and organizational behavior experts.

Many researchers have studied technology adoption (Bervell & Umar, 2017; Irfan & Ahmad, 2018). They have proposed numerous theories to explain or predict user acceptance of technology, including UTAUT (Venkatesh et al., 2003). This research did not rely on more modern versions of the UTAUT, such as the UTAUT 2, because of their emphasis on experience, habit, and influence of moderating factors regarding hedonic motivation (Venkatesh, Thong, & Xu, 2012). These factors were irrelevant to the present study, which is concerned with BI to adopt technology prior to use and not use behavior after adoption.

Other researchers have examined organizational adoption of technology and use behavior and developed theories that distinguish different practical situations that are characterized by specific types of technology and organizational contexts (Chau, 1996; Hu, Chau, Sheng, & Tam, 1999). Still, others have studied health-care environments and focused on adoption perceptions from the perspectives of physicians or patients (Achituv & Haiman, 2016; Hu et al., 1999; Jha et al., 2009; Lu, Xiao, Mills, Soeken, & Vaidya, 2006; Ralston et al., 2007; Snyder & Fields, 2007). Some researchers examined HIT adoption for specific tasks, such as enhancement of patient safety (Brooks, Menachemi, Burke, & Clawson, 2005; Cheng & Kuo, 2020) or reduction of medical errors (Bates et al., 2001; Mcaleamey et al., 2007), but most focused intensely on technical issues or solutions and benefits. In the study, I evaluated adoption from the perspectives of decision-makers, specifically nursing home practitioners and technicians who have direct input into, and control over, evaluation and adoption decisions. The reason for choosing this group was significant because it highlighted the fact that decisions for enterprise deployments, such as IoT systems in skilled nursing homes, are made at the individual level and, usually, the individuals are the same people who decide to accept, adopt, and implement the technology (Harper, 2016). These decision-makers form the population identified for the study and also represent their entire organizations.

This quantitative casual study investigated the adoption factors of M-IoT devices in the context of nursing home decision-makers. This research provided insight into how the factors under review influenced decision-makers to adopt M-IoT, thereby, identifying possible adoption success factors in this type of environment. The constructs of the UTAUT (Venkatesh et al., 2003) and PR framed the research in the context of social influencers. The adoption in this type of environment is significant because the rate of adoption in skilled nursing homes will significantly affect the organizations' abilities to increase safety, efficiency, compliance, and revenue (Zakaria & Yusof, 2016). The study contributes to advancing research in the field and can help decision-makers understand the factors that limit the adoption of this type of technology in health-care environments.

Theoretical Framework

When facilitating the adoption of M-IoT, the UTAUT is a promising theory that may explain why nursing home employees accept or reject M-IoT devices. Many researchers have developed and tested the UTAUT for the examination of the acceptance of diverse technologies. Martins et al. (2014) applied the UTAUT to investigate the adoption factors of e-services in the financial services industry. Mardikyan, Besiroglu, and Uzmaya (2012) applied the UTAUT to study behavioral intentions toward the use of third-generation wireless mobile technology in Turkey. Zhou, Lu, and Wang (2010) used a model based on the UTAUT to explain user adoption in mobile banking. Marchewka, Liu, and Kostiwa (2007) applied the UTAUT model to understand student perceptions when using course management software in universities.

Contextual differences between typical organizations and nursing homes raise questions regarding the application of the UTAUT to nursing home settings. In conventional organizations, job performance and use of technology have financial consequences, such as productivity and promotion. In a nursing home, nurses are the health-care providers who provide the majority of care and intervention to patients and are the most likely to intercept, identify or cause medical errors (Trevino et al., 2017). In this setting, nurses are also health-care professionals with the most complex set of tasks without redundancy. In many cases, they represent the last layer of defense against medical error. Nurses are trained in professional ethics and the duties of caring for patients, many of whom are elderly. Changes to their practice, including any use of technology, can have adverse effects on the health of the patients they care for (Trevino et al., 2017).

This study relied on the UTAUT (Venkatesh et al., 2003) combined with PR. In the UTAUT, the four main determinant factors are PE, EE, SI, and facilitating conditions, which have a direct influence on BI (Venkatesh et al., 2003). The study used only three factors from the UTAUT and an additional variable, PR. The constructs are defined as follows:

1. PE is the degree to which a person believes that using a computer system will increase job performance (the UTAUT is primarily concerned with testing IT and information systems solutions).
2. EE is the degree of ease associated with the use of the system.
3. SI is the degree to which a user believes that important or influential people want him or her to use the system.

4. PR is the degree to which users believe that using M-IoT causes possible physical, emotional, or mental harm to patients or leads to a loss of privacy of patient data.

The UTAUT model includes two additional variables: facilitating conditions and use behavior. These constructs relate to quantifying the actual acceptance of technology after BI is clear. This study does not include measurement of facilitating conditions and use behavior, because the study is concerned with the early stages of the decision-making process prior to technology acceptance or adoption. I also omitted analysis of the relationship between facilitating conditions and BI, the relationship between BI and use behavior, and the influence of moderating factors. For clarity, Figure 1 illustrates the factors from the UTAUT that were investigated in this study.

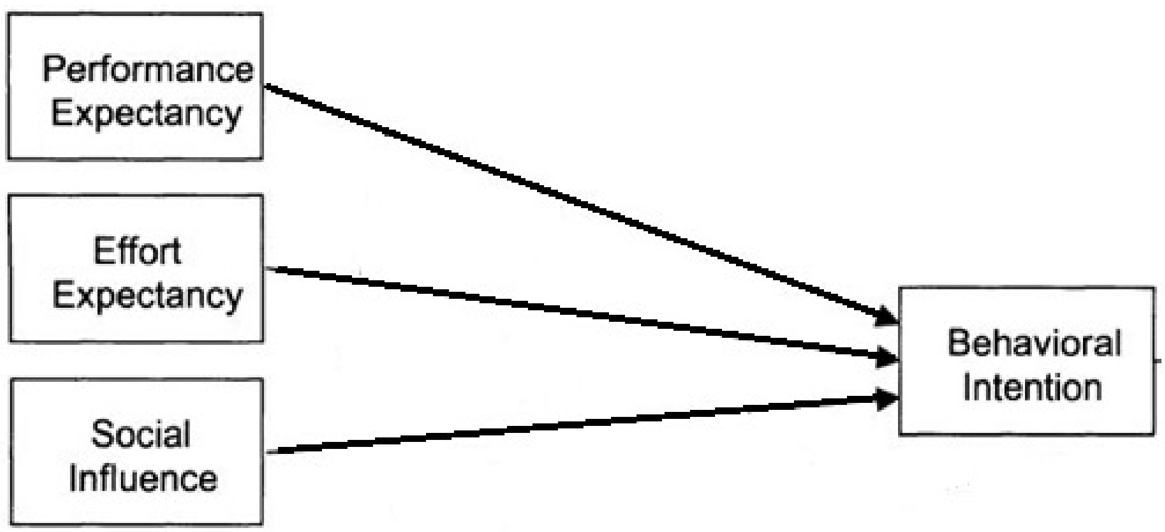

Figure 1. Modified model based on the unified theory of acceptance and use of technology. From "User Acceptance of Information Technology: Toward a Unified View," by V. Venkatesh et al., 2003, *MIS Quarterly*, *27(3)*, pp. 425-478. Copyright 2003 by Regents of the University of Minnesota. Adapted and printed with permission.

The additional variable in the study is PR (Despins et al., 2010; Trevino et al., 2017). According to Trevino et al. (2017), PR is “the potential for physical or mental harm to the patient either via medication side effects, delivery, drug interaction or other risks related to nurse training in the administration of the medicine or care of the patient” (p. 22). In this research, risks categorized are either known risks (learned from training) or impact risks based on how impactful or invasive a certain procedure is to a patient (Keers et al., 2013; Bowblis & Roberts, 2018; Trevino et al., 2017). The purpose of their research was to discover how nurses perceive risk in common nursing environments and how PR affects their daily decision-making. The authors stated the importance of including a measure of PR in models or technology acceptance and adoption because consumers recognize and value risk when assessing products or services for purchase or adoption, which may create anxiety and discomfort for them (Keers et al., 2013; Bowblis & Roberts, 2018; Trevino et al., 2017).

The selected variables were relevant to the study because IoT adoption in health care is viewed as a complex activity system involving different types of technologies, users, and tasks at both the individual and social level (Sun & Qu, 2014). I chose to interpret these variables as simple primary indicators in the complex environment of long-term care. The constructs used all aligned well with the study because each variable identified played a role in the adoption of technologies in this environment.

Conceptual Framework

Because the focus of the study was IoT adoption, which is a form of acceptance of innovative technology intertwined with social systems and personal characteristics, the integration of the UTAUT (Venkatesh et al., 2003) and PR had to be comprehensive. The integration of PR with the UTAUT resulted in the exclusion of constructs from the original models, necessitating a conceptual model. The conceptual model, illustrated in Figure 2, shows the modifications. In the rest of this section, I clarified the model and justified the removal of certain constructs.

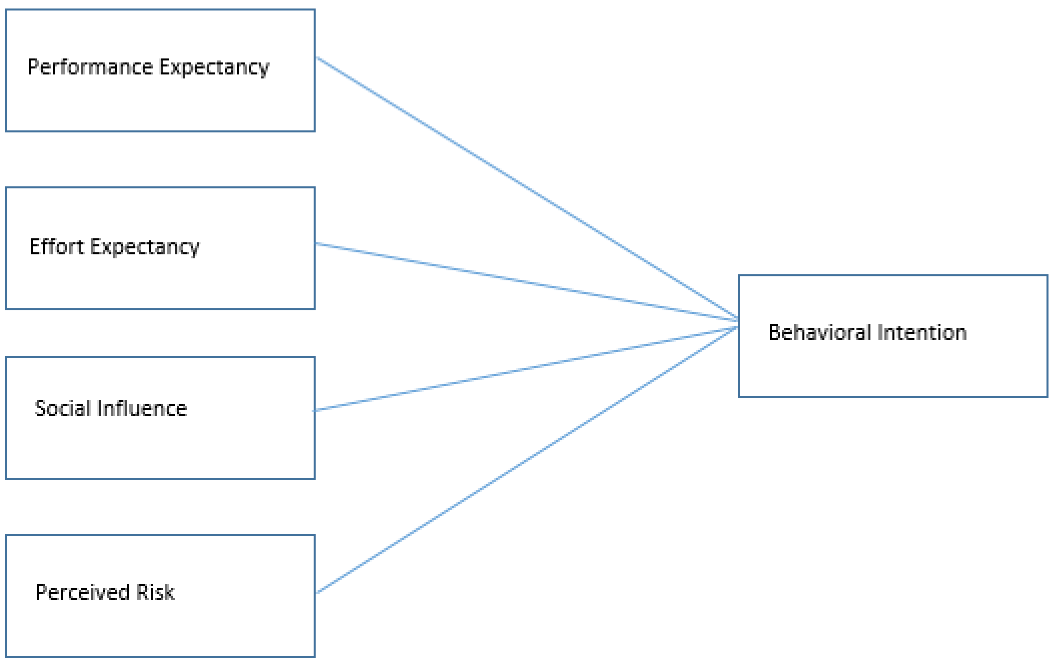

Figure 2. Modified UTAUT model. From "Understanding the Internet Banking Adoption: A Unified Theory of Acceptance and Use of Technology and Perceived Risk Application," by C. Martins, T. Oliveira, and A. Popovic, 2014, *International Journal of Information Management*, *34*(1), pp. 1-3. Copyright 2013 by Elsevier. Adapted and printed with permission.

I adopted the model because prior research had widely applied the UTAUT (Venkatesh et al., 2003) to examine IT use and digital or electronic service acceptance (M. Lee, 2009; Martins et al., 2014). Researchers have increasingly focused on integrating the UTAUT with factors of risk or trust in these investigations because they complement each other, and the integrated model has had better exploratory power than the UTAUT or PR alone (Martins et al., 2014).

Researchers have used this model to examine a wide range of technologies (Williams, Rana, Dwivedi, & Lal, 2011), including in many quantitative studies examining the acceptance of HIT (Achituv & Haiman, 2016; Chiuchisan et al., 2014; Phichitchaisopa & Naenna, 2013), and thus making the UTAUT theoretically and practically useful for employing a combined UTAUT-PR model as the theoretical basis for the study.

Venkatesh et al. (2003) examined eight prominent models to derive the UTAUT, which can explain as much as 70% of the variance in BI. The eight models studied were the theory of reasoned action (TRA; Fishbein & Ajzen, 1975), the technology acceptance model (TAM; Davis, 1989), the motivational model (MM; Davis, Bagozzi, & Warshaw, 1989), the theory of planned behavior (TPB; Ajzen, 1991), a hybrid model combining constructs from TAM and TPB (Taylor & Todd, 1995), the model of personal computer use (MPCU; Thompson, Higgins, & Howell, 1991), the theory of innovation diffusion (TID; Moore & Benbasat, 1991, 1996; Rogers, 1995), and social cognitive theory (SCT; Compeau & Higgins, 1995). The UTAUT includes four constructs that act as determinants of BI and use behavior: PE, EE, SI, and facilitating conditions. It also includes four moderator variables: gender, age, experience, and voluntariness of use, which are not included in the study.

Since its inception, the UTAUT (Venkatesh et al., 2003) has been extremely popular with researchers investigating technology adoption. Researchers have applied the model to several types of technologies, such as cloud computing (Dominguez, 2013), instant messaging (Lin & Anol, 2008), Internet banking (Chi-Lee, 2009), and web-based learning (Chiu & Wang, 2008). Tan, Chong, Loh, and Lin (2010) studied the adoption factors of Internet banking and mobile banking in Malaysia with the UTAUT. Similarly, Im, Kim, and Han (2011) conducted research to discover whether culture affected the UTAUT constructs by comparing MP3-players and Internet-banking technologies in Korea and the United States. Yuen, Yeow, Lim, and Saylani (2010) tested the UTAUT model in two groups of culturally different countries, both developed (the United States and Australia) and developing (Malaysia). The researchers found that attitudes toward using e-services and performance expectancy were the most important factors affecting customer acceptance of e-services.

The authors discussed PR with respect to clinical decision-making. I could not find any published evidence regarding how PR affects nurses' decision-making relating to M-IoT adoption. In this study, PR is a determinant of M-IoT adoption and continued use.

This theoretical model corresponds well to the needs of the study because the determinants involved are remarkably simple, and the constructs are common in technology use environments and are applied widely to solve acceptance problems. As mentioned above, the combined model of the UTAUT (Venkatesh et al., 2003) with PR has produced more dependable results than using either of them alone. Because the focus of this study is IoT adoption, the integration of the UTAUT and PR into the conceptual framework permits examination of nurses' intentions toward, and acceptance of, IoT-based technologies.

Significance

The study is significant because it sought to investigate the challenges related to the adoption of M-IoT in small and medium-sized skilled nursing homes in the United States and how they inform strategic decision-making to improve efficiency, safety, and compliance in health-care environments. Regarding expanding the body of knowledge regarding M-IoT technology, the study fills a gap in the existing literature by evaluating the potential contributory factors affecting decision-makers' adoption and use of M-IoT. It further expands knowledge by applying the UTAUT-PR model using partial-least-squares structural equation modeling (PLS-SEM). The study is also significant because researchers using the UTAUT have in the past, overwhelmingly focused on conventional organizational settings, such as businesses or schools. The study complemented existing work by investigating the application of the UTAUT, along with PR, in environments where the use of technology can potentially result in permanent harm (even death) to the patients for whom the technology users provide care. The addition of PR is especially significant, as results showed nursing home decision-makers do not consider PR an important factor for adoption decision making.

The adoption of IoT devices in the health care industry is relevant to the research community because the findings of the proposed study can contribute to and improve understanding of the factors involved in the adoption of this type of technology. This understanding could lead to increasingly successful adoptions of IoT-based technologies in other environments and industries. The reduction of failure in technology adoption projects in these types of environments can save money and time that could be reallocated elsewhere in organizations. The improved understanding of tech adoption in these environments can provide clarity on how long-term care facilities select, adopt, and implement technology. The use of the modified theory of UTAUT-PR can illuminate the role risk plays in the adoption decision-making of individuals in different environments. HIT adoption frameworks have not incorporated risk, so identification of an all-encompassing model is beneficial.

The study also provided valuable insights for U.S. nursing home decision-makers regarding the influence of social and behavioral variables on acceptance and use of M-IoT systems. These insights can be helpful to decision-makers and IT professionals working in nursing homes as they plan and facilitate the introduction of M-IoT devices in their own organizations. The findings revealed which factors influence employees' acceptance of, or resistance to, M-IoT and facilitated strategic decisions within these types of organizations so that they can realize the significant strategic, operational, and financial benefits that M-IoT systems offer.

According to Steverson (2018), in a World Health Organization fact sheet, the number of people over the age of 80 years will increase to 395,000,000 by 2050. Steverson predicts that 25%–30% of seniors will have some form of cognitive decline by the age of 85. Many of these people will lose the ability to live independently and will require long-term care. Providing adequate staffing in long-term care facilities such as skilled nursing homes has been challenging, and thus the implementation of technology is one strategy that can be implemented to change care delivery in these environments (Bowblis & Roberts, 2017). Because of this, leaders of long-term care facilities have increasingly focused on productivity and efficiency by increasing the use of technology.

According to Hung (2016), spending on health care IoT solutions will reach $1,000,000,000,000 by 2025 and will hopefully set the stage for highly personalized, accessible, and on-time health care services. According to Sun and Qu (2014), HIT is the most important means to improve service delivery, quality, efficiency, and effectiveness of health-care services. Kalva (2016) and Rath (2020) believe that the primary purpose of IoT in health care will be to harness data from multiple devices and sensors that reveal what is going on with patients. There will be a wide diversity of endpoints ranging from familiar medical monitoring to innovative devices like patient-embedded nanosensors. These new capabilities will yield new sources of profit for companies that quickly adopt IoT-based technologies.

The adoption of IoT-based technologies in health care has been significant for patients and practitioners who rely on technology for many reasons. Baek, Seo, and Kim (2016) believe that the emerging IoT technology will contribute significantly to the advancement and evolution of health-care services. New improvements in remote monitoring, smart sensors, and medical device integration have the potential to keep patients safe and healthy, but also to improve how physicians deliver care. Health care IoT can also boost patient engagement and satisfaction by allowing patients to spend more time interacting with their doctors.

Although unprecedented capabilities for predictive diagnosis hold promise for advancing health care, IoT-based technologies also pose unique security challenges (Kalva, 2016). The successful deployment of M-IoT depends on ensuring security and privacy in ways that adapt available processing capabilities. Baek et al. (2016) believe that IoT is vulnerable to attacks because communication is mostly wireless. IoT has inherent security and privacy risks, even though it provides convenience and has economic benefits. If these possible obstacles, along with other challenges like ease of use, performance, and SI, significantly affect the ability of skilled nursing homes to adopt IoT technology, there could be far-reaching effects on the long-term success of these organizations. Companies that adopt this technology quickly will have opportunities to increase patient population, improve public relations and reputation, tap into new profit streams, and increase industry market share. The potential benefits make it clear that information gathered from the study will be valuable to decision-makers in the health-care industry.

Researchers have tended to focus too much on the functionality of technology, such as performance and ease of use (Achituv & Haiman, 2016; Hu et al., 1999; Jha et al., 2009; Lu et al., 2006; Ralston et al., 2007; Snyder & Fields, 2007). Few researchers have considered some form of risk involved in technology consumption or adoption in the information age (Achituv & Haiman, 2016; Alasmari & Anwar, 2016; Chao, 2019). However, the addition of PR should contribute to future studies of technology adoption—not just in long-term care facilities but also with humans in the workplace in general.

Definition of Terms

This section defines several technical and specialized terms used throughout the study.

Cloud Computing. Cloud computing refers to the means through which computing power and infrastructure, applications, business processes, personal collaboration, and more can be delivered as a service wherever and whenever individuals need it. A cloud is a group of interconnected network servers or personal computers that may be private or public. The data and the applications served by the cloud are accessible to a group of users throughout the network (Ganesan, Sivakumar, & Thirumaran, 2020; Rittinghouse & Ransome, 2016).

***Denial of Service* (DoS)**. Denial of service attacks are attempts by attackers to disable victims' machines by depleting network or computing resources. An attack performed with more than one computer is called a distributed DoS (DDoS) attack (Mehic, Slachta, & Voznak, 2016).

Effort Expectancy (EE). Effort expectancy is the perceived ease of use of a technology (Venkatesh et al., 2003). EE evolved from the constructs of other models, such as the perceived ease of use of the TAM (Davis, 1989). In the assessment of UTAUT constructs, EE significantly predicted BI would use a technology, but only on the first use of the technology; as users became more familiar with the technology, this construct lost power (Venkatesh et al., 2003). According to Venkatesh et al. (2003), other factors such as age, gender, and experience moderate this construct.

