Factor Analysis of Implantable Medical Device Adoption for Efficient Healthcare Management in the United States

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Approval Page

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Abstract

On the heels of the COVID-19 pandemic, discussions within healthcare institutions and the public at large concerning the inefficiencies pertaining to health management in the United States have heightened. Innovative technologies for efficient health management include implantable medical devices, yet their adoption rates remain low. The purpose of this quantitative, nonexperimental correlational study was to examine whether U.S. patients' perceptions of device performance expectancy, perceived credibility, facilitating conditions, attitudes, and social influence, determine their behavioral intent to use an implant in a voluntary setting. An extended unified theory of acceptance and use of technology model constituted the theoretical research framework. A sample of 363 randomly selected Facebook IMD Support Group members residing within the United States was anonymously surveyed, after which 246 entirely completed responses were considered satisfactory for data analysis. Exploratory factor analysis was initially conducted using the Statistical Package for the Social Sciences version 28 software followed by confirmatory factor analysis in the analysis of moment structures software version 26, to ascertain the significant factors and the validity and reliability of the measurement model. The structural model was subsequently investigated using the covariance-based structural equation modeling and path analysis techniques within AMOS. Model-fit statistics of, $\chi 2/df = 1.438$, $p < .001$; CFI = .965; IFI = 0.966; RMSEA = 0.042; TLI = 0.949; NFI = 0.90; RMSR = 0.077; GFI = 0.922; PRatio = 0.696; PCFI = 0.671; PNFI = 0.623; RFI = 0.849, suggested the model was well suited to the data. The research findings suggested that perceived credibility, performance expectancy, and social influence were the significant prognosticators that positively predicted the behavioral intent to use an implantable medical device. Utilizing multiple linear regression analysis, the partial mediating effect of perceived credibility on performance expectancy was also established as positive.

These findings will assist healthcare policymakers, device manufacturers, and medical doctors take well-informed decisions which will inure to the benefit of U.S. patients. Recommended for future research is the examination of the extent to which U.S. patients’ attitudes toward implantable medical device adoption is mediated by facilitating conditions.

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Chapter 1: Introduction

In the United States, inefficiency within the healthcare delivery system continues to be problematic. The inefficiency within the U.S. healthcare system has become a source of concern for healthcare institutions, the U.S. government, and the U.S. public at large (Himmelstein & Woolhandler, 2020; Ratna, 2020; Speer et al., 2020; Wu, 2020). The inefficiencies are partly derived from the United States spending more on healthcare as a share of the economy, precisely 17.7% of its gross domestic product (GDP). The 17.7% of GDP is more than twice as much as the average organization for economic cooperation and development (OECD) country, 8.7% of GDP, yet has the lowest life expectancy among the 11 member-nations (OECD, 2020). This trend reflects a relatively low life expectancy along with higher COVID-19 mortality rates and a generally weak economic outlook.

More recently, during the COVID-19 pandemic, some of the inefficiencies could be observed in the management of healthcare facilities in forms such as low physician-to-patient ratios, lapses in emergency room admission protocols, overwhelmed healthcare facilities, inefficiencies in the delivery of COVID-19 vaccines, among many other issues (Kemp et al., 2021; O'Reilly-Shah et al., 2020; Peters, 2020; Russo et al., 2020; Sassone et al., 2020). Some of these inefficiencies could have been reduced and tens of thousands of lives saved with the help of innovative healthcare technologies such as implantable medical devices (IMDs). Other technologies that could make the healthcare system more efficient include telemedicine, wearable personal Internet-of-Things (IoT) devices, and chatbotting for diagnosis based on patients' identified symptoms.

IMDs are implanted to treat and monitor various patients with diverse types of individual or multiple medical conditions such as heart disease, lung disease, and nervous system complications (Food and Drug Administration [FDA], 2017; Sasangohar et al., 2020; Wu, 2020). Further research must build on what is already known and what would benefit the patient as the end-user in terms of usability, safety, security, cost-effectiveness, and other parameters that may not be immediately evident. The low IMD adoption rates may as well be an aspect of a broad landscape consisting of factors such as the increasing complexity of medical devices, the business environment in which medical devices are developed, the innovation process, and the global medical device regulatory consortium (Banerjee et al., 2019; O'Reilly-Shah et al., 2020). Critical to public health is the long-term security of the devices, the safety of the patient, and general effectiveness of the devices (Rohrich et al., 2022). When treatment risks and outcomes are not guaranteed, leading to the reluctance of the patient to adopt the device(s), patient engagement with healthcare managers (physicians) may become necessary.

Previous research has suggested that patient engagement on the issues and decisions bothering IMD adoption were not encouraged by their physicians (Banerjee et al., 2019; De Larochellière et al., 2020). There is limited research on IMDs from a patient acceptance viewpoint. Gagliardi et al. (2017) investigated the factors constraining patient engagement in IMD discussions and decisions, and yet interviews were conducted with physicians instead of the patients. Speer et al. (2020) and Wu (2020) have suggested that everyday use of IMDs and especially when used in times of pandemics, will help to reduce congestion at hospitals, emergency rooms, reduce physician fatigue, and improve the well-being of many who use these devices for disease condition management. However, Alsuwaidi et al. (2020) and Longras et al. (2020) have cited security, cybersecurity, and privacy concerns with using these devices. Further, Yaqoob et al. (2019) stated that IMDs are vulnerable to cybersecurity attacks. Repeatedly, researchers have established that a proven method of establishing factors influencing individuals to adopt new technology such as e-learning technologies (Twum et al., 2022), mobile internet use (Jacob & Pattusamy, 2020), and college students reception of social networking tools (Alvi, 2021) is by making use of the unified theory of acceptance and use of technology (UTAUT) model. Similar instances where the UTAUT was used include, motivating information system engineers' acceptance of privacy by design (Bu et al., 2021), and the adoption of biometric technology (Chen et al., 2021).

Decision-makers and stakeholders may be interested in this research because IMD adoption at the hospital and patient levels have implications for health technology assessments. Therefore, this study explored the technological and behavioral factors influencing the IMD adoption decision, drawing inspiration from UTAUT, the theoretical model for my research. Five factors were explored to ascertain the most critical factors patients consider before adopting IMDs for efficient healthcare management.

This research study will help contribute to a better understanding of the factors of IMD adoption for more efficient healthcare management in U.S. healthcare facilities. The relationship between these factors influencing the choices patients make about the adoption of IMDs were the focus of this research. Implications for the study include recommendations to healthcare policymakers, healthcare information systems management policymakers, IMD security policymakers, and physicians. Recommendations will cater to user concerns of device effectiveness, device affordability, device regulation, and patient-physician relationship reasons, which may become the basis for physicians to tailor IMD choices to the needs of patients and improved regulations by regulators for improved IMD adoption rates, and efficient healthcare management, which will further translate to lower healthcare costs.

Medical implants or IMDs have been in existence for well over a decade; however, the market penetration rates have not been encouraging (Gagliardi et al., 2017; Kemp et al., 2021; Zhang et al., 2020). This phenomenon may be due to several factors that have not been explored. The proliferation of the IoT, social media, cloud technologies, machine learning technologies, 5G networks, etc. makes the healthcare landscape even more complex for the average U.S. patient as well as the entire healthcare fraternity (Sasangohar et al., 2020; Zhang et al., 2020). Distributed systems and supersonic-speed internet connections coupled with agile software application development have led to innovative interconnections of two or more implantable devices, rendering the security of the devices a cybersecurity concern for patients and the entire healthcare continuum.

The results of this study are helpful to IMD manufacturers, device regulators, and physicians when presenting to patients the necessity of an IMD. In addition, other stakeholders such as the FDA and other healthcare decision-makers will be interested in this research because IMD adoption at both the hospital and patient levels, apart from helping to save lives in emergencies, have implications for health technology assessments. With the knowledge discovered after the analysis of results, the lack of theoretical knowledge of the important IMD adoption factors will be resolved and will lead to well-informed decision-making at the various stakeholder levels. Consequently, higher IMD penetration rates may be observed, leading to positive and more efficient healthcare outcomes, which will subsequently translate to the improvement of the entire U.S. economy.

Statement of the Problem

The problem addressed in this study is that, while IMDs are primarily accessible, well over 60% of U.S. patients who could have benefitted from IMD usage are not interested in taking advantage of this life-saving technology for varied reasons (Banerjee et al., 2019; Longras et al., 2020). The causes influencing the behavioral intention to use an IMD may include patients' attitudes, social influence, facilitating conditions, perceived credibility, and performance expectancy (Loughlin et al., 2021). Zhang et al. (2020) identified that 8% to 10% of the population in the United States and 5% to 6% of people in industrialized countries have experienced an IMD for rebuilding body functions, achieving a better quality of life, or for reducing mortality rates. The above statistics suggest that IMD penetration rates are low, and further research into patient IMD adoption factors is paramount to higher usage rates (De Larochellière et al., 2020), leading to reduced fatalities in emergencies improved life expectancy, among other advantages.

The salient factors influencing IMD adoption intent are not yet known because there is a lack of knowledge of the important IMD adoption factors amongst the relevant IMD stakeholders, and the relationships between the influencing factors and the IMD adoption decision have not yet been established in the literature (Alsuwaidi et al., 2020; Maresova et al., 2020). This situation has led to device regulators, physicians, healthcare managers, and cybersecurity experts having a limited understanding of the critical factors leading to the IMD adoption decision (Easttom & Mei, 2019; Yaqoob et al., 2019). Without an improved understanding of the important factors that influence a patient's IMD adoption intent, the various stakeholders will not be able to make well-informed decisions to help improve patients' well-being and save lives in critical conditions leading to a more efficient healthcare system.

Purpose of the Study

The purpose of this quantitative, correlational study was to investigate the relationships between the key factors that may influence the U.S. patient's behavioral intent (BI) to use an

IMD. United States patients' perceptions on the key influencing factors for IMD adoption as well as the extent of the relationship between the independent variables of social influence (SI), attitude (Att), facilitating conditions (FC), perceived credibility (PC), and performance expectancy (PE), and the dependent variable of U.S. patients' behavioral intent (BI) to use an IMD was explored. This study also aimed to evaluate the extent to which the predictions of PE on BI to use an IMD will be mediated by the PC variable. The study will add to stakeholders' understanding of why patients adopt IMDs, such that improved systems for designing and implementing IMD technology can be developed sustainably to increase the prospect of IMD user acceptance. The investigation's framework made use of Yeow et al.'s (2013) extension of the UTAUT model introduced by Venkatesh et al. (2003), which includes PC, PE, FC, and SI as determinants, and expand the model by including Att as an additional determinant variable.

The research instrument (see Appendix A) items was adapted from the instruments developed by Morosan (2016), Kohnke et al. (2014), and Yeow et al. (2013). Survey distribution was via Qualtrics. Sample recruitment was conducted by group moderators posting survey recruitment flyers with survey links in the relevant Facebook support groups. The population will consist of patients over 18 years of age residing within the United States suffering from a disease condition for which a physician would recommend an IMD. Relevant Facebook support group members constituted a sample size of 246 respondents. Structural equation modeling (SEM) within the Statistical Package for the Social Sciences (SPSS) Analysis of Moment Structures (AMOS) version 26 was used in factor analyses and SEM.

Introduction to Theoretical Framework

The theoretical framework for my study is the UTAUT, introduced by Venkatesh et al. (2003). Behavioral intent has been used as a reliable determinant of technology use

(Attuquayefio & Addo, 2014; Thomas et al., 2020). Developed by Venkatesh et al. (2003), UTAUT is a well-accepted framework for technology adoption theory and hence suitable to this study and the study's construct of BI to use an IMD. This new unified theory indicates the behavioral intention to accept and use modern technology (Sundaravej, n.d.; Venkatesh et al., 2003).

The four critical constructs on which UTAUT was built consist of: (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating condition. These four unique constructs of the UTAUT have been used to understand the acceptance and the use of different technology types in varied environments. This model's usage has proven to have both satisfactory validity and reliability (Attuquayefio & Addo, 2014; Lancelot Miltgen et al., 2013). With the incorporation of the eight concepts, UTAUT offers an improved understanding of technology adoption by users. The UTAUT model has been applied in several areas to investigate issues concerning technology adoption in e-shopping (Hino, 2015), telemedicine (Kohnke et al., 2014), and the national smartcard use in Malaysia (Yeow et al., 2013). The four UTAUT constructs form part of the independent variables for this study.

Gender, age, experience with devices, and voluntariness are moderation components that interact with the four UTAUT constructs to influence the BI (Srivastava & Bhati, 2020) within the UTAUT. These moderation components of the UTAUT can be compared to the internal and demographic factors of age and education (experience) to be represented in the survey scale, which may influence behavioral intention toward IMD adoption. These constructs of the UTAUT give a reason for it to be used as a suitable framework for this study's purpose and research questions. The dependent variable of BI to use an IMD also finds applicability in the UTAUT. Since UTAUT is a consolidation of adoption theories, it has significant conceptual similarities with those theories. For instance, its SI is equivalent to the subjective norm in the TPB, performance expectancy and effort expectancy are similar to the perceived usefulness and ease of use under the TAM model (Bagozzi & University of Michigan, 2007; Morchid, 2020; Rahman et al., 2017). As a suitable framework for this study, UTAUT is a more comprehensive technology adoption model, and it intertwines with the TAM framework.

Because the purpose of this study was to provide a better understanding of U.S. patients' behavioral intention to adopt and use an IMD, the UTAUT model was applied. This study made use of Yeow et al.'s (2013) UTAUT-extension. Also, predicted was whether the PE variable would be mediated by variable PC as well as the expansion of the model to include the variable Attitude. Although attitude is not part of the constructs within the UTAUT, attitude was regarded, for the purpose of this investigation, a valuable element in the determination of the levels of approval towards IMD usage. Proposed by Yeow et al. (2013), the *anxiety* variable will not be included because stress does not emanate from the use of IMD when one voluntarily opts to use an IMD, i.e., voluntary use of technology. Venkatesh et al. (2003) stated that there is an indirect relationship between the anxiety factor and BI via effort expectancy (EE). Effort expectancy has also been sidelined from this investigation because the use of an IMD requires no added time or effort as patients carry the devices internally, and experts maintain the devices when needed.

Introduction to Research Methodology and Design

Mohajan (2020) stated that it is appropriate to apply a quantitative, non-experimental, correlational approach if the researcher is investigating constructs in their original form without manipulation, where SEM or other statistical analyses methods are used in measuring the extent to which two or more constructs are associated when there is no random allocation of subjects to groups. The quantitative methodology was suited to my research because the research aimed at establishing the extent of the relationship between constructs in their original form without manipulation as the independent and dependent variables (Moote et al., 2020). In a quantitative, correlational study, Guan et al. (2022) involved the retrospective study of real-time observations of vaulting using the RESCAN 700 system. Using quantitative magnetic resonance imaging, Saccenti et al. (2020) performed a correlation study to compare the various imaging techniques in multiple sclerosis patients. Pairwise correlations were calculated using Spearman's correlation analysis. According to Alberts et al. (2020) and Mohajan (2020), when the aim of the study is the testing and verification of theories to generalize and replicate the results in other subjects and environments, the quantitative method is more suitable.

In a similar IMD study, Madjid et al. (2019) studied the effect of high influenza activity on risk of ventricular arrhythmias (VA) requiring therapy in patients with implantable cardiac defibrillators (ICD)s and cardiac resynchronization therapy defibrillators. Significant correlation was found between the influenza activity and the incidence of VAs requiring ATP treatment. Menebo (2020) conducted a quantitative correlation study to analyze correlations between the weather and the COVID-19 pandemic in Oslo, Norway, where a non-parametric correlation test was performed during data analysis. A non-experimental, correlational, quantitative approach was the most appropriate for conducting this study because none of the independent variables (Att, PC, PE, SI, and FC) was manipulated to identify their influence on the DV, BI to use an IMD. Moreover, the study evaluated the mediation of predictability for the predictor construct of PE by the mediating construct of PC.

Data was collected using the adapted survey instruments mentioned beforehand. The research instrument items were adapted from the instruments developed by Yeow et al. (2013, see Appendix B); Kohnke et al. (2014, see Appendix C), and Morosan (2016; see Appendix D). This survey allowed for the collection of data from a large enough sample obtained from Facebook users residing in any of the 50 states within the United States and belonging to IMD support groups on Facebook. Permissions were sought through emails and Facebook Messenger to the respective administrators of the relevant IMD support groups on Facebook.

Once permission was granted from the group moderators, permission was requested by this researcher from the Northcentral University (NCU)'s Institutional Review Board (IRB) for data collection. Once IRB approval was obtained, invitations to group participants was posted together with informed consent details (see Appendix E). The survey responses were transmitted into Excel files which were subsequently loaded by this researcher into SPSS for data analysis. SEM within SPSS AMOS version 26 software was used to both access and assess the variables under consideration, as well as used in performing correlational, factor analyses, SEM, and path analysis.

Research Questions

The following six research questions emanated from the theoretical framework of the UTAUT model and the study's purpose.

RQ1

What is the degree of relationship, if any, between Attitude and U.S. patients' behavioral intent to use an IMD?

RQ2

What is the degree of relationship, if any, between performance expectancy and the U.S. patients' behavioral intent to use an IMD?

RQ3

What is the degree of relationship, if any, between facilitating conditions and U.S. patients' behavioral intent to use an IMD?

RQ4

What is the degree of relationship, if any, between social influence and U.S. patients' behavioral intent to use an IMD?

RQ5

What is the degree of relationship, if any, between perceived credibility and U.S. patients' behavioral intent to use an IMD?

RQ6

What is the degree of relationship, if any, between performance expectancy and U.S. patients' behavioral intent to use an IMD when accounting for perceived credibility?

Hypotheses

The six null and six alternative hypotheses with direct correspondence to the six Research Questions above are as follows:

$H1_0$

Attitude is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD

$H1_a$

Attitude is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD

***H2*$_0$**

Performance Expectancy is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

***H2*$_a$**

Performance Expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use IMD.

***H3*$_0$**

Facilitating conditions is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

***H3*$_a$**

Facilitating Conditions is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

***H4*$_0$**

Social Influence is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

***H4*$_a$**

Social Influence is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

***H5*$_0$**

Perceived credibility is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

$H5_a$

Perceived credibility is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

$H6_0$

Performance expectancy is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD when mediated by perceived credibility.

$H6_a$

Performance expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD when mediated by perceived credibility

Significance of the Study

This study may prove considerable significance by way of advancing knowledge in the following professional and academic areas: Management field and profession, Healthcare information systems management, advancing the UTAUT theory and IMD body of knowledge, advancing IMD implementation practice, serving as a resource for physicians, IMD manufacturers, IMD regulators, health information managers, and finally as a positive social change catalyst by promoting efficient healthcare management within U.S. healthcare institutions.

IMDs in themselves are part of information systems (IS)s which need to be managed. The device gathers information and either processes it for further action or forwards the information further for processing and a related action performed at another terminal of the IS. IMDs are particularly important when it comes to the discussion of device effectiveness due to their very nature of serving as life-saving devices or equipment (Golinelli et al., 2020; Pycroft & Aziz, 2018). In improving on the efficiency of the healthcare system, IMDs may help to reduce pressure on scarce resources such as ventilators during pandemics, may help to improve on the doctor-patient ratio, may help patients reduce doctor-visits per year and rather spend more time on the job, which will lead to improved economic growth.

Obtaining viewpoints from patients and prospective users may help inform healthcare professionals, physicians, healthcare information systems managers on what factors influence patients' IMD Adoption decisions and each factor's magnitude of influence on the BI to use an IMD. There is growing concern about the vulnerability of IMDs' security and patient safety when using these devices. As people live in the era of digital kingdoms, there is the need to reliably secure their medical devices and related information (Thomasian & Adashi, 2021; Tomaiko & Zawaneh, 2021). This study may contribute to understanding and identifying the dynamics that influence IMD Adoption intent.

Definitions of Key Terms

In this section, specific acronyms and terms were defined to include their operational significance. This list of terminologies will provide readers scholarly clarity and understanding of the definitions.

Affordability

Affordability means having the financial means for acquiring the device (Wirth & Grimes, 2020).

Attitude

Attitude is an individual's posture of disapproval or approval towards a technology such as IMD (Seyal & Turner, 2013).

Efficiency

It describes the relationship between the inputs and outputs of a product, e.g., the engine; an organ, e.g., the heart; or an industry such as the healthcare industry (Papanicolas et al., 2018).

Efficient Disease Condition Management

It is the ability to control a condition within the body which constitutes a challenge to the human health with the best possible means and with least resources (Briggs et al., 2020). The aim of disease condition management is to prevent or delay health complications, making it more economical than when disease conditions worsen (Peters, 2020).

Healthcare Efficiency

The comparison of delivery-system outputs, such as health outcomes, relative value units, and physician visits, with delivery-system inputs such as materials, time, and costs. It is often reported as a ratio of the outputs to inputs. The latency times and delay times between when a care order is placed and when the care order is fulfilled with accomplishments stated in relation to the estimated effort (Papanicolas et al., 2018).

Implantable Medical Device

Any article or healthcare product intended for use in the diagnosis of disease or other condition, or for use in the care, treatment, or prevention of disease, which does not achieve any of its primary intended purposes by chemical action or by being metabolized (Wang et al., 2021a). Examples of IMDs include electrodes, pacemakers, implantable arrhythmia devices (IADs), and implantable cardiac devices (ICDs), and catheters.

Patient-Health Manager Relationship

The relationship between the physician or medical doctor acting as the manager of the patient’s healthcare needs. All the interactions between a patient and a health care professional help to establish the basis for interpersonal communication, trust, compliance, and satisfaction (Barello et al., 2020).

Regulation

The act of adjusting or state of being adjusted to a certain standard (Food and Drug Administration, 2017).

Technology-Education Understanding

Understanding the knowledge related to IMD technology (Moote et al., 2020).

Summary

The United States spends more than other countries without obtaining better health outcomes (Speer et al., 2020), and this is troubling. Current observations have raised some concerns with respect to the ballooning costs of healthcare, imbalance of medical resources, inefficient healthcare-system administration, and inconvenient medical experiences (Papanicolas et al., 2018). Nevertheless, bleeding-edge technologies including but not limited to, Artificial Intelligence, Cloud Computing, Machine Learning, Deep Learning, Big Data, IoT, and 5G wireless transmission technology are developed by the hour to meet these challenges and thereby improve patients' experiences (Tran et al., 2021; Xu et al., 2021). These technologies, including IMDs, will inevitably improve healthcare service quality while reducing healthcare costs for the United States. However, refusal to adopt and make use of IMDs is identified as a failing factor in IMD technology implementation.

The many benefits IMDs present to society have not been reciprocated with sufficient and effective security and safety implementations to prevent the possible dangers that attacks and unintentional manipulations on the devices may cause the patient (Wang et al., 2021a; Welch et al., 2020). From the literature, there is evidence for the need to significantly improve on the effectiveness of IMD security and consequently on the safety and general wellbeing of the patient (Pycroft & Aziz, 2018; Sabogal-Alfaro et al., 2021). The research problem is currently, there is a lack of understanding of the factors that influence IMD Adoption decisions, and the relationships between these factors have not yet been established, leading to the societal problem of inefficiencies within the U.S. healthcare system.

A general overview of the topic establishing the study's context, the relevance of the topic, past research on the topic, theoretical importance of the topic, the growing importance of IMD technology for efficient healthcare management, the lack of understanding of the factors of IMD Adoption intent, were discussed within the introduction of this study. The problem of the key factors of IMD adoption not yet identified, and the magnitude of effect of the key factors on the BI to use an IMD not yet investigated were also discussed. The purpose of the study was included after the problem statement. The significances of the study were explained. Other inclusions within the chapter were the theoretical framework within which the study was based as well as the operational definition of key terms and acronyms. The research questions that guided this study were examined and stated. The proposed research methodology and research design were also discussed. Appropriateness of design and methodology to the study problem, purpose, and research questions were considered.

In Chapter 2, literature from peer-reviewed journal articles, doctoral dissertations, technical publications, seminal works, white papers, and previous studies on BI towards IMD technology and its adoption were reviewed. The possible underlying factors that affect IMD adoption intent were explained. The theoretical framework for this study, UTAUT, was discussed into detail. Application of UTAUT in similar and recent research were discussed.

Alternative and divergent theories will also be discussed, and justification provided for the selected theoretical framework.

Chapter 2: Literature Review

The purpose of this quantitative, correlational study was to investigate key factors that contribute to the patient's BI to use an IMD, and to investigate each factor's magnitude of influence on the BI to use an IMD. There is a lack of understanding of key factors influencing the adoption of IMD technology for efficient healthcare management amongst the relevant stakeholders. This problem not only distorts patients' IMD adoption decisions but also denies the healthcare sector a great tool for efficiently managing patients' health (Breese & Zwerling, 2020).

This study is valuable because research results and interpretations may assist in offering recommendations that may be useful for physicians, regulators, cybersecurity experts, and health information managers. IMD recalls do not account for all incidents of IMD failure, and some errors are not brought to the attention of the proper authorities. The implementation of an effective IMD system is crucial for effectively controlling disease conditions and for efficient healthcare information management (Liu et al., 2018). With an improved understanding of the critical factors, manufacturers, healthcare information managers, regulators, and physicians would benefit from understanding patient choices and making more informed decisions.

This chapter presents a review of the literature from peer-reviewed journal articles, doctoral dissertations, technical publications, white papers, and previous studies on behavioral intent towards IMD adoption and usage. Significant sections of the chapter include the literature search strategy and the theoretical framework, UTAUT, on which the study was grounded. A review of the literature on IMD adoption factors of attitudes, performance expectancy, social influence, perceived credibility, and facilitating conditions were conducted. Other points of interest include IMD security and safety issues, medical device regulations and IMD, and patient perceptions of IMD. This chapter also discussed demographic or human factors and how they impact the IMD decision-making process.

This literature review aimed at searching and obtaining information related to this study to offer a critical appraisal of the existing literature (Haddaway et al., 2020; Paul & Criado, 2020). The full-texts on IMD technology and its effectiveness, regulations guiding the use of medical devices, technology-education understanding, and patient-health manager relationship, were reviewed into detail. Other important topics reviewed included IMD security, IMD safety, IMD usability, IMD cybersecurity, and IMD affordability.

Important theories such as the technology acceptance model (TAM), UTAUT, constructs within the UTAUT, behavioral intents, demographic and human factors, and other pertinent scholarly literature were obtained from ProQuest databases through the NCU Library, the University of Maryland's Digital Repository, University of California, Berkeley Digital Library, and the Stanford University Library. The library resources provided database searches across Science Direct, SpringerLink, ProQuest, NCU dissertations hosted by ProQuest, IEEE Xplore, Elsevier, and the American Computing Machines Digital Library.

Critical search terms included *healthcare information systems management, implantable medical devices, information technology design, medical device design, healthcare choices, demographic factors, internal factors, age, education, wealth, health, job, customer features, IMD usability, cost-effectiveness of IMD implementations, the business aspects of IMDs, efficient disease condition management, IMD management, IMD as an information system, IMD security, IMD designs.* Other important terms researched included, *technology acceptance model, theory of planned behavior, UTAUT, theories on IMDs, benefits of IMDS, the future of IMDs, history of IMDs, IMD recalls, IMD research, IMD adoption, economic advantage and importance of*

IMD's, IMDs as information systems, securing medical device information, medical information system, managing medical information, attitudes towards IMDs, patient safety, patient-physician relationship, technology-education understanding, IMD affordability, and IMD regulations. The AND/OR Boolean operators were used in implementing combinations of the search terms to provide more refined and relevant search results.

Other sources included recent peer-reviewed professional journal articles, information technology, information management peer-reviewed publications, business management, and healthcare publications, business, and management reports, white papers, magazine publications, seminal works, and other academic databases. Keywords, phrases, and titles were used to search appropriate texts. Google Scholar, information management and healthcare management textbooks, and mostly peer-reviewed journal articles within 5 years of publication of this dissertation (2018–2022) were also used in compiling the literature review.

Theoretical Framework

This section outlines the theoretical foundation on which the study was grounded. A theory is a systematic explanation of an event in which constructs, and concepts are identified, relationships are proposed, or predictions are made (Post et al., 2020; Ryan & Deci, 2020). Theory may be descriptive, prescriptive, or predictive, and inductive theory is directed towards bringing knowledge into view. Just as the literature survey sets the stage for the theoretical framework, a good theoretical framework, in turn, provides the logical base for developing testable hypotheses.

There are several developed applied technology adoption models used in technology and innovative systems research for the evaluation and measurement of user acceptance of newer systems, in addition to their behavioral intent to make use of the technologies or innovations

(Chang & Lee, 2020; Kaur & Arora, 2020; Racero et al., 2020). These adoption models include diffusion of innovations (DOI) (Rogers, 2003), theory of planned behavior (TPB) (Ajzen, 1991), TAM (Davis, 1989), technology-organization-environment (TOE) (Tomatzky & Fleischer, 1990), theory of reasoned action (TRA) (Hill et al., 1977), and UTAUT (Venkatesh et al., 2003). TRA, TAM, TPB, DOI, and UTAUT are applicable towards individual acceptance levels, such as patients.

Complementary Theoretical Frameworks

The UTAUT was the chosen model for this study. However, several other models were studied to ascertain which model would best fit this research study. Several complementary frameworks are discussed in this section to include the TAM, Diffusion of Innovations, and the general systems theory.

UTAUT. The theoretical foundation of this study was based on the UTAUT. Developed by Venkatesh et al. (2003), UTAUT is a well-accepted framework for technology adoption theory (Lolic et al., 2021; Philippi et al., 2021; Srivastava et al., 2021; Zainab et al., 2018). UTAUT is a combination of eight innovation adoption theories to include TRA (Hill et al., 1977), TAM (Davis, 1989), TPB (Ajzen, 1991), DOI (Rogers, 2003), motivational model (MM) (Davis et al., 1992) combined TAM and TPB (C-TAM-TPB), model of personal computer utilization (MPCU) (Thompson et al., 1991) and social cognitive theory (SCT) (see Appendix F). This new unified theory indicates the behavioral intention to accept and use modern technology (Sundaravej, n.d.; Venkatesh et al., 2003). The four critical constructs on which UTAUT was built consist of: (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) perceived credibility, and (e) facilitating conditions.

Development of the UTAUT framework. Applying longitudinal research investigations, Venkatesh et al.'s (2003) steered a comparison, and a conceptual study of the similitude of factors acknowledged in each of the unified theories that impact BI and the use of technologies that build the UTAUT framework. Venkatesh et al.'s (2003) studies were performed in four different businesses with workers in both non-compulsory and compulsory environments to forecast the workers' BI to adopt technologies. Because SCT offers considerable insights into the causes of a person's adoption of characteristic behaviors, SCT was integrated into the UTAUT model (Bandura, 2002, p. 96).

In their investigations, Venkatesh et al. (2003) discovered that the most influential constructs from the integrated theories were *effort expectancy, performance expectancy, facilitating conditions, and social influence*. Venkatesh et al. (2003) also identified *voluntariness, experience, age, and gender* as the most significant determinants impacting the BI to adopt technologies. Furthermore, Venkatesh et al.'s (2003) model accounted for 80% of the variance in BI to use technology. With the institution of the UTAUT model, several scholars have demonstrated the model's validity in predicting BI in different settings across various technologies (Khechine et al., 2014; Lolic et al., 2021; Philippi et al., 2021; Srivastava et al., 2021; Zainab et al., 2018). Moreover, many researchers argued that UTAUT provides a robust theoretical base for the exploration of utilization and user technology adoption (Alvi, 2021; Bu et al., 2021; Chen et al., 2022).

Similar Studies Using UTAUT. Studies on the adoption and usage of IT have notable and numerous forms of UTAUT to fit diverse technological settings (Attuquayefio & Addo, 2014; Khechine et al., 2020; Lolic et al., 2021; Patil et al., 2020; Petersen et al., 2020; Philippi et al., 2021; Purwanto & Loisa, 2020; Wei et al., 2021). Some scholars have asserted that UTAUT, although is extensively validated, requires expansion to provide a more thorough understanding of IT acceptance. Attuquayefio and Addo (2014), in a systematic analysis, scrutinized 20 research studies making use of UTAUT or extensions of the UTAUT model to elucidate technology adoption. Attuquayefio and Addo (2014) found that the factors of IT acceptance or IT use often differed across technologies, countries, and settings.

Yet another analysis of 173 research studies using the UTAUT framework discovered that BI and PE remained important determinants of technology acceptance (Williams et al., 2015). Additionally, Williams et al. (2015) observed that most of the UTAUT investigations laid emphasis on technology acceptance within the context of online learning, online banking, electronic government, and electronic commerce. Williams et al. (2015) recommended further examination of the model using more variables across various innovations and contexts to identify more influencing factors which could become significant prognosticators of technology use and acceptance.

Due to its potential to improve precision management of chronic conditions such as atrial fibrillation (AF), Patient-generated health data (PGHD) collected digitally with mobile health (mHealth) technology has garnered recent excitement. In a mHealth technology study, Reading et al. (2018) investigated individual patient differences in sustained engagement among individuals with a history of atrial fibrillation (AF) who are self-monitoring using mHealth technology. An adapted UTAUT guided both data collection and analysis through directed content analysis. According to Reading et al. (2018), apart from discovering differences between engaged and unengaged patients within each predictor in the adapted UTAUT (FC, PU, and perceived ease of use), four extra factors were recognized as being directly related to sustained engagement in the sample population. The additionally discovered factors included feedback and guidance, supportive environments, relationship with healthcare provider, and internal motivation to manage health. The adapted UTAUT model was helpful in comprehending the parameters of sustained engagement.

Liu et al. (2018) investigated caregivers as a proxy for responses of dementia clients in a Global Position System (GPS) technology acceptance study. The study was designed to determine the extent to which caregivers could be used in providing proxy responses for dementia clients. The objective of this study on the acceptance of GPS technology was to examine the extent to which caregivers can be used to provide proxy responses for dementia clients. Liu et al. (2018) applied the UTAUT framework in creating two questionnaires. The one was for the demented clients and the other for caregivers serving as proxies. Four out of six UTAUT constructs, PE, SI, BI to use, and Actual Use, were statistically significant and correlated. From the results, Liu et al. (2018) discovered that caregivers could respond on behalf of demented clients on technology acceptance questionnaires.

Patil et al. (2020) adapted a meta-UTAUT model with individual difference variable attitude as the principal construct and extended the model with consumer-related constructs such as grievance redressal, trust, anxiety, and personal innovativeness. An empirical examination of the model among 491 Indian consumers revealed grievance redressal, behavioral intention to use, and performance expectancy as significant positive predictors of consumer-use behavior towards mobile payment (Patil et al., 2020). Moreover, BI to use was significantly influenced by FC, SI, and attitude. The major contribution of this study includes re-supporting the pivotal role of attitude in consumer adoption studies and examining usage behavior in contrast to most existing studies, which examine only BI.

Khechine et al. (2014) investigated undergraduate IT students that were registered in a class at a Canadian university to ascertain the important factors that influence their decision to implement a web conferencing system. The results of Khechine et al. (2014) supported the assumptions of Venkatesh et al. (2003) that FC, PE, and SI had an impact on the BI towards the system. Khechine et al. (2014) also demonstrated that the effects of FC and PE were moderated by the age factor. However, there was no interaction with gender or core determinants. Khechine et al. (2014) suggested that the variance explained by their framework with mediators increased to nearly 72% when compared to examinations of UTAUT without moderating factors which produced an approximation of 50%.

In another study, Magsamen-Conrad et al. (2015) used Venkatesh et al.'s (2003) UTAUT framework for the exploration of tablet-computer acceptance among individuals of different genders and ages. Magsamen-Conrad et al. (2015) reported that the FC and EE constructs had a tremendous impact on individuals' BI to use tablet computers. It was also found that age differences moderated the effects of FC and EE. Nevertheless, Magsamen-Conrad et al. (2015) discovered minimum support for the effects of SI and PE on BI and that no interactions were found with gender or core variables on BI. Furthermore, in Magsamen-Conrad et al. (2015), the FC and EE factors were only able to explain 24% of the variance in BI to use tablet computers when the mediating effects of experience, age, and gender were included. Though the variance reported in Magsamen-Conrad et al. (2015) study was lower than the variance for Venkatesh et al. (2003) UTAUT framework, Magsamen-Conrad et al. (2015) advocated that Venkatesh et al.'s (2003) UTAUT model provided a rather robust foundation for the examination of novel technology acceptance within and across age groups.

Weng et al. (2012) conducted an empirical study, in the city of Kaohsiung, amongst metro riders using Venkatesh et al.'s (2003) UTAUT for the examination of the determinants of Taiwanese's adoption and usage of a public-transportation smartcard known as the I-Pass. In their findings, Weng et al. (2012) supported the relevance of the effect of SI and EE on BI. Weng et al. (2012) further demonstrated that BI and FC played an essential role in the determination of I-Pass utilization. Weng et al. (2012) also confirmed that UTAUT constructs' effects were moderated by age, gender, voluntariness, and experience. Yet, PE was not determined as an important factor on transport users' BI to use the I-Pass (Weng et al., 2012). Weng et al. (2012) discovered fascinating factors: performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and use behavior, relating to travelers' expectations of smartcard technology in transportation systems and offered recommendations for effective implementation of transport mechanisms with smartcard ticketing.

Other scholars have also applied the UTAUT framework towards the examination of various issues accompanying technology adoption in biometric technology in consumer's purchase intention (Chen et al., 2021), college students reception of social networking tools (Alvi, 2021), motivating information system engineers' acceptance of privacy by design in China (Bu et al., 2021), e-shopping (Hino, 2015), healthcare telemedicine equipment (Kohnke et al., 2014), and the use of an innovative national identity card (SNIC) in Malaysia (Yeow et al., 2013). Twum et al. (2022) also used the UTAUT framework, personal innovativeness, and perceived financial cost to examine students' intention to use e-learning. Because UTAUT has been legitimized across a variety of innovations (Attuquayefio & Addo, 2014; Hino, 2015; Khan et al., 2022; Kim & Lee, 2020; Purwanto & Loisa, 2020; Wan et al., 2020; Yeow et al., 2013), and the model has also been recommended as a solid approach to understanding user technology adoption (Agyei & Razi, 2022; Alghazi et al., 2021; Al-Saedi et al., 2020; Khechine et al., 2020; Patil et al., 2020; Petersen et al., 2020; Wei et al., 2021), this theoretical framework can be envisaged as a reasonable method for exploring the U.S. public's BI to use an IMD.

UTAUT in Relation to this Study. In the context of this study, the constructs of UTAUT found use for the research questions on the proposed critical factors of IMD adoption and relationships between the constructs of performance expectancy, perceived credibility, social influence, and facilitating conditions. Device users expect that their devices will perform effectively, thereby increasing their use of the devices (Breese & Zwerling, 2020; Cristina et al., 2021; FDA, 2017; Liu et al., 2018; Luštrek et al., 2021). Facilitating condition in UTAUT refers to enablement or enabling condition (Abbad, 2021; Himang et al., 2020; Jena, 2022). The attributes of facilitation embedded in IMD affordability, regulation, and patient-health manager relationship make the three possible factors relate to UTAUTs construct of FC. Performance expectancy is also akin to the expectancy of the device's effectiveness. The effort is the expense and, when it is low, meets the cost-effectiveness expectation of patients (Pycroft & Aziz, 2018). Less effort in using the device means less cost, making it relate to P. E. construct in this study. The four constructs of the UTAUT framework are a part of the five assumed factors to be studied in this research.

Gender, age, experience with devices, wealth level, educational level, and voluntariness are moderation components that interact with the four constructs to influence the behavioral intention (Alvi, 2021; Chen et al., 2021; Srivastava & Bhati, 2020) within the UTAUT. These moderation components of the UTAUT can be compared to the internal and demographic factors of age, education (experience), and wealth (decidability or voluntariness) represented in the scale, which may influence behavioral intention toward IMD adoption. These constructs of the

UTAUT give a reason for it to be used as a suitable framework for this study. The dependent variable of BI to use an IMD also finds applicability in the UTAUT (Chen et al., 2022; Khan et al., 2022; Kim & Lee, 2020; Wan et al., 2020). Since UTAUT is a consolidation of adoption theories, it has significant conceptual similarities with the other theories. For instance, its social influence is equivalent to the subjective norm in the TPB. Performance expectancy and effort expectancy are similar to the perceived usefulness and ease of use under the TAM model (Al-Saedi et al., 2020; Bagozzi & University of Michigan, 2007; Patil et al., 2020; Twum et al., 2022). UTAUT, as a suitable framework for this study, is a more comprehensive technology adoption model and intertwines with the TAM framework.

Technology Acceptance Model. Developed by Davis in 1986 (Venkatesh & Davis, 2000), TAM was derived from the TRA of Ajzen and Fishbein (Davis, 1989). TRA explained that human behavior consists of two factors, namely, attitudes toward behavior and subjective norms (Davis, 1989). These two factors affect behavioral intentions. TRA further posits that behaviors subsequently inform human actions (Buabeng-Andoh & Baah, 2020; Wahid, 2007). Human action in this study relates to IMD Adoption decisions, and behaviors relate to the perceptions and attitudes of patients. TAM is often used in conjunction with TRA. TAM explains and predicts technology-user behavior (Buabeng-Andoh & Baah, 2020; Gupta & Sahu, 2020; Wang & Khan, 2021). TAM consists of three influential factors of, perceived usefulness, ease of use, and attitude toward using, all affecting the perception of an individual, which in turn, is influential to the behavioral intention to accept innovative technology (Ahnan, 2021; Ammenwerth, 2019; Mariani et al., 2021; Setiawan et al., 2021). Researchers have widely used this theory in various technology adoption studies and demonstrated that it is a valid and reliable theory to provide a reasonable prediction on user acceptance for innovative technology deployment (Ahnan, 2021; Setiawan et al., 2021).

TAM Development. TAM was developed by Davis in 1986 (Venkatesh & Davis, 2000). Several researchers such as Nadlifatin et al. (2020), Talantis et al. (2020), Kamal et al. (2020), and Rafique et al. (2020) have used the theory in several Information Technology (IT) research. TAM is an essential theoretical contribution toward understanding technology acceptance and usage (Tovar-Rivera, 2019; Wang & Khan, 2021). The relationship is such that the more widely accepted the technology, the greater the use of the technology, for example, IMD technology in this study.

Key constructs (components) of TAM are perceived usability and perceived usefulness (Ammenwerth, 2019; Assaker, 2020) which are two significant factors that will lead to IMD adoption and intent to use. TAM further predicts that external variables such as system design characteristics, to include security, usability, and safety features, may impact the use of modern technologies (Tovar-Rivera, 2019; Wahid, 2007). TAM framework has been used in studies similar to this study to include Ahmad et al. (2020), Nadlifatin et al. (2020), and Talantis et al. (2020); however, the constructs perceived usability, and perceived usefulness were investigated as part of the significant factors enabling the acceptance and adoption of technology.

TAM, which was derived from TRA, has proven a robust and very well accepted framework for how it can be used in explaining and forecasting the public's IT acceptance (Camilleri & Falzon, 2021; Rafique et al., 2020). The premiere version of TAM postulated that individual user's actual usage and BI to use a specific system are explainable by ease of use of the system, user's perceptions of usefulness, and finally user's attitude towards the system (Davis et al., 1989). The *perceived usefulness* factor is based on the perception that the society tends to reject or accept a system's use to the extent they expect the innovative technology to help them improve their performance (Davis et al., 1989).

According to Davis et al. (1989), the "perceived ease of use" construct has the societal viewpoint that the use of an innovative system will be less complicated. Davis et al. (1989) further explained that perceived usefulness and perceived ease of use function as the foundation for individual attitudes regarding technology use, which, in turn, influences their behavioral intention of technology usage and triggers actual use. In addition, Davis et al. (1989) indicated that external determinants intercede indirectly by influencing perceived usefulness and perceived ease of use. A current literature review of over 70 scholarly articles referencing TAM illustrated several extensions of this model, fitting different technological settings. The review also suggested that notions of TAM have been previously supported by various investigations, which highlighted TAM's immense applicability to several IT systems (Camilleri & Falzon, 2021; Vanduhe et al., 2020).

Variations of TAM have led to important extensions of the model. In one instance, Taylor and Todd (1995) incorporated perceived behavioral control and subjective norms factors from the TPB model in TAM, and further developed a disintegrated TPB. With the combination of TPB and TAM constructs Taylor and Todd (1995) revealed that, the BI factor was an important predictor of the actual technology usage for individuals with prior understanding of the system. For first time system users, the perceived ease of use and perceived usefulness factors were discovered to be robust determinants in the prediction of the BI to use the system (Taylor & Todd, 1995). Furthermore, Taylor and Todd's (1995) discoveries showed that, perceived behavioral control factor influenced the BI factor for individuals who had previous experience, more than the perceived usefulness factor did influence.

In enhancing TAM's predictive strength, Venkatesh and Davis (2000) added more constructs to TAM to develop TAM2, a successful extension of TAM (Rafique et al., 2020). Venkatesh and Davis (2000) demonstrated job relevance, image, and subjective norms, were combined into TAM, and assessed as plausible determinants of perceived usefulness. The moderating effect of voluntariness and the experience factors, have a moderating effect on subjective norms and this aspect was also evaluated (Venkatesh & Davis, 2000).

In TAM-2, Venkatesh and Davis (2000) postulated that the image construct was based on an individual's yearning to maintain a positive standing with others. The extent to which the system was appropriate, was indicated by the job relevance construct, and the degree to which the system satisfactorily operated according to its specifications, was denoted by the output quality (Marangunić & Granić, 2015). In the end, the result demonstrated how evident the system functionality was to users in addition to the numerous advantages (Marangunić & Granić, 2015). Venkatesh and Davis (2000) studied TAM2 in both non-compulsory and compulsory settings and the results offered empirical evidence to support TAM2 assumptions. Venkatesh and Davis' (2000) findings were in tandem with the initial TAM assumptions that the BI to use a system was substantially associated with the perceived ease of use and perceived usefulness factors.