Heterogeneous Networks. Heterogeneous networks are networks connecting computers and other devices with different operating systems and protocols. For example, local area networks (LANs) that connect computers running Microsoft Windows, Linux, and Apple macOS are heterogeneous (Patel & Mistry, 2015).

Internet of Things (IoT). The Internet of Things is a dynamic global network infrastructure reliant on the use of the Internet infrastructures and communication mechanisms for ubiquitous connectivity (Xu et al., 2014).

Network Function Virtualization **(NFV)**. Network function virtualization provides an architectural, vendor-neutral overview of the issues surrounding the high data-storage and transmission requirements of modern companies (Gray, 2016). NFV provides several benefits for enterprises (Gray, 2016).

Performance Expectancy (PE). Performance expectancy is an individual's expectation that the use of a technology will aid in the performance of his or her job. PE originates from other constructs, including the perceived usefulness of the TAM (Nyembezi & Bayaga, 2017). In the assessment of UTAUT constructs, PE was the strongest predictor of BI to use technology and is moderated by age and gender (Venkatesh et al., 2003).

Radio-frequency identification **(RFID)**. Radiofrequency identification is an automatic identification method that relies on storing and remotely retrieving data using devices called *RFID tags* (or *transponders*). The core functionality of an RFID system is the communication between a reader and a tag. The communication is carried out using radio waves (Bertoni, Sarti, Benelli, Pozzebon, & Raguseo, 2010).

Social Influence (SI). Social influence is the perception an individual has that others would like him or her to use a technology (Venkatesh et al., 2003). SI derives from models outside of the TAM and, in the assessment of UTAUT constructs, was a significant predictor of BI to use technology (Venkatesh et al., 2003). According to Venkatesh et al. (2003), age, gender, experience, and voluntariness moderate this construct.

Technology Adoption. Technology adoption is a perspective from which success is defined as the degree to which a system is liked and used by consumers (Venkatesh et al., 2003). Several models have been developed to measure user adoption of technology. The TAM, developed by Davis (1989), has likely been the most widely used model (Abu-Al-Aish & Love, 2013). Building on the TAM and seven other models, the UTAUT explains technology adoption better than its predecessors. The core constructs of the UTAUT are PE, EE, and SI.

Ubiquitous Sensing **(US)**. Ubiquitous sensing encompasses the integration of different sensor data sources (static and mobile wireless sensor networks [WSNs]) and is the next step in the evolution of WSN research (Perez, 2011).

Wireless Sensor Networks (WSN). Wireless sensor networks are computer networks composed of small, battery-powered devices deployed in areas of interest for sensing, monitoring, and reporting data about events. Initially, WSNs were used to report data about environmental variables, but other applications have emerged, and currently, WSNs are popular in security, military, health, construction, and many other domains (Perez, 2011).

Assumptions and Limitations

Assumptions

Several theoretical, methodological, and statistical assumptions comprised the basis of this research. I assumed that the participants would have had previous experience using and deploying M-IoT devices at the organizational or personal level and were familiar with some of the functions these devices serve, such as remote monitoring and reporting, automated workflows, and drug dispensing and management.

Appropriateness of the unified theory of acceptance and use of technology. I assumed that the UTAUT would be a useful model to measure the adoption of M-IoT. Because the UTAUT is a widely used model for measuring technology adoption, I assumed that the model would apply to this study. Further, the decision was made to extend the model because countless other authors have employed the same approach to describe the phenomenon of technology adoption in different industries.

Honesty of participants. I assumed that the participants would honestly and diligently answer the survey questions to the best of their ability. Although I could not measure the honesty of the users, a data cleaning procedure was utilized to remove outliers and incomplete responses.

Inclusion criteria. I assumed that the chosen criteria were appropriate and that participants would have an interest in the study.

Limitations

The study was limited to only collecting responses from decision-makers within U.S based skilled nursing homes. Members of this population received an electronic survey via Survey Monkey, creating a further delimitation for the population. An additional limitation of the study was the possibility of researcher bias and perceptual misrepresentations since the respondents were self-reporting on their attitudes and intentions. As the surveys were conducted via anonymous self-assessment, it was not possible to determine whether a bias existed for those who responded to the survey and those who declined to participate.

I limited the study population to the decision-makers (technicians, practitioners, administrators, and directors) in U.S. skilled nursing homes. Members of this population are responsible for IT-adoption decision-making in the environment that uses M-IoT devices to improve work efficiency and accuracy. In addition, the study was limited to the social and human factors that influence the acceptance, adoption, and intended use of IoT devices. This study was based on the assumption that social and human factors always have an effect on the adoption and intended use of IoT-based technologies.

Another limitation of the proposed study was the exclusion of moderating factors, such as experience, gender, and age. Venkatesh et al. (2003) initially used these factors as a way to provide details to the UTAUT.

Limitations of the researcher. The researcher did not have extensive experience performing quantitative studies. However, by close adherence to guidelines, design methodology, and principles of statistical analysis, the researcher was able to conduct a valid study. This was mitigated by relying on the research committee and participants in the field test to increase the research validity.

Limitation of generalization. The manner in which the sample was taken was also a limitation of a study. Sampling was done by employing a random (probabilistic) method (Gheondea-Eladi, 2014). The Survey Monkey online survey tool was used to collect a simple random sample from registered and active participants. At the time of writing, the volunteer audience panel of Survey Monkey included more than 30,000,000 individuals. Membership of the panel required awareness and registration on the Survey Monkey site, so it may not accurately represent the broader population. Therefore, the generalization of the proposed study may be affected.

Organization of the Remainder of the Study

The remainder of this study is organized as follows. Chapter 2 provides an in-depth review of IoT use in health care, along with an overview of theoretical models used to analyze the nature of IT adoption in the health-care industry. The theoretical models provide a framework or context to understand the conceptual elements in HIT adoption and the relationships among them. Chapter 3 contains information on the study's methodological approach, including details on the research design, a description of the population and sample, a summary of the data collection and analysis steps, and a review of the ethical considerations that guided the research. Chapter 4 presents the results of the data analysis process. Chapter 5 concludes the study with a summary of the results, a review of the implications for scholars and practitioners, and suggestions for further research.

CHAPTER 2. LITERATURE REVIEW

Introduction

This chapter will cover the literature review conducted for this study, including the methods used to locate articles related to the topic, the theoretical orientation for the study, a comprehensive review of the research literature related to the topic, and the research regarding technology adoption in health care environments. This chapter includes the definition of IoT, a brief history of the IoT, types of M-IoT devices, why companies use IoT devices, a thorough discussion of IoT benefits and limitations, risk factors, and theoretical perspectives, as well as research regarding UTAUT, TPR (Featherman & Pavlou, 2003; Venkatesh et al., 2003) and constructs found to be related to technology adoption. The chapter will conclude with a synthesis of the findings, a critique of previous research methods used to explore the topic, and a summary of the literature review.

This study intended to evaluate variables that may have a direct effect on the adoption of M-IoT technology within the context of small and medium-sized skilled nursing homes in the United States. A goal of the research was to place the topic research in a historic context, provide an assessment of previous studies, justify the selection of the research topic, the list of references, and assist in the selection of the research design and methodological procedures. This study was influenced by the reality that skilled nursing homes do not have the information and understanding of additional adoption factors for M-IoT (Gregory & Madsen, 2018; Stempniak, 2018) and, as a result, are not adopting the technology as quickly as expected. It was found that, based on a comprehensive review of the existing literature, academic studies related to acceptance and adoption of M-IoT devices are limited in numbers and content. Finally, of those studies that address the topic, few consider the social factors that influence the acceptance and adoption of this type of technology. A thorough summary of the existing literature confirmed the need to conduct the present research. An analysis and compilation of references were provided to validate the selection of a quantitative approach, along with the application of regression analysis to evaluate the different constructs under study.

Internet of Things, Health Care, and Skilled Nursing Homes

The Internet was built to foster human-to-human interaction, but the rise in the popularity of Internet-connected smart objects has resulted in a significant increase in object-to-object and human-to-object communication (Xu et al., 2014). Internet technologies have steadily evolved from being an email focused technology for web browsing, encyclopedia-type research, to constituting a diverse communication medium that allows devices to be more autonomic and implemented in a broader range of places and applications. This new object-to-object paradigm with electronic elements tethered to the Internet is known as the IoT (Voas, 2016). IoT devices display self-constructing capabilities based on standard, interoperable communication protocols, where physical and virtual *things* have identities, physical qualities, and virtual identities using intelligent interfaces (Jyotheeswari & Jeyanthi, 2020; Maras, 2015). These characteristics allow IoT devices to become interconnected systems where living and inanimate objects in the physical world and sensors within or attached to the devices are connected to the Internet via wireless and wired network connections (Maras, 2015). Interoperability and self-configuration qualities explain why the use of IoT technology can potentially increase convenience and efficiency in daily life. In a world where “things” are hyper-connected, objects have the possibility of understanding and reacting to their environment. These objects may leverage RFID, NFC, wireless sensors, and actuator networks (WSANS). IoT encompasses different communication standards, protocols, and data formats, creating a heterogeneous, decentralized, and complex environment.

These characteristics, coupled with network access, give the IoT the potential to revolutionize many industries, with the medical industry at the top of the list (Achituv & Haiman, 2016). The IoT is considered the greatest impactful socio-technological development influencing health services (Achituv & Haiman, 2016). Hung (2016) forecasted that there would be approximately 8.4 billion connected IoT devices in 2017. As projections show, this number could reach 20.4 billion in 2020. In the health care industry, IoT has been termed a real game-changer, with the potential to lower costs, improve efficiency, and bring the focus back to quality patient care (Gregory & Madsen, 2018).

Information-detection and human connections with the physical world are essential concepts for the provision of human value-added services in IoT environments (Hou & Yeh, 2015). Among these services, IoT-based health care support systems are some of the most promising opportunities for development and, subsequently, a major focus of industry research. For example, the integration of some forms of IoT technology into medical devices improves the quality and effectiveness of service, especially for the elderly, patients with chronic conditions, and those requiring constant supervision (Hou & Yeh, 2015). The proliferation of IoT in health care has been immensely beneficial in remote clinical monitoring, chronic disease management, preventive care, assisted living, and personal fitness monitoring (Gregory & Madsen, 2018).

Despite the large number of articles on the benefits and drawbacks of IoT, there is little research associated with this type of technology on adoption approaches or the investigation of possible success factors. Many studies have examined the technical factors affecting the adoption of M-IoT, but very few existing studies have sufficiently addressed the interactions among all the socio-technical factors relating to people, processes, and technologies within organizations (Shin, Kim, Hong, Chung, & Jeong, 2015). If decision-makers understand the factors that lead to the adoption of M-IoT, then they can better plan and strategize IoT deployment and implementation plans.

Definition of IoT

Xu et al. (2014) defined IoT as a dynamic global network infrastructure, reliant on the use of the internet infrastructures and communication mechanisms for ubiquitous connectivity. IoT devices exhibit self-configuring capabilities based on typical, interoperable communication protocols where physical and virtual *things* have identities, physical attributes, and virtual personalities using intelligent interfaces (Maras, 2015). These characteristics allow IoT devices to become an interconnected system where living and inanimate objects in the physical world and sensors within or attached to them are connected to the Internet via wireless and wired network connections (Maras, 2015). If an object has an IP address, an identifier, and internet connection, the object is classified as an IoT-enabled solution. These products send out and receive data from different sources to create an entire IoT ecosystem. This architecture also includes IoT software, sensors, gateways, and any other sort of hardware needed to capture and distribute that data. The attributes above are the reasons why the use of IoT has the potential to increase convenience and efficiency in daily life (Maras, 2015).

The term IoT was at first used to portray extraordinarily identifiable interoperable associated objects with RFID innovation (Xu et al.,2014). Later, scientists related IoT technology with more advancements, such as sensors, actuators, GPS gadgets, and cell phones. Another accepted definition of IoT is a dynamic, robust worldwide system framework with self-arranging abilities, in view of standard and interoperable communication protocols, where physical and virtual *things* have characters, physical characteristics, and virtual identities (Chiuchisan et al., 2014). The IoT represents a small subset of what will be known as the *Internet of everything,* which is a subset of what will become known as the *Internet of anything* (Bojanova et al., 2014). Before *the Internet of everything* can become a reality, several issues involving security and privacy that persist in the same way the early Internet had issues must be resolved. So just as the Internet has changed society in incredible ways, the IoT is poised to do the same.

The Nature of IoT

The evolution of IoT would not have occurred without intercommunication between different technologies. So, networking issues, such as scalability, transport, discovery, and protocol types, have become particularly important when trying to link multiple devices of various intelligence and autonomy (Mahmoud, Yousuf, Aloul, & Zualkernan, 2015). Historically RFID has been the cornerstone of the IoT, particularly in manufacturing (Bi, Xu, & Wang, 2014). RFID sensors come in two types, active and passive. Active sensors contain batteries and may actively initiate communication, whereas passive sensors do not contain batteries and must harvest their power from a nearby transmitting reader (Atzori, Iera, & Morabito,2010). Passive sensors provide communication in otherwise resource-starved situations, such as when no battery is present or permitted because of size limitations. Although RFID research has focused on privacy, wide-scale adoption remains limited because of other elements of security, such as data tampering and physical security (Han et al., 2011; Jyotheeswari & Jeyanthi, 2020). Han et al.

(2011) proposed a form of tamper detection using digital watermarks to help address this issue. However, the gap in the literature on securing IoT communications, such as the protection of data in transit, is disturbing. In situations involving spontaneous, temporary networks are anticipated when sensors are deployed in an ad-hoc manner, in which trust is a matter of control, not security (Lacuesta, Palacios-Navarro, Cetina, Peñalver, & Lloret, 2012). In this scenario, the sensors (or nodes) will connect and disconnect as required without human intervention.

Sensors

The inclusion of sensors is what makes the IoT far more significant than just representing an extension of the Internet. These sensors give IoT-enabled devices the ability to sense the network environment and make decisions autonomously. For example, when an RFID sensor in a car goes under a highway toll meter, the user does not need to acknowledge the financial transaction, it just happens (Gao & Bai, 2014). Swan (2012) revealed that in 2008 the number of sensors connected to the Internet exceeded the number of humans on the planet and projected that, by 2020, that the number is expected to surpass 50 billion. What makes the IoT special is the ability to connect devices and to enable devices to act autonomously. Sensors gather data and make decisions based on that new knowledge. Researchers have argued that sensors will operate in two modes (or loops), gathering, and sensing (Zaslavsky & Jayaraman, 2015).

Application of IoT in Other Industries

The literature on the technical aspects of IoT outnumbers the behavioral and attitudinal aspects. Few studies have examined the acceptance of IoT by consumers and industries (Gao & Bai, 2014). Though issues related to IoT have been widely discussed in practical and academic fields, most prior studies have focused on overview descriptions, concepts, business models, opportunities, and challenges (Hsu & Chuan Lin, 2016). These examinations distinguished important issues, advances, guidelines, compositional components, security, and protection challenges (Hsu & Chuan Lin, 2016). However, minimal observational research has analyzed the authoritative elements that influence the reception of IoT-based innovations in various enterprises.

These smart objects are being used in many industries and are extremely popular, even in most homes. They are increasingly used in the energy industry to simplify the management of smart grids, nuclear plants, generator stations, and hydro-electric plants, and the information stored in these devices is valuable to the stakeholders (Majed, Ibrahim, & Shaaban, 2014). This has led to an increasingly growing interest in the adoption of IoT technologies in other industries. IoT projects have been conducted in multiple industries, such as food processing, agriculture, environmental monitoring, security surveillance, and many others. RFID represents a foundational technology of IoT. It permits embedded microchips to transmit the identification information to a reader through wireless communication (Xu et al., 2014). RFID readers allow people to identify, track, and monitor any objects attached with RFID tags automatically. This technology has been implemented in pharmaceutical production, retailing, logistics, and supply chain management for over three decades. Another foundational technology for IoT is WSN, which mainly uses interconnected intelligent sensors to sense and to monitor (Xu et al.,2014). The applications include environmental health care, industrial, and traffic monitoring, and so on. The advances in both RFID and WSN have significantly contributed to the improvement of IoT-based technologies. However, these improvements have come with some drawbacks and negative properties.

The IoT creates new vulnerabilities and security risks that device manufacturers and application developers have not anticipated. The devices that have become part of the IoT enable the storage, analysis, monitoring, and sharing of vast quantities of data with other networked devices and users (Maras, 2015). The privacy of users is threatened because of their limited control and choice over the collection, retention, and dissemination of their data. The risk of an inadequate legal framework regulating the IoT requires urgent action in legal analysis and may require new approaches in legislation (Jyotheeswari & Jeyanthi, 2020; Maras, 2015). IoT allows objects to easily integrate with the Internet, thus forming a vast network of related objects. This attribute gives users greater convenience in connecting to and interacting with the system regarding tasks, including identification, sharing, querying, monitoring, and recording patient health status and actions. These advantages create a perception of benefit to the adopting organization, but also perceived risk.

Application of IoT in Health Care

In the health care industry, the collection of medical devices and applications that connect to health care IT systems through online computer networks are called the M-IoT, IoMT (Internet of Medical Things), or health care IoT (Park & Park, 2017). Medical devices equipped with Wi-fi allow the machine to machine communication that is the basis of M-IoT. These medical systems often link to cloud platforms such as Amazon Web Services, Azure, or Google on which captured data can be stored and analyzed (Park & Park, 2017). Examples of M-IoT systems include remote patient monitoring, patient medication order tracking, infusion pumps that connect to analytic dashboards, and smart beds that measure patients' vital signs.

The existing literature indicates that although both academics and practitioners recognize IoT as a source of competitive advantage, it does not mean that organizations know how to adopt them (Luthra, Garg, Mangla, & Berwal, 2018). Because of the social nature of human to object communication, IoT can be considered a socio-technical system, so many of the challenges affecting the adoption of IoT will be social and political. Business stakeholders will need to understand that all organizations are complex organizational systems that should be approached as socio-technical systems in which social and technical systems are considered together to increase productivity (Ada, Sharman, & Gupta, 2009). While many studies have looked at the technical factors affecting the adoption of IoT-based devices (Hsu & Chuan-Lin, 2016; Maras, 2015; Xu et al., 2014), very few existing studies have sufficiently addressed the interactions among all the socio-technical factors relating to people's processes and technologies within organizations (Luthra et al., 2018). If organizations understood the factors that affect this adoption, this understanding could assist them in planning and strategizing IoT mitigation and implementation plans.

IoT is changing the traditional concept of health care. Whereas in the past, patients and providers had to be physically in contact with wireless health care, patients and providers are no longer tied physically. Wireless technologies, such as RFID, allow for monitoring, tracking, and delivery of medical services and drugs (Bandyopadhyay & Sen, 2011). Potentially, medical services can be provided without much human interaction. The location of doctors and other staff may be tracked, real-time, and redirected using wireless technology (Dlodlo, Foko, Mvelase, & Mathaba, 2012).

Potential Benefits of IoT

Hung (2016) forecasted that there would be approximately 11.4 billion connected IoT devices worldwide by 2018, which would represent a 56% increase from 2016. The primary benefits include improved business process efficiency, productivity, and quality of digital life. In the health care industry, IoT has been termed a real game-changer, as it has transformed the sector by lowering costs, improving efficiency, and bringing the focus back to quality patient care (Gregory & Madsen, 2018). IoT-based devices are usually implemented when technology can provide human value-added services. This is generally not possible without the presence of information-sensing and human interaction with the physical world (Hou & Yeh, 2015). IoT-based health care support systems represent the most promising forms of these types of services. Because of this, they continue to be the focus of industrial and government research. For example, the integration of some forms of IoT technology into biomedical devices significantly improves the quality and effectiveness of service, bringing exceptionally high value for the elderly, patients with chronic conditions, and those requiring constant supervision (Hou & Yeh, 2015). The new rush of data and the recent introduction of IoT-based technology in health care settings have given doctors and nurses more tools and data to manage, causing a technology overload (Hou & Yeh, 2015). Additionally, the proliferation of IoT in health care has been immensely beneficial in remote clinical monitoring, chronic disease management, preventive care, assisted living, and personal fitness monitoring (Gregory & Madsen, 2018).

In IoT-based environments, information-sensing and human interactions with the physical world are fundamental concepts for the provision of human value-added services (Hou & Yeh, 2015). Among these services, IoT-oriented health care support systems are among the most promising and important directions for development and a major focus of government and industry research. For example, the integration of some forms of IoT technology into medical devices improves the quality and effectiveness of service, bringing exceptionally high value for the elderly, patients with chronic conditions, and those requiring constant supervision (Hou & Yeh, 2015). Furthermore, the proliferation of IoT in health care has been immensely beneficial in remote clinical monitoring, chronic disease management, preventive care, assisted living, and personal fitness monitoring (Gregory & Madsen, 2018). The ability to collect large amounts of long-term data and monitor patients in real-time has become a reality with the development of medical devices. This development provides a solution for the elderly with diseases to be monitored, provides round the clock connection to health care providers, and offers treatment at more accurately precise schedules (Chung, 2014).

Potential Limitations of IoT

Despite the benefits of using IoT, there are some possible drawbacks and implications to this technology that affect its overall adoption. The new rush of data and the recent introduction of IoT-based technology in health care settings are giving doctors more tools and data to manage, causing a technology overload (Hou & Yeh, 2015). Additionally, in environments with a need for rapid deployment and urgency to generate, store, and transmit private information, IoT technology adoption may encounter adoption delays due to lack of security standards (Jyotheeswari & Jeyanthi, 2020; Xu et al., 2014). For example, poorly planned IoT installations could be used as unsecured access points in a LAN, with a possibility of becoming central points for the propagation of malware and, ultimately, even bringing down or altering critical systems (Abomhara & Køien, 2014; Rath, 2020). Jing, Vasilakos, Wan, Lu, and Qui (2014) believe IoT is built on the basis of the internet, so security problems related to the internet will also show up in IoT. “Such security issues may include activities such as DOS/DDOS attacks, forgery/middle attack, heterogeneous network attacks, application risk of IPv6, and WLAN application conflicts, which also affect the transport security of IoT” (Jing, Vasilakos, Wan, Lu, & Qui, 2014, p. 15) (2014. Because IoT refers to the integration of multiple heterogeneous networks, the technology should address compatibility issues between different networks prone to security issues (Jing et al., 2014). Additional issues with the potential to slow the successful adoption of IoT technologies include factors such as high cost, uneven performance quality levels, and ease of use of the technology (Lee & Han, 2015).

Skilled nursing homes are not immune to IoT adoption limitations. For example, the current lack of standards and communication protocols for IoT devices has somewhat hindered their development (Charania, Nair, Rajadhyaksha, & Shinde, 2016). This problem is creating a massive amount of unwanted information that needs to be sorted before it can aid patient treatment. Leaders and other decision-makers in health organizations must understand the critical role the network plays in successfully adopting IoT technologies. Old and outdated legacy networks cannot manage and analyze these massive volumes of data coming from all the M-IoT devices (Charania et al., 2016). The lack of an SDN, NFV, and cloud computing infrastructure are all potential obstacles that can hamper the successful adoption of IoT in a health care environment.

Information insecurity poses an increasing threat to the continued development of the IoT. IoT is progressively applied to a diverse set of social environments, such as smart homes, utility grids, intelligent transportation, and smart security (Jing et al., 2014). While the application of IoT-based technologies can solve many real-life issues and bring efficiency and convenience to many people's lives, this convenience cannot guarantee the security and privacy of personally identifiable information. With the impending mass adoption of IoT, there will be an explosion of information, so the risk of exposure to such information will increase. If IoT security issues continue without solutions, they will hamper the long-term development of the technology. The possible long-term effects of security issues are one of the most important matters facing IoT adoption. Meanwhile, there are several other challenges plaguing IoT. With respect to mass implementation, scalability becomes difficult for many organizations, as IoT applications often require significant time, memory, processing, and energy constraints (Elkhodr, Cheung, & Shahrestani, 2016). Also, it is expensive to transmit large volumes of raw data in the complex and heterogeneous network, so data compression and data fusion are usually requirements of an IoT network. Other factors holding back health care IoT are the lack of standards among the different manufacturers, the overload of data, high cost, and uneven performance quality levels (E. Lee & Han, 2015).

Specific Ethical and Legal Issues of the IoT in Health Care

Health care is another area where privacy, security, and safety are of the utmost importance. The introduction of technology into these environments not only seeks to improve production, efficiency, and reporting capabilities but also inherently creates more ethical and legal issues that need to be addressed. For example, the use of RFID tags in the health care industry is common; however, there are serious security and privacy concerns (Abomhara & Køien, 2014). Many of these devices are IoT-enabled, connected, and automated and hold medical/patient data and are used for the efficient processing, scheduling, and management of health care for the benefit of patients (Friedewald & Raabe, 2011). These same devices are trusted to protect the privacy and integrity of patient data. This poses a considerable threat to the organizations that rely on these devices; if data is leaked to unauthorized persons, sensitive medical data may be used for fraudulent and more nefarious purposes. Also, sick patients may fall victim to fraud. Furthermore, if sensitive data is tampered and altered, it could have life-impacting risks. In addition to health care security and privacy, there are other areas of concern in nursing home environments.

Health Insurance Portability and Accountability Act of 1996 (HIPAA) compliance is of major importance to medical institutions. “The HIPAA is a United States legislation that provides data privacy and security provisions for safeguarding medical information” (Kalva, 2016, p. 19). Health organizations must ensure that they protect patient privacy and data in compliance with HIPAA. The adoption of M-IoT has raised concerns that may limit the ubiquitous adoption of IoT devices in health care environments (Rosenbaum, 2014). Failure to address these issues before the implementation of these types of devices could lead to non-compliance because of poor protection and security of patient data, which could lead to fines from HIPAA (Kalva, 2016).

Relevance of IoT to the SMEs

According to Hung (2016), spending on M-IoT solutions will reach $1 trillion by 2025 and will hopefully set the stage for highly personalized, accessible, and on-time health care services for everyone. M-IoT has been recognized as one of the most important means to improve the quality, efficiency, and effectiveness of health care services (Sun & Qu, 2014). Kalva (2016) believes the primary purpose of IoT in health care will be to harness data from multiple devices and sensors that monitor a patient's vitals. Endpoints will range from familiar medical monitoring to new devices, such as nanosensors embedded in patients to watch for the earliest indicators of specific conditions.

The adoption of M-IoT devices in skilled nursing homes is relevant to the health care research community in that the research could contribute to and improve understanding of the factors involved in the adoption of this type of technology. The adoption of IoT-based technologies in health care is significant to patients and practitioners who rely on technology for many reasons. Baek et al. (2016) believe the emerging IoT technology will continue to provide significant improvements to the delivery of health care services. New enhancements in device integration, monitoring, and smart sensing have the potential to not only improve patient health and safety but also improve the way physicians deliver care. Health care IoT has the potential to improve patient participation and satisfaction by allowing patients to spend more time interacting with nurses and caretakers.

While unprecedented capabilities for predictive diagnosis hold great promise for advancing health care, IoT-based technologies also pose unique security challenges (Kalva, 2016). The successful deployment of IoT depends on ensuring security and privacy that need to adapt to their processing capabilities. Baek et al. (2016) believe IoT is vulnerable to attacks since communication is mostly wireless. If these possible obstacles, along with other challenges like ease of use, performance, and social influence, significantly affect the ability of skilled nursing homes to adopt the IoT, then it can have far-reaching effects on the long-term success of the organization. The companies that are successful in adopting this technology will quickly be able to increase patient population, improve public relations and reputation, tap into new profit streams, and ultimately increase industry market share. It is clear that the information gathered from this type of study will be valuable to decision-makers in the health care industry.

Acceptance and Adoption Studies of IoT in Health Care

In the health care environment, there are many examples where the adoption of similar types of technologies was hampered by the same issues that may affect successful M-IoT adoption in health care environments. RFID has been implemented in the health care environment for many years, but its use has not exploded due to concerns about authentication, medication safety, patient tracking, and blood transfusion medicine (Rosenbaum, 2014). Due to the importance of protecting patient and data privacy and the increasing importance of HIPAA compliance, there have been many concerns that may limit ubiquitous adoption of M-IoT devices in a health care environment (Rosenbaum, 2014).

Past researchers have examined the adoption of HIT either at the organizational level, such as hospitals (Jha et al., 2009), or at the individual level, such as patients (Ralston et al. 2007), nurses (Lu et al., 2006), and physicians (Hu et al., 1999; Snyder et al., 2007). Other researchers have examined HIT adoption for specific tasks, such as reduction of medical errors (Menachemi et al., 2007; McAlearney, 2008) or improvement in patient safety (Menachemi et al., 2007). Of the studies addressing the topic of IoT adoption, some of the most noteworthy research includes the work of Achituv and Haiman (2016), who did research on physician's attitudes towards the use of IoT medical devices (IoT-MDs) for use in their practice. The researchers developed an exploratory study to provide insights into the way physicians perceive FDA approved IoT-MDs. A questionnaire was developed and sent to 126 physicians in 2014 and then another 50 a year later. The results from both efforts were reviewed and analyzed. The results showed that there is still not enough awareness and readiness for the use of IoT-MD and that physicians' attitudes in 2015 compared to 2014 did not drastically change. However, the results revealed some differences between physicians who had previously been exposed to IoT technology and those who had not. Another major conclusion of the study was that the authors believed that IoT-MDs generate data that is too raw for practical use, thereby limiting potential effectiveness when deployed (Achituv & Haiman, 2016).

Previous theoretical models to explain HIT adoption have included the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975), the theory of planned behavior (TPB) (Ajzen, 1991), the technology acceptance model (TAM) (Davis, 1989), the theory of innovation diffusion (TID) (Moore & Benbasat, 1991; Rogers, 1995), the task-technology-fit model (TTF) (Goodhue & Thompson, 1995), the technology organization and environment model (TOE) (Tornatzky, Fleischer, & Chakrabarti, 1990), and activity theory (Su & Qu, 2014). The methodologies used in the research I found were split into two groups. The first group was centered on identifying vulnerabilities, threats, and risks associated with IoT-enabled smart devices and the controls that can mitigate these risks. The research conducted by Majed et al. (2014) on the "Energy Smart Grid Cyber-Threat Exposure Analysis and Evaluation Framework" used a quantitative approach to collect and analyze the threat exposure to a large scale smart grid. The other group of studies done centered on the adoption of IoT-based technologies that sought to clarify the perception of customers about the adoption and usage of IoT-based technologies. The most popular theories used were the theory of technology acceptance (TAM) and "the unified theory of acceptance and use of technology ([UTAUT], Al-Momani, Mahmoud, & Ahmed, 2016)." The similarity in each study was that they all used a conceptual framework that sought to link the ease of use and usefulness in TAM, with the social influence of UTAUT and other factors such as cost, trust, IT knowledge, security, and privacy of the organizations that use IoT (Al-Momani et al., 2016).

The issues related to IoT have been widely discussed in practical and academic fields (Hsu & Chuan Lin, 2016). However, most prior studies have focused on overview descriptions, concepts, business models, opportunities, and challenges (Hsu & Chaun-Lin, 2016). The literature revealed that previous studies had proposed important issues, such as key technologies, standards, architectural elements, security, and privacy challenges (Hsu & Chaun-Lin, 2016). These studies also mostly focused on the benefits, security, and technical issues of using IoT. Issues such as architectural elements (Gubbi, Buyya, Marusic, & Palaniswami, 2013), attribute-based signature (Su et al., 2014), and wireless sensor networks (Turkanović, Brumen, & Hölbl, 2014).

Less attention has been paid to the social factors that affect the adoption of IoT devices, such as the degree to which an individual believes that using the system will affect job performance or the degree of ease associated with the use of the system. Little empirical research exists that examined the determinants of M-IoT adoption from an individual perspective. This study will look at the social factors that affect the intention to use and adopt the IoT-enabled medical devices in skilled nursing homes from an individual perspective.

In order to understand the behavior of these users, I will be using a theoretical model comprised of Venkatesh et al.'s (2003) unified theory of acceptance and use of technology (UTAUT) and Featherman and Pavlou's (2003) theory of perceived risk (TPR). Both have been proven to be a reliable theoretical foundation with relevant constructs in predicting attitudes and behaviors (E. Lee & Han, 2015). The scattered literature on HIT adoption implies a great need for further synthesis of the knowledge via a systematic literature review.

Theories on Technology Adoption

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT is a model used in the study of technology acceptance and usage (Venkatesh et al., 2003). The theory was developed from eight other theories, which include the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980), Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989), Motivational Model (MM), Theory of Planned Behavior (TPB) (Ajzen, 1985), Combined TAMTPB (C-TAM-TPB) (Taylor & Todd, 1995), Model of PC Utilization (MPCU) (Compeau & Higgins, 1995), Innovation Diffusion Theory (IDT) (Roger, 1995; Moore & Benbasat, 1991) and Social Cognitive Theory (SCT) (Bandura, 1986). It was introduced as the new IT acceptance theory. The UTAUT proposes four main determinants of behavioral intention regarding people using information technology which are, PE, EE, SI, and FI. The model also includes four moderators that affect the determinants, age, gender, experience, and voluntariness of use, which will not be considered for this study. Performance expectancy is defined as the performance of information technology for the user. According to Sudaryati and Agustia (2017) effort expectancy is defined as the degree of ease associated with the use of the system. “Social influence is defined as the degree to which an individual perceives the importance that others give to whether he or she should use the new system” (Sudaryati & Agustia, 2017, p. 88). Social influence is considered to be system or application-specific, whereas subjective norm relates to non-system-specific factors. According to Venkatesh et al

(2003) “facilitation conditions are defined as the degree to which an individual believes that an organization’s technical infrastructure exists to support their use of the system” (p. 453).

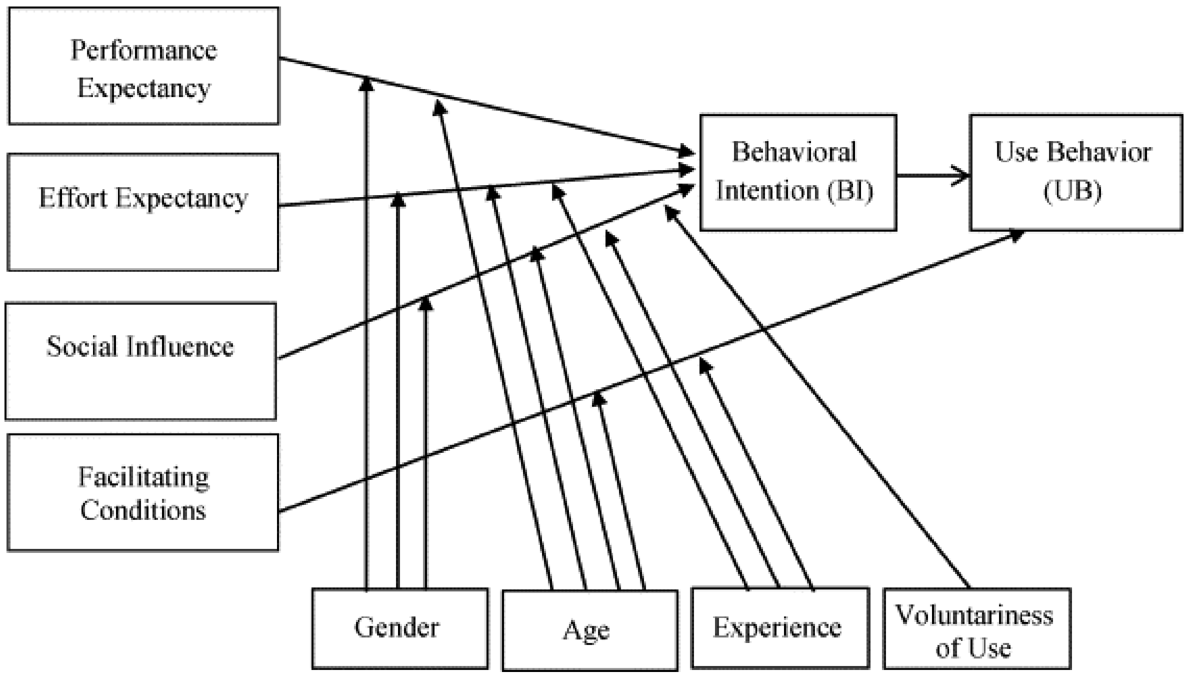

Figure 3. Unified theory of acceptance and usage of technology model (UTAUT). Reprinted with permission from Venkatesh et al. (2003).

Since its creation in 2003, UTAUT has been immensely popular with researchers investigating and testing technology adoption. It has been applied to several technologies, such as Internet banking (Chi-Lee, 2009), web-based learning (Chiu & Wang, 2008), and instant messaging (Lin & Anol, 2008). For example, Tan et al. (2010) used this model to investigate the adoption factors of electronic and mobile banking in Malaysia with the use of this model. Similarly, Im et al. (2011) undertook research to discover that the UTAUT constructs were ultimately affected by the culture when comparing digital audio players and internet banking technologies in the United States and Korea. Finally, Yuen et al. (2010) tested the UTAUT model in the United States, Australia, and Malaysia.

Theories Used to Develop the UTAUT Model

This section provides a summary of each component theory used to develop the UTAUT model, as well as the individual constructs used during its development. The summary will provide an explanation of core variables for each theory accompanied by examples that will assist in illustrating how factors can be considered in real-life environments.

Technology acceptance model. The TAM model was originally developed and proposed by Davis (1989). The focus is on predicting the specific behavior of people in reference to the acceptance of new information systems. The TAM is remarkably similar to the TRA model. However, the TAM is different in that it is centered on the acceptance and usage behavior of computer users within the context of business settings (Legris, Ingham, & Collerette, 2003). Originally the TAM consisted of five variables including (a) perceived usefulness (PU), (b) perceived ease of use (PEOU), (c) attitude toward using (A), (d) behavioral intention (BI), and (e) actual system use (USE; Legris et al., 2003). However, in later versions, the attitude variable was removed from the model (Venkatesh & Davis, 2000).

With respect to the constructs added to the TAM, perceived usefulness describes people's positive or negative perceptions that when using a given information system could help them improve job performance. The predictor, perceived ease of use, refers to how people perceive how easy it will be for them to use the system. Both constructs are used within the TAM as direct predictors of behavioral intention.

Motivational model. The motivational model (MM) was proposed by Davis et al. (1992) to study information technology adoption and use. The foundation of the model is based on the motivational theory, which is built on the premise that there are intrinsic and extrinsic motivations that shape the behavior of the user (Davis et al., 1992). Extrinsic motivation is defined as the perception that users want to perform an activity "because it is perceived to help in achieve valued results that are distinct from the activity itself, such as improved job performance, pay, or promotions" (Davis et al., 1992, p. 1112) Examples of extrinsic motivation are perceived usefulness, perceived ease of use, and subjective norm. The new motivational model, however, is different and proposes two constructs: enjoyment and perceived usefulness (Davis et al.,1992). The combined existence of these two constructs was demonstrated to account for over 60% of usage intention in two studies. The construct enjoyment was described as the "extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" (Davis et al., 1992, p. 1113). This construct was explained based on a previous examination within the context of computer games, where the research confirmed that the effect of enjoyment was of significant importance on the intentions and behaviors associated with computer acceptance and implementation in the workplace (Davis et al., 1992).

Theory of reasoned action. Fishein and Ajzen's (1975) theory of reasoned actions (TRA) provides a model for evaluating and predicting people's behavioral intention and subsequent voluntary behavior. The theory is rooted in a social psychology setting and proposes three general constructs. The three constructs are behavioral intention (BI), attitude (A), and subjective norm (SN). According to Fishein and Ajzen (1975), the behavioral intention of a person depends on his attitude and subjective norms. This can be interpreted to mean that behavioral intention is the summation of attitude and subjective norms. Additionally, the intention of a person is likely to change to action if there is the intention to behave in a specific manner that is strong enough. The attitude construct refers to the perception that a person places for performing a given behavior according to the persons existing beliefs, as well as that performing the behavior, could result in a desirable or adverse consequence (Fishein & Ajzen, 1975).

The ideas and perceptions a person forms about the thoughts and beliefs of other people in reference to the person's actions are called subjective norms (Fishein & Ajzen, 1975). These perceptions are also combined with the importance of a person to meet or comply with other peoples' expectations (Fishein & Ajzen, 1975). Later, more limitations in the TRA model were discovered by Ajzen (1991). They included the likelihood of confusing people’s attitudes with subjective norms, as well as recognizing that the intention to perform a behavior could be limited by additional constraints.

Theory of planned behavior. The theory proposes that behavior is still determined early on by a person's behavioral intention (Ajzen, 1991). Behavioral intention is a function of current attitudes, perceived behavior control, and existing subjective norms. Perceived behavioral control was also theorized to be a direct determinant of behavior in this model. Perceived behavioral control indicates peoples' perceptions about how difficult or easy it could be for them to execute a given behavior (Ajzen, 1991). An example of perceived behavioral control is described in the example below. A business director has the intention to purchase a new financial computer system for the accounting department. However, the director’s control beliefs about his or her technical proficiency may cause doubts about his or her ability to select the appropriate accounting system. If the director's doubts are strong, this will have a direct but inverse effect on his or her behavior intention and actual behavior to purchase the accounting system.

Innovation diffusion theory. The innovation of diffusion theory (IDT) was evaluated for addition in the UTAUT model through the work of Moore and Benbasat (1991), whose research focused on measuring the perception of adopters of new technology. The core elements of the theory are based on the idea that there are four constructs that influence the spread of a new idea: innovation, communication channels, time, and social system (Roger, 1960). The diffusion process consists of five stages, namely, knowledge, persuasion, decision, implementation, and confirmation. This results in six categories of users: innovators, early adopters, early majority, late majority, laggards, and leapfroggers (Roger, 1960). The model recommended, tested, and validated by Moore and Benbasat, had a total of seven core constructs. The constructs included (a) ease of use, (b) relative advantage, (c) image, (d) compatibility, (e) visibility, (f) voluntariness of use and (g) results demonstrability.