To improve on efficiency in the U.S. healthcare system, the following methods have been suggested to include reduction of administrative costs, care coordination, access increment, variations in provider practices, increasing quality, cost sharing, simplifying information, and increasing information (Himmelstein & Woolhandler, 2020; Ratna, 2020; Speer et al., 2020; Wu, 2020). The research questions and hypotheses in this study, on facilitating conditions corresponded to TAM's construct of PEOU, and performance expectancy (PE) in this research, corresponds to perceived usefulness (PU) construct within the TAM framework. Finally, the Att construct in UTAUT finds traction in the TAM construct of attitudes towards technology acceptance. TAM was not chosen because unlike UTAUT which has four factors relied on for this research, TAM has only three constructs and therefore would not be comprehensive enough to resolve the research questions and fulfil the purpose of the study.

Examples of Studies Using TAM. In their research and use of the TAM framework, Rafique et al. (2020) stated that attitudes toward adoption depict prospective adopters' negative or positive orientation about adopting a recent technology. Other factors such as perceived ease of adoption and a user's apprehensiveness (Assaker, 2020; Rafique et al., 2020; Tovar-Rivera, 2019) also influenced users' attitudes and behavior toward adoption. Perception is therefore relevant not only when introducing a medical product into the market but also when convincing the patient to make use of the device.

In another study, Reynolds (2020) employed the Technology Acceptance Model 2 (TAM 2) in testing relationships between technology acceptance and the variables impacting surgeon behavior. The research further examined the adoption of 3D-printed implants, used for surgery, by spine-surgeons. The research results were suggestive of the fact that output quality, job relevance, and subjective norms, represent predictors of a positive intent to use technology. The results also point to a positive influence on technology adoption. The results also pointed to economic hospital factors and environmental factors having a moderating effect on the relationship between 3D-printed implant adoption and intention to use. Reynolds (2020) contributed to research by way of extending the TAM2 framework to include clinical adoption while testing for additional factors yet unknown. The findings also offered practitioners with valuable insights for creating marketing campaigns for addressing behavior variables influencing surgeon adoption of technology.

Theory of Reasoned Action. Hill et al. (1977) in the TRA stated that an individual's rejection or acceptance of a given system is determined by the individual's attitudes (Atts) in addition to the subjective norms to perform the desired act. Hill et al. (1977) further asserted that a particular attitude is made up of the assessment of a belief and the power of the belief. The assessment of the belief is the degree to which a behavior is desirably or undesirably appraised, whilst the power of the belief, denotes the intensity of an individual's convictions (Ellis & Helaire, 2021; Ng, 2020; Schillings et al., 2021).

In the same vein, subjective norms comprise of two elements, namely, *motivation to comply* and *normative belief* (Kim et al., 2020b; Ng, 2020). Motivation to comply denotes the significance of an individual acting in accordance with expected behavior (Ellis & Helaire, 2021; Schillings et al., 2021), and normative belief denotes the belief an individual has, of how society expects them to behave. TRA has been applied severally in research related behavioral intention in varied settings (Copeland & Zhao, 2020; Kim et al., 2020b; Lin et al., 2020; Mishra et al., 2014; Xiao, 2020). Mishra et al. (2014) utilized TRA in exploring Information Technology (IT) experts' aspirations of undertaking green IT and found out that *Attitude and subjective norms* played a role in their intent to use and in actual utilization of green IT.

Irrespective of the significance of the TRA model in diverse applications, Ahmed et al. (2007) recognized some setbacks, for instance, the peril of combining subjective norms and Att, because Att could regularly be reconsidered as subjective norms and vice versa. There is also an assumption that human conduct evaluated using TRA is voluntary, and this is also considered a setback. However, involuntary behaviors and constraints on the environment could tamper with free will decisions. Ahmed et al. (2007) stated that, in the quest to manage the shortcomings of TRA, whilst enhancing TRA's predictive strength, Ajzen (1991) established the TPB, which added the perceived behavioral control factor to the TRA model. The TPB serves as an additional determinant of BI. Ajzen (1991) stated that perceived behavioral control has to do with the perceived effortlessness or the complexity of conduct implementation.

The general idea is that, with perceived behavioral control, the perceptions of the existence of elements for control, such as, the external environment, self-efficacy, and knowledge, either impede or enable the society to continue with the behavior of interest (Seyal & Turner, 2013). Some researchers such as Morchid (2020) and Mainardes et al. (2020) have argued that the TPB does present the same limitations as the TRA, with the assumption that an individual's behavior is voluntary and solely based on reasoning and ignores the involuntary behaviors and unconscious reasons which could restrict actions taken out of the free will. On the contrary, other researchers demonstrated that the TPB can explain associations between variables whilst revealing some factors which could influence system-use approvals (Copeland & Zhao, 2020; Sawang et al., 2014; Seyal & Turner, 2013; Xiao, 2020).

As an example, Sawang et al. (2014) conducted a survey of 132 students at a specific Chinese college, where it was discovered that the subjective norms and Att factors impacted Chinese undergraduate students' intent to adopt electronic learning systems. Concurrently, Sawang et al.'s (2014) investigation concluded that the predictions of the "Attitude" variable toward e-learning were statistically mediated by the "subjective norms" factor. In addition, the forecast of BI was statistically mediated by the variable, perceived behavioral control. Seyal and Turner (2013) discovered that the "Attitude" factor was positively correlated with behavioral intention to use biometric technology. The subjective norms factor determined, behavioral intention, perceived behavioral control, and the actual use of BIO technology. Copeland and Zhao (2020) used TRA to investigate U.S. consumers' influence of online peers and their purchase intentions on the Instagram social media platform. Lin et al. (2020) also applied TRA to investigate the adoption of Nike + Run Club App, by the club members. TRA was also applied by Xiao (2020) to investigate the factors influencing eSports viewership.

IMD Design Framework. Halperin et al.'s (2008) theory involves IMDs, their effectiveness in terms of security, privacy, and safety levels and evaluating designs for next-generation IMDs. Theoretical propositions of the framework include improving effectiveness variables such as security and safety for IMDs which introduce mobility. The main constructs of the theory are IMD effectiveness in terms of security and device-user safety. Halperin et al. (2008) stated that essential statistics such as body temperature and blood pressure can be monitored without having the patients tied to the hospital bed. This aspect or construct of mobility ties in with usability, which is another aspect of device effectiveness. Their framework also discourages the present conflict between cost-effectiveness and usability goals, safety goals and device security goals (Madjid et al., 2019; Miller et al., 2021). My independent variable of PC is firmly grounded in Halperin et al.'s (2008) theory as PC consists of safety and security.

Halperin et al.'s (2008) theory also relates to this study because the hypotheses and research questions include the factor of PC (safety and security) which may influence patients' BI to use an IMD. Halperin et al. (2008) vouched for devices with customized security solutions. In applying Halperin et al.'s IMD design framework, Shang et al. (2021b) proposed research directions to help mitigate conflicts between traditional IMD design goals of safety and utility and the goals of security and privacy of IMDs, but solutions will require design trade-offs and the collective expertise of the healthcare management community, security community, and regulatory bodies.

Gondauri et al. (2020), Hwang et al. (2019), and Yu et al. (2021) also agree with Halperin et al.'s (2008) in that, with increments in the use of wireless IMDs, there is the consequent need to address IMD security and patient privacy under adversarial conditions. Adversarial conditions cannot be ruled out as global societal conditions are rife for cyber warfare (Gondauri et al., 2020; Maschmeyer et al., 2021; Shang et al., 2021a) and medical devices cannot be ruled out as potential targets. In a similar study where Halperin et al.'s (2008) theoretical framework was applied, Brantly and Brantly (2020), stated that despite the advances in IMD technologies, understanding of how device security and privacy interact with and affect medical safety and device effectiveness is limited.

Brantly and Brantly (2020) buttressed their point of ineffective devices by stating that balancing security and privacy with safety and efficacy will become increasingly important as IMD technologies evolve. In improving on the Halperin et al. (2008) IMD Design framework, this study built upon the clinical deployment scenarios by way of soliciting perceptions from the very patients using the devices and potential device users. In doing things differently from other researchers, this researcher sought to develop theory and a scientific model on the key factors influencing IMD adoption intent.

Diffusion of Innovation (DOI). The DOI theory developed by Rogers (2003) was considered by several scholars as an acceptable approach to exploring technological-inventions adoption and understanding how inventions, i.e., novel notions, systems, or behaviors, diffuse within groups and between groups (Dearing & Cox, 2018; Mo et al., 2021; Warner et al., 2021). DOI is a theory seeking the explanation of why, how, and the rate at which technological innovation spreads or diffuses into the market environment (Kim et al., 2020a; Lund et al., 2020). Rogers (2003) suggested that amongst participants in any given social system, diffusion becomes the dynamic process through which innovation-communication occurs over time. According to Dedehayir et al. (2019), the four influential factors for the diffusion to happen include the social system, time, channels of communication and not excluding the innovation itself.

Development of DOI. Rogers (1987) explicated adoption as an individual's decision to acquire and use an innovative technology and illustrated diffusion as the mode by which technological inventions diffuse amongst societies with passing time. The DOI model theorized that factors such as (a) observability, (b) trialability, (c) complexity, (d) compatibility, and (e) relative advantage (Rogers, 1987) either decreased or increased the likelihood that the society would implement a new and innovative system. The first DOI factor assessed the extent to which the novel system delivered visible results (Rogers, 1987). The second factor investigated the faculty of a novel system to be assessed first, before a significant commitment or investment was made (Jung Moon, 2020; Rogers, 1987). The third factor measured how challenging the novel system was to operate or even to understand (Rogers, 1987). The fourth factor referred to the uniformity of the novel system in terms of requirements of potential users, know-hows, standards, and principles (Rogers, 1987). The fifth factor relates to how people perceive the benefits of the innovative system as being better than the substituted technology (Rogers, 1987).

In addition, Rogers (1987) maintained that people are inclined to accepting a novel system in a time succession, because individuals understand the contributing factors of adoption in different shapes and forms. Rogers (1987) segregated the adopters of an invention into five major classes to include the laggards, later majority, earlier majority, early adopters, and innovators. Rogers (1987) furthermore described innovators as individuals, willing to absorb innovative ideas and be the first to use the novel system.

Early adopters on the other hand are knowledgeable about the new system and are also prone to accepting the new system rather rapidly (Kim et al., 2020a; Lund et al., 2020; Mo et al., 2021; Warner et al., 2021). The earlier majority contains persons willing to accept the new system only if it is as advantageous as expressed (Rogers, 1987). In the later majority category, the society adopts the new system, but only after the majority has assessed and experienced it (Rogers, 1987). Individuals in the laggards' category are presumptuously traditionalists and often resistant to adopting newer systems (Rogers, 1987).

Rogers (1987) hypothesized that,

> Technology acceptance was a sequence of proceedings involving the learning of inventions, being swayed to accept inventions because of presumed advantages, deciding to accept the invention, putting into operation the invention, and corroborating the determination to accept the invention. (p. 82)

From the viewpoint of IT systems adoption, Moore and Benbasat (1991) revised Rogers' (1987) DOI model by untying the observability construct into two distinguishing variables, namely, visibility and result demonstrability which renamed complexity as *ease of use*, misplaced trialability, integrated voluntariness, and image. The result demonstrability construct not only appraised the degree to which the novel system generated visible results, but also the ability to propagate the results (Moore & Benbasat, 1991). On the other hand, the visibility construct assessed the degree to which an individual observed other individuals utilizing innovative technology and images related to how society perceived that the utilization of the new system boosted their status (Dearing & Cox, 2018; Mo et al., 2021; Moore & Benbasat, 1991).

The use of DOI theory within the IT field provided methods of evaluating the attributes of inventions and their influence on use. DOI theory considers public perceptions of the attributes of innovations systems as considerable determinants affecting an individual's judgement to accept them.

IMD is an innovation and like all innovations, a diffusion rate can be ascertained depending on how widespread the innovation's adoption is (Dedehayir et al., 2019; Kim et al., 2020a; Lund et al., 2020). In relation to my study, the 'channels of communication' construct corresponds to one of the factors in my study, facilitating condition. Regulations are channels of communications through which tenets of IMD innovation are communicated. The other factor of the innovation itself is linked to my dependent variable BI to use an IMD, because the decisions determine diffusion, and the diffusion rate. To self-sustain, the IMD innovation needs a wide scope of adoption and the IMD adoption rate must not have reached point of saturation or technically, the critical mass. The 'channels of communication' construct also finds use in my independent variable, social influence. The 'social influence' factor provides a channel of communication where the patient begins to understand the importance and advantages of using IMDs for effective disease condition management.

Contrasting Theories

In the above section, complementary theoretical frameworks were deliberated. Several contrasting theories were discussed in this section. Theoretical models presented here would not fit well for this research but give a description of other views or perspectives to IMD adoption for efficient disease condition management.

MPCU. MPCU is a theory in contrast to theories which seek to elucidate an individual's BI towards system acceptance. According to Thompson et al. (1991), MPCU sought to explain an individual’s actual system use, specifically computers. MCPU theorizes that technology-use behavior can be determined by constructs such as long-term consequences, social norms, fit between the job and PC capabilities, and complexity of use (Thompson et al., 1991). MCPU also projected that FC factors and affective reactions to computers, intervene directly to influence an individual’s actual system use. However, Thompson et al. (1991) discovered that these constructs are not important predictors of system use.

Motivational Model. MM is another model which has been used in research to explain the adoption and use of IT novelties (Bhat et al., 2020; Chen et al., 2021). MM is founded on the self-determination model, which underscored two major motivating forces. These forces include extrinsic and intrinsic forces (Ryan & Deci, 2020). From the adoption and usage of IT innovations perspective, Davis et al. (1992) characterized the intrinsic motivational factor as one’s inherent joy to perform an activity and the extrinsic factor, as the perceived usefulness, which indicated the individual’s incentive to perform an activity, because seemingly it generates a net positive gain.

Davis et al. (1992) empirically investigated MM as utilized in the IT field revealed that the two forms of motivation can predict very well and clarify a person’s BI and system use. Davis et al.’s (1992) findings were corroborated in several studies attempting to determine the impact of extrinsic and intrinsic motivations on technology adoption such as in deployment of outcome-based education (Bhat et al., 2020), measuring motivational relationship processes (Schönbrodt et al., 2021), determining the effects of motivational adaptive instruction on student motivation (Wong & Wong, 2021), and internet-based Q&A communities (Chen et al., 2022). Lucht et al. (2020) used a modified form of the MM in their investigation to validate the motivational phase of the integrated motivational-volitional (IMV) Model of suicidal behavior, a modified form of the MM, in a German high-risk sample. Cleare et al. (2021) also used the IMV model of suicide behavior to differentiate those with and those without suicidal intent in hospital treated self-harm.

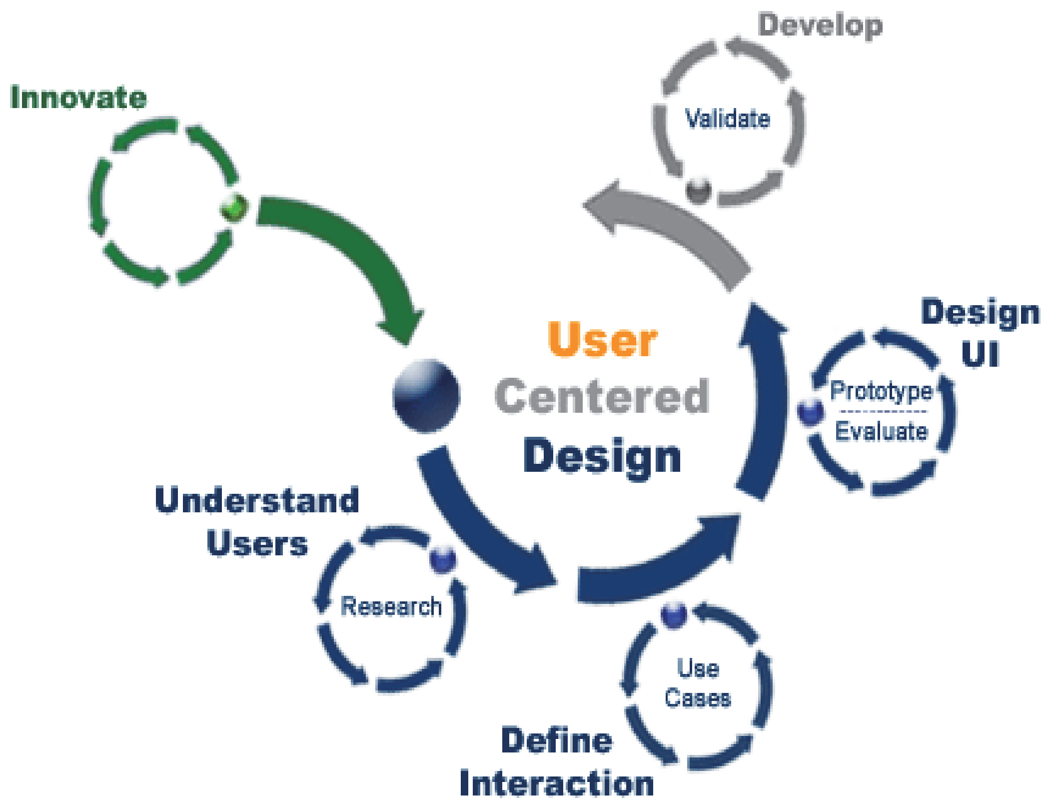
Other Theoretical Frameworks

User-Centered Design Framework. In addition to Halperin et al. IMD Design Framework and TAM, User-Centered Design (UCD) can be considered a neighboring framework with relevance to my study since it provides the framework in which customer perceptions are solicited and design solutions meet FDA requirement of designers soliciting input from their customers for customer-centered designs (Code et al., 2020; Copeland & Zhao, 2020). User-centered design is considered a framework which is based on the interests and requirements of the user, with a focus on making products understandable and usable (Alberts et al., 2020; Tobias & Spanier, 2020).

Involving the customers in the UCD process is a common method of ensuring that their requirements and interests are being met. The relevance of user-centered design can easily be understood by realizing its popularity among producers due to its features (Kim et al., 2020c). User-centered design plays an important role in integrating human factors activities into development. Due to the UCD, every manufacturer considers the end user and allows them to participate on a continuous basis throughout the entire process (Daley et al., 2020). This not only improves the quality of products but also proves helpful in satisfying a large number of customers. Figure 1 is a representation of the UCD framework.

Figure 1

User Centered Design Framework



Note: Steps within the User Centered Design Framework. From "User Experience in Mobile Application Design: Utility Defined Context of Use" by M. Lubis, E. Sutoyo, M. Azuddin, & D. Handayani, 2019, *Journal of Physics: Conference Series*, p. 1361. (https://doi.org/10.1088/1742-6596/1361/1/012043). Copyright 2019 by Creative Commons Attribution 3.0 License.

User-Centered Design in Medical Device Design. Most of the healthcare products are designed to achieve ultimate success within organizations. However, the level of success will be determined by the extent to which most users find it useful. User Centered Design (UCD) is an approach that has been utilized by many organizations in the design of healthcare products and services aimed at meeting organizational goals and objectives (Holden & Boustani, 2021; Lubis et al., 2019). UCD takes into consideration the involvement of patients in the design of different products by involving them within the decision-making process (Reich-Stiebert et al., 2020). The end user is therefore involved in all the steps of development of a product in such a way that technology provides the perceived value to the user, allows easy operations, and supports organizational tasks effectively. Intended health outcomes can be achieved under the involvement of patients throughout the product design and testing processes (Alberts et al., 2020; Kim et al., 2020c; Tobias & Spanier, 2020). UCD adequately achieves usability and functionality of the products involved. Interactive health technologies are a major shift within which most organizations have utilized in business processes to aid in the provision of more integrated healthcare services.

Under UCD, User centered activities are considered throughout the design of medical devices to ensure that the systems developed, effectively match user behavior and expectations (Daley et al., 2020; Holden & Boustani, 2021; Reich-Stiebert et al., 2020). For this reason, the end user can influence the shape and design of the products delivered to them. The level of usability will also be dependent on the existing knowledge and their willingness to utilize various medical devices (Cheong et al., 2020). Their knowledge on the systems could therefore be enhanced through their involvement in the design process.

In using design and usability methods Holden and Boustani (2021) investigated agile innovation and evaluated interventions for families and patients. In another study applying the UCD, Daley et al. (2020) investigated the involvement of patients as key stakeholders in the design of cardiovascular implantable electronic device data dashboards. Daley et al. (2020) further investigated the implications for patient care. By means of a UCD approach Reich-Stiebert et al. (2020) explored university students' preferences for educational robotic designs. In another study, Alberts et al. (2020) applied the UCD to investigate the development of the

InCharge Health Mobile App for improving adherence to hydroxyurea in patients with sickle cell disease.

General Systems Theory. General Systems theory identifies that any function or practice is made of unique parts coming together to form a complete entity or product (Cadenas, 2019; von Bertalanffy, 1950). IMD can therefore be considered as a system as it is made of distinct parts to include the patient, computer terminals connected to devices, databases for data storage and retrieval and the IT network infrastructure. Each aspect of the system is dependent on the next part. This interdependence identifies that there is a need to gain a holistic view of each process to ensure it is successfully conducted. Systems theory identifies that the failure of one aspect leads to the failure of other aspects of the system identifying the need to promote quality measures in each step of the system design (Carr-Chellman & Carr-Chellman, 2020; von Bertalanffy, 1950).

According to Cadenas (2019), general system theory identifies the interdependence of each action and step to the success of the entire system. The success of one step or its failure transitions onto the next process which leads to the translational success or failure of the project being developed. According to Roth (2019), the general systems theory offers a cyclical and systematic approach to understanding system design. Roth (2019) further asserted that implicit moralization is an epistemological obstacle for the general system theory. von Bertalanffy (1950), in addition postulated that general systems theory (GST) provided a realistic and holistic view of sociological phenomena: something needed because of their higher complexity. For instance, due to their complex nature of being able to function as computers and taking logical decisions, IMDs are needed for their high complexity.

In GST, corporate social responsibility seeks to address corporate citizenship within the larger society (Cadenas, 2019; Fröhlich, 2019; Valentinov et al., 2019; von Bertalanffy, 1950). IMD adoption-for-usage has its place in protecting the patient with the specific design to protect patient information, healthcare information assets, and protect the patient's dignity during the continued safe use of IMDs for efficient disease condition management. von Bertalanffy (1950) also stated that in the act of creating systems, important processes may be omitted. Fröhlich (2019) and Hammond (2019) considered GST as the science of synthesis and further explored the social implications of the GST. Combing the literature there was no resource found on the involvement of GST and IMD research. Hence it was not a suitable framework to use considering the research questions and research purpose.