Social cognitive theory. Bandura (1986) initially proposed this theory, but researchers later evaluated it within the context of computer usage by researchers (Compeau & Higgins, 1995). The model was based on five specific constructs derived from the elements of constant and mutual relationships between cognitive, behavioral, and environmental factors. The purpose of the research was to investigate how peoples' beliefs would play a role in their abilities to competently use a computer system (Compeau & Higgins, 1995, p .189). This led to the creation of the idea of computer self-efficacy. This is a concept that refers to "the belief that one has the capability to perform a particular behavior" (Compeau & Higgins, 1995, p. 189). The second construct outcome expectations emanated from the information system literature (Bandura, 1986). This construct originated from two other subcomponents: (a) outcome expectations-performance and (b) outcome expectations-personal (Compeau & Higgins,1995). Other variables in the model included anxiety and affect. Anxiety explained the uneasiness or anxious feelings that a person may experience when using a computer (Compeau & Higgins, 1995). Affect was aligned with how much a person would like to be engaged in a particular behavior, such as using a computer (Compeau & Higgins, 1995).

Combined TAM and TPB (C-TAM-TPB). The combined TAM and TPB models were proposed by Taylor and Todd (1995) using social and control factors derived from earlier studies. Taylor and Todd sought to create a new model because they felt like the original models were formed to assess populations of people who were already accustomed to or versed in using technology. This new combined model was then created to be applied to populations where participants were inexperienced with information systems. Consequently, the model had two main purposes: first, to evaluate previous technology adoption theories within the context of inexperienced IT users and, second, to look for similarities and differences by comparing the inexperienced IT users' adoption behavior against those of more experienced IT users (Taylor & Todd, 1995).

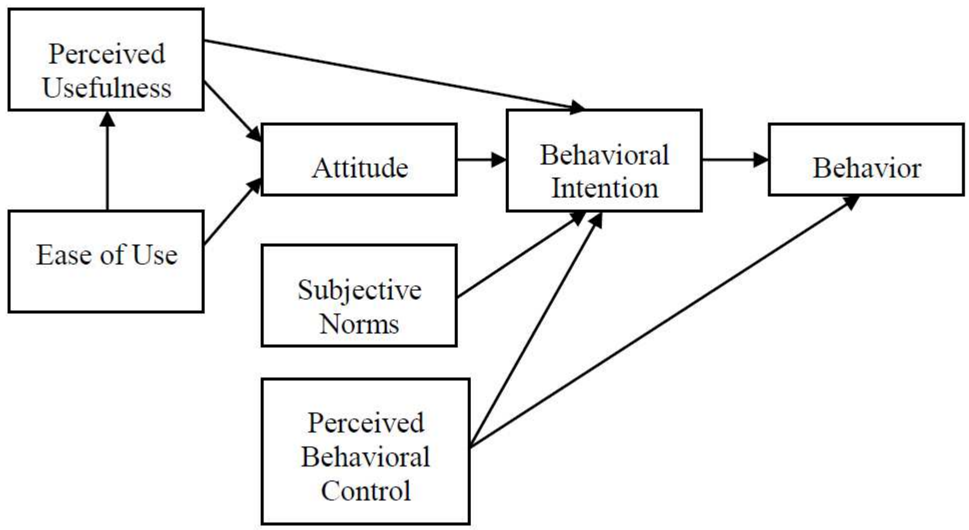

Figure 4. Combined TAM and TBM model. Adapted from "Understanding Information Technology Usage: A Test of Competing Models," Taylor & Todd (1995). Reprinted with permission from Martins et al. (2014).

In the combo model, the core variables, attitude toward behavior, subjective norms, perceived behavioral control, behavioral intention, and actual behavior were adapted from the TRA and TPB model (Fishein & Ajzen, 1975). Perceived usefulness and ease of use were adapted from TAM.

Model of PC utilization. An alternative to the TRA and TPB model is the model of PC utilization (MPCU), developed by Thompson et al. (1991). The MPCU's main goal was the prediction of use behavior within the context of PC utilization in businesses (Thompson et al., 1991). The MPCU foundation is based on a sub-set of the theory of human behavior (Triandis, 1971). The model consisted of six core constructs, all of which are thought to have a direct influence on computer usage. The six constructs are (a) social influence, (b) affect, (c) complexity, (d) job fit, (e) long-term consequences of PC use, and (f) facilitating conditions. The first construct is described as "the individual's internalization of the reference group's subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations" (Thompson et al., 1991, p. 126). This means that a person’s behavior is significantly affected by what they think is important that others may want him or her to do in accordance with existing norms. The second construct, effect, is suggested to reflect "the feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act" (Triandis, 1980, p. 127). The next three constructs, job-fit, complexity, and long-term consequences, were associated with perceived consequences, a foundational factor in human behavior theory (Triandis, 1971). According to Triandis (1971), perceived consequences suggest that for any given behavior, there are several possible and expected value-granting consequences, such as an increase in work satisfaction or a chance for attaining an important work assignment. The final construct proposed in the MPCU is facilitating conditions. This construct was also based on Triandi’s (1980) model and described as "the provision of support for users of PCs" (Thompson, 1991, p. 129). This variable is related to the training of users in the correct use of a given system application or providing technical support.

Theory of perceived risk. The theory of perceived risk can be divided into six components, according to Cunningham (1967). These components are financial risk, social risk, psychological risk, time risk, privacy, and performance risk. Performance risk is the possibility of the product or device malfunctioning and thus not providing the expected benefits (Faroughian, Kalafatis, Ledden, Samouel, & Tsogas, 2012). Financial risk is the possible monetary loss related to the difference between the procurement price and the ensuing maintenance/ownership cost of the product or device (Dwyer & Tanner, 2009). The psychological risk is the risk that the selection of a vendor from which a purchase is made will have a negative impact on the consumer's peace of mind. The social risk is the potential loss of social status due to the adoption of a product or service (Yang et al., 2015). Furthermore, time risk is the risk that consumers may lose precious time examining, searching, and waiting for the products they want if they make a wrong decision (Veloutsou & Bian, 2008). Privacy or safety risk is the possible loss related to personally identifiable information being used incongruously (Crespo, del Bosque, & de Los Salmones Sánchez, 2009). In general, perceived risk refers to the degree of uncertainty associated with specific purchase and usage conditions.

If the actual adoption and usage experience of customers differ from their usage goals, they will perceive higher risk (Martins et al., 2014). According to Featherman and Pavlou (2003), perceived risk is defined as "the potential for loss in the pursuit of a desired outcome of using an e-service." The researchers sought to discover how vital the risk perceptions are to the overall e-services adoption decision. They identified seven types of risks, namely, (a) financial risk, (b) psychological risk, (c) time risk, (d) performance risk, (e) social risk, (f) privacy risk, and (g) overall risk. Featherman and Pavlou (2003) believed that it was essential to include a degree of perceived risk into TAM because customers identify and value risk when evaluating products/services for purchase/adoption, which may create concern and anxiety for them. Therefore, regarding perceived risk, they tested (a) if e-service's perceived risk reduces their perceived usefulness and adoption; (b) if perceived ease of use of e-service significantly reduces perceived risks of usage; (c) and if perceived ease of use influences e-service's adoption (Martins et al., 2014).

According to Im, Kim and Han (2008), "previous studies on technology adoption varied regarding the comparative magnitude of the effects of perceived usefulness and perceived ease of use" (p. 1). Still, these studies did not include moderating variables as part of the investigation. It has been proven that people's confidence in their decisions is affected when they are uncertain or perceive some type of risk. This means that if a situation where the probability of the outcome cannot be clearly determined, is considered risky (Martins et al., 2014). In prior investigations on consumer research, PR was defined as the perceived uncertainty in a purchase situation. PEU was defined as someone's personal assessment of performance and effort; usually, differences exist between someone's conclusions and actual performance. This creates the sense of a "risk" because users do not know the degree or magnitude of these differences. If a type of technology fails to provide its anticipated outcome, it will result in one of the four types of loss (financial, psychological, physical, or social) to the user. Over the past 20 years, researchers (Lui & Jamieson, 2003; Pavlou, 2003; Thiesse, 2007) have empirically and rigorously explored the impacts of perceived risk on the key constructs of TAM, which is an important component of UTAUT. Therefore, it is imperative to conduct an empirical study to explore the relationships among perceived risk and the key constructs of the UTAUT model.

UTAUT investigated a construct similar to perceived risk, called anxiety. However, this construct differed from PR in that it focused mainly on the concerns or fears involved when trying a new piece of technology, rather than the long-term effects. In real-world situations, anxiety can be alleviated, whereas PR will remain consistent for an extended period. Thus, a significant issue regarding PR in technology acceptance is whether PR directly influences PU/PEU or BI (as an antecedent) or whether it moderates the effects of PU/PEU on BI (as a moderator). Perceived risk has been a common extension of UTAUT (Williams et al., 2011); unlike the driving constructs included by UTAUT, perceived risk represents a detractor in the adoption process. In a recent study, Thakur and Srivastava (2014) measured perceived risk as a second-order factor consisting of security risk and privacy risk; their findings supported their hypothesis that risk negatively affects adoption intention. However, the effect of perceived risk as a singular construct on adoption intention of MP has been both supported in some studies (Chen, 2008; Liébana-Cabanillas, Sánchez-Fernández, & Muñoz-Leiva, 2014; Lu et al., 2011; Shin, 2010; Yang et al., 2012) and rejected in others (Kapoor et al., 2014; Tan et al., 2014; Wang & Yi, 2012). Therefore, verification of this construct is of particular theoretical use (Slade, Dwivedi, Piercy, & Williams, 2015). For the purposes of this study, perceived risk is defined as a consumer's beliefs about the uncertainty concerning the improvements or losses resulting from IoT acceptance and adoption (Martins et al., 2014). The different models are depicted in Figure 5 (Im et al., 2008).

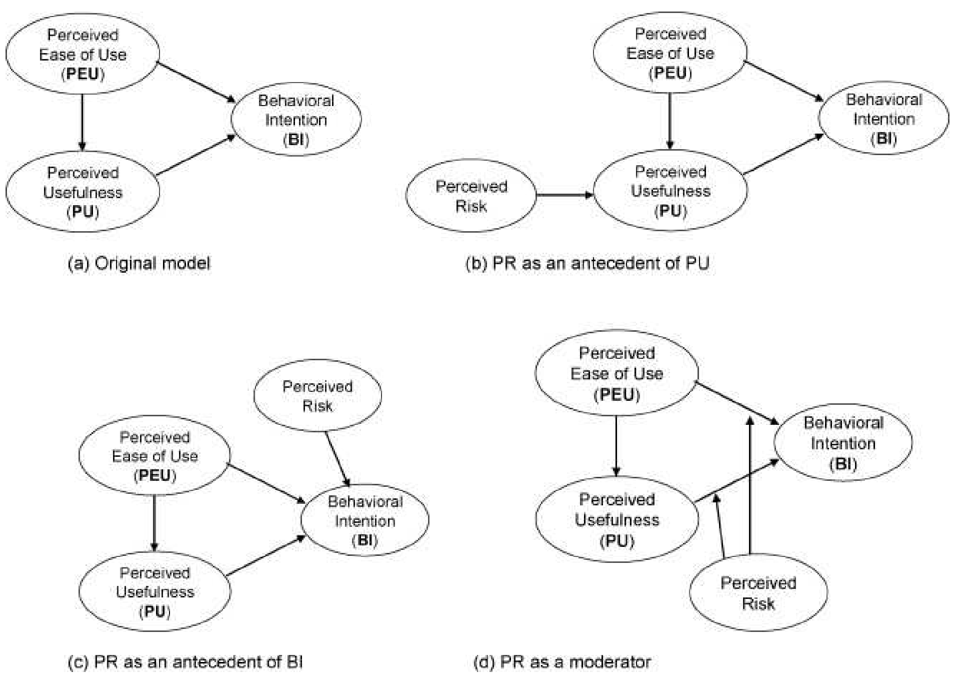

Figure 5. Alternative conceptualizations of Perceived Risk. Reprinted with permission from Martins et al. (2014).

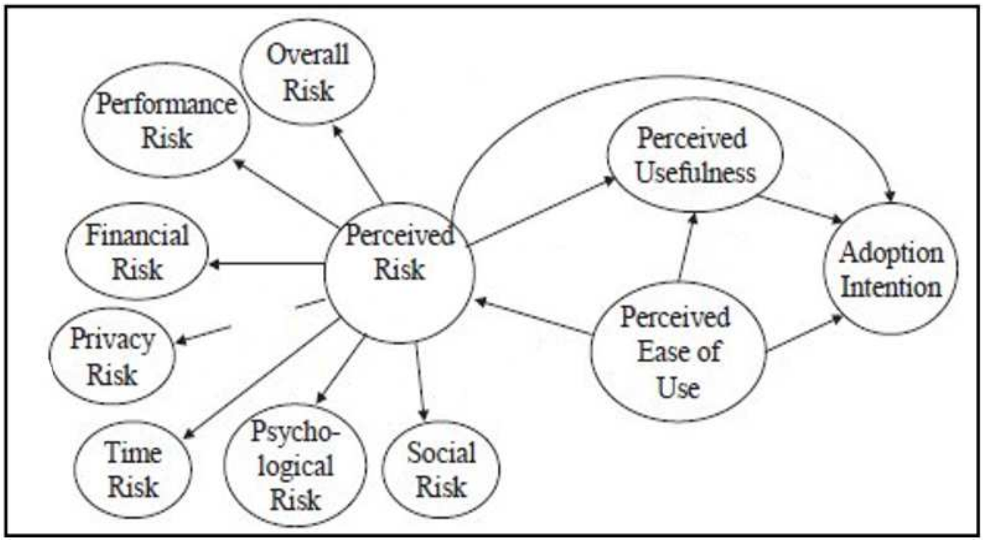

Figure 6. Research model based on the theory of perceived risk. Reprinted with permission from Martins et al. (2014).

Theories to Develop TPR

Perceived risk theory has been used to explain consumers' behavior for over four decades (Chi-Lee, 2009). There are six core types of perceived risk that have been identified: performance, financial, privacy, social, physical, and time-loss (Martins et al., 2013). The components of perceived risk usually vary according to the device/product or service (Featherman & Pavlou, 2003). In this study, the perceived risk will be used as a determinant of M-IoT adoption and continued use.

Conclusion to the Theoretical Background

The final constructs that comprise the UTAUT model all came from past models that evolved over time. The UTAUT model fused these common components into conjoint factors, along with the factors from TPR. The results created a total of six main constructs, including EE, PE, SI, FR, PR, PCR, and BI. Hence, in this study, only the variables PE, EE, SI, PR, FR, PCR, and BI will be included. Table 1 summarizes the variables of interest used in this investigation and provides a brief definition for each construct.

Table 1

UTAUT and TPR Construct Definitions

Construct	Definition
Performance Expectancy (PE)	This construct represents the degree in which a person believes that using a system; in this case, M-IoT technology will increase his or her job performance. It is expected that PE will have a positive direct influence on BI
Effort Expectancy (EE)	This construct represents the degree of how easy it is to use M-IoT technology. It is expected that EE will have a positive direct influence on BI
Social Influence (SI)	This construct represents the degree into a person believes that other people relevant to the person consider that he or she should use M-IoT technology in the organization (eg. managers, colleagues, vendors). It is expected that SI will have a positive direct influence on BI
Behavioral Intention (BI)	This construct represents a person's behavioral intention to accept the use of M-IoT technology in the organization. It is expected that BI will be positively influenced by PE, EE, and SI
Perceived Risk (PR)	This construct represents the degree to which users believe that using M-IoT causes possible physical, emotional, or mental harm to patients or leads to a loss of privacy of patient data threat to a user’s valuable or personally identifiable information. It is expected that PR will negatively affect BI.

[a] Behavioral Intention is considered a dependent variable for evaluation of the relationship with performance expectancy, effort expectancy, social influence, and perceived risk.

Relevance of the Model UTAUT-TPR to the Study

The theoretical model works well for this research in that the determinants involved are amazingly simple, and the factors are common in technology-usage settings and can be applied widely to solve the acceptance problem. The study will focus on evaluating behavioral intention to accept the use of M-IoT devices in skilled nursing home environments. The research will focus on the early stages of decision-making prior to the adoption of the technology. This makes the application of the UTAUT-TPR model appropriate for many reasons. The combined model of TPR and UTAUT has produced more dependable results than using either of them alone. Since the emphasis of this study is IoT adoption, it involves the acceptance of pioneering technology entwined with social systems and personal properties. The incorporation of UTAUT and TPR for the research framework will examine the consumers' intentions toward, and acceptance of, IoT-based technologies.

The modified UTAUT model (see Figure 2) postulates that three constructs act as determinants of behavioral intention and use behavior: (a) performance expectancy, (b) effort expectancy, and (c) social influence (Venkatesh et al., 2003). The variables used in both theories are relevant to this study because the concept map of IoT adoption in health care can be viewed as a complex activity system involving different users, technologies, and tasks at both the individual level and the social level (Sun & Qu, 2014). These variables can be interpreted as simple key indicators in the complicated environment that exists in skilled nursing homes. The constructs found in both theories align well with my study because each variable identified plays a role in the adoption of technologies in this unique environment. For the purposes of this study, the researcher only used the constructs of perceived risk (privacy and health risk) from the TPR, as the other constructs are repeated in UTAUT or do not apply to this research.

The combined model representing TPR and UTAUT combines constructs of TPR mentioned above with constructs of UTAUT. Over the past decade, UTAUT and TPR have been widely applied to examine IT usage and e-service acceptance (Martins et al., 2014). Neither UTAUT nor TPR has been found to provide consistently superior explanations or behavioral predictions (Chen et al., 2007). Recently, there has been an increased frequency in the use of the integrated model to examine IT acceptance and adoption, and the results have shown that this hybrid model has better exploratory power than the individual use of UTAUT and TPR (Chi-Lee, 2009). Since the emphasis of this study is M-IoT adoption, which is a subset of acceptance of innovative technology entwined with social systems and personal characteristics, the integration of UTAUT and TPR for the research structure should be comprehensive in order to examine the consumers' intentions towards, and acceptance of, M-IoT-based technologies. The combined theory conceptual model is shown in Figure 7.

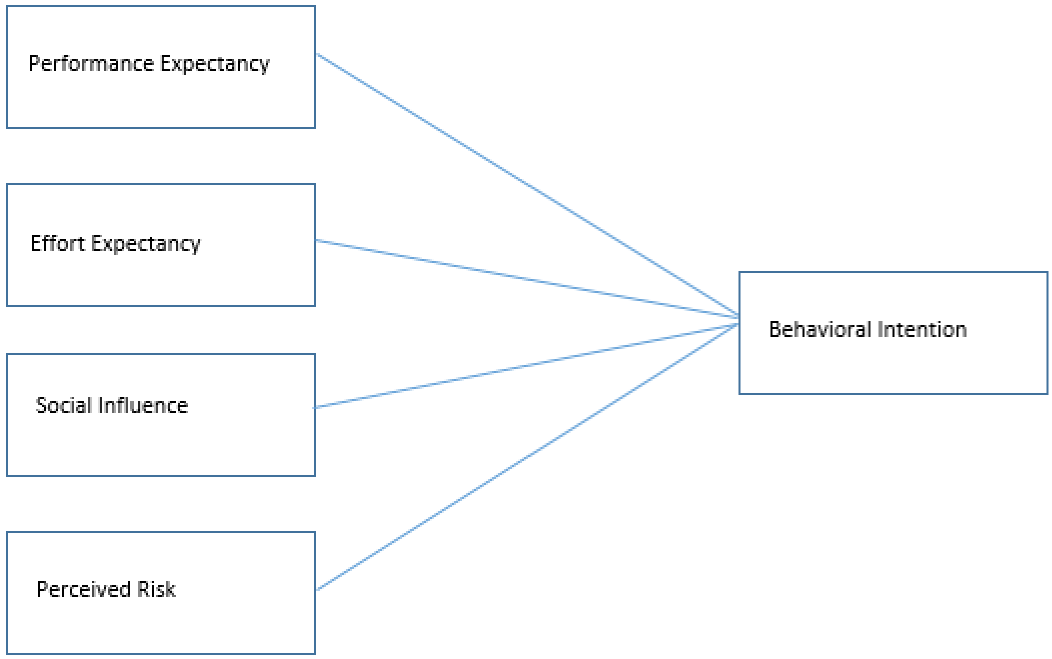

Figure 7. Adapted research model of the unified theory of acceptance and usage of technology and perceived risk. From "Understanding the Internet Banking Adoption: A Unified Theory of Acceptance and Use of Technology and Perceived Risk Application," by Martins et al., 2014, *International Journal of Information Management*, *34*(1), pp. 1-3. Copyright 2013 by Elsevier. Adapted and printed with permission.