Review of the Literature

The following literature review provides background research supporting and framing this research on IMD adoption and usage. This section moves from a discussion on the influencing factors of IMD adoption, before exploring the demographic aspects as determinants of IMD adoption and usage. This review is also a synthesis of the major research findings between 2018–2022 as well as a critique of previous research work in the field of IMD adoption and usage.

Influencing Factors

Yeow et al. (2013) pioneered an investigation which studied Malaysian citizens' adoption of SNIC for homeland-security. They clarified that extensive research focusing on users' acceptance of smartcard technology based on the roles it was created to support was required. To determine factors shaping the U.S. patient's acceptance of IMD, this study used Yeow et al.'s (2013) UTAUT-extension to include FC, SI, PC, and PE as the independent variables, and expand the model to include Att as the fifth independent variable. These forementioned variables have been identified as essential rudiments in the determination of the level of approval towards the use of innovative technology (Kaye et al., 2020; Kohnke et al., 2014; Morosan, 2016; Venkatesh, 2022; Yeow et al., 2013).

Proposed by Yeow et al. (2013), anxiety, nervousness, or stress does not arise from using a specific technology, when technology adoption is assumed voluntary. According to Venkatesh et al. (2003), the anxiety variable has an indirect impact on the *BI to use* variable, only through EE and therefore the anxiety variable was omitted. The EE variable was also omitted in this study because using IMD requires no time or effort on the part of the patient as the IMD is subcutaneously embedded through surgical procedures. Furthermore, according to Wu et al. (2007), the EE construct may be used to predict BI to use a system. However, it may not function well in predicting BI to use a technology. Therefore, the EE and anxiety constructs were considered as not applicable to this study.

Attitudes. Attitudes (Att) refers to the individual's posture of approval or disapproval (Petersen et al., 2020; Seyal & Turner, 2013; Soh et al., 2020). It is however not an explicit construct in the UTAUT framework. For the purposes of this study, Att was well-thought-out as an important component in the determination of the level of approval towards IMD use. Other researchers have investigated how attitude affects biometric adoption and proposed that the Att construct is a predictor of *BI to use* a technology and also a predictor of acceptance of a technology (Patil et al., 2020; Seyal & Turner, 2013; Soh et al., 2020). According to Kim and Lee (2020), the Att variable indicates negative or positive behaviors to technology use. Previous studies have combined Att with the UTAUT framework to examine its correlations with the UTAUT factors (Angelia et al., 2021; Han & Conti, 2020; Venkatesh, 2022). For example, Thomas et al. (2020) specified that Att is positively correlated with EE, FC, and PE factors and that Att has a direct impact on the use and adoption of technology.

Hwang et al. (2019) postulated that Att has an important impact on an individual's intention toward the use of a novel system and correlates with PE. Venkatesh et al. (2003) advocated that when PE and EE are omitted from UTAUT framework, the Att's effect should be considered instead. Therefore, the exclusion of EE, allowed for the inclusion of Att. Att in this study represented the degree to which the U.S. patient favors or disfavors the acceptance and utilization of IMD in current forms of disease management (Shang et al., 2021a; Tiwari et al., 2020).

An individual's attitude toward a specific technology is a major determining factor for the adoption and usage of that technology (Han & Conti, 2020; Tovar-Rivera, 2019; Wahid, 2007). Tiwari et al. (2020) suggested that an individual with a positive impression and attitude toward IMD technology will exhibit positive behavior toward using IMD technology. Many studies including Mainardes et al. (2020) and Angelia et al. (2021) have been conducted to ascertain the impact of attitudes towards acceptance of a product, be it technological, medical, or educational. Studies examining user attitudes towards technology were extensively drawn from theories of social psychology and innovation adoption (Altalhi, 2021; Jung Moon, 2020). The TAM of Fred Davis (Setiawan et al., 2021), the TRA of Ajzen and Fishbein (Copeland & Zhao, 2020; Kim et al., 2020b; Ng, 2020; Xiao, 2020) have helped describe individual attitudes towards adoption and acceptance of technological systems such as IMDs. Adoption and innovation theories are refined with time and with new research in different demographic situations.

The attitude–behavior relationship influences adult's positive or negative affirmation toward technology acceptance Altalhi, 2021; Angelia et al., 2021; Han & Conti, 2020). According to Wang et al. (2020) study on IMDs, affirmative attitude encourages the use of IMD technology. Angelia et al. (2021) also asserted that once attitudes are formed according to the attributes of relevant technologies, such attitudes will either enhance or reduce usage, or influence adoption. Peer influence, which is akin to the social influence construct is another factor that has been identified in other fields of attitudinal studies such as education (Altalhi, 2021; Han & Conti, 2020; Tiwari et al., 2020; Tovar-Rivera, 2019).

Positive attitudes toward IMD technology are gradually increasing due to the technology becoming accepted, as patients continue to recognize its usefulness in disease condition management and healthcare professionals recognize its importance in effective healthcare information management (Cristina et al., 2021; Pycroft & Aziz, 2018). According to Aileni et al. (2020) IMDs ability to provide disease condition management and corrective measures in times of critical conditions are major benefits. User perceptions of IMDs may include perceptions such as device effectiveness, device affordability, device regulation, technology-education understanding, patient-health manager relationship and possibly many other factors (Gill, 2019). There may be several other unexplored patient perceptions and reasons for adopting an IMD. Improvements in security, safety, and usability requirements for accessing resources on networks may also be reasons for positive attitudes towards IMD Technology (Ćwiklicki et al., 2020; Haynes et al., 2020; Shang et al., 2021b).

Patients may consider IMD technology an alternative to frequent doctor visits (Giansanti, 2021). Hassija et al. (2021) also discovered that about 70% of survey respondents alluded to convenience as the topmost benefit of using IMD technology. In Hassija et al. (2021), the research participants demonstrated positive attitudes towards IMDs because it offered convenience and protection. Hassija et al. (2021) concluded that convenience, personal privacy, and data security affected acceptance of IMDs.

Haynes et al. (2020) found that patients were open to the technology as an alternative to frequently visiting the doctor, and emergency room visits in the case of an emergency. Based on the device's behavior, a patient can know what type of corrective measure to take before calling in or visiting the hospital (Ćwiklicki et al., 2020). According to Aileni et al. (2020), telemetry could also be used where physicians can receive signals from the devices and can diagnose the patient's medical condition. Aileni et al. (2020) explored cybersecurity technologies for the internet of medical wearable devices (IoMWD).

Performance Expectancy. Several researchers have proven that PE is a keen predictor of technology adoption, for instance in home telehealth services (Cimperman et al., 2016), in Malaysian SNIC (Yeow et al., 2013), biometric authentication in electronic shopping (Hino, 2015), in mobile banking adoption (Shaikh et al., 2021), social media in academic libraries (Williams et al., 2021), and in acceptance of enterprise resource planning (ERP) system (Andwika & Witjaksono, 2020). According to Andwika and Witjaksono (2020), PE is described as the degree to which individuals projected that their work-related functions would improve with the use of a specific technology. The PE factor involves an amalgamation of five predictors in technology adoption to include outcome expectations (social cognitive theory), relative advantage (innovation diffusion theory) job-fit (the model of PC utilization) extrinsic motivation (MM theory), and perceived usefulness (TAM/TAM2 and C-TAM-TPB) (Venkatesh et al., 2003).

In this study, PE represented the degree to which the U.S. public anticipates that using IMD will improve their disease management efforts. In another study, Fedorko et al. (2021) studied the EE and SI factors as the main prognosticators of PE using electronic banking. Shaikh et al. (2021), also investigated the relevance of risk perceptions, EE, and PE in mobile banking adoption. According to Yeow et al.'s (2013), the PE of a Malaysian SNIC revolves around its PC, which subsequently, influences Malaysians' intention to use SNIC. To determine if the same phenomenon applies to IMD, the degree to which the prediction of BI, as measured by the PE scale, will statistically be mediated by PC was examined.

Behavioral Intent to Use. UTAUT theoretical viewpoints on the acceptance and usage of technologies have discovered some important predictors of BI to use including innovativeness, perceived risk, trust, privacy, and compatibility (Sujood et al., 2021); PC (Kaur & Arora, 2020), hedonic motivation (Nikolopoulou et al., 2021); PE (Himang et al., 2020; Jena, 2022; Shaikh et al., 2021), and FC (Hamzat & Mabawonku, 2018). Other predictors of BI to use include Att (Thomas et al., 2020) and service innovation (Chang & Lee, 2020). Thomas et al. (2020) integrated the Att variable into the UTAUT framework to study factors that could influence the acceptance of mobile-learning among college students from the Caribbean and discovered that this adaptation led to an increment in the predictive power of the model.

Lancelot Miltgen et al. (2013) combined DIT, TAM, and UTAUT theoretical frameworks and other prognosticators, such as risk perceptions, privacy, trust, and innovativeness into their study on the BI to adopt and recommend biometric technologies. Lancelot Miltgen et al. (2013) demonstrated the substantial influence of risk, innovativeness, trust, privacy, FC, perceived usefulness, and compatibility on BI. However, perceived ease of use and SI had no impact on BI.

Jacob and Pattusamy (2020) defined the BI construct as a replication of how keen individuals are to adopt and use a system.

Seyal and Turner (2013) advocated those intents are assumed to describe the driving forces behind an individual's behavior and to convey the extent to which individuals are eager to implement the behavior. Nikolopoulou et al. (2021) investigated how technological pedagogical knowledge, performance expectancy, hedonic motivation, and habit affect teachers' intention to use mobile internet. Several studies have suggested that BI is directly influenced by Att, FC, SI, PC, and PE (Andwika & Witjaksono, 2020; Hino, 2015; Nikolopoulou et al., 2021; Seyal & Turner, 2013; Williams et al., 2021; Yeow et al., 2013). In this study, BI to use an IMD measured the degree to which the U.S. patient is willing to adopt and use an IMD.

Madigan et al. (2017) enhanced the UTAUT framework to include the construct of hedonic motivation, i.e., the delight in an innovation, to examine Greeks' BI to accept automated vehicles amongst Trikala citizens. Madigan et al. (2017) discovered that the addition of hedonic motivation helped augment the power of the entire study and suggested that although EE did not influence BI, FC, SI, and PE, which are the other constructs of hedonic motivation, were significant prognosticators of BI to adopt automated cars. Yeow et al. (2013) investigated the influence of anxiety, FC, SI, PC, and PE on Malaysian's BI to adopt a national identity SC, using an extension of UTAUT. Yeow et al. (2013) study's results suggested PC and PE as the direct determining factors of BI to use and demonstrated that the prediction of the PE factor was mediated by the PC factor.

Since the purpose of this investigation was to provide an improved understanding of the issues surrounding the U.S. patient's BI to adopt an IMD, and the wide-ranging literature on technology adoption distinguishes UTAUT as a renowned model (Jacob & Pattusamy, 2020;

Jeon et al., 2020; Kaye et al., 2020; Khechine et al., 2014; Petersen et al., 2020), and therefore the UTAUT theoretical framework was applied. Studies in IMD technology adoption are limited in comparison to investigations in the acceptance of other technological innovations (Agyei & Razi, 2022; Jacob & Pattusamy, 2020; Khan et al., 2022; Petersen et al., 2020; Seyal & Turner, 2013; Yeow et al., 2013). In an experiential analysis, Morosan (2016) established a theoretical model that combined UTAUT with compatibility and privacy concerns to elucidate U.S. airline passengers' BI to use biometric gates. Morosan (2016) explained that, though compatibility and privacy concerns did not have a substantial influence on BI to use, EE and PE constructs remained essential but weak predictors of U.S. air passengers' BI.

Furthermore, Morosan (2016) revealed a significant impact of effort expectancy on PE and identified PE as a direct determining factor of BI to use biometric electronic gates. Another method to examine biometric technology acceptance suggested combining PC and perceived privacy as direct prognosticators of BI to use, in the UTAUT model and analyzing the moderating effects of experience, gender, and age (Hino, 2015). Hino (2015) discovered that BI was determined by SI, PE, privacy, and PC while exploring online consumers' BI to use biometric technology in online shopping. Hino (2015) also demonstrated that the impact of PC and perceived privacy were moderated by the experience variable, however there was no interacting effects from neither core determinants, nor age, nor from gender.

Perceived Credibility. Hwang et al. (2019) defined PC as the extent to which people believe that a specific technology is dependable, robust, secure and could be trusted. Researchers have advocated that credibility is associated with technology safety concerns (Long et al., 2022; Yeow et al., 2013), security concerns Granlund et al. (2021), and privacy (Yu et al., 2021). Specific areas of concern embrace the suitability of safety measures for information collection, keeping the information safe, and managing the information properly (Giansanti, 2021; Hsu & Yang, 2021; Shang et al., 2021a), as well as the confidence in the information system's defense mechanisms, system's accuracy, and system reliability (Biasin, 2021; Grimes & Wirth, 2021; Shin et al., 2017).

Pragmatic studies have supported the idea that PC influences people's intention to adopt and use technology, for instance the Malaysian SNIC (Yeow et al., 2013) health informatics (Shin et al., 2017), biometric technology in electronic applications (Hino, 2015; Pinto & Santos, 2020), purchase intentions (Hsu & Yang, 2021; Kim & Song, 2020), mobile money usage (Odoom & Kosiba, 2020), M-Wallet Apps (Thanigan et al., 2021), assessment in medical education (Long et al., 2022), and internet banking systems (Malik, 2020). Thus, in conjunction with the previous literature, PC was operationalized in this study as the degree to which the U.S. patient anticipates that IMD will be a usable, secure, and safe system in which data can be kept in confidentiality, managed securely and effectively, and difficult to modify.

The perceived credibility variable could be spread into three areas of device security, device safety, and device usability (Manrai et al., 2021; Shin et al., 2017; Yeow et al., 2013). Multiple IMD implants that are wirelessly interconnected will increase the complexity dimension of IMDs (Gardašević et al., 2020). With complex designs, come complex security protocols which may interfere with device safety goals. For instance, a neural signal transmission from the backbone to a robotic prosthetic limb influences a broader set of integrated neurons which will increase the difficulty in identifying and neutralizing security vulnerabilities (Yildiz et al., 2020). These scenarios call for more research into finding appropriate designs, suited to the patients' needs, to mitigate the consequences of the devices' security complexities, and improve IMD effectiveness.

Device Security. Device security is often downplayed until major damage to the system is experienced (Shang et al., 2021b; Thomasian & Adashi, 2021; Tomaiko & Zawaneh, 2021). The computing capabilities through wireless communication for software-based control of therapies and network-based transmission of patients stored medical information introduce security and privacy risks, yet only an insignificant amount is known about the prevalence of such risks within the clinical setting (Cristina et al., 2021). Alsuwaidi et al. (2020) assert that the close connections between computer networks and medical devices have led to the proliferation of cybersecurity threats. The authors added that security vulnerabilities have increased due to the corresponding increase in interconnected medical devices. The purpose of their research was to suggest a network model of medical devices. Under examination were the attack methods and security vulnerabilities inherent in medical devices.

According to Baranchuk et al. (2018), the possibility of hacking cardiac devices (defibrillators and pacemakers) has claimed the attention of health care providers, patients, and the media. This is a growing problem according to the authors. Baranchuk et al. (2018) discussed various aspects of new vulnerabilities and threats with respect to recent incidents that involved the hacking of cardiac devices. Patient risks possibilities were explored in addition to the effects of reconfiguring devices against cybersecurity threats. Gathering from the perspective of the patient, physician, government, and manufacturer, Baranchuk et al. (2018) provided an outline of what could be done for the improvement of cybersecurity for medical devices.

According to Sethuraman et al. (2020) phishing attacks, eavesdropping, denial of service (DoS) attacks are all cyber-based attacks that IMDs may fall victim to due to the proliferation of wireless technology. Drones or Unmanned Aerial Vehicles (UAV) also present attack surfaces leading to wireless healthcare systems being easily compromised according to Sethuraman et al., (2020). Wireless attacks capable via drone technology include cloud-enabled and stepping-stone attacks. The authors developed a real UAV for testing and demonstration of healthcare systems' vulnerabilities to the new threat-vectors. The newly built UAV was able to attack a simulated smart hospital successfully.

According to Yaqoob et al. (2019), medical devices are networked, portable, and capable of facilitating human lives. However, the healthcare sector is experiencing massive security breaches because of the existence of security vulnerabilities inherent in medical devices. Yaqoob et al. (2019) added that due to interconnectivity of these devices, they no longer operate as stand-alone systems and consequentially have profoundly increased their attack surfaces. Medical devices unfortunately were not designed with security-constraints from the ground up. Both academic and industry experts acknowledge the existence of security vulnerabilities in the devices including IMDs.

Media attention and publication of attack incidents and security vulnerabilities may influence the usage patterns and a patient's intention to use an IMD. According to Chang (2020) information privacy concerns have been raised amongst users of wearable smart medical devices (wSMDs). This is due to the large amounts of personal health data having to be transported through multiple communications channels and health information technology systems working in a distributed fashion. According to Chang (2020), privacy concerns along with perceived risk, usability, and trust in wSMD systems have resulted in limited success of the devices in healthcare.

Device Safety. The rapid dissemination of medical devices capable of storing and transmitting patients' medical information and the theoretical possibility of remotely reprogramming implanted medical devices raise important concerns regarding security, privacy, and safety (Breese & Zwerling, 2020; Keikhosrokiani, 2021; Luštrek et al., 2021). Investigators have demonstrated limitations of the security and safety functions for implantable cardioverter-defibrillators (ICDs), for example, by proving the feasibility of communicating with an ICD through an unauthorized radio-based approach that theoretically could interfere with appropriate device therapy (Cristina et al., 2021; Liu et al., 2018).

Up-to-date commercial IMDs do not employ robust security and safety mechanisms. A growing list of confirmed cybersecurity vulnerabilities in medical devices pose challenging risks to patients whose privacy or disease management depends on the proper functioning of devices (Easttom & Mei, 2019; Keikhosrokiani, 2021; Pycroft & Aziz, 2018). In the United States, post-market surveillance of medical devices identifies potential risks and connects device malfunction to adverse events in patients.

Usability. Post-market events may trigger recalls or advisories depending on the nature of the device problem that is identified. (Sabogal-Alfaro et al., 2021; Siddiqi et al., 2021). These reports provide valuable information about safety and effectiveness and have led to revision of regulatory practices for devices such as ICD leads and automated external defibrillators (Wang & Yang, 2021). The following segment is a discussion on the importance of device affordability in finding lasting solutions for improving IMD usage rates. The literature suggests there continues to be security, safety, and usability lapses but all the research is from technical viewpoint and not from patient views. It is therefore imperative to harness the viewpoint of patients on their perceptions of the factors that influence the BI to use an IMD.

Social Influence (SI). The SI factor refers to the observation that somebody who is in a significant position in someone's life thinks they should adopt and use the system (Cokins et al., 2020; Jeon et al., 2020; Liu et al., 2021). Several researchers have advocated that an individual's resolve to engage in a specific behavior is often affected by their image (Andrews et al., 2021), their peers (Widyanto et al., 2021), social pressure (Stöckli & Hofer, 2020; Yeow et al., 2013), superiors (Goette & Tripodi, 2020), and relatives (Al-Adwan et al., 2022). Pragmatic studies have supported the idea that SI is a prognosticating factor in an individual's inclination to use technology, such as adopting artificial intelligence (AI) and neighboring technologies (Andrews et al., 2021), accounting platforms (Cokins et al., 2020), self-service technology (Jeon et al., 2020), mobile internet use (Jacob & Pattusamy, 2020), behavior prediction on Facebook (Stöckli & Hofer, 2020), and mobile payment (Widyanto et al., 2021). With respect to the previous literature, SI in this study measured whether the U.S. patient's BI to utilize an IMD is influenced by the views of people or someone holding a significant position in their lives.

Facilitating Conditions. Cimperman et al. (2016) suggested that FC described the extent to which an administrative and technological structure is existing to reinforce the acceptance of technology. Several studies predicting peoples' willingness to use technology have found FC a significant predictor, because the presence of adequate infrastructure promotes technology use (Abbad, 2021; Chauhan & Jaiswal, 2016; Cimperman et al., 2016; Ikhsan et al., 2021; Jacob & Pattusamy, 2020). Yet, other researchers have not conformed and argued that FC has no direct influence on technology adoption and usage (Jadil et al., 2021; Palau-Saumell et al., 2019; Vallerie et al., 2021). Despite the unpredictable function of FC in predicting technology acceptance and use, FC is deemed by numerous researchers to be a significant component in the determination of what encourages people to adopt and use technologies (Anil et al., 2018; Jewer, 2018; Rachmawati et al., 2020; Salloum & Shaalan, 2019; Thomas et al., 2020; Yeow et al., 2013). Thus, in this study, FC (Venkatesh et al., 2003) represented the degree to which the U.S.

patient recognizes that the existence of specialized, administrative, and technological structures facilitates IMD acceptance and usage.

Device Affordability and its Impact on BI to Use IMD. With ever-increasing pressures from buyers, price variability is inevitable as medical device companies seek to optimize individual deals and agreements. The keys are to strategically manage this price variability and to avoid prolific, one-off exceptions that can ultimately drive down average prices, and destroy company value (Rachmawati et al., 2020; Tortorella et al., 2022). A well-designed customer segmentation framework is the first step toward establishing structure and logic to manage price variability in the market. Customer segmentation simply recognizes differences in value perceptions, motivations, and willingness-to-pay among groups of similar buyers, forming the basis for tiered offerings at various price points (Anil et al., 2018; Salloum & Shaalan, 2019).

The Design-To-Value approach is helping medical device companies obtain a richer understanding on customers' needs and helping to meet those needs more cost-effectively (Fox et al., 2021; Rachmawati et al., 2020). According to Zhao et al. (2020) the healthcare industry has undergone a proliferation of innovations aimed at enhancing quality of life as well as the efficiency and cost-effectiveness of the healthcare system. Design and engineering teams in the medical device sector strive to identify the most cost-effective ways of delivering features able to maximize product margin (Jewer, 2018). Although value customers are concerned about costs, they also have standards for product quality, efficacy, safety, and service (Anil et al., 2018). They are generally reluctant to pay for additional features or services once their basic expectations of a product have been satisfied.

Companies that do attempt to match product features and capabilities more closely to their customers' perceptions of value must answer the question of who exactly their customers are (Aljumaie et al., 2021; Dearing & Cox, 2018). Fragmented decision-making in many healthcare markets makes it extremely difficult for companies to understand the requirements of all key stakeholders. To be selected for use, a device might have to be approved by a national or regional authority, selected by a healthcare provider, specified by a clinical team, and then chosen by doctors, often in consultation with patients (Alghazi et al., 2021).

It is possible the patient's own reactions to the device defines its success in use. According to Daley et al. (2020) each of these stakeholders will have an incomplete picture of product attributes: payors might not understand the importance of usability in patient compliance, while a physician may be unaware of the ongoing cost of supporting a product in the field. Thus, the incentives to purchase in many medical device markets may be fundamentally different from the benefits ultimately enjoyed by end users. The patient's reactions to the device, and overall usability and affordability must therefore be factored into the design approach for the devices.

Regulations and IMD. According to Maresova et al. (2020), the use of medical devices is subject to several strict standards, certification processes, laws, and regulations. The aim of the research was to analyze medical device patent-activity of the Czech Republic, comparing it with other countries and discussing the development of the medical device industry in relation to new Medical Device Regulation (MDR) implementation. The research was based on the theoretical concept of the relationship between innovation and regulation. According to Maresova et al. (2020), the primary challenge is to be able to implement new medical device regulation in tandem with innovations such as IMDs, with the reason being that most innovative research is conducted by small-to-medium-size enterprises (SMEs) rather than by large corporations.

Due to the accompanying high administrative costs, SMEs are considered more vulnerable than their big company counterparts when it comes to development (Tortorella et al., 2022). Economic regulations arise due to market inconsistencies which do not benefit society. According to Maresova et al. (2020), redressing medical device regulation would therefore benefit not just society but also the implantable medical device industry. Russo et al. (2020), Tortorella et al. (2022) and Yaqoob et al. (2019) also reviewed the applicable regulations and state-of-the-art solutions to the vulnerability problems of medical devices.

Influence of Regulations on BI to Use an IMD. IMDs are regulated to ensure that they do not cause harm to the users, and this is done through a systematic process. This process can be viewed from a systems theory perspective with each adding value to each step of the regulatory process. The regulatory lifecycle as identified by Herder (2019) and Hwang et al. (2019) is critical to identifying how regulatory bodies such as the Food Drugs and Administration (FDA) implement the systems theory in regulating IMDs. It starts with the development of standards and requirements that the IMD must meet for it to be approved.

Early planning meetings are part of the preclinical tests which helps to identify just what the product does and its effectiveness. The next step is the investigational device exception phase which helps to determine the level of risk the device passes to the users and subsequent classification of the IMD. The premarket authorization process takes place next. It is the step which is termed as the scientific and regulatory review of the device to evaluate its effectiveness and safety (Bitkina et al., 2020). This is the most stringent aspect of medical device regulation conducted by the FDA. This is done by involving clinical scientists to clinically assess the device.

After the approval for the device at the premarket analysis, the next step is the post-market studies which involves analyzing the product once it has hit the market to determine its impact on the consumers (Bitkina et al., 2020). If safety alerts arise at this stage warning letters are issued, and the IMD is recalled back to the organization for product development and to undergo the regulatory cycle again. The quality of the cycle is maintained by strict standards set for each regulatory stage to ensure that the final product approved is effective and poses minimal risk to the users.

In the United States, IMDs are regulated by the Food and Drug Administration (FDA) as well as the Center for Devices and Radiological Health (CDRH). These bodies focus on testing devices for safe and effective functioning during different environmental conditions, and testing for the resilience to cyberattacks (FDA, 2017). The FDA is further concerned with producing regulations to streamline the industry and to protect the well-being of patients, the targets of these devices. From the literature, current devices are engineered without considering threat of a potential hacker rendering the devices vulnerable (Biasin, 2021; Sappal & Prowse., 2021). It cannot be ascertained the impact of device regulation on IMD Adoption, as there are no such studies found in the literature.

Effect of Technology-Education Understanding on BI to Use an IMD. Patients are the users of the technology and therefore their opinions and views matter in the discussion for solutions to improve IMD adoption rates. The rapid proliferation of medical devices, and their growing sophistication, presents internet-age challenges for multiple stakeholders (Gill, 2019). Increasingly, regulatory consideration is being given to the value that patients place on products based on the Eucomed commissioned study from The Economist Intelligence Unit, Future-Proofing Western Europe's Healthcare, on the future price-regulatory framework for the

European medical device industry (Pinto & Santos, 2020). According to the Rönkkö et al. (2021), whichever decision they make, they risk contradicting one of the fundamental tenets of medical practice, and that is, the doctor should not knowingly do harm to the patient. In a good relationship with the patient, the physician or health-manager would seek the patient's best interest when prescribing an IMD (Rönkkö et al., 2021).

According to Rocha Fernandes et al. (2018), patient preferences must be placed in context by physicians to mitigate design tensions with single vs. multiple options. Although the results from the previous literature suggested that patients may be served by providing a range of options, the landscape is complex and consists of more than patients' preferences (Rönkkö et al., 2021). In IMD usage, usability and speed-of-use can translate into direct safety benefits for patients and in a medical emergency, small time delays can have serious effects (Code et al., 2020). Having multiple security systems means that medical staff would require extra time to identify which system the patient is using, locate any appropriate equipment, and then respond accordingly. Patient views are not being incorporated into design solutions making the devices not all user-friendly and devices continue to be partially secure and not cost-effective (Rocha Fernandes et al., 2018; Rönkkö et al., 2021).

The FDA has taken steps to stop this trend. According to Malikova (2020), the Center for Devices and Radiological Health (CDRH) recognizes that while scientists, clinicians, device developers, and regulators play critical roles in understanding and communicating the benefits and risks of medical devices, only patients live with their medical conditions and make choices regarding their personal care. Patients provide a unique voice and unique perspective. Malikova (2020) also stated that the goal of the Patient Preference Initiative (PPI) of the (CDRH) is to develop a systematic way of eliciting, measuring, and incorporating patient preference information, where appropriate, into the medical device Total Product Life Cycle (TPLC) and ultimately to drive more patient-centric innovation, evaluation, and delivery to U.S. patients. The method of the physician just informing the patient of the decision already taken does not conform to best practices (Niiranen, 2021). Rather, the patient should be able to discuss the pros and cons of using the device, from a technology-education understanding standpoint, with the physician as health-manager (Code et al., 2020; FDA, 2017; Gumbo, 2018; Niiranen, 2021)

Demographic Aspects as Determinants of IMD Adoption. Healthcare choices are determined by many factors that are encountered with the environments surrounding the delivery of product and service within the health institutions. Such factors include wealth, health, age, education, and job. These factors may have a massive impact towards the development and design of medical devices thus forming an integral part in customer value (Code et al., 2020; Niiranen, 2021). The decisions made under the consideration of these factors plays a vital role in shaping the quality of delivery of healthcare services. The personal factors encountered among the patients and provider of health services as well as those pertaining healthcare environment and organizations itself affect the service quality.

Healthcare choices refer to making healthcare decisions when one needs to choose the best medical care (Gumbo, 2018). According to Zhou et al. (2019), effects of job, age, health, education, and wealth on healthcare choices are highly predominant in today's world as without considering these necessary elements, the information required to access the medical information seems incomplete. These factors are necessary for describing how to make correct healthcare decisions in relation to the medical device choices, keeping in view effects of job, age, health, education, and wealth (Code et al., 2020; Rocha Fernandes et al., 2018; Zhou et al., 2019).

However, how these inner and demographic factors affect the BI to use an IMD is yet to be investigated as it cannot be found in the literature.

Synthesis and Critique of the Literature

This literature review expanded on the available research between 2018–2022 and the germane research efforts important to the field of IMD adoption and usage. The methodologies used in the research findings studied cut across quantitative, qualitative, and the mixed methodology. The capabilities of a highly effective IMD implementation cannot be underestimated (Granlund et al., 2021; Sappal & Prowse, 2021). This literature review demonstrated some favorable user attitudes toward IMD technology. However, this literature review also noted significant problems associated with IMD adoption, the intensifying criticisms, device recalls, device security, usability, and general safety concerns elaborated by the healthcare community (Haddaway et al., 2020; Rafique et al., 2020; Zhao et al., 2020). These and many other concerns if not tackled immediately, could lead to reduced life expectancy and unnecessary deaths within the populace especially in times of a global pandemic.

The general observation is that several renowned researchers have conducted primary research to suggest IMDs are vulnerable to various forms of third-party attacks (Biasin, 2021; Giansanti, 2021; Granlund et al., 2021; Grimes & Wirth, 2021; Sappal & Prowse, 2021). Attacks against IMDs may include the alteration of the functions of the device, manipulation of sensitive patient data or even incapacitating the device altogether (Ćwiklicki et al., 2020; Haynes et al., 2020). In instances of device attacks, human lives are involved, and the damage caused by such attacks may become irreparable (Rafique et al., 2020; Sabogal-Alfaro et al., 2021; Zhao et al., 2020).

To counter the possibility and aftereffects of any third-party attacks, there is ongoing research to significantly improve on the security of these devices and their related peripherals (Siddiqi et al., 2021; Wang et al., 2021a; Welch et al., 2020; Zhang et al., 2019). Nevertheless, IMD adoption research is still an emerging field. Several of the behavioral research models that could and were applied to IMD research efforts were borrowed from other domains such as transportation, ecommerce, and education. While these models helped propel IMD research forward, they have not taken all the critical factors into consideration and therefore have only been able to describe a portion of the IMD Adoption and usage problem (Cristina et al., 2021; Liu et al., 2018).

Balancing security, usability, and privacy with safety and efficacy will become increasingly important for device effectiveness as IMD technologies evolve (Pycroft & Aziz, 2018; Welch et al., 2020; Zhao et al., 2020). Device recalls are documented over the years, but some adverse events have escaped recalls due to patients not mentioning it to healthcare professionals or healthcare professionals refusing to mention it to regulatory bodies to avoid penalties and sanctions (Keikhosrokiani, 2021; Luštrek et al., 2021; Madjid et al., 2019). It behooves regulatory bodies to find ways and means of having patients directly report recalls and adverse events which healthcare professionals refuse to report.

In terms of the theoretical framework, the main trend that IMD studies have in common is the use of UTAUT or an adapted form of UTAUT (Jewer, 2018; Rachmawati et al., 2020; Venkatesh et al., 2003). Each study has attempted to explain the public's acceptance and use of innovative systems such as IMDs. The purpose of the above-mentioned investigations retrieved from the literature, was the enhancement of technology provisions for consumers of various forms of technology, based on their perceptions (Andwika & Witjaksono, 2020; Nikolopoulou et al., 2021; Seyal & Turner, 2013; Williams et al., 2021; Yeow et al., 2013). Irrespective of the diverse settings within which the different examinations were conducted, the research studies within this literature review and their corresponding findings have offered advantageous and important research conclusions and recommendations that contributed to the success of this study.

Furthermore, the information presented in the literature review of this study implied a research-literature gap exists in terms of no research publications on the key factors influencing IMD adoption. This literature gap specifically aligns with the problem statement, purpose statement, and research questions presented in Chapter 1. There is also a theoretical gap existing where there is no established scientific model, or regression model for determining BI to use an IMD. The practical gap is there is no scientific model on IMD adoption factors that healthcare information systems professionals, manufacturers, regulatory bodies, and physicians can count on for effective IMD network implementation.

A study showing the application of factor analysis to create an IMD adoption predictive model for U.S. patients is yet to be found. Prior work in the field of IMDs has focused mainly on assessing the technical security risks with IMDs, as well as exploring technical approaches for improving IMD security (Shang et al., 2021b; Thomasian & Adashi, 2021; Tomaiko & Zawaneh, 2021). While these technical investigations are fundamentally important, it is also fundamentally important to understand other non-functional requirement factors such as Att, SI, PE, PC, and FC. To do otherwise might eventually lead to solutions that are technically viable but significantly undesirable from a patient's perspective.

In addition, the research studies in the literature review suggest that no single security or safety approach may be attractive to all patients, but rather, diverse types of security, safety, and other approaches may appeal to different patients (Giansanti, 2021; Shang et al., 2021a). The literature review also revealed significant knowledge gaps in the research literature in terms of patient perceptions of device effectiveness, device affordability, patient-physician relationship, technology-education understanding, and regulation and their relative impact on IMD Adoption as there are no published studies on these topics. This study sought to fill the knowledge gaps in the literature using the UTAUT model to improve understanding of the key factors that influence the BI to use an IMD.

Summary

IMDs are designed to be imbedded subcutaneously and aimed at aiding disease condition management more efficiently. However, the IMD penetration rates are not encouraging (Iacopino et al., 2021; Piro et al., 2020; Simovic et al., 2022). Recent surges in Emergency Room departments across U.S. hospitals during the COVID-19 pandemic could have been reduced if more patients that need an IMD had an IMD (Antonini et al., 2021; Dilaveris et al., 2020; Garzotto et al., 2020; Golinelli et al., 2020). This research was an attempt to investigate the key factors influencing the BI to use an IMD.

This chapter began with a discussion on the various sources relied on for the theoretical framework and literature review. UTAUT, the theoretical framework on which this research is based, was discussed in addition to complementary frameworks, contrasting frameworks, other pertinent frameworks, and theoretical models. The literature review presented in this chapter increased the knowledge about possible causes for IMD failures and low IMD penetration rates, regulatory bodies and frameworks impacting IMDs, as well as the usability, security, and safety concerns of IMDs. The constructs within the UTAUT framework which were used in composing the survey items (see Appendix G), and other demographic factors which could possibly impact

IMD adoption were also discussed into details. Previous research findings and methods were also synthesized and critiqued to provide a comprehensive study of the literature.

In Chapter 3, the research method and research design for the study is explained. Justification for the selected design approach is also included. In addition, the next chapter highlights data collection instrument and techniques, population, sample, sampling procedures, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), multiple linear regression (MLR) and other statistical methods for statistical analyses. Other sections covered in the next chapter include survey design and implementation, generalizability, reliability of scales, external and internal validity, and this study's ethical considerations.

Chapter 3: Research Method

In this chapter, the research approach that was used for this quantitative correlational study is explained. The problem addressed in this study was that, while IMDs are largely accessible, well-over 60% of U.S. patients who could have benefitted from IMD usage are not interested in taking advantage of this life-saving technology for varied reasons (Banerjee et al., 2019; Longras et al., 2020). The reasons influencing the behavioral intent to use an IMD may include patients' attitudes, social influence, facilitating conditions, perceived credibility, and performance expectancy (Loughlin et al., 2021; Sabas & Kiwango, 2021; Sołtysik-Piorunkiewicz & Zdonek, 2021). The purpose of this quantitative, correlational study was to investigate the relationships between the key factors that may influence the U.S. patient's behavioral intent (BI) to use an IMD. U.S. patients' perceptions on the key influencing factors for IMD adoption as well as the extent of the relationship between the independent variables of social influence (SI), attitude (Att), facilitating conditions (FC), perceived credibility (PC), and performance expectancy (PE), and the dependent variable of U.S. patients' behavioral intent (BI) to use an IMD was explored.

This chapter starts with a brief discussion of the appropriateness of the methodology and design in relation to the study problem, purpose, and research questions. Alternative methodologies and designs and why they were deemed less appropriate than the elected ones will be discussed. Next, the research design, target population, sample, sampling procedures, sample size, and operational definition of the variables were discussed. Furthermore, materials and instrumentation, data gathering, validation and reliability methods, and data analysis plan are discussed. Also, the study's assumptions, limitations, delimitations, publication of research findings, and the ethical procedures for protecting research participants are presented. Several research methods were available to include the qualitative approach (Janssens et al., 2018; Prosek & Gibson, 2021; Renjith et al., 2021), the quantitative technique (Moote et al., 2020; Rutberg & Bouikidis, 2018), and mixed methodology (Moraga et al., 2020), however, the quantitative method with correlational design was found the most appropriate based on the problem statement, research questions, and purpose of the study.

Research Methodology and Design

The nature of the research problem influences the selection of methodology (Creswell, 1996). Quantitative and qualitative research differ fundamentally although their objectives and applications may overlap in numerous ways. Quantification of data is considered the main purpose of quantitative research (Reumers et al., 2021). This allows generalizations of results from a sample to an entire population of interest and the measurement of the incidence of various views and opinions in each sample (Zhang et al., 2019).

Qualitative research is considered particularly suited to gaining in-depth understanding of underlying reasons as well as motivations. The main differences between quantitative and qualitative research relate to data sample, data collection, data analysis, and finally, to outcomes (Prosek & Gibson, 2021; Renjith et al., 2021). Data collection in qualitative research is seldom based on unstructured or semi-structured, but methodologically flexible techniques (Haynes et al., 2020), e.g., individual depth interviews or group discussions, which are suited to elicit detail and a comprehensive view.

Quantitative research uses highly structured, rigid techniques such as online survey. Unlike qualitative research, which allows unlimited expression from respondents, quantitative research relies on responses to pre-formulated questions (Prosek & Gibson, 2021; Reumers et al., 2021). Previous studies on IMDs used either quantitative, or qualitative, but the most used quantitative experimental methods. Examples of IMD studies based on the quantitative method are Breese and Zwerling (2020); Cristina et al. (2021); Halperin et al. (2008); Luštrek et al. (2021); Keikhosrokiani (2021); Pycroft and Aziz (2018); Zhang et al. (2019). Examples of IMD research employing the qualitative methodology for IMD research include Cheong et al. (2020), Gagliardi et al. (2018), and Haynes et al. (2020).

Rationale for Quantitative Methodology

The goal of this quantitative correlational nonexperimental, study was to observe the relationships between the independent variables of FC, SI, PC, PE, and Att on the dependent variable of the U.S. patient's BI to use an IMD, and also to investigate the degree to which predictions of PE were mediated by the PC variable. This study sought to provide an improved comprehension of problems surrounding the U.S. patient's BI to use an IMD for efficient disease condition management. According to Moraga et al. (2020), when the aim of the study is the testing and verification of theories to generalize and replicate the results in other subjects and environments, the quantitative method is more suitable. The quantitative methodology is therefore suited to my research because the study seeks to test and verify the UTAUT theory to generalize and replicate the results in other subjects and environments. The quantitative methodology was applied because the research questions require the relationships between independent and dependent variables, and quantitative methods are suitable for exploring relationships (Basias & Pollalis, 2018; Bauer et al., 2021; Rutberg & Bouikidis, 2018).

The quantitative approach is by far the most favorable option because it has been used in several technology acceptance investigations to include Ahmad et al. (2020) evaluation of factors influencing diabetic patients' continuous usage of digital health wearables, Abbad (2021) investigation of students' usage of e-learning systems in developing countries, Angelia et al.

(2021) investigation of the effect of attitude on mobile banking acceptance. , and Banerjee et al. (2019) analysis of the factors that determine whether current registries are adequate to expose safety and efficiency issues in IMDs. Other studies where the quantitative methodology has been applied include Jadil et al.'s (2021) use of the UTAUT model to investigate mobile banking and Kamal et al.'s (2020) acceptance of telemedicine through the extended TAM.

In this research where the primary aim of investigations was for the testing and verification of theories and corresponding assumptions for the generalization and replication of results in other environments and jurisdictions, the quantitative approach is most preferred. A quantitative nonexperimental correlational approach would be most appropriate to conduct this research since no independent variable (PC, PE, FC, Att, and SI) was manipulated for identifying their influence on the dependent variable IMD Adoption intent. The quantitative methodology is again suited to my research because the research purpose was to establish the extent of relationship between UTAUT constructs in their original form without manipulation as the independent variables, and BI to use an IMD, as the dependent variable. In addition, the quantitative methodology is the most suitable option because it has also been the primary method of choice in several IMD acceptance investigations such as Menebo (2020) and Madjid et al. (2019).

Qualitative research methods were inappropriate for analyzing the extent to which the variables contribute to adoption and for studying the simultaneous interaction effect of variables on BI to use an IMD. Moraga et al. (2020) explained that once the study's aim is the uncovering of knowledge or the development of new theoretical concepts, or the explanation of phenomena, the qualitative approach is justifiable. Qualitative research methods were inappropriate for analyzing the extent to which the variables contribute to adoption (Creswell, 1996; Janssens et al., 2018), and for studying the simultaneous interaction effect of variables on the BI to use an IMD.

Rationale for Correlational Design

The research design used was correlational. The quantitative correlational research method was selected because the research intent was to quantify the extent to which five IMD adoption factors can be useful in predicting BI to use an IMD. As a correlational study, this study sought to prove the hypotheses using the dependent and independent variables (Kumatongo & Muzata, 2021). Apart from the factor analysis method, multiple linear regression was chosen to determine relationship with the goal of analysis to confirm the results of the parsimonious model (Gomes et al., 2020). Logistic regression was considered but it was realized it would not be suitable because the dependent variable (DV) of BI to use an IMD is not categorical, but rather quantitative. Discriminant analysis was also considered, however, was also not suitable because the DV is not categorical.

Guan et al. (2022), in a quantitative, correlational study, involved the retrospective study of real-time observations of vaulting using the RESCAN 700 system. Using quantitative magnetic resonance imaging, Saccenti et al. (2020) performed a correlation study to compare the various imaging techniques in multiple sclerosis patients. Pairwise correlations were calculated using Spearman's correlation analysis.

In a similar IMD study, Madjid et al. (2019) studied the effect of high influenza activity on risk of Ventricular Arrhythmias (VA) requiring therapy in patients with Implantable Cardiac Defibrillators (ICD)s and cardiac resynchronization therapy defibrillators. Significant correlation was found between the influenza activity and the incidence of VAs requiring ATP treatment. Menebo (2020) conducted a quantitative, correlation study to analyze correlations between the weather and the COVID-19 pandemic in Oslo, Norway, where a non-parametric correlation test was performed during data analysis. A non-experimental, correlational, quantitative approach was the most appropriate for conducting this study because none of the independent variables (Att, PC, PE, SI, and FC) was manipulated to identify their influence on the DV, BI to use an IMD. Moreover, the study assessed the mediation of predictability for the predictor construct of PE by the mediating construct of PC.

Kumatongo and Muzata (2021) stated that it is appropriate to apply a quantitative, non-experimental, correlational approach if the researcher is investigating constructs in their original form without manipulation, where SEM or other statistical analyses methods are used in measuring the extent to which two or more constructs are associated when there is no random allocation of subjects to groups. A correlational design was applied because the research purpose was to evaluate the degree of relationship between the independent and dependent variables. The proposed independent variables were PE, PC, SI, FC, and Att and were presumed predictive of the dependent variable of the U.S. public's BI to use an IMD. The extent to which the predictions of PE are mediated by the PC variable was also explored.

Population and Sample

The basic research model defines the population from which the target research subjects were selected (Gąsieniec & Stachowiak, 2021; Roberts, 2021). This gives the opportunity to conduct the study on the target population, whilst inferring the study results from the sample back to the target population(Gąsieniec & Stachowiak, 2021). The target population of the study was restricted to patients in the United States (not territories, and not provinces) who either use or do not use an IMD but are suffering from a disease condition for which a physician would prescribe an IMD and belong to a Facebook IMD Support Group.

Demographic features of the study population include males and females, of age 18 years or older, the insured and uninsured, about 300 users and non-users of IMDs suffering from a disease condition that a physician could recommend an IMD. A total of over 40,000 individuals belong to the various Facebook IMD Support Groups contacted for recruitment. In situations with the population exceeding 5,000 people, the population size will no longer affect the sample size, and a 300-subjects sample suffices (Wang et al., 2021b). However, with G*Power analysis the minimum sample size was further reduced to 226 as described under the sample size calculation section.