Recently, a growing body of research has focused on integrating the two models to examine IT usage and e-service acceptance because they are complementary to each other, and the results have shown that the integration model has had better exploratory power than the individual use of UTAUT or TPR (Martins et al., 2014).

Nursing Home Populations

The selection of nursing home administrators and directors as the population of the study is significant for several reasons. In the first place, this populace speaks to the general population in the nursing home condition, which has been foreseen to comprehend the requirements of their patients and have working information on the physical and mental impacts of the maturing process. Secondly, while the decision-making processes of nursing home administrators tend to revolve around the needs of senior residents, they must also balance the needs of personnel to be equally effective. They must be able to provide their staff with the right tools for them to be successful in their day-to-day responsibilities. To do this, they must be able to evaluate and analyze the tools and technology available for adoption and implementation. A core function of nursing home administrators' jobs is to propose projects or improvements that they believe there is a need to have funds allocated to (Center for Disease Control and Prevention (CDC), 2014).

This means that the decision to adopt M-IoT devices in a nursing home environment that is seeking improved efficiency, productivity, and privacy is made by the nurse administrator.

Another significant reason for choosing this population is because there is a limited amount of academic research literature that investigates the unique social and environmental issues, problems, and management challenges that they face in order to adopt wireless internet-enabled devices, such as the M-IoT. However, the limitations in the literature are in contrast to the overall relevance of this population as essential drivers of the ongoing modernization of the health care environment and also as the primary consumers and users of these devices.

Research Approach and Methodology Selection

In this quantitative causal research, a non-experimental methodology was used as the main method of investigation. A survey design was employed as the main method of investigation. This method aids gathering and evaluating the attitudes and opinions of a particular selected sample of the population to deduce probable relationships with respect to a larger population (Creswell, 2014). This approach is substantiated by Vogt (2011), who also believes that surveys are suitable when the study assesses social attitudes and subjective data.

The survey questions in this study were derived from the UTAUT-TPR instrument and considered of a social nature since they investigated the attitudes and beliefs of participants with respect to technology adoption.

Attitude scaling was used in this study to assess the attitudinal disposition of the study population using a number that represents a person's score (Cooper & Schindler, 2014). This score was on an attitudinal continuum ranging from an extremely favorable disposition to an extremely unfavorable one. According to Cooper and Schindler (2014), "attitude scales are among the most difficult to construct" (p. 270). Also, the survey approach is conducive for accessing very busy, hard-to-reach participants, such as nurse administrators, the reduction of research costs and data collection time, and the increase in response rates compared to other alternatives (Cooper & Schindler, 2014; Vogt, 2011).

Additionally, the survey format is in line with similar approaches used in other technology adoption studies, for example, Abdullah and Shamsuddin (2015), Martins et al. (2016), and Ismail, Zakaria, and Yusof (2016) who successfully used surveys in their research where they applied the UTAUT model. An additional significant factor for selecting surveys over other forms of data collection, such as face-face interviews, is that surveys make presenting close-ended questions requiring no direct physical participation from the researcher possible. Most importantly, the proper research design allows for the scientific investigation of the variables influencing organizational predisposition toward the use of IoT-based technology.

CHAPTER 3. METHODOLOGY

Introduction

The literature review provided a thorough analysis of the research related to the topic of M-IoT adoption. This includes research regarding the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) with an additional variable of perceived risk (PR) to the patient (Bowblis & Roberts, 2018; Despins et al., 2013; Scott-Cawiezell & Rouder, 2010; Trevino et al., 2017). In this chapter, I cover the research design, methodology, and justification of the design. Additionally, I describe the sampling design, target population, participant selection details, instruments used to measure the constructs, data collection and procedures, research questions and hypotheses, and data analysis. The chapter concludes with a summary.

The study utilized a quantitative design in line with post-positivist philosophical assumptions (Creswell, 2014). Creswell stated that quantitative research is the study of a business problem that is based on testing a theory, through the use of numbers, to determine whether it is sound. I employed a modified version of the UTAUT-PR instrument to investigate the significance of antecedents of intention to adopt M-IoT technology for a population of decision-making officials within U.S. based skilled nursing homes. Based on G* Power (version 3.1) calculation, I surveyed a minimum of 129 nursing home decision-makers across the country to determine whether the individual factors of technology adoption in the UTAUT and PR are applicable to M-IoT technology. I also employed reductionist research techniques to investigate the connections between PE, EE, SI, and PR, the independent variables, and BI, the dependent variable. The independent variables were correlated with individual intentions to adopt M-IoT devices.

Design and Methodology

I used quantitative multivariate regression analysis to investigate the factors affecting participants' decisions to adopt and use M-IoT systems. A quantitative, post-positivist philosophical approach recognizes the subjective nature of observations based on the viewpoints and experiences of researchers and research participants (Creswell, 2014). Creswell (1994) recommended this methodological approach because it is suitable for testing theories through the use of numbers that can be analyzed through statistical means to determine whether a given theory or model is sound. Cooper and Schindler (2014) further justified the approach as a means of allowing thorough investigation via the use of attitude scales to evaluate variables. The study of attitude-behavior relationships is not linear, though clear associations may exist. The authors explained that "attitudes and behavioral intentions do not always lead to actual behaviors; and although attitudes and behaviors are expected to be consistent with each other, that is not always the case" (Cooper & Schindler, 2014, p. 270).

A qualitative or mixed-method approach was not chosen because the study did not rely on the experiences, meanings, or perspectives of the study population. This research did not investigate beliefs, attitudes, and concepts of normative behavior or seek views on a focused topic, background information, or an institutional perspective to understand a condition, experience, or event from a personal perspective (Creswell, 2014). The researcher investigated the relationships among constructs using the prediction of one dependent variable when the independent variables are known. The research employed causal analysis to determine the strength, direction, and shape of the relationships. The non-experimental causal design made use of an online survey to collect data required to answer the research questions. A causal design was suitable for the study because the purpose of the research was to determine the relationship each factor had with BI to adopt M-IoT devices. Cooper and Schindler (2013) stated that in a quantitative, nonexperimental, causal study, the primary objective is to determine the relationships between independent and dependent variables. Similarly, Warner (2013) argued that quantitative, causal studies are appropriate when examining the relationships between numerical constructs. I considered other research designs, such as experimental or quasi-experimental designs; however, there were no pretest and posttest measurements to examine the effects on a particular group, which made those approaches unsuitable. I selected this design based on multiple stances.

The factors of PE, EE, SI, and PR were empirically assessed to explore the relationships among them. The relationships observed closely followed those presented in the UTAUT-PR Model. Creswell (2014) argued for using causal research design when researchers try to answer certain social questions that inquire into specific areas, such as (a) recognizing the influence of factors and a number of outcomes, (b) the predetermined estimation of a given mediating or directing variable, and (c) the distinguishing proof of ideal indicator factors in the condition. Venkatesh et al. (2003) affirmed comparable contemplations in investigations performed using the UTAUT model.

There were several reasons for this choice of design. In a real experimental environment, it would be difficult to replicate the conditions under examination in this study, which would make research impractical. The current design allowed the researcher to make full use of the environmental settings, which would not be possible while working in a research laboratory. A point in favor of surveys over other data collection methods is that I was able to fully utilize closed-ended questions, which simplified data collection without requiring face-to-face participation. The UTAUT-PR model was applied in a nursing home setting with initial exploratory investigation data supporting the application of regression analysis to examine the direction and strength of relationships between several independent or predictor variables and the dependent or criterion variable.

Definition of Constructs

The constructs were derived from the UTAUT and PR (Keers et al., 2013; Bowblis & Roberts, 2018; Trevino et al., 2017; Venkatesh et al., 2003).

Figure 8 shows each of the constructs and the relationships in the theoretical framework.

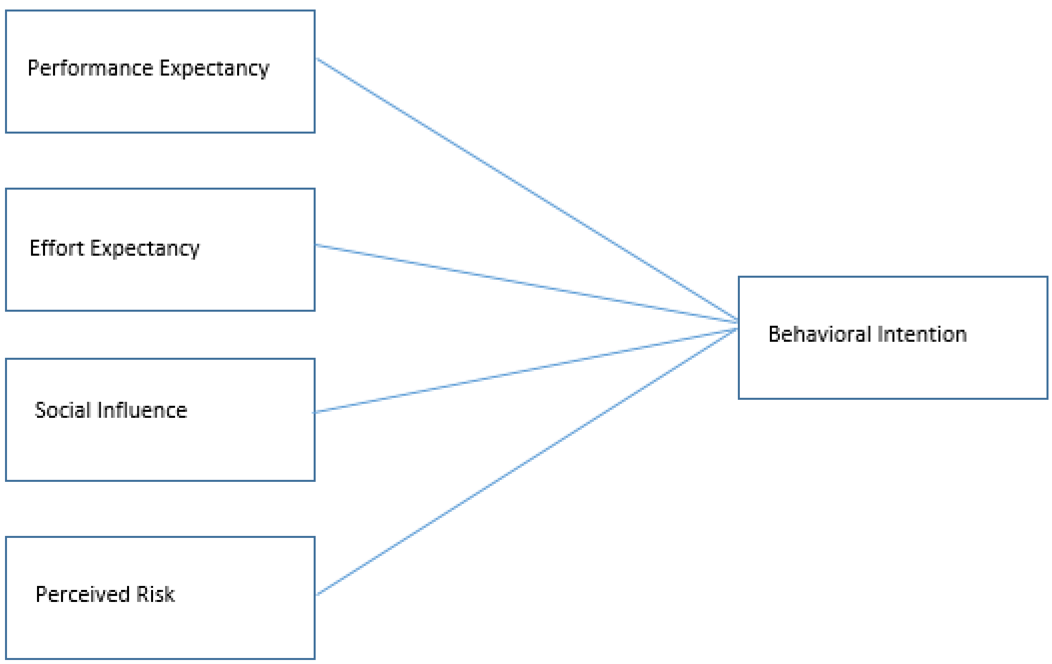

Figure 8. Theoretical framework showing the different constructs of the combined model.

The UTAUT-PR model identifies four variables as direct determinants or predictors of BI to accept or adopt technology: PE, EE, SI, and PR. I derived the basis for correlating predictors and outcomes directly from the examination performed by Venkatesh et al. (2003) when developing the UTAUT model and from the existing work on PR (Bowblis & Roberts, 2018; Keers et al., 2013; Trevino et al., 2017).

Definition of Variables

Each construct had an associated variable (Table 2). These variables were divided into two types: independent and dependent.

Table 2

Constructs, Variables, and Their Characteristics

Construct	Variable	Type of Variable
Performance expectancy	PE	Independent
Effort expectancy	EE	Independent
Social influence	SI	Independent
Behavioral intention	BI	Dependent
Perceived risk	PR	Independent

Note. All variables are at the interval level of measurement.

The independent variables were PE, EE, SI, and PR, which are all present in research questions RQ 1–RQ 5. Within the UTAUT-PR model, independent variables are considered direct determinants of BI. Independent variables are potential predictors of BI to accept technology. The measurements for these variables came from answers provided by study participants in an electronic survey.

The survey (see Appendix) included Likert-type attitude scales that ranged from 1 to 7 with anchors as follows: *completely disagree* (1), *mostly disagree* (2*), slightly disagree* (3), *neutral* (4), *slightly agree* (5), *mostly agree* (6), and *completely agree* (7). The dependent variable was BI. The dependent variable is addressed in research questions RQ 1–RQ 5, and the survey measured the variable using a three-item attitude scale developed by Venkatesh et al. (2003) with the same Liker-type scales as those used for the independent variables.

Population and Sampling

The population considered for this study consisted of practitioners, technicians, managers, and owners in small and medium-sized skilled nursing homes in the United States. Sample size calculations were based on research questions and took into account all available information, support services, and ethical requirements of the research. According to Gogtay (2013), the sample size is crucial in planning academic research because it is usually the most important factor determining the schedule and time needed for the investigation. Therefore, the number of participants and data sources relied on numerous factors, such as the scope of the study, nature of the topic, quality of data, study design, and research method. To address this uncertainty of population size, the number of study participants was calculated using G*Power (Version 3.1) statistical power analysis software, using medium statistical power, and the four predictor variables.

The Sample Frame

According to Cooper and Schindler (2013), the sample frame is a thorough list of an accessible portion of the population from which a sample is to be drawn. Based on the large number and diverse types of nursing homes, I concluded it would be too difficult to target the entire population for the study. The source of the sample frame was, therefore, a list of qualified survey panelists provided by Survey Monkey, an online market research company that specializes in providing academic and scientific researchers with their targeted audience (Woznyj, 2017).

Survey panels, such as those provided by Survey Monkey, are frequently used in dissertation research. According to Woznyj (2017), panels of participants can be customized based on a researcher's specific requirements. Random selection of potential participants will occur once a frame is established (Woznyj, 2017) and will adhere to all institutional review board (IRB) regulations with respect to frame selection. Online survey panels are alternative approaches to traditional academic and market-research surveys. Academic researchers have suggested that such panels make it possible to have larger response rates for completed surveys (Cooper & Schindler, 2013; Denissen, Neumann, & Van Zalk, 2010). Researchers have also claimed that when panelists are used, the overall population is better represented because panelists tend to be more knowledgeable about the topics under examination (Denissen et al., 2010; Duffy et al., 2005). According to Comley and Beaumont (2011), the use of survey panels can also help reduce the total time required for data collection.

Online surveys have some disadvantages. Some researchers have suggested possible limitations on electronic survey panel responses compared to traditional methods, such as face-to-face interviews (Duffy, Smith, Terhanian, & Bremer, 2005). For example, neutral answers are given to online survey questions, such as *don't know* or *neither/not sure,* cannot be clearly interpreted in an online survey as "satisfying behavior or a true reflection of views when there are no interviewer effects" (Duffy et al., 2005, p. 638). However, Duffy et al. (2005) also suggest that this limitation could be associated more with the survey design than with the use of an online survey.

The Sample

The sample was randomly derived from the survey panel provided by Survey Monkey. The sample consisted of decision-making officials employed by skilled nursing homes in the U.S. All specific sampling criteria was provided to Survey Monkey. Random sampling permitted increased sample representativeness, eliminated possible bias, and maximized external validity (Creswell, 2014). Criteria for sample selection accounts for the inclusion of nursing home administrators and other decision-makers directly involved with the selection, approval, recommendation, or implementation of IT solutions for the entire organization. The research did not consider the socioeconomic characteristics of participants because the respective constructs were not measured. The research required participants to possess some practical familiarity with basic M-IoT concepts so that they could answer specific survey questions. Participants who did not meet the preliminary requirements were excluded as potential participants. Those selected were required to provide full responses to the survey questions.

Sampling Procedures

The process for recruiting and selecting participants proceeded according to Survey Monkey’s procedures. Sampling criteria were provided to Survey Monkey to narrow the sample frame appropriately. Once the sample frame was defined, Survey Monkey selected the actual sample based on precise instructions about the minimum sample size from the results of the power analysis calculation that supports distribution-based statistical tests (Faul, Erdfelder, Buchner, & Lang, 2009).

I instructed Survey Monkey to exclude any potential participant who was

- under the age of 21;
- not a nurse administrator, nursing director, or decision-making official directly involved with the evaluation, selection, and approval of IT systems for the organization; or
- worked at an organization with more than 250 beds.

Candidate participants received a letter of invitation via Survey Monkey. The letter followed the guidelines set forth by Capella University regarding informed consent, and participants electronically gave their consent before completing the survey. The form described the purpose of the study, the voluntary nature of participation, the right of participants to withdraw from the study at any time without consequence, a statement that no risks are anticipated for participants, and a notification disclosing the preservation of privacy and confidentiality for all data gathered in the survey. Individuals who chose to take part in the study received additional instructions to access the online survey hosted at a web site provided by Survey Monkey.

Data collection occurred over a period of 30 days, and all collected data were retrieved and downloaded by the researcher only. During data collection, Survey Monkey maintained all data associated with the surveys on their own servers. Upon completion of the surveys, I downloaded all collected survey data from Survey Monkey to my personal computer using a secure connection protected by encryption software. The researcher took full responsibility for safeguarding all the data, with a plan to destroy all data sixty days after analysis.

Sample Size

One of the strengths of structural equation modeling is its flexibility, permitting examination of complex associations, use of various types of data (e.g., categorical, dimensional, censored, and count variables), and comparisons across alternative models. However, these features of SEM also make it challenging to develop generalized guidelines regarding sample size requirements. According to Clark et al. (2013), when contemplating sample size, investigators usually prioritize achieving adequate statistical power in order to observe true relationships in the data. Power depends on (a) the chosen probability of a type I error, typically $\alpha = 0.05$, (b) the magnitude of the effect of interest, and (c) the sample size.

Vogt (2007) stated that a power analysis determines the sample size required to measure the effect of a given size according to a given degree of confidence. Statistical power equates to the probability of rejecting the null hypothesis when it is false, which is the probability of not making a type II error (Clark et al., 2013). Power analysis allows for a design that is both statistically significant and statistically powerful by determining a meaningful sample size and providing controls for the level of error tolerance (Vogt, 2007). To calculate the required sample size, I assumed medium statistical power ($1 - \beta = .95$; Clark et al., 2013) for a fixed model linear multiple regression test with four predictors to arrive at an a priori sample size of 129. The results of the G*Power (Version 3.1.7) analysis appear in Table 3.

Sample Selection Rationale

The rationale for sample selection and sample size determination took into consideration the research questions proposed in the study. The intention of the leading research question was to assess PE, EE, SI, and PR to patients as potential determinants of BI to use M-IoT within skilled nursing homes. Each sub-question inquired about the specific relationship between one of the independent variables and the dependent variable. Academic researchers have indicated that sample selection must be carefully designed to achieve a desired level of certainty when making generalizations about the entire population (Cooper & Schindler, 2013; Vogt, 2007). Participants in the proposed study were selected at random by Survey Monkey from their online panel based on the criteria I provided. The criteria aligned with the targeted population of decision-makers working in small and medium-sized skilled nursing homes in the United States who evaluate, select, influence, or approve the use of IT in their organizations.

Table 3

Sample Size and Power Calculation

Parameter	Value
Input	
Effect size (f_2)	0.15
α (type I error probability)	.05
Power (1 – β)	.95
Number of predictors	4
Output	
Noncentrality parameter (λ)	19.35
Critical F	2.44
Numerator df	4
Denominator df	124
Total sample size	129
Actual power	0.95

Note. The statistical test belongs to the F-test family (linear regression with a fixed model—R^2 deviation from 0). The type of power analysis is a priori (compute required sample size given α, power, and effect size).

Setting

A description of the environment in which the study was conducted provided an important context in terms of the applicability of the study results, the existence, and type of applicable local restrictions and ethics oversight, and the type of health care and technical infrastructure available (Cooper & Schindler, 2014). These considerations can vary substantially within and between different social, physical, and cultural environments. The setting for this research was various skilled nursing homes in the United States. These skilled nursing homes were selected from each of the 50 states, and each was either nonprofit or for profit. The selection of skilled nursing homes in both categories ensured the representation of a wide range of administrators and directors of different age groups, ethnic and socioeconomic backgrounds, and degrees of experience with M-IoT. I surveyed approximately 75 nursing home decision-makers across 75 skilled nursing homes in the United States.

Data Collection

The modified UTUAT survey instrument was delivered to the target population using Survey Monkey, which is one of the market leaders for electronic survey solutions. The survey was sent to a random probability sample of respondents per the respondent criteria outlined in the sample frame, which included decision-makers within U.S. based skilled nursing homes, such as owners, managers, practitioners, directors, managers, supervisors, and technicians, who engage in decisions regarding the adoption and use of M-IoT. Based on Survey Monkeys' self-reported sampling methodology, the respondents were randomly selected using survey routers that directed the electronic surveys by matching the qualifying demographic information to a panel of respondent profiles; all processes related to respondent selection were randomized to avoid source bias (SurveyMonkey, 2019).

The survey included 25 items associated with the factors under investigation; each answered using a 7-point Likert scale that ranged from s*trongly disagree* to *strongly agree*. The survey also included questions that gather demographics and details of work experience and job titles. Prior to taking the survey, participants were provided with a description of the study, a consent form, a confidentiality agreement, a definition of M-IoT, and examples of common IoT-enabled medical devices, along with medical IT terms and IoT computing definitions as provided by the National Institute of Standards and Technology (NIST). This aided in removing participant uncertainty associated with different IoT delivery models. Clear communication and instruction aids in producing quality responses on the surveys and leads to the collection of clean data.

Additionally, the survey used screening questions to categorize the respondents for the present research. The screening questions included a pre-survey vetting process that was set up within the Survey Monkey platform; respondents were verified to ensure that they were in the right sample pool. They were then prompted to agree to continue to the survey, where they were prompted to complete the survey. The screening questions and survey had previously been validated through a field test to ensure that the respondents included in the sample pool would be categorized correctly according to the requirements for this research. Any respondents who were deemed to be non-compliant with the requirements for the research pool were not allowed to resume the survey. All responses were temporarily saved on Survey Monkey's servers for the duration of the collection period. After the collection period, the information collected was downloaded, encrypted, and stored on servers that were accessible only to the researcher. All other media was maintained in a vault after completion of the data analysis. All collected data will be retained for a period of 7 years following the completion of the study, as required by Capella University.