Sampling and Sampling Procedures

Sampling is the method of selecting a portion, piece, or segment that is representative of the whole (Wang et al., 2020). Quantitative studies must follow a five-step approach to sampling to include selection of the target population, selection of the accessible population, stating the eligibility criteria, outlining the sampling plan, and recruiting the sample. As part of its strengths, the simple random sampling strategy which was used for this study is such that for every given sample within the population, generalization can be applied to the research results (Zyphur & Pierides, 2017).

In addition, with the random sample selection process, systematic bias is eliminated from the selection procedure. Population parameters were more accurately estimated as the sample was representative of real values found in the total population. The disadvantage of the random sampling method is learning to use the appropriate statistical tables and/or statistical software to be able to read the results accurately. The sample frame was the U.S. IMD Support Groups' members online.

Sample Frame. The sample frame consists of list of names and contact information of group members, maintained by the Facebook IMD Support Group's administrators. Examples of IMDs include pacemakers, stents, catheters, implantable cardioverter defibrillators (ICDs) and implantable arrhythmia defibrillators (IADs). Examples of disease conditions qualifying for the study include, cardiovascular diseases, heart attacks, heart disease, diseases pertaining to the ear, dental complications, and nervous system complications within the population of U.S. Facebook IMD Support Groups' members. The total population for the online U.S. IMD Support Groups for which permissions from the administrators of the groups to recruit participants were sought and obtained, was well beyond 23,000 members. The sampling frame of this study was therefore estimated at 23,000 patients using and not using IMDs and beyond the age of 18. This was good for the research because, even a survey response rate of 1% was adequate to meet the minimum required sample size of 226.

Sample Size Calculation

A sample is a subset of the population data that serves as the basis for generalizations (Adam, 2020; Roberts, 2021). According to Zyphur and Pierides (2017), a sample is representative if the analyses made using the sampling units produce results similar to those that would be obtained had the entire population been analyzed. In determining the appropriate sample size for this study, the G*Power software version 3.1.9.7 (Kang, 2021) for Power Analysis was used by this researcher.

There exists several other statistical software for computing sample size such as MPlus and statistical techniques such as the Monte Carlo simulations, however G*Power was chosen for its reliability and suitability to simple SEM analysis such as in this study. Monte Carlo was not used because, to the extent there was only one mediation to deal with in the model, G*Power sufficed to determine the minimum sample size. In situations where large and very complex models with multiple mediations and moderation are to be analyzed, Monte Carlo simulations are recommended (Napchan & Holt, 2021). Zhou et al. (2022), used G*Power to calculate the *a priori* required sample size in an SEM analysis involving the influence of planned behavior on purchase behavior on social media. Ng et al. (2022), also used G*Power to calculate the *a priori* required sample size in a dual-stage predictive SEM analysis of factors affecting usage behavior and cross-category usage in mobile fashion shopping.

Statistical measures input into the G*Power software included statistical power, alpha, and effect size values. Sampling strategies that use the statistical power, alpha, and effect size values will have a stronger research study than studies that do not use them (Johnston et al., 2019; Liu et al., 2020). The statistical power is defined as the probability that a given statistical test will detect a real treatment effect or real relationship between variables (Kang, 2021). The alpha value is predetermined, which gives the opportunity to reject the null hypotheses when selecting a large value to expand the rejection region. In effect, selecting a small value for alpha can weaken a quantitative study (Adam, 2020; Harden & Friede, 2018). From experience with statistical software, the effect size value is either estimated or calculated unlike the statistical power and alpha values which are predetermined. According to Johnston et al. (2019), a large effect size decreases the required number of participants, and this might not be a positive sign for generalizability. With respect to effect size conventions, 0.1 is considered a small effect size, 0.3 is considered a medium effect size, whilst 0.5 is considered a large effect size (Johnston et al., 2019).

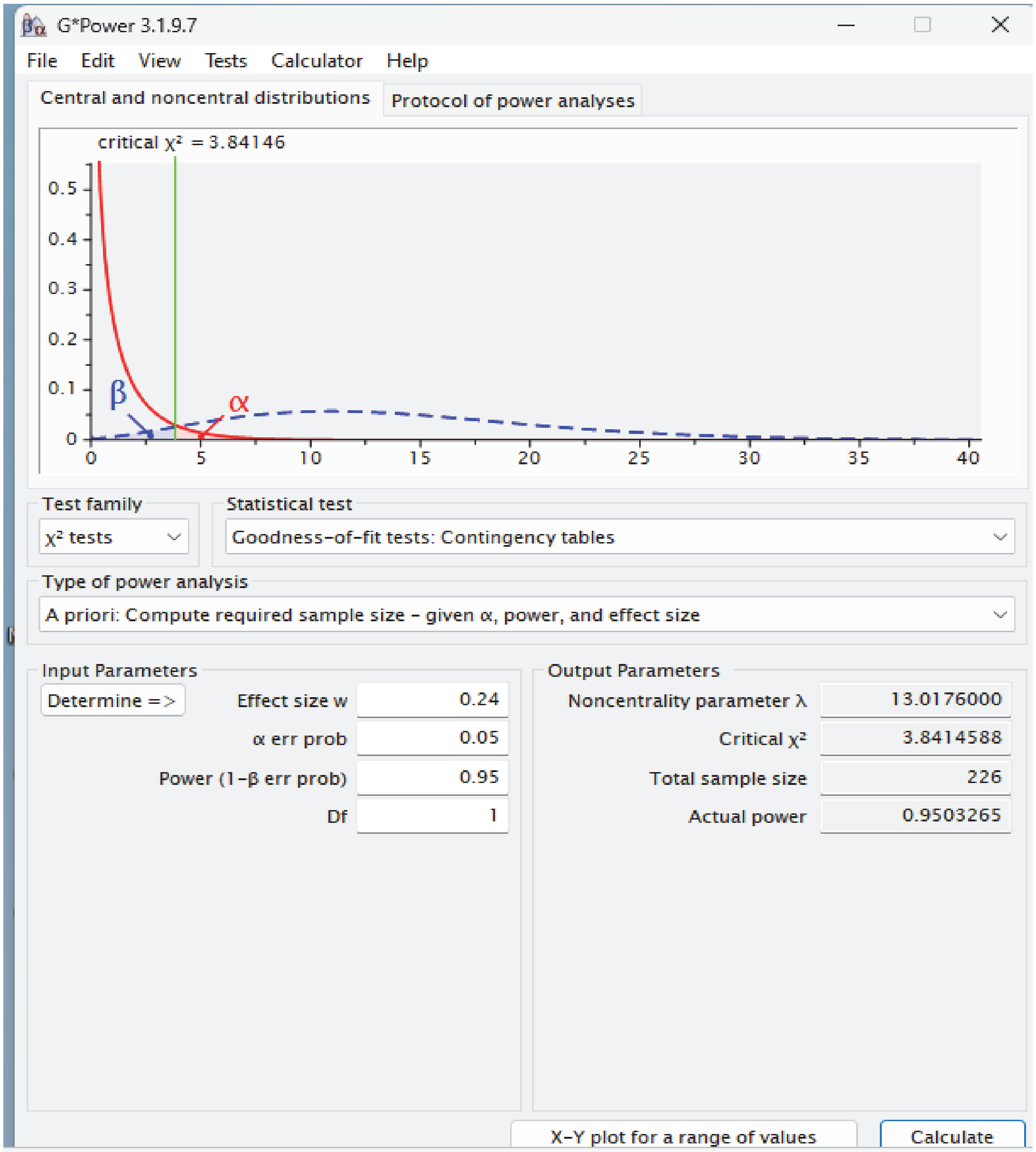
The optimum value for power, i.e., the probability that a test will detect a real treatment effect or real relationship is 95% (Adam, 2020; Kang, 2021). The allowable range is between

80% and 99%. For this research, the power was predetermined at 0.95 or 95%. The alpha value was also predetermined at 0.05. It is standard practice to set the alpha level at .05, for social science, psychology, technology, and medical research (Kang, 2021). This is in relation to confidence interval (C.I.) of 95% (Zhou et al., 2022). In the absence of any statistical data, the researcher may estimate the sample size using a small, medium, or large effect size (Harden & Friede, 2018; Liu et al., 2020). A high effect size, i.e., 0.5 and above will give a smaller sample size which will not produce generalizability of research results.

The Chi-squared family of tests category was used, and the specific test is referred to as the 'Goodness-of-fit tests: Contingency tables'. Using a power of 0.95, a significance level of 95%, and medium effect size of 0.24 to improve on generalizability, with one degree of freedom, the *G*Power* analysis (Kang, 2021) estimated a minimum sample size of 226 (see Figure 2). The power calculation elements were set, by this researcher, based on similar power calculations in similar studies demonstrating appropriate use of study (Ng et al., 2022; Zhou et al., 2022). Per calculations in G*Power (Kang, 2021), and an average response rate of 25% for online surveys (Qualtrics.com, 2021), about 370 online questionnaires were distributed via Qualtrics, only after this researcher received approval from NCU's IRB.

Figure 2

*G*Power Minimum Sample Size Calculation*



Once permission was granted by group administrators or moderators via Facebook's instant messaging application, email, or group wall post, to survey group members, recruitment flyers were posted by this researcher to the relevant Facebook support groups' wall pages. After approval of the dissertation proposal by the NCU IRB, the recruitment flyers were posted into each group's wall page to enable group members access the survey link. Eligibility criteria included Facebook IMD support group members that are currently using an IMD, members who have used an IMD in the past, members who are prospective IMD users, and those that have declined to use an IMD after it was recommended by a physician. Group members must also reside in any of the 50 U.S. states, and not territories nor provinces, and are 18 years or older.

Instrumentation

Research instrument items were adapted by this researcher from previous studies using the UTAUT framework (Yeow et al., 2013) and other components (Kohnke et al., 2014; Morosan, 2016) to provide a better understanding of key factors impacting the public's adoption of innovative technologies. It was anticipated that the entire survey could be completed within 15 minutes. All the three instruments' scales, for which permission was sought (see Appendices B-D), were integrated, and slightly modified to fit the U. S. and IMD contexts. These questionnaires have been validated and shown to be dependable and valid for the assessment of users' acceptance and intentions in other jurisdictions (Kohnke et al., 2014; Morosan, 2016; Yeow et al., 2013).

The survey questionnaire in this quantitative correlational design involves three sections using an ordinal and nominal measurement and adapted from Yeow et al., (2013). The first survey segment investigated the demographic information of respondents to provide respondents' individual profiles. Annual household income, education level, gender, and age were the demographic questions adapted with permission from Yeow et al. (2013) and Morosan (2016). From Yeow et al.'s (2013) instrument, monthly income level, nature of occupation, and race were excluded, and city of current residence modified to state of current residence.

The second section assessed, Att, FC, SI, PC, and PE. The third section measured BI to use an IMD for disease condition management. In sections two and three, the constructs were presented to respondents in question format applying a 5-point Likert scale format which ranged from Strongly Disagree – 1, Disagree – 2, Neither Agree nor Disagree – 3, Agree – 4, Strongly Agree – 5. The PC and PE scales adapted from Yeow et al. (2013) consisted of three items in each scale. Items included in the PE scale measured the extent to which respondents perceive that IMD is useful for efficient disease condition management. Items included in the PC scale measured the degree to which IMDs are perceived as secure and safe to use. The SI scale adapted from Yeow et al. (2013) includes three items measuring the degree to which respondents perceived whether individuals who are important in their lives, people they know who use IMDs, individuals in their Facebook IMD Support Groups or the government impacts their BI to use IMDs.

The FC scale adapted with permission and also derived from Yeow et al.'s (2013) work, include three items measuring the degree to which respondents perceive that enabling conditions exist to encourage IMD acceptance. Enabling conditions included the availability of IMD network infrastructure, and ability to discuss with physician treatment options. The second FC item in Yeow et al.'s (2013) survey was omitted because it was a misfit for this investigative context. The anxiety factor was considered inapplicable to the research objectives and therefore was excluded from the investigation's measurement model. The adapted Att scale was included in measuring the extent to which respondents perceive that the use of an IMD is a good idea and improves on the individual's standard of living (Kohnke et al., 2014). Adapted from Yeow et al. (2013), the BI to use scale included three main items that measured the degree to which respondents will in the future use IMD for efficient healthcare management.

All the five scales were integrated and slightly modified to fit the U.S. and IMD contexts from validated instruments that were used by other researchers (Kohnke et al., 2014; Morosan, 2016; Yeow et al., 2013). In other investigations, researchers have demonstrated that the questionnaires relied on for this study are robust and valid for the assessment of the users' BI and acceptance in different environments (Rafique et al., 2020; Widyanto et al., 2021). Creswell (1996) suggested that researchers making use of a pre-existing instrument must ensure that the instrument and scales are suitable to the research objectives for producing accurate research data. The instrument and scales adapted to this research are suited to this study's research objectives.

The study variables, BI to use, Att, FC, SI, PC, and PE were measured using a 5-point Likert scale format. The data type for these survey items is ordinal in nature but transformed into continuous variables. The corresponding composite variables could be treated as continuous variables because once the survey item values for the corresponding composite variable are added, the resulting value becomes interval data (Aneiros et al., 2022; Lyons & Kass-Hanna, 2021). Sung and Wu (2018) indicated that Likert-type scales may be ordinal data, but researchers can analyze with interval procedures as long as the scale item has at least five to seven ordinal categories. The argument is that with sufficient scale categories, the survey values mostly fall into a normal distribution. Hence Spearman rank correlation was not applied in this study since the ordinal data was transformed into interval data.

Yeow et al. (2013) stated that a reliability coefficient of alpha which is above 0.7 suggests an acceptable reliability of the measure. A Pearson coefficient of correlation below 0.8 suggests that the "inter-construct-correlations" (p. 724) have no multicollinearity problems. An Average Variance Extracted (AVE) with a 0.5 or more value is a good indication of convergent validity. Yeow et al. (2013) also stated that content validity can be established by the documentation of a thorough literature examination of constructs under investigation and discriminant validity is established by substantiating that the square roots of the AVE values are greater than “the inter-construct correlations” (p. 724). Yeow et al.’s (2013) measurement model stated that the coefficient of Cronbach’s alpha for BI to use is 0.71, for PC is 0.75, and for PE is 0.8. The AVE values for BI to use is 0.69, PC is 0.6, and for PE is 0.64. The square root of AVE for BI to use is 0.83, for PC is 0.77, and for PE is 0.8, and the inter-construct Pearson correlations for PC and BI are 0.62, PE and BI are 0.62, and for PE and PC are 0.41.

The SI and FC constructs were omitted from the Yeow et al. (2013) investigation because the confirmatory factor analysis suggested that the items that were included in the SI and FC variables demonstrated loading values below 0.7. Although Yeow et al.’s (2013) measurement model suggests a small loading value for SI and FC variables, SI and FC variables were maintained in this study. Kohnke et al. (2014) also found the SI and FC variables delivering high alpha variables and demonstrating validity in addition. Kohnke et al. (2014) using a CFA determined each construct’s validity during the investigation of the factors influencing healthcare personnel and patients to use telemedicine systems. Kohnke et al. (2014) suggested that a root mean square error of approximation (RMSEA) value of below 0.08, a ratio value lower than 2 of a Chi-square given the change in degrees of freedom (X^2/df), a comparative fit index (CFI) having a minimum of 0.9, are all indications of a satisfactory model with good discriminant and convergent validity.

In Kohnke et al.’s (2014) study, the RMSEA was 0.79, CFI was 0.924, the factor loading for FC was 0.914 and SI was 0.883, the ratio of X^2/df was 1.8. In the reliability computations, the coefficient of alpha of BI to use was 0.941, FC was 0.801, and of SI was 0.865. As in this study, Kohnke et al. (2014) also included the Att construct to the UTAUT design to demonstrate validity and reliability. The reliability computations reported a coefficient of alpha of 0.872 and factor loadings of 0.8 for each Att item. Because the three adapted instruments' constructs and items have undergone validation, and demonstrated reliability and dependability (Han et al., 2020; Lawson et al., 2020), a pilot study was not conducted in this study.

Operational Definition of Variables

The questionnaire in this quantitative, correlational design includes the use of an ordinal and nominal scale in three sections adapted from Yeow et al. (2013). The first segment investigated demographic information to produce respondents' profiles. Yeow et al. (2013) and Morosan (2016) demographic questions adapted included annual household income, education level, gender, and age. The second segment assessed the independent variables of Att, FC, SI, PC, and PE. The third segment measured the dependent variable BI to use an IMD. The third section also described the operationalization of both independent and dependent variables used in the study.

Performance Expectancy. PE can be defined as the degree to which individuals anticipate that their work-related activities will continue with the use of a specific technology (Magsamen-Conrad et al., 2015; Sabas & Kiwango, 2021; Sołtysik-Piorunkiewicz & Zdonek, 2021). Several researchers have demonstrated that this variable is a reliable predictor of technology adoption such as in the Malaysian SNIC (Yeow et al., 2013), biometric authentication in electronic shopping (Hino, 2015), and home telehealth services (Cimperman et al., 2016). PE involves five different predictors in technology adoption, namely, *outcome expectations* (social cognitive theory) (Venkatesh et al., 2003), relative advantage (innovation diffusion theory), job-fit (the model of PC utilization); extrinsic motivation (Motivational Model); and perceived usefulness (TAM/TAM2 and C-TAM-TPB).

In this study, PE represented the degree to which the U.S. patient expects that by using an IMD they will be able to efficiently manage their disease conditions. PE was measured as an independent variable, based on Yeow et al.'s (2013) scale and it was derived from respondents' opinions to three scale items with the help of an ordinal scale. A five-point Likert scale response format ranging from 1 – Strongly Disagree, 2 – Disagree, 3 – Neither Agree nor Disagree, 4 – Agree, and 5 – Strongly Agree (see Appendix A) was used by each of the three scale items.

Yeow et al.'s (2013) findings suggested that the public's PE of a Malaysian SNIC focusses on its PC, which subsequently influences Malaysian's intent to use. In determining if similar phenomenon applies to IMDs, the degree to which the "BI to use" prediction, as measured by the PE scale, is statistically mediated by PC was investigated. The items in the PE scale measured the degree to which the U.S. patient trusts that using IMDs will help them manage their disease conditions more efficiently and enhance their living conditions.

Perceived Credibility. PC is the extent to which people trust that the specific technology is robust, secure, can be trusted, and dependable (Shin et al., 2017). Researchers have implied that PC is associated with privacy (Hino, 2015) and technological safety concerns (Yeow et al., 2013). Areas of concern encompass the appositeness of safekeeping, information handling, and safety measures for collection, reliability, accuracy, as well as confidence in the systems defense mechanisms (Shin et al., 2017). Previous studies have supported the notion that PC drives BI to adopt and use technology such as biometric technology in electronic applications (Hino, 2015), Malaysian SNIC (Yeow et al., 2013), and health informatics (Shin et al., 2017).

In synchronization with the previous literature, PC was operationalized in this study as the degree to which U.S. patients expect that IMDs will be a secure system where data is difficult to modify by hackers, managed effectively and securely, and data is kept confidential. PC was measured as an independent variable based on Yeow et al.'s (2013) questionnaire and as derived from the respondents' opinions concerning three items on an ordinal scale. Each of the three items used a 5-point Likert scale response-format which ranged from Strongly Disagree - 1, Disagree - 2, Neither Agree nor Disagree - 3, Agree - 4, and Strongly Agree – 5 (see Appendix A). The items included in the PC scale measured the degree to which IMDs are difficult to hack, secure, and can prevent unauthorized access to patients' personal information.

Social Influence. SI is defined as the perception an individual has that another individual who holds a valuable position in someone's life thinks he or she should accept and use the system (Magsamen-Conrad et al., 2015). Several researchers have suggested that an individual's resolve to participate in a specific behavior is oftentimes affected by social pressure (Yeow et al., 2013), affected by image (Chauhan & Jaiswal, 2016), and relatives (Palau-Saumell et al., 2019). Previous studies have maintained the idea that SI is a predicting factor of an individual's willingness to use technology, such as mobile internet use (Jacob & Pattusamy, 2020).

With reference to the previous literature, SI in this study measured whether or not the U.S. patient's BI to use an IMD is influenced by the views and motivation of someone holding a meaningful position in their lives. SI was measured by this researcher, as an independent variable, adapted from Yeow et al.'s (2013) questionnaire and derived from patients' opinions to three items using the ordinal scale. The three items used a 5-point Likert scale response-format ranging from Strongly Disagree – 1, Disagree – 2, Neither Agree nor Disagree – 3, Agree – 4, and Strongly Agree – 5 (see Appendix A). The items included in the SI scale measured the degree to which individuals perceive that people important to their lives, individuals who they know use the technology, or government functionaries influence their BI to use an IMD.

Facilitating conditions. FC is defined as the extent to which an administrative, specialized, or technological structure is presented, to support technology acceptance (Chauhan & Jaiswal, 2016). Research predicting people's willingness to technology-use have included FC as a significant predictor, because the existence of adequate infrastructure will promote the use of technology (Chauhan & Jaiswal, 2016; Cimperman et al., 2016; Jacob & Pattusamy, 2020). Contrarily, other researchers disagreed and postulated that FC has no direct impact on technology-use (Palau-Saumell et al., 2019). Irrespective of the volatility of FC in predicting technology adoption and usage, several researchers have always considered FC a valuable construct in the explanations of what encourages individuals to accept and use technologies (Abbad, 2021; Ikhsan et al., 2021; Thomas et al., 2020; Yeow et al., 2013).

In this study, FC represented the degree to which U.S. patients consider that the existence of administrative, specialized, and technological structures facilitates the adoption and use of an IMD. FC was measured as an independent variable, which was constructed based on Yeow et al.'s (2013) work. FC was derived from respondents' opinions to the three items using an ordinal scale. Each one of the three items made use of a 5-point Likert scale response-format ranging from Strongly Disagree – 1, Disagree – 2, Neither Agree nor Disagree – 3, Agree – 4, and Strongly Agree – 5 (see Appendix A). The FC factor includes three items measuring the degree to which respondents perceive that enabling components are in existence to encourage the acceptance of IMDs. Enabling components consist of the availability of IMD network infrastructure within the U.S. public and private healthcare facilities for managing disease conditions more efficiently, availability of contact centers for responding to questions in relation to IMD usage, and expectations that the IMD network infrastructure will keep improving.

Attitude. Attitude construct is an indication of an individual's negative or positive response behavior to technology-use (Chatterjee, 2021; Nasri, 2021). Previous studies have included Att in the UTAUT framework to assess its correlation with the other UTAUT constructs. For example, Thomas et al.'s (2020) results suggested that Att is positively correlated with FC, PE, and EE constructs, and that Att directly impacts on technology adoption and usage. Hwang et al. (2019) suggested Att directly correlates with PE and has a significant impact on individuals' intention towards the use of an innovative system.

Venkatesh et al. (2003) stated that when EE and PE are excluded from UTAUT, the effect of Att should be considered. In this study, the EE construct was not considered because IMD is simple to use considering it is implanted and does not interfere with the daily activities of the patient. The absence of effort expectancy allows Att to be incorporated into the research constructs. Various researchers have also reflected on Att as a valuable construct in explaining BI to use (Chatterjee, 2021; Nasri, 2021; Seyal & Turner, 2013; Thomas et al., 2020).

With respect to the previous literature, Att is defined as the degree to which U.S. patients' disfavor or favor the adoption and use of an IMD. Att was measured as an independent variable. Att was adapted from Kohnke et al.'s (2014) questionnaire scale and was derived from patients' opinions to three items on the ordinal scale. Att factor includes three items measuring the degree to which patients perceive that using an IMD is a good idea, is beneficial, and improves their standard of living. The three items used a 5-point Likert scale response-format to range from Strongly Disagree -- 1, Disagree -- 2, Neither Agree nor Disagree -- 3, Agree -- 4, to Strongly Agree – 5 (see Appendix A).

Behavioral Intent. BI defines how willingly individuals adopt and use a system (Jacob & Pattusamy, 2020). According to Seyal and Turner (2013), BI presumably describes the propelling forces behind an individual's behavior and to denote the extent to which individuals are willing to execute the particular behavior. Several studies have demonstrated that BI is directly impacted by Att, FC, SI, PC, and PE (Hino, 2015; Seyal & Turner, 2013; Yeow et al., 2013).

In this study, BI measured the degree to which the U.S. patient is willing to adopt and use an IMD. Additionally, BI was evaluated as a dependent variable adopted from Yeow et al. (2013) and as was derived from the respondents' opinions to three items with the use of the ordinal scale. BI included three items measuring the degree to which the respondents will adopt and use an IMD for disease condition management, predict utilization of IMD, and continue to use an IMD. Each of the three items used a 5-point Likert scale response format ranging from Strongly Disagree -- 1, Disagree -- 2, Neither Agree nor Disagree -- 3, Agree -- 4, to Strongly Agree – 5 (see Appendix A).

Study Procedures

This quantitative, correlational study investigated the relationship between the independent variables of Att, FC, SI, PC, and PE, and the dependent variable of the U.S. patients' BI to use an IMD for managing disease conditions efficiently. To determine factors shaping the U.S. patients' acceptance of an IMD, the investigative framework utilized Yeow et al.'s (2013) extension of UTAUT: PE, PC, SI, and FC while expanding the model to add Att. This researcher adapted the survey format from Yeow et al.'s (2013) questionnaire. All scales in the measuring instrument are from surveys that have demonstrated to be dependable and valid for examining users' intents and acceptance in other specific environments (Kohnke et al., 2014; Morosan, 2016; Yeow et al., 2013). The scales were integrated and slightly modified, to fit the

U.S. and IMD investigative contexts. Due to the adapted instruments' items having undergone reliability and validity testing, a pilot study was not conducted in this study.

In this quantitative, correlational study the questionnaire includes three sections using an ordinal and nominal scale of measurement adapted from Yeow et al. (2013). Data for this research was collected by this researcher, through online survey instrumentation for assessing respondents' perspectives with distribution via Qualtrics. A survey was deemed the most appropriate instrument for data collection as it allowed patients to respond truthfully and anonymously while identifying which key variables are significant towards BI to use an IMD. The survey consisted of 29 Likert-type items (questions or variables) related to each of the factors to gather significant data for analysis.

A summary of items operationalizing all six constructs is presented in Appendix G. That is, each Likert-type item corresponds to a variable within the Likert-type survey. The survey format was adapted from Yeow et al. (2013) questionnaire. It was administered to the relevant Facebook Support Group members who are resident within any of the 50 states within the United States. The online survey was considered the most favorable choice because surveys are the most prominent and most robust instrument in academic research (Natarajan et al., 2017). Rahman et al. (2017) constructed questionnaires using SurveyMonkey, administering them via Amazon Mechanical Turk to respondents, for the evaluation of the relevance of TBP, TAM, and UTAUT in explaining motorists' intent to utilize the Advanced Driver Assistance System (ADAS).

Sample Recruitment

This researcher conducted sample recruitment by posting Survey Recruitment flyers with survey link (see Appendix H) in the various and relevant Facebook IMD Support Groups, after obtaining permissions from group administrators (see Appendix I). The invitation text included a weblink to the Qualtrics website, where participants were presented with the survey introductory letter and the informed consent form, providing the purpose and study intent as well as safety measures ensuring anonymity and confidentiality. With research results and analyses from this study, pertinent information for patients, doctors, healthcare policy regulators, healthcare information systems managers etc. may be provided leading to social change of increased number of patients adopting IMDs for efficient disease condition management.

Respondents' confidentiality was maintained throughout the survey. The survey was anonymous with no phone numbers, names, IP addresses, or email addresses collected from respondents. Questionnaires were distributed via the survey link by the group moderators to group members, after approval was received from the NCU IRB. Each construct was assessed by three items and measured with a 5-point Likert scale ranging from Strongly Disagree to Strongly Agree, 1-5 respectively.

The measuring instrument of this study did not put respondents at any risk of harm. Online surveys remained anonymous with no identifying information collected, such as names, phone numbers, or emails, to protect the confidentiality of respondents. Surveys were distributed only after receiving approval from NCU's IRB. After authorization was given, participants were randomly selected from Facebook IMD Support Groups. They were issued survey consent letters explaining the study purpose, safety measures ensuring anonymity, data handling procedures, and notified that their participation is voluntary. In addition, Qualtrics does not make audience members' personally identifying information (PII) accessible to anyone, including the researcher.

Data Analysis

Structural Equation Modeling (SEM) and Statistical Package for the Social Sciences (SPSS) AMOS version 26 software was used by this researcher in assessing the research variables. Confirmatory factor analysis and exploratory factor analysis were conducted to investigate the model's relationships as well as to assess any fit of the postulated measurement model. Furthermore, causative correlations amongst the independent and dependent variables were assessed. Correlational designs aim at exploring linear inter-relationships between independent variables as well as relationships between independent and dependent variables (Talantis et al., 2020). Gondauri et al. (2020), in a quantitative study on the novel coronavirus COVID-19 focused on the COVID-19's spreading statistics which were based on examples of the cases from different countries. Determinants and Pierson correlation coefficients were computed to determine the relationships between the total volumes of virus spread and recovery from the virus.

Assumptions

Research assumptions are what researchers believe to be true (Liu et al., 2018). Researchers link the assumptions to the deployed theory, the observed phenomenon, the accuracy of the measuring system, the selection process for the research participants, and the analysis of the survey results (Cristina et al., 2021). The first assumption was that the research participants will be a good representation of individuals residing within the 50 U.S. states, not territories, and not provinces. Another important assumption by this researcher was that the participants are literate, i.e., survey respondents will be able to read and comprehend the survey instrument presented to them as well as follow instructions on how to complete the surveys.

Also of importance was the assumption that the survey participants will not be necessarily knowledgeable about IMD technology as both users and nonusers of the technology were employed to participate in the survey. Of further importance was the assumption by this researcher, that the respondents will answer the research questions to the best of their ability, and with honesty. The participants were assumed by this researcher to have knowledge of the functions and importance of IMDs for disease condition management.

Delimitations

The objective of this quantitative, correlational study was to investigate the relationship between the key factors that may contribute to the BI to use an IMD for disease condition management. The specific aspects of the research problem to be addressed are the lack of research, knowledge, and limited understanding of key factors that affect patients' IMD adoption choices. This knowledge and improved understanding may be used by physicians, health information managers, and policy makers, for improving IMD usage rates and efficient IMD usage. The specific focus was chosen because with improved understanding, physicians, policy makers, and health information managers would be able to take decisions that would help improve IMD adoption rates. A delimiting factor was the dependence on only five independent factors of PE, PC, FC, SI and Att.

Another delimiting factor is the use of the UTAUT. To mitigate the risk of not choosing the right framework, other innovation and technology adoption theories including the TAM and DOI, as well as the IMD Design Framework by Halperin et al. (2008) were researched and analyzed based on the literature review to determine whether the above theories could be combined and used in addition to the user-centered design (UCD) and the general systems theory (GST) to help provide the theoretical framework of potential influential factors for IMD adoption. The research questions regarding the key factors of IMD adoption and their relative influence has a facilitative objective of identifying the possible key factors for influencing IMD adoption.

To mitigate the risk of not using the proper analysis method to help answer the research question, other statistical methods such as Logistic Regression and Discriminant Analysis were compared and analyzed to conclude that neither of the two statistical methods was suitable for analyzing the assumed key factors. The period when the research was conducted was also a delimiting factor, as events occurring at that time might affect the results. The geographical boundaries of the study were limited to the 50 U. S. states, leaving out territories and provinces.

Limitations

In terms of methodology, the quantitative methodology is a limitation as it can only be useful in determining influences (Bauer et al., 2021; Creswell, 1996; Kang, 2021), and cannot be used in determining why and how IMD adoption decisions come about. The objective was to find out which of the five key factors has a significant influence on IMD adoption. Quantitative research is the commonly applicable method for investigating relationships between independent and dependent variables (Creswell, 1996). The other limitation is that statistical analysis was the basis of this research, lacking in-depth exploratory power as in qualitative research methods. The openness and honesty levels of the participants may also a significant limitation. The openness and trustworthiness of the participants was relied on, and this affected to an extent the validity and reliability of the study.

Ethical Assurances

Ethical Procedures: Protection of Research Participants

In this study, ethical considerations included risks to the data quality and participants in the study (Perrault & Keating, 2018; Roberts, 2021). The researcher's primary role has been to design the survey instrument from pre-validated survey questionnaires and then analyze the data. Using human subjects in research raises issues of research participants' privacy and protecting their data. Collaborative Institutional Training Initiative (CITI) training to permit conducting of this research with human participants was completed as part of ethical assurance procedures (see Appendix J).

Informed Consent. According to Chen et al. (2022), the Belmont report requires human subjects participating in research to provide their consent voluntarily. In voluntariness, the participant must not be influenced or coerced. Useful information must be disclosed to the participant, such as the purpose of the study, any associated risk, potential benefits, and contact information (Tse et al., 2021). Each study participant was informed that participation is voluntary and given the informed consent form to complete online before moving on to the survey questions. Moreover, participants were reminded that anyone can withdraw from the study if they wish to do so. Participants may withdraw by clicking the exit button on the survey and closing their web browser.

Informed consent was obtained from participants via approved procedures as required by the NCU IRB. The online consent form contains the purpose of the study, participation requirements, anonymity and confidentiality statements, and withdrawal statements. To authorize participation in the survey, patients consented to the anonymity and confidentiality terms, and would be required to select "I Agree" to proceed with the survey. If they click on 'I Agree' they go on to the survey, if not, the survey closes. Participants may print a copy of the consent page for future reference.

Confidentiality. Data collected by the researcher in this study was confidential. Automatically generated pin codes were provided to respondents at the time of survey completion such that participant emails or online closed-group account names are not associated with the data. In case a participant wishes to withdraw later after having completed the survey, they would provide me with their unique survey pin code in the withdrawal email and the individual's survey data and unique code will be deleted from the sample to reduce the survey sample by one. In addition, the coded survey data was made available only to the dissertation committee, IRB, and primary researcher associated with this study. In this way, the confidentiality and anonymity of the subjects were maintained. Confidentiality ensures willingness, cooperation, and honesty in the responses to the Likert-type survey questions. Participants' personal data were de-identified and anonymized through Qualtrics, to ensure the confidentiality of participants' data.

Based on the purpose of protecting research participants' privacy and confidentiality, there was no access to participants' identifying data. A statement of confidentiality within the consent form presented to participants, fostered a sense of trust, which in turn influences survey response rate. Data is being kept confidential by password protecting the downloaded survey data on my laptop, and backups stored on my Microsoft One Drive and Google Drive accounts. Hard copies of the data are being kept in a locked file cabinet accessible by the primary researcher only. After three years, the hard copies will be destroyed through shredding and the softcopy by deleting from the primary researcher's laptop hard drive. This researcher is the only one maintaining the database, cloud data-storage drives, and other peripheral devices. Research participants' data will also be safeguarded using access control mechanisms (username-and-password requirement) for mitigating unauthorized use.

Other procedures included participants making their inputs anonymously and voluntarily as stated in the survey invitation letter. To ensure objective data analysis, all standard statistical tests for factor analysis and SEM were applied by this researcher. Permissions were sought and received from 12 online closed-group administrators for U.S. IMD Support Groups to survey about 23,000 members suffering from disease conditions that warrant the use of an IMD, and either using or not using IMDs for treatment. Data collection and analysis work began only upon receipt of the NCU IRB approval and if the survey participants had any questions and concerns, they would contact the research supervisors at irb@ncu.edu.

Summary

In this chapter, the research methodology and design method were described and their appropriateness to the study problem, purpose, and research questions elaborated. The research design is a quantitative, non-experimental, correlational design. Alternative methodologies and designs were identified and their inappropriateness to this study was indicated. The population and relevant characteristics were described. The appropriateness of the population was explained in addition to a description of the sample to be obtained. The sampling procedure was explained in addition to the sample size calculation. IRB procedures and recruitment of participants were also explained. The survey instrument that was used with the study participants was described into detail. The research variables were operationally defined to identify how each variable was used in the study. Data gathering procedures and the data analysis plan that were used to evaluate each hypothesis were also discussed. The limitations and delimitations of the study were also discussed into detail.

Finally, ethical considerations on how to protect research participants' rights and welfare were included. In the following chapter, the analysis of data and the research results in relation to the research questions and hypotheses are presented. The extent to which the data will meet the assumptions of the statistical tests are explained in addition to identifying factors affecting the interpretation of the findings. The overall study is discussed, and the presentation of results organized by the research questions and hypothesis. The research findings were finally evaluated, and the results interpreted with respect to the existing research and the theoretical framework.

Chapter 4: Findings

Implantable technologies and other innovations such as telemedicine, wearable personal IoT devices for health, and chatbots for diagnosis based on patients' identified symptoms have become prevalent. The problem addressed in this study was that, while IMDs are largely accessible, well-over 60% of United States patients who could have benefitted from IMD usage are not interested in taking advantage of this life-saving technology for varied reasons (Banerjee et al., 2019; Longras et al., 2020). The reasons influencing the behavioral intent to use an IMD may include patients' attitudes, social influence, facilitating conditions, perceived credibility, and performance expectancy (Loughlin et al., 2021; Sabas & Kiwango, 2021; Sołtysik-Piorunkiewicz & Zdonek, 2021). The purpose of this quantitative, correlational study was to investigate the relationships between the key factors that may influence the U.S. patient's behavioral intent (BI) to use an IMD. U.S. patients' perceptions on the key influencing factors for IMD adoption as well as the extent of the relationship between the independent variables of social influence (SI), attitude (Att), facilitating conditions (FC), perceived credibility (PC), and performance expectancy (PE), and the dependent variable of U.S. patients' behavioral intent (BI) to use an IMD were explored.

This correlational study was built upon six research questions emanating from the UTAUT model's conceptual framework and the study purpose and was completed using the online survey method. The main focus of this chapter was to discuss the study's statistical results and assessment of the findings. The section on the reliability and validity of the data begins the chapter. The extent to which the research data satisfies the assumptions of the statistical tests were explained. Evidence of the reliability and validity of the instrument in this study was also provided. An overview of the demographic data gathered was tabulated with all information de-identified. Research results were reported using tables and figures when appropriate.

An outline of the questionnaires and information gathered begins the discussion on the statistical results. All the applied statistical tests are explained. The interpretation of results follows the results reporting, with reference to the research questions, the research hypotheses, and the theoretical framework. To end the chapter, the main points covered are outlined. The last part of this chapter provides an outline of the main points covered and an introduction to the next chapter.

Validity and Reliability of the Data

In this investigation, the survey instrument items were adapted from previous studies making use of the UTAUT theory (Yeow et al., 2013) and its auxiliary components (Kohnke et al., 2014; Morosan, 2016). These studies provided an enhanced comprehension of the determinants that influence the public's adoption of innovative technologies (see Appendices B-D). Philippi et al. (2021) suggested that researchers make use of research instruments already in existence because their validity and reliability have been reliably evaluated and demonstrated in various replicated studies. Two significant limitations on the internal and external validity of this study were sampling bias and maturation effects. Maturation effects refer to the respondent's behavioral changes due to diverse issues including stress, fatigue, and other factors happening within a brief time period.

At the beginning of the survey, participants were provided an informed consent letter. The consent letter explained the aim of the study and the precautions taken to guarantee anonymity. According to Van Mol (2017), when the questionnaire is lengthy, a low response rate is expected. Some individual responses may vary because of the state of mind or exhaustion of the participant at the time the survey was being taken. To deal with the limitation of maturation, the demographic questions were placed at the end of the survey to prevent participants from having the perception of a lengthy survey. The sight of the first demographic question would suggest an end in sight to the survey. A higher response rate resulted from steps taken to mitigate maturation.

Flannelly et al. (2018) suggested that sampling bias could derail the investigation's internal validity depending on the method used for participant selection. The manner in which respondents answered the questionnaire might also explain variations in the dependent variables instead of the independent variables. External validity was also positively impacted as the findings can be generalized because the respondents are a representative sample of the population targeted, i.e., the 50 states within the US, minus territories, and provinces (Srivastava et al., 2021). The demographic information was used only in producing a profile of the participants and not used in the assessment of variations within the study variables.

All respondents were randomly sampled from Facebook IMD Support Groups and the data collected only generalized to U.S. residents living within the 50 U.S. states, and not territories or provinces. The results gathered were processed and examined using SPSS version 28 and SPSS AMOS version 26 software for structural equation modeling (SEM). The SPSS AMOS v. 26 software was selected because it is the latest version with a plugin (PatternMatrixBuilderAMOSv26.dll) for automatically building model diagrams for SEM analyses using the pattern matrix obtained from SPSS, instead of drawing the diagram manually where human errors may occur (Martynova et al., 2018; Reyes-Fournier et al., 2020)

Convergent validity was ascertained by checking that all survey items that measured a precise variable loaded, particularly in that variable. It was also confirmed that the average variance extracted (AVE) for that variable was higher than 0.5 (Luo et al., 2019; Roberts et al., 2019) and that the composite reliability value was greater than 0.7 (Purwanto & Sudargini, 2021). Subsequently, discriminant validity was established by confirming that the square root of AVE of each factor studied in relation to the study was higher than the inter-factor correlation. It was also verified that the AVE was higher than the Maximum Shared Variance (MSV) for all factors (Purwanto & Sudargini, 2021). MSV is calculated as the square of the highest correlation coefficient between the latent constructs and derived from regression analysis in SPSS.

Confirmatory factor analysis and exploratory factor analysis were conducted to investigate the fundamental relationships within the model and to authenticate its reliability and validity, as explained by (Luo et al., 2019; Roberts et al., 2019). According to Luo et al. (2019), to be considered significant, a factor loading in factor analysis must be larger than .4. Selecting the Promax rotation option and the principal axis factor (PAF) extraction method to divulge the nature of the variables having a significant effect on a group of responses, EFA was conducted (Luo et al., 2019; Roberts et al., 2019). Promax rotation outcomes are viewed as more accurate than other PAF rotation methods (Deng et al., 2018; Scherer & Teo, 2020). Similarly, the PAF analysis is also considered more dependable than the Principal Component Analysis (PCA) extraction method due to its ability to take measurement errors into consideration without choosing one specific error as the initial communality. In addition, PAF has the capability of detecting vulnerable factors and revealing the factor structure (Roberts et al., 2019).

The SEM and CFA, on the contrary, were conducted with the use of the maximum likelihood estimator (MLE) (Reyes-Fournier et al., 2020). In SEM, the use of the MLE is very common (Martynova et al., 2018; Maydeu-Olivares, 2017). Because the MLE of SEM statistical and analyses techniques depend on multivariate normality assumptions (Maydeu-Olivares, 2017;

Reyes-Fournier et al., 2020), each and every variable used in this investigation was examined for normality using the Mardia's normalized multivariate kurtosis value. Furthermore, the tolerance and variance inflation factor (VIF) were engaged to investigate relationships between factors to ascertain multicollinearity. A VIF value of less than ten and a tolerance value higher than 0.10 suggests the absence of multicollinearity (Martynova et al., 2018; Reyes-Fournier et al., 2020).

Correspondingly, a Pearson correlation coefficient larger than 0.9 indicates the existence of collinearity (Armstrong, 2019; Melucci & Paggiaro, 2019). A Pearson correlation was preferred because the bivariate associations (linear relationships) among observed variables involved continuous data variables. Spearman rank correlation was not appropriate because monotonic relationships were not under evaluation (Armstrong, 2019). In addition, if the dependent variable was a dichotomous variable (yes or no values), then a point-biserial correlation would have been more appropriate (Melucci & Paggiaro, 2019). The suitability of the data and sample size for factor analysis was evaluated with the use of anti-image correlations, Bartlett's test of sphericity, and the Kaiser-Meyer-Olkin (KMO) index before factor analysis was conducted.

According to Jin et al. (2021), if the KMO index is less than .6, a factor analysis should not be conducted. Similarly, Luo et al. (2019) explained that for factor analysis to be considered adequate, Bartlett's test Chi-square value should be less than .05 of the significance levels. Taber's (2018) Cronbach's alpha coefficient benchmark of ($0.6 < \alpha < 0.7$) was used to evaluate the reliability of the exploratory and confirmatory analyses results, and to also demonstrate a reasonable internal consistency.

Results

The survey flyers were distributed via the wall pages of the relevant FB support groups only after obtaining NCU's IRB approval (see Appendix K). The data was gathered via Qualtrics between February 1, 2022, and March 27, 2022. All participants were provided with an informed consent form explaining the study purpose, the data-handling procedures, the measures taken to guarantee anonymity, and clarifications that the respondent's participation was voluntary. Per explanations in the informed consent form, all the respondents' data collected have been securely stored with password protection and kept on a laptop computer locked in a safe file cabinet. All the data gathered will be destroyed after three years.

Since Qualtrics provided the option of anonymity, the respondent's personally identifying information (PII) were anonymized. This study's measurement instrument did not put respondents at risk of harm. In addition, no names, emails, or phone numbers were collected. By keeping the survey anonymous, the confidentiality of respondents' data remained intact. The survey format was modified from Yeow et al.'s (2013) questionnaire and administered via Qualtrics. With reference to the G*Power sample size calculation, a minimum sample size of 226 participants was to be achieved.

Exactly 363 Facebook IMD Support Group members residing within the 50 U.S. states, but not territories nor provinces, participated in the survey. This amount exceeded the 226 required, and therefore, sufficiency of responses was achieved. The online-survey method utilized in this quantitative correlational investigation improved the probability of each participant responding to questions at their own pace and participating in a low-pressure context with the option of returning several days later to complete the survey on any device of choice. Questions could also be skipped, and participation abrogated at any time without prejudgment or penalty assigned to the respondent (Story & Tait, 2019). A total of 363 responses were downloaded from Qualtrics.com and saved as an SPSS file (.sav) later to be uploaded into SPSS 28 and SPSS AMOS 26 for data analysis. The responses were also downloaded as a Microsoft Excel 2021 file (.xlsx), serving as a backup copy. Within SPSS, all of the data collected was examined for discrepancies, missing values, and errors.