The collected data were analyzed using both descriptive and associational techniques. The descriptive analysis provided the opportunity to describe and summarize the data collected, such as means and standard deviations, which were used to study each of the variables (Vogt, 2007). The quantitative regression analysis determined the relationships between the independent variables of performance expectancy, effort expectancy, social influence, and perceived risk and the dependent variable: behavioral intention. This analysis indicated the strength of the relationships identified between the variables, allowing the researcher to conclude the degree of influence that individualistic and socio-organizational variables have on a user's intentions to adopt M-IoT.

Instrumentation

Instrument Validity and Reliability

The researcher employed a modified survey and tested it for reliability and validity (Featherman & Pavlou, 2003; Venkatesh et al., 2003). Vogt (2007) suggested that any instruments applied to a new population should always be tested for validity and reliability, and the results of these tests should be published. In order to meet the required systematic rigor, the instrument underwent two forms of validity tests (face and content validity).

The modified instrument was used to investigate performance expectancy, effort expectancy, social influence, perceived risk, as the independent variables, as well as behavioral intention as the dependent variables. The instrument developed by Venkatesh et al. (2003) employs a 7-point Likert scale and has been used extensively to assess acceptance factors in a variety of settings and for many types of IS (Venkatesh et al., 2003). This scale was appropriate for use in the present investigation, because of the structure of the instrument and measures that generated interval data for both the independent and dependent variables. After obtaining permission, the instrument was adapted to evaluate M-IoT technology among decision-makers in U.S. skilled nursing organizations.

Field Testing

A field test was conducted to determine the face validity and content validity of the modified instrument. The survey was made available to three field testers. The first field tester was an associate professor and researcher at a world-class university with degrees in nursing and mental health; this field tester specializes in nursing research for populations of underserved and multicultural patients. The second field tester was an associate professor and researcher at a regional university with multiple degrees in nursing and experience as a nursing supervisor; this field tester specializes in patient safety and technology adoption in nursing home environments for the purpose of improved safety and efficiency. The third field tester was a director of nursing information systems for the second-largest health-care delivery system in the United States; this field tester holds multiple degrees in nursing and a doctorate in health-care technology implementation. All three field testers accepted the survey as written; however, one field tester made recommendations for a future research construct based on his practitioner experience and area of interest in health information technology adoption

Research Questions and Hypotheses

The purpose of this study was to investigate the potential effects of the social factors of PE, EE, SI, and PR on BI to adopt M-IoT devices among nursing home decision-makers. The following research questions and hypotheses guided the study.

The main research question RQ 1 asked what the relationship was between the variables of PE, EE, SI, and PR and the variable of BI to use M-IoT among nursing home practitioners and technicians in small and medium-sized nursing homes in the United States.

The subquestions of the research were as follows.

RQ 2: What is the strength of the relationship, if any, between PE and BI to adopt M-IoT technology?

RQ 3: What is the strength of the relationship, if any, between EE and BI to adopt M-IoT technology?

RQ 4: What is the strength of the relationship, if any, between SI and BI to adopt M-IoT technology?

RQ 5: What is the strength of the relationship, if any, between PR and BI to adopt M-IoT technology?

The aforementioned research questions resulted in the following hypotheses:

$H_0$1: PE, EE, SI, and PR are not statistically significant predictors of BI to adopt M-IoT devices in nursing home environments.

H_a1: PE, EE, SI, and PR are statistically significant predictors of BI to adopt M-IoT devices in nursing home environments.

$H_0$2: PE does not significantly influence BI to adopt M-IoT.

H_a2: PE significantly influences BI to adopt M-IoT.

H_03: EE does not significantly influence BI to adopt M-IoT.

H_a3: EE significantly influences BI to adopt M-IoT.

H_04: SI does not significantly influence BI to adopt M-IoT.

H_a4: SI significantly influences BI to adopt M-IoT.

H_05: PR does not significantly influence BI to adopt M-IoT.

H_a5: PR significantly influences BI to adopt M-IoT.

Data Analysis

The data were analyzed using partial least squares structural equation modeling (PLS-SEM), employing predictive measures to forecast the values of one variable based on the values of one or more other variables (Vogt, 2016). PLS-SEM is appropriate for the proposed study because it allows for the exploration of data patterns between variables based on existing theories and concepts, such as the UTAUT. In the current study, the independent variables of PE, EE, SI, and PR were used to determine the degree of influence they each have on the dependent variable BI via the PLS-SEM (Vogt & Johnson, 2016). PLS is justified because the proposed study involved measuring latent or unobservable variables that were attributed to the abstract concepts of behavioral attitudes and intention to adopt and use M-IoT (Hair, Hult, Ringle, & Sarstedt, 2016).

The PLS method has been a common approach for quantitative regression analysis when studying intention to use technology, as well as usage behavior. Several researchers have used it in similar studies, including Bischoff, Aier, Haki, and Winter (2015), Kiriakou (2012), Venkatesh et al. (2003), and Williams, Rana, and Dwivedi (2015). This method also supports the recent recommendations of many researchers for quantitative analysis of acceptance behavior for M-IoT (Achituv & Haiman, 2016; Bowles et al., 2015; Hogail, 2018; Kiriakou, 2012).

Smart PLS (3.X) employs SEM using the PLS path modeling method (Clark et al., 2013). This path modeling method was used to test and estimate causal relations using a combination of statistical data and causal assumptions (Martins et al., 2014). According to Martins et al. (2014), there are two types of SEM: covariance-based and variance-based. PLS is a variance-based technique and was utilized in this study because (a) it was used in similar studies where data were not distributed normally with results showing $p < .01$, (b) the research model had not been tested in the literature, (c) the research model was considered complex because it involved intertwining two models. PLS is well suited to estimate the variance of dependent constructs and associated latent variables and relies on principal component analysis (Wolf, Harrington, Clark, & Miller, 2013). SEM incorporates PCA by summarizing the original predictors into fewer new variables, which are then used as predictors to fit the linear regression model. According to Vogt and Johnson (2016), PLS is appropriate for empirical analysis, especially for research with relatively few participants and variables and when using ordinal data. The measurements for the study were at the interval level, and so the corresponding variables were used with the PLS-SEM method (Hair et al., 2016).

In addition to PLS, descriptive statistics were utilized to analyze, illuminate, and summarize the data. Methods used for descriptive statistics include histograms, models, scatter plots, calculations of frequency distributions, central tendencies, and homoscedasticity, and a review of research assumptions to ensure that the sample represents the population (Vogt, 2007). Descriptive analysis of the results utilized Microsoft 2016; SmartPLS v3 (Ringle, Wende, &

Becker, 2015) to determine the significance of the relationships between the independent and dependent constructs.

Validity and Reliability

I empirically assessed the survey instrument's internal consistency, indicator reliability, and convergent validity to support the structural model. Between September 2003 and December 2014, 1,267 studies employed either the original or a modified version of the instrument (Venkatesh et al., 2016). Many researchers have used the instrument to determine acceptance factors impacting the use of new technology, and Venkatesh et al. (2016) recommended it as the baseline model for explaining technology adoption in many different settings. The modified version of the instrument was tested via a field test to assess "the relevance of the test items to the content the test is supposed to measure" (Vogt, 2007, p. 118). Subject-matter experts reviewed the survey for content and face validity for measuring the targeted variables in the context of U.S. skilled nursing homes.

Researchers have traditionally established validity and reliability via a two-step approach (Heale & Twycross, 2015). This approach includes calculating the quality of the measurement models by assessing reliability, construct validity, and discriminant validity to determine their suitability for inclusion in path modeling. The researcher used two indicators to evaluate internal consistency: composite reliability and Cronbach's alpha. According to Martins et al. (2014), the most common measure of reliability is Cronbach's alpha, which estimates reliability based on intercorrelations and assumes that all factors are equally reliable. The composite reliability quantifies the reliability and consistency of each variable and the degree to which the items represent the underlying variables (Hair, Ringle, & Sarstedt, 2011).

Composite reliability is a test of the outer loadings of the variables and tends to overvalue internal consistency. In Table 4, I report both the lower bound (Cronbach's alpha) and the upper bound (composite reliability) of reliability. Composite reliability takes into account that indicators have different loadings (and Cronbach's alpha does not), so it is more suitable for PLS, which prioritizes indicators according to their individual reliability. As Table 4 illustrates, all reliability measures were above the recommended target of .7 for either approach (Martins et al., 2014).

Table 4

Reliability Measures—Cronbach's Alpha and Composite Reliability

Variable	α	Composite reliability
Performance expectancy	.93	.95
Effort expectancy	.94	.96
Social influence	.87	.89
Perceived risk	.97	.97
Behavioral intention	.99	.99
Use behavior		

Ethical Considerations

The ethical safeguards of the study followed the standards laid out in the *Belmont Report* (U.S. Department of Health and Human Services, 1979). All implemented safeguards align with the three core principles of respect, beneficence, and justice. Prior to the data collection, the researcher secured approval from the IRB at Capella University. Due to the vested interest in safeguarding the rights of research participants, the IRB review ensured the research complied with federal and ethical guidelines for human protection. I also requested permission from each individual who was selected to take part in the study, adhering to the principle of respect. In an effort to ensure anonymity and maintain the security and integrity of the collected data, I conducted the survey via Survey Monkey using their online portal. The survey package included an informed consent form to be completed by participants prior to accessing the survey. In addition, the study followed data protection designs to ensure confidentiality of the data collected, protection strategies for the data while in storage, and plans for the destruction of the data once it was no longer required. All data collected was initially housed securely on Survey Monkey servers before it was downloaded to a password-protected encrypted drive and deleted from Survey Monkey's servers. As required by the IRB, the survey data will be maintained on the aforementioned drive in a secure location accessible only by me for seven years and destroyed at the end of that time. The survey disclosure also informed respondents of the right to withdraw from the study at will. The disclosure provided the researcher's contact information so that respondents could request the final results of the research documents upon completion of the study.

Summary

I sought to determine the significance of the intrinsic and external factors affecting attitudes toward, and intention to use M-IoT technology. The general goal of the study was to contribute knowledge regarding technology acceptance, especially within the long-term care industry. To achieve this goal, I used a modified version of the UTUAT instrument to investigate the predictor variables of performance expectancy, effort expectancy, social influence, and perceived risk to gain insight on how they influence the dependent variable of behavioral intention. The following section summarizes the results of the survey.

CHAPTER 4. RESULTS

Introduction

This chapter presents the findings of the current study, undertaken to provide insights into the factors that influence decision-makers within U.S.-based skilled nursing organizations regarding the adoption of M-IoT technology. Chapter 1 presented the business technical problem and provided an overview of the theoretical and conceptual model. Chapter 2 expounded on the topic by grounding the study in the literature and providing a context regarding why the current research is relevant to this business problem. Chapter 3 discussed the research design, methodology, and hypothesis under investigation. The summary and implications of the findings are discussed later in Chapter 5.

Chapter 4 begins with a description of the data collection procedures and demographic information of the respondents, along with the sample size and power. Next, there is a discussion of the analysis of the measurement model to establish the validity and reliability of the model and then an evaluation of the structural model, as illustrated in Figure 11. Then, the chapter concludes with a discussion of variance and effect, hypothesis testing, and a summary of the findings.

PLS-SEM Model

The PLS-SEM analysis method is composed of two models, an outer model (the measurement model) and the inner model (the structural model). The measurement model represents the relationships between the observed data and the latent variables. The structural model represents the relationships between the latent variables in the theory (Hair et al., 2016). For this research, the measurement model included in the PLS-SEM analysis method was the outer model, as shown in Figure 9, and was used to measure the relationship of the construct and its corresponding indicator variables. The constructs of the structural model are not directly observable, so the indicators were used to measure the effect of each variable included in the structural model. For the current research, the indicators included in the modified UTAUT instrument were the basis for the measurement model, along with a 7-point Likert scale (Despins et al., 2010; Trevino et al., 2017; Venkatesh et al., 2003). The specific questions represented the indicators related to each construct, and the answers to the questions represented a measure for the construct (latent variable) (Hair et al., 2016). The modified survey instrument was comprised of these indicators, and the collected data from the survey responses were used to calculate the strength of the test the hypotheses.

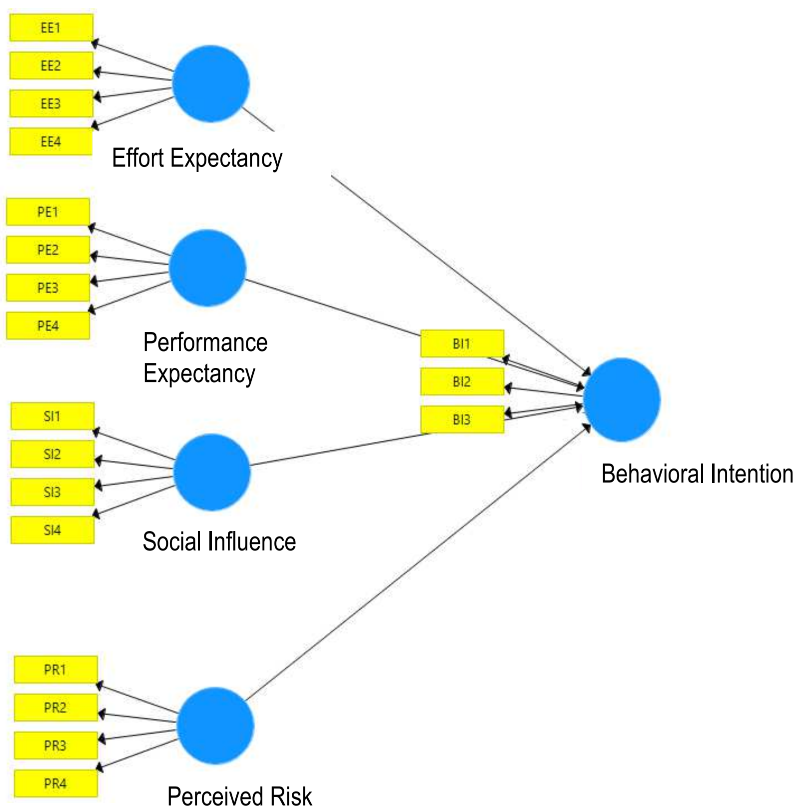

Figure 9. PLS-SEM measurement model.

The structural model (inner model) was comprised of the independent variables of performance expectancy, effort expectancy, social influence, and perceived risk, as well as the dependent variable of behavioral intention, which were represented within UTAUT (Venkatesh et al., 2003) and the Perceived Risk (Despins et al., 2010; Trevino et al., 2017). The structural model aligned with the causal relationships represented in each of the hypotheses to empirically test the theory. The structural model represented the hypothesized relationships, as shown in Figure 10.

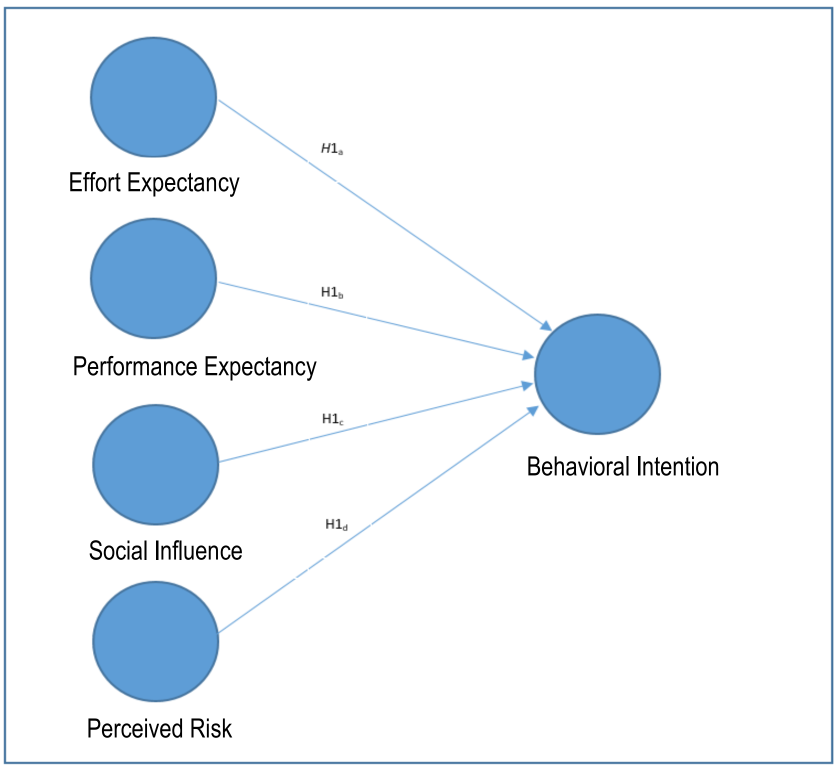

Figure 10. PLS-SEM structural research model.

The following section discusses data collection along with the findings from the investigative data analysis.

Data Collection

The targeted population for the current study was employees who were decision-makers in U.S. based skilled nursing organizations. The sampling frame consisted of members of the Survey Monkey marketing panels who were decision-makers working within U.S.-based skilled nursing organizations. The sample size required for the research was determined using G*Power 3.1 statistical power analysis software (Faul et al., 2009). The power analysis used the medium effect size, with the criteria of $f2=0.15$, the alpha value equaling 0.05, and the statistical power (1-β err prob; Clark et al., 2013) equaling 0.95; the power analysis included an input of four predictors and resulted in the a priori sample size of 129 responses.

Survey Monkey was used to send electronic surveys to panel participants who met the criteria of being in a role of ownership, supervision, and management within a U.S.-based skilled nursing home and who were tasked with making decisions to adopt M-IoT as part of either the organization's future strategies or day-to-day operational activities. The Survey Monkey invitation to participate in the survey resulted in 465 potential participants, and the survey's weblink was open during the data collection period of three weeks. The first section of the survey included a consent form informing participants of their rights of participation in accordance with Capella University's ethical guidelines (Capella, 2019), including the researcher's and university's contact information. Respondents were withdrawn from the study if they declined to consent. Additional screening questions included verification of the respondent's age, that the respondent did work in a U.S. nursing home, and that they participated in decision making within their organization. Data collection ended once the survey campaign had yielded

129 complete and valid surveys. The next section presents additional discernments into the survey sample demographics.

Descriptive Analysis

The collected demographic information included gender, age, education level, job title, experience level with M-IoT, and organization size based on the number of employees. Of the 129 participants in the study, 19% were male (*n* = 24) and 81% were female (*n* = 105). Level of experience with M-IoT systems varied, with the largest category having used the technology for more than five years (*n* = 43); this was followed by those with 1 to 2 years of experience (*n* = 38); those with 3 to 4 years of experience (*n* = 30); and, finally, those with less than one year of experience (*n* = 18). Regarding age, most respondents were between the ages of 25 and 34 (43%; *n* = 55). Table 5 shows the respondents' age categories.

Table 5

Respondent Age Groups

Age Group	Frequency	Percent
18–24	21	16
25–34	55	43
35–44	26	20
45–54	10	8
55–64	17	13
65+	0	0

Table 6 illustrates the respondents' self-reported working disciplines. There is not an equal distribution for the reported disciplines, and there is a wide variety of different disciplines. To simplify the multitude of job categories, all functions were grouped into two major categories, nurse practitioners and directors/owners. The largest categories of job functions accounted for over 70% of the respondents (n = 91) identifying as nursing aides/practitioners/assistants, followed by members of management or ownership (30%; n = 38).

Table 6

Respondents' Working Disciplines within Nursing Homes

Discipline	Frequency	Percent
Management/Ownership	38	30
Nursing Aide/Assistant/Practitioner	91	70

Exploratory Data Analysis

Post data collection, the data were reviewed to determine the completeness and suitability to continue data analysis using the PLS-SEM method. The first step included a visual inspection of the data; this inspection of the results ensured that individual responses did not follow unwanted patterns or outliers with an excess of neutral or extreme responses. No surveys exhibited unwanted patterns often found in straight-lining, speeding, and incongruent responses, so they were all retained. The data were also checked for normal distribution, although it is not a prerequisite for a PLS-SEM analysis (Hair et al., 2017). The data did not satisfy conditions for normal distribution, but the data exhibited skewness and excess kurtosis (Hair et al., 2017).

Skewness assesses the extent to which a variable's distribution is symmetrical (Vogt, 2007). While a normal distribution has a skewness of 0, left-skewed data have a negative skewness statistic less than 0; right-skewed data have a positive skewness statistic greater than 0 (Vogt, 2007). The skewness for this data set ranged from -1.025 to 0.229, with 18 of the 20 indicators exhibiting left skewness. The data were examined for excess kurtosis once the analysis for skewness was completed.

Kurtosis is another statistical measure used to describe data distribution. But whereas skewness differentiates extreme values in one tail versus the other, kurtosis measures extreme values in either data tail. Distributions with large kurtosis exhibit tail data exceeding the tails of the normal distribution (e.g., five or more standard deviations from the mean). Distributions with low kurtosis exhibit tail data that are generally less extreme than the tails of the normal distribution. Kurtosis occurs when the shape of the data follows a very narrow distribution with most of the responses in the center (Hair et al., 2017). While a normal curve has a kurtosis of 0, a statistic greater than +1 indicates the distribution is too peaked, and a statistic less than -1 indicates a distribution that is too flat (Hair et al., 2017). For this data set, the values for excess kurtosis ranged from -0.984 to 1.186, resulting in a platykurtic distribution, meaning most of the values occurred closer to the mean. While normal distribution is not a precondition for a PLS-SEM analysis, the non-normal distribution of this data set indicated that PLS bootstrapping would be essential to analyze the results, as recommended by Hair et al. (2017).

PLS Bootstrapping Method

The PLS-SEM is a nonparametric statistical method and, as such, does not usually make assumptions about data distributions (Hair et al., 2017). Despite this property of PLS-SEM, it is still recommended to verify that the data exhibits properties of distribution that are not too far from normal, as extremely non-normal data can prove problematic in the assessment of the parameters significances (Hair et al., 2017). More specifically, extremely non-normal data tends to augment standard errors obtained from bootstrapping and thus decrease the likelihood that some relationships will be assessed as significant (Hair et al., 2017). The existence of this distinctive characteristic means that more traditional parametric tests, which regression analysis uses, cannot be applied to determine significance (Hair et al., 2017). The attribute has important consequences for testing the significance of the model coefficients, as the technique does not assume any specific distribution.

The PLS-SEM method, which is a non-parametric bootstrapping method, was used to produce accurate statistical inferences for the various estimates, including the means, correlations, and regression coefficients (Hair et al., 2017). It is recommended to use a minimum of 500 subsamples to randomly draw from for the observations in the original data set with replacement (Streukens & Leroi-Werelds, 2016; Hair et al., 2016). For this study, 5000 subsamples were used to estimate the path models and to derive the standard errors for the PLS-SEM results (Streukens & Leroi-Werelds, 2016; Hair et al., 2016). From these results, the t-values, p-values, and confidence intervals were calculated to assess the significance of the relationships within the structural model (Streukens & Leroi-Werelds, 2016; Hair et al., 2016). The subsequent section discusses the validation of the measurement model for the suitability of the PLS-SEM analysis.

Validation of the PLS-SEM Measurement Model

The primary function of the PLS-SEM algorithm is to employ iterative procedures to perform calculations in two stages. The first step calculated the measure of each indicator in the outer model for every construct, then iteratively estimated the relationships among the constructs in the inner model (Hair et al., 2017). In the second stage, the final estimates of the outer weights and loadings were calculated, as well as the structural model's path coefficients and the resulting

R^2 values of the endogenous latent variables (Hair et al., 2017). However, before this procedure was conducted, both the outer and inner models were checked for validity and reliability (Hair et al., 2017).

The measurement model was initially analyzed for internal consistency, convergent validity, indicator reliability, and discriminate validity (Hair et al., 2017). These measurements were used to indicate the uniqueness of the construct measurements within the model. As shown in Table 7, the composite reliability and Cronbach's alpha exceeded 0.70 in all cases. Concerning the composite reliability, Hair et al. (2017) explained that although Cronbach's alpha may be affected by the number of items included in the scale, the internal consistency can be further evaluated using composite reliability, which accounts for the outer loadings of the model. All values in the model were found to be between 0.70 and less than 0.95, confirming that the construct measurements were not redundant.

Table 7

Latent Variables, Indicators, and Cronbach's Alpha

Latent Variable	Indicators	Cronbach's Alpha	Composite Reliability
Behavioral Intention (BI)	BI1, BI2, BI3	0.92	0.94
Effort Expectancy (EE)	EE1, EE2, EE3, EE4	0.86	0.90
Perceived Risk (PR)	PR1, PR2, PR3, PR4	0.85	0.85
Perform Expectancy (PE)	PE1, PE2, PE3, PE4	0.86	0.91
Social Influence (SI)	SI1, SI2, SI3, SI4	0.88	0.92

With respect to convergent validity, Hair et al. (2017) explained that the outer loadings of the indicators and the average variance extracted could be used to evaluate convergent validity. This evaluation is crucial to investigating the extent to which a measure correlates positively with the alternative measure of the same construct. As shown in the table below, all outer loadings exceeded 0.708, and the average variance extracted exceeded 0.5 for all variables. These values confirm that each measure correlated positively with alternate measures of the same construct.

Table 8

Outer Loadings and Average Variance Extracted

Latent Variable	Indicators	Outer Loading	AVE
Behavioral Intention	BI1	0.90	0.81
	BI2	0.86	
	BI3	0.85	
Effort Expectancy	EE1	0.84	0.70
	EE2	0.86	
	EE3	0.82	
	EE4	0.86	
Perceived Risk	PR1	0.87	0.60
	PR2	0.80	
	PR3	0.78	
	PR4	0.81	
Performance Expectancy	PE1	0.85	0.71
	PE2	0.88	
	PE3	0.86	
	PE4	0.82	
Social Influence	SI1	0.86	0.73
	SI2	0.85	
	SI3	0.77	
	SI4	0.78	

The discriminate validity was established using both the cross-loadings, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT) (Hair et al., 2017). The discriminant validity is the extent to which a construct is distinct from other constructs. It implies that a construct is unique from all other constructs in the model (Hair et al., 2017). According to Hamid, Sami, and Sidek (2017), the assessment of discriminant validity is crucial in any research that involves latent variables for the prevention of multicollinearity issues.

The cross-loadings were first evaluated to investigate the indicator's outer loading to the associated constructs concerning other constructs; the cross-loadings for the associated construct should be greater than all of the constructs loadings on other constructs to fulfill the criteria of cross loading and construct validity, (Hair et al., 2016; Hair et al., 2017). As shown in Table 8, all outer loadings of the associated constructs were greater than the loadings for any other constructs.

The additional step of evaluating the Fornell-Larcker criteria further established the discriminate validity by assessing the square root of the average variance extracted (AVE) when compared with the latent variable correlations. The Fornell-Larcker criterion (1981) is the most widely used method to assess the degree of shared variance between the latent variables of the model (Hamid et al., 2017). According to this criterion, the convergent validity of the measurement model can be assessed by the Average Variance Extracted (AVE) and Composite Reliability (CR). AVE measures the level of variance captured by a construct versus the level due to measurement error; values above 0.7 are considered exceptionally good, whereas the level of 0.5 is acceptable. CR is a less biased estimate of reliability than Cronbach's Alpha, where the acceptable value of CR is 0.7 and above (Hamid et al., 2017). As shown in Table 9, the square root of each construct's AVE should be greater than its highest correlation with any other construct. This confirms that the constructs are unique within the model and are exhibiting phenomena that are not represented by the other constructs, thus proving discriminate validity.

Table 9

Fornell-Larcker Criterion

	Behavioral Intention	Effort Expectancy	Performance Expectancy	Perceived Risk	Social Influence	Ave Squared Root
BI	1.000	0.795	0.799	-0.169	0.519	0.897
EE	0.795	1.000	0.835	-0.147	0.518	0.838
PE	0.799	0.835	1.000	-0.100	0.675	0.843
PR	-	-0.147	-0.100	1.000	0.238	0.775
SI	0.169	0.518	0.675	0.238	1.000	0.856
	0.519					

For the final step, a more modern method of assessing discriminant validity was used called HTMT. Hamid et al. (2017) believed that HTMT is a stringent measure that can detect the possible indiscriminate among the latent variables. The use of HTMT further established the discriminate validity by assessing the correlation between the construct based on the average of HTMT correlation, as suggested by (Henseler, Ringle, & Sarstedt, 2015). The ratio of HTMT is expected lower than 0.90 at a 95% confidence level, and all values have to be significantly different from 1. Any value of HTMT higher than 0.9 indicates there is a lack of discriminant validity.

Table 10

Confidence Intervals Bias Correct

Predictor -> Dependent Variables	2.5 %	97.5%	Confidence interval does not include 1
EE -> BI	0.152	0.645	YES
PE -> BI	0.795	1.000	YES
PR -> BI	0.799	0.835	YES
SI -> BI	-0.169	-0.147	YES

Collectively, the tests indicated that the measurement model constructs were both reliable and valid. The following section describes the validation process for the structural model.

Validation of the PLS-SEM Structural Model

Assessment of the structural model results allows for the opportunity to determine the model's capability to predict one or more target constructs. After establishing validity and reliability, the structural model was assessed using five different tests: collinearity, significance (t-test), significance (p-test), adjusted coefficient of determination (R2), and effect test. The first test applied was collinearity. Collinearity is a distinctive assessment here because the model is evaluating several variables simultaneously (Hair et al., 2017). Collinearity arises when two indicators are highly correlated. If the variables under investigation are subject to collinearity, then the redundant variables must be identified and excluded to preserve the integrity of the statistical analysis (Hair et al., 2017). Collinearity was assessed using the variance inflation factors (VIFs). If the VIFs are above 5.0, then this indicates collinearity issues among the predictor variables (Hair et al., 2017). Collinearity was assessed for the dependent variable behavioral intention and was found to be a concern for this model, as indicated in

Table 11

Evaluation of Collinearity Based on Variation Inflation Factors

Dependent Construct	Predictor Construct	Variation Inflation Factor
Behavioral Intention	Effort Expectancy	3.356
	Performance Expectancy	4.643
	Social Influence	2.232
	Perceived Risk	1.229

Path coefficients assessed the structural model due to the lack of collinearity issues. The path coefficient is the coefficient linking construct in the structural model. It represents the hypothesized relationship or the strength of the relationship. For example, path coefficients close to +1 indicate strong relationships and vice versa for negative values. The closer the estimated coefficients are to 0, the weaker the relationships. The path coefficients were determined by using bootstrapping of 5,000 subsamples to determine critical *t* values for significance levels of 0.05 and 0.10, along with the *p* values (Hair et al., 2017). Table 12 shows the results of the SmartPLS bootstrapping significance tests for the structural path model coefficients, *t* statistics, and *p* values.

Table 12

Significance Tests for Structural Model Path Coefficients, t Values, and p Values

Structural Model Path	Path Coefficients	*t* Values	*p* Values
Effort Expectancy → Behavioral Intention	0.409	3.34	0.001***
Performance Expectancy → Behavioral Intention	0.425	3.27	0.001***
Perceived Risk → Behavioral Intention	-0.075	0.97	0.333
Social Influence → Behavioral Intention	0.038	0.5	0.618

Note. $*p < 0.05$, $*p < 0.01$, $**p < 0.001***$

Measures of Variance and Effect Size Based on the PLS-SEM Model

The adjusted coefficient of determination (R^2) was used to estimate the model's predictive power. R^2 indicates the variance explained of the endogenous variable by the exogenous variable (Hair et al., 2017). The exogenous variables are representative of the independent constructs within the model, and the endogenous variables are representative of the dependent constructs within the model (Hair et al., 2017). R^2 is calculated as the squared correlation between the actual and predicted values for a given endogenous construct. The R^2 value ranges from 0 to 1, with higher levels indicating greater predictive accuracy, with values of 0.75, 0.50 0r 0.25 being substantial, moderate, and weak (Hair et al., 2017; Henseler et al., 2009). As shown in Table 13, behavioral intention indicated substantial predictive accuracy.

Table 13

Adjusted Coefficient of Determination (R^2) and Effect Size (f^2)

Endogenous Construct	Adjusted R^2	Exogenous Construct	f^2 (Effect Size)
Behavioral Intention	0.687	Effort Expectancy	0.165
		Performance Expectancy	0.128
		Social Influence	0.002
		Perceived Risk	0.015

Assessment of the effect size allows for the observation of the effect of each exogenous construct on the endogenous construct (Hair et al., 2017). The effect sizes, or f^2, were evaluated by excluding specified exogenous constructs from the model and measuring the change in R^2 for the endogenous construct (Hair et al., 2017); this indicates whether the specified exogenous construct has a significant impact on the endogenous construct. The effect size of 0.02 represents a small effect, 0.015 for a medium effect, and 0.35 for a large effect on the endogenous construct (Hair et al., 2017). As indicated in Table 14, the effort expectancy had the largest effect on behavioral intention (f^2 = 0.165), followed by a slightly smaller effect by performance expectancy (f^2 = 0.128) a medium effect by perceived risk (f^2 = 0.015) and the smallest effect by social influence (f^2 = 0.002).

Analysis of Hypotheses

Tables 14 and 15 describe the path coefficients and significance used for hypothesis testing discussed below.

Research Question 1 and Hypothesis 1

RQ 1 asks what the relationship is, if any, between the variables of PE, EE, SI, and PR and the variable of BI to use M-IoT among nursing home decision-makers (practitioners, technicians, and owners) in small and medium-sized skilled nursing homes in the United States.

The aforementioned research questions resulted in the following hypotheses:

$H_0$1: PE, EE, SI, and PR are not statistically significant predictors of BI to adopt M-IoT devices in nursing home environments.

H_a1: PE, EE, SI, and PR are statistically significant predictors of BI to adopt M-IoT devices in nursing home environments.

The null hypothesis is rejected based on the PLS-SEM method. Rejection of the null hypothesis is due to the evidence showing performance expectancy, effort expectancy, and social influence are statistically significant predictors of behavioral intention, while the perceived risk is not a statistically significant predictor, as shown in Table 14. This analysis indicates that performance expectancy, effort expectancy, perceived risk, and social influence can explain 69% of the intention to use M-IoT. The following section discusses the details of the path coefficients for each independent construct examined in the research, along with related sub-questions and hypotheses.

Table 14

Summary of Hypothesis 1 Testing Results

Endogenous Construct	Adjusted R^2	Exogenous Construct	Path Coefficient	f^2 (Effect Size)
Behavioral Intention	0.687	Performance Expectancy	0.425	0.128
		Effort Expectancy	0.409	0.165
		Social Influence	0.038	0.002
		Perceived Risk	-0.075	0.015

Subquestion 1a and Hypothesis 2.

RQ 1_a. What is the possible association between performance expectancy and behavioral intention for the adoption of M-IoT within the context of small and medium-sized skilled nursing home environments organizations in the U.S.?

H_o2: The independent variable of performance expectancy is not a statistically significant predictor of behavioral intention to use M-IoT systems.

H_a2: The independent variable of performance expectancy is a statistically significant predictor of behavioral intention to use M-IoT systems.

The null hypothesis is rejected based on the PLS-SEM method. Evidence shows that performance expectancy is a statistically significant predictor of behavioral intention to use M-IoT systems ($\beta = 0.425$, $p < 0.001$), as shown in Table 15.

Table 15

Summary of Hypotheses 2 Testing Results

Structural Model Path	Path Coefficients	R^2	f^2
Performance Expectancy → Behavioral Intention	0.425	0.687	0.128

Sub-Question 1b and Hypothesis 3.

RQ 1_b. What is the possible association between effort expectancy and behavioral intention for the adoption of M-IoT within the context of small and medium-sized skilled nursing home environments in the U.S.?

H_o3: The independent variable of effort expectancy is not a statistically significant predictor of behavioral intention to use M-IoT.

H_a3: The independent variable of effort expectancy is a statistically significant predictor of behavioral intention to use M-IoT.

The null hypothesis is rejected based on the PLS-SEM method since the evidence shows that effort expectancy is a statistically significant predictor of behavioral intention to use M-IoT systems ($\beta = 0.409$, $p < 0.001$), as shown in Table 16.

Table 16

Summary of Hypotheses 3 Testing Results

Structural Model Path	Path Coefficients	R^2	f^2
Effort Expectancy → Behavioral Intention	0.409	0.687	0.165

Subquestion 1c and Hypothesis 4.

RQ 1_c. What is the possible association between social influence and behavioral intention for the adoption of M-IoT within the context of small and medium-sized skilled nursing organizations in the US?

H_o4: The independent variable of social influence is not a statistically significant predictor of behavioral intention to use M-IoT systems.

H_a4: The independent variable of social influence is a statistically significant predictor of behavioral intention to use M-IoT systems.

The null hypothesis is rejected based on the PLS-SEM method since the evidence shows that social influence is a statistically significant predictor of behavioral intention to use M-IoT systems ($\beta = 0.038$, $p < 0.01$), as shown in Table 17.

Table 17

Summary of Hypotheses 4 Testing Results

Structural Model Path	Path Coefficients	R^2	f^2
Social Influence → Behavioral Intention	0.038	0.687	0.002

Research Question 1d and Hypothesis 5

RQ2. What is the possible association between perceived risk and behavioral intention as possible determinants of the usage behavior for M-IoT technology within the context of small and medium-sized skilled nursing home organizations in the U.S.?

H_o5: The independent variable of perceived risk is not a statistically significant predictor of behavioral intention to use M-IoT systems.

H_a5: The independent variable of perceived risk is a statistically significant predictor of behavioral intention to use M-IoT systems.

The null hypothesis is accepted, and the alternate hypothesis is rejected based on the PLS-SEM method. The evidence shows that perceived risk is not a statistically significant predictor of behavioral intention when it comes to using M-IoT systems, as shown in Table 18.

The following section provides details of the path coefficients for each independent construct for the research sub-questions and hypotheses.

Table 18

Summary of Hypotheses 5 Testing Results

Structural Model Path	Path Coefficients	R^2	f^2
Perceived Risk → Behavioral Intention	-0.075	0.687	0.015

Summary

This exploratory analysis uncovered non-normally distributed data. This finding justified the use of PLS-SEM non-parametric bootstrapping method to produce accurate statistical inferences for the various estimates, including the means, correlations, and regression coefficients (Hair et al., 2017). This statistical foundation allowed for the investigation of the factors that influence individuals within U.S.-based SME skilled nursing organizations with respect to adopting M-IoT technology.

The multivariate analysis associated with RQ 1 suggested that PE, EE, and SI are significant predictors of BI, capable of explaining 69% of the variance in BI. The analysis of PR revealed a negative relationship with BI. Therefore, the null hypothesis $H_0 1$ was rejected, and the alternative hypothesis, $H_a 1$, was accepted.

In reference to RQ 2, the p calculation, path coefficient, and effect size all revealed a moderate correlation between the PE and BI. PE alone can account for approximately 20% of the variance in BI. Therefore, the null hypothesis, $H_0 2$, was rejected, and the alternative hypothesis, H_{a2}, was accepted.

In reference to RQ 3, the p calculation, path coefficient, and effect size all revealed a moderate correlation between the EE and BI. EE alone can account for approximately 24% of the variance in BI. Therefore, the null hypothesis, $H_0 2$, was rejected, and the alternative hypothesis, $H_a 2$, was accepted.

In reference to RQ 4, the p calculation, path coefficient, and effect size all revealed a minimal correlation between the SI and BI. SI alone only accounts for less than 1% of the variance in BI. Therefore, the null hypothesis, $H_0 2$, was rejected, and the alternative hypothesis, H_{a2}, was accepted.

In reference to RQ 5, the p calculation, path coefficient, and effect size all revealed a negative correlation between the PR and BI. PR showed no significance as a predictor of BI. Therefore, the null hypothesis, $H_0 2$, was accepted, and the alternative hypothesis, H_{a2}, was rejected.

The analysis of the measurement model for the current study, as shown in Figure 9, revealed internal consistency, indicator reliability, convergent validity, and discriminate validity. Also, there was no evidence of collinearity issues within the structural model (Hair et al., 2017). Three of the four latent variables within the model showed positive predictive value toward the dependent constructs, though with varying levels of impact. The PR is the only latent variable to exhibit a negative predictive value towards the dependent construct. Chapter 5 provides a discussion of the implications of these findings, which includes suggested recommendations for additional investigation and insights for future research.

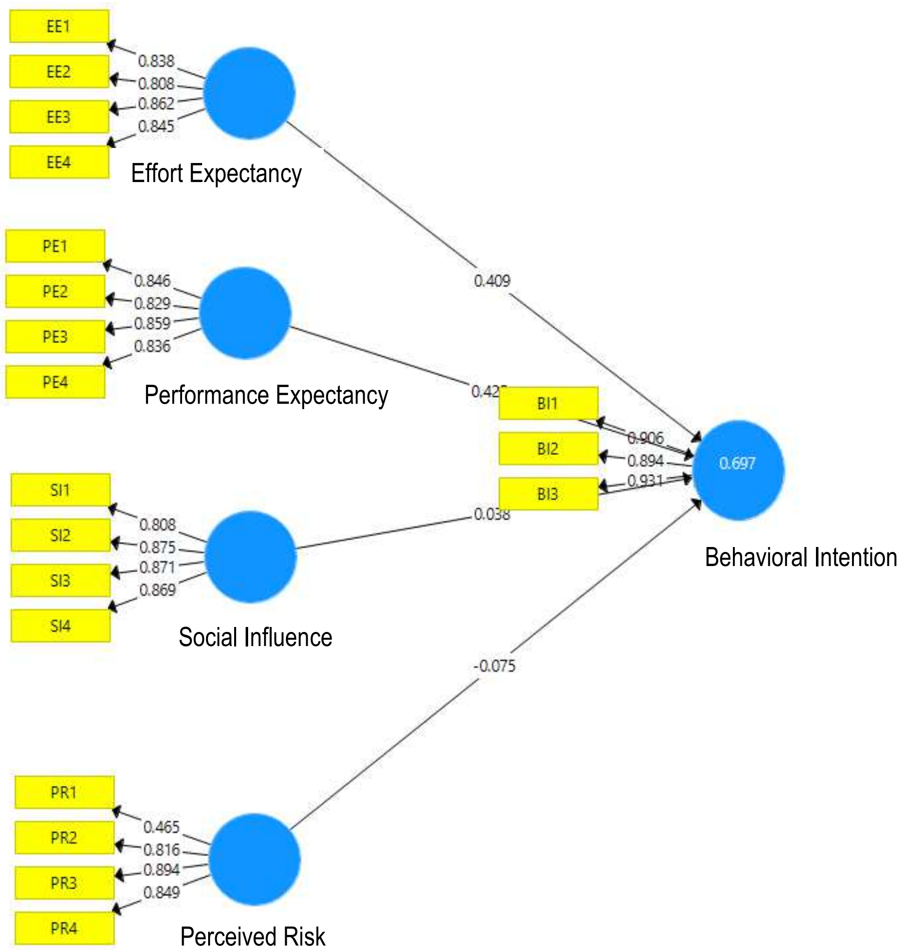

Figure 11. Research model results. Significance levels are based on probability denoted as *$p < 0.05$, **$p < 0.01$, *** < 0.001.

CHAPTER 5. CONCLUSIONS

Introduction

The present research investigated a modified version of the UTAUT model (Venkatesh et al., 2003), here relating the human factors of performance expectancy, effort expectancy, perceived risk, and social influence to behavioral intention to adopt M-IoT technology. The current research extended the understanding of the acceptance of technology for U.S.-based SME skilled nursing organizations to determine whether these factors significantly impact the adoption of M-IoT. The chapter commences with a summary of the results, followed by a review of the findings and the implications of the research. The chapter concludes with a discussion of the research limitations and recommendations for future research.

The motivation behind the investigation centered on three main issues. First, despite the apparent technical, operational, and financial benefits of using M-IoT, adoption rates of this technology among skilled nursing homes have remained below anticipated rates (Achituv & Haiman, 2016; Alexander et al., 2016). Second, the dynamics of technology adoption for small to medium-sized organizations contrast from adoption approaches taking place in larger organizations (Achituv & Haiman, 2016; Hou & Yeh, 2015). Therefore, findings from technology adoption studies conducted in large industries are not good indicators of factors influencing technology adoption for small to medium-sized organizations. Thirdly, there is a limited body of academic literature focused on factors influencing the behavioral intention of decision-makers to adopt M-IoT solutions. Based on these issues, the study established several research questions and a hypothesis, which provided the foundation for gaining insight on the answers to these issues; the following sections provide a summary of the results summarized in Table 19.

Evaluation of the Research Questions

The study employed data obtained from an online survey panel of 129 participants consisting of decision-makers who are responsible for the selection, approval, implementation, and support of M-IoT at their respective organizations. A modified version of the UTAUT instrument (Venkatesh et al., 2003) was used to measure the antecedents of intention to adopt M-IoT technology. The PLS-SEM method (Hair et al., 2017) was used to analyze the data and perform various statistical tests. Overall, the findings explain 69% of the variance for the use of M-IoT among U.S.-based small to medium-skilled nursing home organizations. This section provides a summary of the findings related to each of the central research questions and their null hypotheses.

Research Question 1

What is the relationship between the variables of PE, EE, SI, and PR and the variable of BI to use M-IoT among nursing home decision-makers in small and medium-sized nursing homes in the U.S.? The statistical analysis indicated a positive correlation between performance expectancy (PE), effort expectancy (EE), and social influence (SI) to adopt M-IoT technology. The analysis revealed that PE, EE, and SI explain 69% of the variance for users' behavioral intentions to adopt M-IoT, while PR had little to no effect on adoption. Of the factors examined, the data indicated that PE ($\beta = 0.43$, $p < 0.001$) is the most significant predictor of behavioral intention (BI). A user's perception of whether the M-IoT technology would be easy to use, which was represented by EE ($\beta = 0.41$, $p < 0.001$) and a user's perception of the importance others place on the use of M-IoT technology, which was represented by SI ($\beta = 0.04$, $p < 0.01$), had less predictive ability but were still shown to be statistically significant. However, a user's perception of risk involved when using M-IoT, which was represented by PR ($\beta = 0.41$, $p < 0.001$), showed almost no predictive value concerning behavioral intention (BI). Therefore, the researcher rejected the null hypotheses for research question 1 and its sub-questions, as shown in Table 22.

Table 19

Summary of Findings for Omnibus Research Question 1

Research Question/ Sub Question	Null Hypothesis	Dependent Variable	Independent Variable	Hypothesis Accepted/Rejected
RQ1	H_o1	PE, EE, SI, PR	BI	Rejected
$RQ1_a$	H_o2	PE	BI	Rejected
$RQ1_b$	H_o3	EE	BI	Rejected
$RQ1_c$	H_o4	SI	BI	Rejected
$RQ1_d$	H_o5	PR	BI	Accepted

Expanding on the results, performance expectancy was identified as the variable with the most significant level of influence on behavioral intention. This finding was in alignment with the work of Venkatesh et al. (2003) while validating the UTAUT model. Eliciting the literature from Chapter 2, performance expectancy is associated with constructs from the literature, such as relative advantage and extrinsic motivation (Davis et al., 1992). Similarly, performance expectancy is also concerned with task accomplishment (Venkatesh et al., 2003). Therefore, the results indicated that decision-makers perceive the use of M-IoT as a favorable information technology solution with the potential for improving business productivity and efficiency.

According to the results, effort expectancy exerted a moderate to low influence on the intention to accept M-IoT solutions. In the work of Venkatesh et al. (2003), effort expectancy was associated with how a person's behavior is influenced depending on how difficult or easy it was to work with a given technology. A possible reason why this factor is not as influential as seen in prior studies can be related precisely to the advances in system integration, application graphical user interfaces, application usability, and the specialized skills required to operate and decipher data captured from M-IoT. Easy-to-use or familiar application user interfaces make reducing the learning curve necessary to master the use of M-IoT solutions. The applications under consideration in this study are associated with functionality and operational structure, similar to those already in use in traditional health systems. It is evident, therefore, that managers perceive the level of effort necessary to use M-IoT solutions less relevant.

Social influence exhibited a low influence when predicting behavior intention. In the context of this study, social influence was characterized by the idea that decision-makers' behavior towards the use of M-IoT is influenced by how they believe that other people think of them based on their use of the technology. On an earlier investigation evaluating IT in small organizations, Premkumar (2003) indicated that decision-makers often rely on the expertise of advisors for their technical expertise. The dynamics of this relationship are easier to understand after considering that even if M-IoT solutions can effectively model other traditional applications and deliver the expected performance, there are still several technical considerations requiring specialized attention for which SMEs may not be ready to engage in on their own. Consequently, the social influence of others, such as external consultants, internal IT experts, and even vendors, may play a critical role in the acceptance of M-IoT solutions.

Perceived risk (PR) did not exhibit any substantial influence when predicting behavioral intention. In the context of this study, perceived risk characterized the idea that decision-makers' behavior towards the use of M-IoT is influenced by how they perceive uncertainty concerning the improvements, losses, and adverse effects to patients resulting from M-IoT acceptance and adoption (Martins et al., 2014; Despins et al., 2010; Trevino et al., 2017). In the current study, PR exhibited a much lower correlation ($\beta = -0.08$, $p < 0.05$) when compared with the other variables. Ultimately, the results showed a negative effect on BI. This finding is consistent with research done in prior studies (Thakur & Srivastava, 2014; Chen, 2008; Liébana-Cabanillas et al., 2014; Lu et al., 2011; Shin, 2010; Yang et al., 2012) who found that users expected they would not want to use a solution that introduced risk into their environment. However, ultimately, the results showed that users are less concerned with the perceived risk of M-IoT than the other factors and are more concerned with the value that can be realized by long-term use of the systems in their environment. The lack of impact of perceived risk is noteworthy because the primary benefits of M-IoT technology emerge from increasing productivity, efficiency, and safety. If adopters are not taking risk into consideration, the very safety they seek can instead inflict harm on their patients; this, in turn, can have a direct negative impact on improving business processes, leading to financial consequences and reduced competitive advantage (Dimitrov, 2016).

Fulfillment of Research Purpose

This section describes how the findings of the current study fulfill the research purpose, which is to provide information and clarity regarding the behavioral antecedents that lead individuals to adopt M-IoT at skilled nursing organizations. This insight will inform acceptance and implementation strategies and lead to greater rates of success when implementing the technology. Similar prior research has found the independent construct of performance expectancy to be the highest contributor toward one's intention to adopt and use technology (Venkatesh et al., 2003).

The results of the current study confirmed that for M-IoT technology, a strong relationship exists between an individual's belief that using the M-IoT will be more beneficial than traditional technology/methods. Within the present study, 96 users reported that they expected to realize performance benefits from the use of M-IoT technology, and, of these, all 100% (n = 96) indicated that they intended to use the system more over the next year. Because M-IoT-based systems are crucial for improving reporting and monitoring in health care environments, communicating ways in which organizations can use the technology to improve productivity and efficiency is vital for its successful implementation (Dimitrov, 2016). The current study is in line with similar research that found that when users understand the benefits of how M-IoT technology can improve their day to day processes and functions, they are much more likely to use the technology (Dimitrov, 2016). The present study also confirms the generally accepted principle that the UTAUT model finds performance expectancy to be the primary predictor of technology acceptance (Venkatesh et al., 2003). More specifically related to M-IoT technology, the current study is in line with the findings from Dimitrov (2016), where the relative advantage resulting from the use of M-IoT technology was the most significant predictor for its adoption.

Additionally, both effort expectancy and social influence were found to be statistically significant predictors of intention to adopt M-IoT technology, although to a lesser degree than performance expectancy, while perceived risk had little to no significance on the intention to adopt M-IoT. With respect to social influence, the present research found that 60% (n = 77) of the respondents indicated that the influence of their co-workers and management is a crucial factor in helping them decide to adopt M-IoT. These findings are also consistent with prior research about the factors surrounding the adoption of M-IoT, showing that the positive acceptance of M-IoT technology is often related to aspects of culture and social influence (Kingsley, 2015).

The findings are also similar to the research put forth by Ghodeswar and Waidyanathan (2007) for technology adoption in the medical sector, which found management support and overall culture to be significant for predicting adoption and use of M-IoT. The results of the current study show that social influence is necessary for the acceptance of M-IoT, in alignment with past research. For instance, Bozan, Davey, and Parker (2015) found that social influence is an essential aspect of organizational culture and that it influences individual-level user acceptance of medical technology. This type of cultural shift toward valuing M-IoT technology at multiple levels of the organization frames social influence as an important contributor for establishing the acceptance of this technology within the decision-making process.

Additionally, regarding effort expectancy, the present study confirmed the evidence found in prior studies that a user's effort perceptions, while slightly essential for shaping intention toward adopting health information technology, are not a primary driver for adoption (Alexander, Deroche, Madsen, & Powell, 2019). The investigation confirms prior research related to medical technology implementations (Bozan et al., 2015), which note that the expectation of learning curves and the acquisition of procedural skills may influence effort expectancy differently than in other non-health-care-based environments. Traditionally, skilled nursing facilities use health information technology in a limited fashion, mainly for administration, billing, and bed control, but not for clinical care (Alvarado, Henry, & Zook, 2017). The success of the M-IoT adoption relies more on trying to use the system to improve productivity and safety for strategic outcomes than demonstrating the ease of use; however, even though effort expectancy is statistically significant, it is less significant for M-IoT implementations than other factors (Chao, 2019). Within the current study, 60% (n = 77) respondents reported that they thought it would be clear and understandable to use M-IoT devices. Additionally, 78% (n = 101) thought learning to use M-IoT devices would be easy. The data showed that the respondents did not expect the technology to be difficult to use. However, the relationship between perceptions of complexity to use the devices was weaker than the relationship between performance and intention to use.

Contribution to Business Technical Problem

The specific technical problem addressed by this study is related to the low adoption of M-IoT in skilled nursing homes in the United States. Skilled nursing homes have not been adopting IoT at the feverish pace that manufacturers initially expected (Achituv & Haiman, 2016). The results of the current study suggest that some antecedents of intention are significant considerations for the successful implementation of M-IoT technology within small to medium

U.S.-based skilled nursing organizations. This research found that the factors of PE, EE, SI, and PR are all statistically significant predictors of M-IoT intention. The three factors of PE, EE, and SI together explain 69% of the intention variance for the technology, while PR exhibited a negative relationship with intention. These results confirm the need for organizations to create unified strategies that focus not only on the technical aspects of implementing a M-IoT solution but also that consider human social behavior factors as well, which may be a crucial driver for successful adoption.

Contribution to Practitioners

This research suggests that for M-IoT acceptance with small to medium-sized skilled nursing homes, the combination of performance, effort expectations, and social influence, are significant for influencing the user's intention to accept the technology. This acceptance affirms that a combination of factors, each to a differing degree, influences the user's decision to adopt M-IoT and merits consideration during implementation strategies. Organizations can leverage this insight by helping to shape performance expectations, educating employees on the benefits of using M-IoT, and providing training and support for using the system (Cohen, Bancilhon, & Jones, 2014; Chung, 2014).

When organizations place greater emphasis on the value gained from using the system for improved decision making, efficiency, and safety and provide adequate tools for users to develop these skills, users are more likely to be aware of the technology's strategic value and form intention to adopt M-IoT (Dominguez, 2013; Elkhodr et al., 2016). The focus on value is especially true for implementations such as M-IoT, where significant effort, combined with the development of specialized skills, may be needed to use the new system. Health care based organizations can leverage this insight by helping to shape performance and efficiency expectations, safety baselines educating employees on the benefits of using M-IoT, and providing training and support for using the system (Bowles et al., 2015; Gregory & Madsen, 2018). When organizations place greater emphasis on the value gained from using the system for productivity and efficiency and provide adequate training and opportunity to users to develop these skills, users are more likely to be aware of the technology's strategic value and form beliefs that lead to intentions to adopt M-IoT (Dimitrov, 2016).

As shown in the acceptance of the alternate hypothesis H_a2, an individual's expectations of how the technology will impact their ability to perform their job successfully is the most significant driver for acceptance of the M-IoT. Along with this, the acceptance of H_a3 indicates that the employee's perception of how hard it will be for them to use the technology also impacts their intention to adopt M-IoT, although to a slightly lesser degree than performance expectancy.

The discoveries related to performance and effort expectations can both be closely tied to the impact of social influence, as evidenced by the acceptance of alternate hypothesis H_a4, since the influence of others, including co-workers and decision-makers, will impact a user's intention toward adoption. The research found that the more a user perceives strong organizational support for the use of M-IoT, the more he or she will be motivated and interested to use the technology. This finding speaks to the need for an organizational culture where the use of M-IoT technology to improve data collection, compliance, safety, and productivity is encouraged and where employees share information freely.

The additional aspect of perceived risk, however, was not a significant factor in affecting how decision-makers viewed the benefits of implementing M-IoT. However, despite this finding, 28% (n=37) of the respondents still believed using M-IoT posed a risk to the patients. This is an indication that future M-IoT design should always consider the risk to patients in this particular environment and that future designs should allow for safe practice and compliance (Bowles et al., 2015; Gregory & Madsen, 2018). Overall, the findings show that adoption strategies should support a culture where decision-makers are encouraged to combine traditional clinical approaches with data-driven approaches that allow for diverse ways of improving productivity, efficiency, safety, and compliance.

Contribution to Scholarly Research

The findings of this study are in alignment with previous research, indicating that both user-level and human behavioral factors are some of the most influential for M-IoT adoption and implementations (Bowles et al., 2015; Broughton et al., 2013). These findings corroborate earlier research on health information technology adoption, which indicates that having management support for pursuing new ways and tools to improve job functions and productivity helps foster an adoption culture where employees are empowered to use the M-IoT technology to enhance production, efficiency, compliance, and safety. This research fills a gap in the existing literature by providing quantitative analysis of the UTAUT model applied to the SME U.S.-based skilled nursing homes for M-IoT technology, a combination of population and technology that has not been well-represented in the literature to date.

Recommendations for Further Research

The current study provided insights into how users develop intentions related to M-IoT technology and what motivates users to adopt this type of technology within U.S.-based SME skilled nursing homes. Even though the research expanded the body of knowledge by focusing on this specific demographic, future studies could examine what motivates the acceptance of this technology. First, the addition of moderating factors, such as age, gender, and prior experience, may provide unique distinctions that could influence the adoption and use of M-IoT technology. Venkatesh et al. (2003) found that some moderating factors affected intention and system use behavior. Therefore, an additional investigation, including these factors, may provide additional insights.

A second suggestion for future study is the evaluation of behavioral intention in a post-implementation phase to determine how well M-IoT-based solutions are accepted over time. For example, in larger settings, Venkatesh et al. (2003) found that behavioral intention represented both an outcome and a direct determinant of usage and that, along with facilitation conditions, the behavioral intention influenced the relatively short-term utilization of technologies. Facilitation conditions, in this case, refer to the presence of various organizational and technical infrastructures that exist to support the technologies. A study of this kind applied to different types of health care organizations can make understanding the long-term effect of M-IoT on the organization possible. Lastly, a suggestion for future study is the combination of theories with human behavioral factors such as those evaluated in this study with additional theories that study technology acceptance based on factors such as trust, security, and privacy. Those two specific components represent key concerns for the successful adoption of medical IoT-based solutions (Chiuchisan et al., 2014; Featherman & Pavlou, 2003; Martins et al., 2014).

However, as the results of this research suggest, the concern for risk is not a significant factor for adoption in this specific environment. So, another suggestion for future study is to expand and explore if age, experience, or other factors make people consider M-IoT sufficiently safe and that risk in this context is not a strong determinant for adoption. With patient safety and information security becoming increasingly more of a concern, especially concerning HIPAA compliance, the expansion of acceptance factors to include security and risk may be compelling for future research.

Conclusion

As skilled nursing homes continue to seek ways to improve efficiency, cost, and safety, the need to adopt new M-IoT technology is rapidly increasing. The organizations who fail to adopt this type of technology can be put at risk of not being able to compete in the marketplace because they cannot capture operational data or maintain safety standards for their patients. Organizational leaders must understand the factors that lead to the increased adoption of M-IoT since the successful adoption and implementation of technology solutions is tied to the human factors of intention and acceptance (Venkatesh et al., 2003).

The present research summarized the findings of the investigation. In general, performance expectancy, effort expectancy, and social influence were found to be direct determinants of behavioral intention to adopt M-IoT devices within the context of small and medium-sized nursing homes. Perceived risk was found to have little to no influence on the intention to adopt M-IoT devices in this demographic. These factors imply the importance of an organizational culture that promotes the benefits of M-IoT to its decision-makers, so they have the opportunity to gain vital insights for decision-making and successfully exploit the strategic value of M-IoT technology.

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APPENDIX. UTAUT SURVEY INSTRUMENT ADAPTED WITH PERMISSION

Please read each statement carefully and select the response that best expresses your view about adopting new medical technology in your work environment.

Definition of the Medical Internet of Things (M-IoT)

The Internet of things (IoT) refers to any physical device which can be connected to the internet but is not used to directly access the web like smartphones or computers are. IoT-enabled medical devices link sensors together via wireless communication to collect medical information through health-care IT systems and online computer networks.

Examples of M-IoT Devices or Systems

Remote patient-monitoring systems

Internet-connected systems used to track patient activity and movement

Internet-connected medication-dispensing systems

Infusion pumps that connect to data-analytics dashboards

Smart beds rigged with sensors that measure patients' vitals (blood pressure, pulse, and breath rate)

Smart glucometers (wireless)

IoT-based environmental-monitoring systems, such as security cameras and fall detection systems.

PART 1

1. Select your gender:

   [ ] Man [ ] Woman

2. Select the category that includes your age:

   [ ] 18–20 [ ] 21–29

   [ ] 30–39 [ ] 40–49

   [ ] 50–59 [ ] 60 or older

3. Select your highest level of education:

   [ ] High school [ ] Associate's degree

   [ ] Bachelor's degree [ ] Master's degree

   [ ] Doctorate

4. Select the category that includes your years of experience using, recommending, approving, installing, and consuming M-IoT devices:

   [ ] Less than 1 year [ ] 1–2 years

   [ ] 3–4 years [ ] Over 5 years

5. Select the approximate number of patients in your nursing home:

   [ ] 50 [ ] 50–75

   [ ] 75–100 [ ] 100–125

   [ ] 100–200 [ ] 200–300

   [ ] 300–500 [ ] Over 500