Missing Data, Errors, and Discrepancies

According to Hair et al. (2017), a significant problem in data analysis that may affect the results of the research purposes is missing data. The issue of missing data becomes more critical when using structural equation modeling in AMOS (Kline, 2018). According to Hair et al. (2017), when there are any missing data in the data analysis, Chi-Square, modification indices, and other measures such as Goodness-of-Fit-Index cannot be computed. Schumacker and Lomax (2015) also posited that when the missing data is distributed non-randomly in the response, the entire response can be ignored. When the missing data occurs non-randomly, the generalizability of results is affected (Hair et al., 2017).

After the initial screening in SPSS 28, it was discovered that 49 of the respondents answered either 27 or fewer questions from the entire 29 questions on the survey and therefore did not meet the below 5% missing data threshold, for inclusion in the data analysis. Schumacker and Lomax (2015) suggested that missing data up to 5% of the total questions is considered acceptable. The percentage of missing data for the 49 participants was more than 5% and therefore could not be considered acceptable.

Responses showing disengagement from the survey were also discarded from the survey as suggested by Kline (2018). There were signs of disengagement from the survey, and these responses were also omitted from the analysis as suggested by Pallant (2020). Five such responses were omitted because the participants gave the same exact response for every item answered, which is a demonstration of disengagement from the survey. A total of 54 responses were therefore discarded for disengagement from the survey. Another 63 respondents selected ‘yes’ on the consent form but did not continue to answer any question in the survey and would therefore be classified as having fully incomplete responses, and therefore, also omitted. Anyone who selected the ‘no’ option on the consent form was not captured by Qualtrics and therefore not recorded. Hence it was not possible to determine the number declining to participate in the survey.

Sample Size Adequacy

In all, 117 of the 363 total surveys downloaded were either missing more than 5% of data, did not consent to begin the survey, or showed signs of disengagement from the survey and were therefore discarded from the analysis (Schumacker & Lomax, 2015). Only 246 participants answered all 29 survey questions and without signs of disengagement. Because the minimum estimated sample size of 226 was obtained through the power analysis in G*Power, the 246 entirely completed questionnaires were adequate for the data analysis. Using a power of 95%, a medium effect size of 0.24, an alpha significance level of 0.05, with 1 degree of freedom, the *a priori* power analysis estimated a minimum sample size of 226. These elements of power calculations were arrived at based on similar studies, having demonstrated appropriate use of power analysis in their respective studies (Antonini et al., 2021; Dilaveris et al., 2020; Yeow et al., 2013).

Demographic Data

This study questionnaire involved three sections using an ordinal and nominal scale of measurement adapted from Yeow et al. (2013) with permission. The first section examined relevant demographic information to create a profile of the participants. Demographic questions adapted included gender, age, and education level (see Appendices B-D). The gathered dataset was examined using SPSS 28 for EFA and linear regression analysis (see Appendix L), whilst SPSS AMOS version 26 software was adopted for CFA and SEM analysis (see Appendix M). Using linear regression, the mediation of predictability for the PE, predictor construct, by PC, the mediating construct, predicting the dependent variable of BI to use an IMD, was also examined. According to Gomes et al. (2020), regression analysis is suited to examining the strength of relationships between constructs.

Demographic data compiled from the questionnaire included the following items: gender, age, the current state of residence, and education level. In this study, the data by state of current residency demonstrated a relatively uniform distribution between the 50 states and also with respect to the five main U.S. geographical regions of Northeast, Southeast, Midwest, Southwest, and West as described by Krug and Kulhavy (1973). The highest number of responses was from the Southeast region with 26.42%, followed by Midwest with 25.61%. Next was the Northeast region with 21.54%, then West with 19.92%, and finally the Southwest region with 6.50% (see Table 1)

Table 1

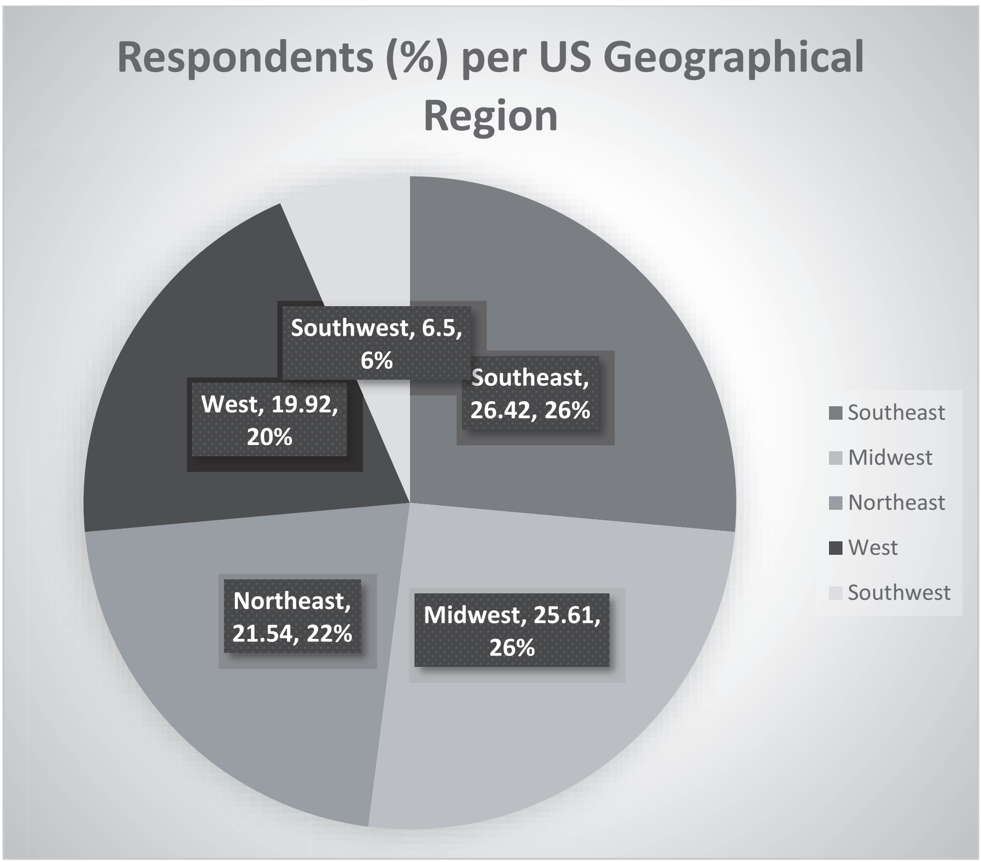
Participation per U.S. Geographic Regions

Demographic characteristics	Values	Number of states in region	Frequency	Percent (%)
Region of current Residence	Southeast	12	65	26.42
	Midwest	12	63	25.61
	Northeast	11	53	21.54
	West	11	49	19.92
	Southwest	4	16	6.50
Total		50	246	100

The distribution of the respondents again was fairly spread considering that the Southwest, with the lowest turnout, has only four states, and the Southeast, with the highest turnout, has up to 12 states within the region. With the exception of the Southwest region which has only four states, each of the remaining four regions has over 20% in response which suggests that the sample was unequivocally representative of the United States (see Figure 3).

Figure 3

Percentage of Respondents per US Geographical Region



Note. Respondents in percentage per U.S. Geographical Region.

The highest number of responses was from the state of Florida within the Southeast region, with some 5.3%. The second-highest number of responses was shared between Virginia and Pennsylvania with 4.9% each, followed by California, New York, and Michigan with 4.5%.

The states with the lowest representation include Utah and Louisiana, with 0.4%. In all, 49 out of the 50 states were represented in the survey (see Table 2). The state of North Dakota had no representation.

Table 2

Demographics of Sample

Demographic characteristics	Values	Frequency	Percent(%)
State of current residence	Alabama	3	1.2
	Alaska	5	2.0
	Arizona	5	2.0
	Arkansas	6	2.4
	California	11	4.5
	Colorado	5	2.0
	Connecticut	4	1.6
	Delaware	2	0.8
	Florida	13	5.3
	Georgia	6	2.4
	Hawaii	5	2.0
	Idaho	5	2.0
	Illinois	6	2.4
	Indiana	4	1.6
	Iowa	4	1.6
	Kansas	2	0.8
	Kentucky	3	1.2
	Louisiana	1	0.4
	Maine	4	1.6
	Maryland	6	2.4
	Massachusetts	2	0.8
	Michigan	11	4.5
	Minnesota	6	2.4
	Mississippi	3	1.2
	Missouri	5	2.0
	Montana	4	1.6
	Nebraska	6	2.4
	Nevada	2	0.8
	New Hampshire	2	0.8
	New Jersey	6	2.4
	New Mexico	1	0.4
	New York	11	4.5
	North Carolina	6	2.4
	North Dakota	0	0
	Ohio	8	3.3
	Oklahoma	2	0.8
	Oregon	2	0.8
	Pennsylvania	12	4.9
	Rhode Island	2	0.8

Demographic characteristics	Values	Frequency	Percent(%)
	South Carolina	6	2.4
	South Dakota	3	1.2
	Tennessee	3	1.2
	Texas	8	3.3
	Utah	1	0.4
	Vermont	2	0.8
	Virginia	12	4.9
	Washington	7	2.8
	West Virginia	3	1.2
	Wisconsin	8	3.3
	Wyoming	2	0.8
Total		246	100

Note. N = 246 (sample size)

Currently or Previously Used IMD. Table 3 shows ICDs are the most used devices with 95 responses, followed by Pacemakers with 82 responses. Another 38 respondents were using other devices, such as dental implants, prosthetic limbs, etc., which were not included in this list of implants. Only 15 respondents indicated they have never used or are currently not using an IMD.

Table 3

Currently or Previously Used IMD

Demographic characteristic	Value	Frequency
Currently or previously used IMD	Pacemaker	82
	Implantable Cardiac Defibrillator	95
	Implantable Arrhythmic Device	25
	Coronary Stent	18
	Cochlea implant	30
	Other	38
	Not currently using an implant	15

Note. N = 246 (sample size)

Age. Similarly, participants between 38-47 years (23.60%) and those between 58-67 years old (19.10%) comprised the highest percentages of the sample, followed by those aged 48-

57 years (16.70%). Those aged 28-37 years accounted for 15.4%, whiles those 18-27 years and 68 years or more had the same number of respondents representing 12.6% each (see Table 4).

Table 4

Demographic Characteristic - Age

Demographic characteristic	Value	Frequency	Percentage
Age	18-27 years old	31	12.60
	28-37 years old	38	15.40
	38-47 years old	58	23.60
	48-57 years old	41	16.70
	58-67 years old	47	19.10
	68 years or more	31	12.60

Note. N=246 (sample size)

Gender. The tabulation of respondents by gender indicated that participants were predominately female with 68.7 %. Male participants accounted for 19.5% of the sample, while 6.9% declared themselves as non-binary/third gender. The remaining 4.9% of respondents preferred not to disclose their gender (see Table 5).

Table 5

Demographic Characteristic - Gender

Demographic characteristic	Value	Frequency	Percent (%)
Gender	Male	48	19.50
	Female	169	68.70
	Non-binary / third gender	17	6.90
	Prefer not to say	12	4.90

Note. N=246 (sample size)

Educational level. On the educational level front, the highest number of participants were bachelor's degree holders with 32.5%, followed by associate degree holders with 23.6%, master's degree holders with 19.1% and doctoral degree holders with 8.5%. High school diploma holders participated with 8.45%, followed by trade / vocational degree holders with 4.1%. The lowest participation was those with some high school at 3.7% (see Table 6).

Table 6

Highest Level of Education

Demographic characteristic	Value	Frequency	Percent (%)
Educational Level	Some High School	9	3.7
	High School Diploma	21	8.5
	Trade / Vocational	10	4.1
	Associates Degree	58	23.6
	Bachelor’s Degree	80	32.5
	Master’s Degree	47	19.1
	Doctoral Degree/ PhD	21	8.5

Note. N=246 (sample size)

IMD Familiarity. On the IMD familiarity front, 39.8% of participants responded as ‘very Familiar’ with IMDs, 26.0% responded as familiar, and 17.5% responded as having expert familiarity with IMDs. Some 12.2% responded as being somewhat familiar with IMDs, whilst 4.5% responded as not at all familiar with IMDs (see Table 7).

Table 7

Familiarity Levels

Demographic characteristics	Value	Frequency	Percent (%)
familiarity levels	Not at all familiar	11	4.5
	Somewhat familiar	30	12.2
	Familiar	64	26.0
	Very familiar	98	39.8
	Expert familiarity	43	17.5
Total		246	100

Note. N=246 (sample size)

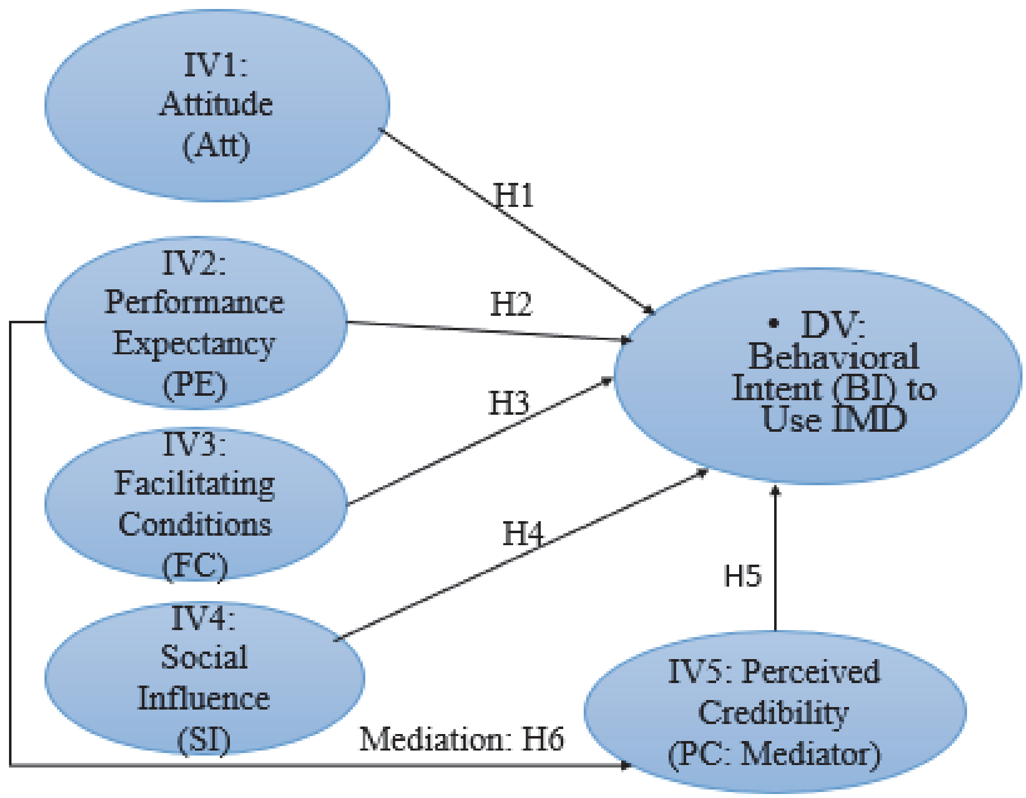
All demographic characteristics of the survey sample were formatted to demonstrate their frequency and percentage in the preceding tables, providing a comprehensive profile of participants, describing the results of each survey item in the demographic data section. The second section of the survey measured the intention to use an IMD for efficient healthcare management. Finally, the third section assessed Att, FC, SI, PC, and PE. The constructs in the final two survey sections were presented to respondents in question form using a 5-point Likert scale response format. In Appendix G, a summary of the items operationalizing all six constructs is presented.

Conceptual Research Framework

To ascertain the determinants shaping the US patient's adoption and use of IMDs, the conceptual research framework used Yeow et al.'s (2013) extension of Venkatesh et al.'s (2003) UTAUT model which included the independent variables PE, PC, SI, and FC. The conceptual framework model was expanded with the inclusion of Att as another independent variable, and BI to use an IMD, as the dependent variable. The direction of influence is depicted with arrows labeled as research hypotheses H1 to H6, ending on BI to use, the dependent variable as shown in the conceptual research framework (see Figure 4).

Figure 4

Conceptual Research Framework



Factor Analyses

Before the discussion of the research questions and attendant analysis, how EFA, CFA, and SEM were performed is discussed into detail. The research questions and corresponding hypotheses were reiterated before factor analysis was conducted. Subsequently, Bartlett's test of sphericity, the KMO index, and anti-image correlations were applied to examine the appropriateness of the data and corresponding sample size for factor analysis (Jin et al., 2021). **Error! Reference source not found.** also depicts the suitability of the sample size and data for factor analysis. Next, EFA and CFA were conducted to determine the most accurate measurement model. Lastly, the SEM analysis was performed to examine the robustness of connection amongst the factors proposed alongside a discussion of the results for each of the research questions. According to Xu et al. (2021), if the KMO index is less than .6, factor analysis should not be conducted. Similarly, Roberts et al. (2019) explained that, for factor analysis to be considered adequate, Bartlett's test Chi-square value should be less than 0.05 of the significance levels. The aptness of the data and sample size for factor analysis was portrayed in Table 8.

Table 8

Suitability of Sample Size and Data for Factor Analysis

KMO Measure of Sampling Adequacy		.800
Bartlett's Test of Sphericity	Approx. Chi-Square	2330.434
	Df	253
	Sig.	.000

The survey questionnaire's KMO index of 0.800 demonstrated that the data set is well suited for factor analysis. Correspondingly, Bartlett's test of sphericity (X^2(df = 253) = 2330.43, $p < 0.001$), specified that there is considerable common variance amongst the survey questionnaire items. The measures of sampling adequacy to include the anti-image covariance was accounted for (see Appendix N) to demonstrate the adequacy of the sample.

In addition to the anti-image covariance, the anti-image correlation matrix demonstrated that all diagonal values were greater than 0.5 (Luo et al., 2019; Roberts et al., 2019). The diagonal values which were all greater than 0.5 suggested that the sample size was adequate, and the correlation matrix was suitable for factor analysis. The anti-image correlation matrix was also generated in SPSS 28 (see Appendix O).

Exploratory Factor Analysis. Furthermore, an exploratory factor analysis was performed to disclose the nature of the variables, having an effect on a group of answers (Luo et al., 2019; Roberts et al., 2019). The Promax rotation outcome is considered more accurate and more reproducible than other rotation methods (Giordano et al., 2020). Due to this reason, the principal axis factor with Promax rotation was chosen based on six fixed number of factors to extract and factor loadings that were higher than 0.5. Luo et al. (2019) explained that to avoid significant errors in the analysis outcome, it is more beneficial to extract several factors than to extract an insufficient number of factors. Besides, according to (Purwanto & Sudargini, 2021), factor loadings should be greater than 0.5 to be deemed significant in factor analysis. The items' loadings for each factor are depicted in Table 9 (with communalities extraction), revealing that only five factors (FC, SI, PC, BI, and PE) played significant roles in the conducted survey.

Table 9

EFA and Communalities

Pattern Matrix[a]						
Constructs Items			Factor			Communalities Extraction
	PE	PC	BI	SI	FC	
PE1	0.87					0.59
PE2	0.55					0.34
PE3	0.79					0.63
PE4	0.72					0.53
PC1		0.89				0.67
PC2		0.94				0.86
PC3		0.65				0.81
PC4		0.58				0.29
BI1			0.88			0.69
BI2			0.93			0.68
BI3			0.68			0.65
SI1				0.40		0.48
SI2				0.87		0.64
SI3				0.59		0.38
SI4				0.52		0.48
FC1					0.47	0.48
FC2					0.43	0.55
FC3					0.61	0.55
FC4					0.49	0.34
Att1					0.15	0.08
Att2					0.15	0.15
Att3					0.21	0.30
Att4					0.06	0.29

Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a Rotation converged in 6 iterations.
PC = perceived credibility; PE = performance expectancy; SI = social influence; FC = facilitating conditions; Att = attitude

Results in the correlation table reproduced (see Table 10), depicted that there were 27 (10%) nonredundant residuals with absolute values larger than 0.05. Luo et al. (2019) suggested that a low residual value implies a high degree of a construct's explanatory power.

Table 10

Reproduced Correlations

Reproduced Correlations																							
		BI1	BI2	BI3	PE1	PE2	PE3	PE4	SI2	SI3	SI4	PC1	PC2	PC3	PC4	FC1	FC2	FC3	FC4	Att1	Att2	Att3	Att4
Reproduced Correlation	BI1	.785[a]	0.775	0.700	0.292	0.233	0.459	0.369	0.045	0.100	0.076	-0.090	0.067	0.158	-0.006	0.292	0.072	0.288	0.059	0.000	0.055	0.187	0.165
	BI2	0.775	.792[a]	0.689	0.240	0.171	0.383	0.319	0.024	0.080	0.048	-0.029	0.124	0.187	0.028	0.259	0.068	0.262	0.072	-0.006	0.083	0.185	0.183
	BI3	0.700	0.689	.665[a]	0.384	0.292	0.502	0.435	0.035	0.070	0.052	0.008	0.168	0.265	0.065	0.371	0.140	0.363	0.144	0.042	0.099	0.242	0.189
	PE1	0.292	0.240	0.384	.580[a]	0.395	0.559	0.535	0.057	0.022	0.024	0.149	0.267	0.374	0.166	0.445	0.187	0.381	0.213	0.148	0.091	0.309	0.078
	PE2	0.233	0.171	0.292	0.395	.400[a]	0.465	0.405	0.102	0.067	0.108	0.037	0.125	0.220	0.075	0.410	0.293	0.409	0.222	0.080	0.074	0.183	0.146
	PE3	0.459	0.383	0.502	0.559	0.465	.647[a]	0.561	0.115	0.090	0.111	0.029	0.167	0.292	0.092	0.482	0.232	0.435	0.184	0.103	0.052	0.261	0.110
	PE4	0.369	0.319	0.435	0.535	0.405	0.561	.530[a]	0.140	0.096	0.107	0.067	0.182	0.281	0.119	0.456	0.255	0.416	0.224	0.143	0.110	0.334	0.119
	SI2	0.045	0.024	0.035	0.057	0.102	0.115	0.140	.630[a]	0.440	0.496	-0.180	-0.236	-0.357	-0.049	0.087	0.323	0.048	0.010	0.126	0.031	0.268	-0.085
	SI3	0.100	0.080	0.070	0.022	0.067	0.090	0.096	0.440	.326[a]	0.360	-0.216	-0.252	-0.315	-0.092	0.051	0.208	0.038	-0.011	0.082	0.021	0.199	-0.042
	SI4	0.076	0.048	0.052	0.024	0.108	0.111	0.107	0.496	0.360	.411[a]	-0.217	-0.258	-0.331	-0.089	0.079	0.271	0.069	0.006	0.082	0.016	0.190	-0.038
	PC1	-0.090	-0.029	0.008	0.149	0.037	0.029	0.067	-0.180	-0.216	-0.217	.674[a]	0.742	0.632	0.427	0.126	0.048	0.048	0.129	-0.032	0.026	-0.116	-0.001
	PC2	0.067	0.124	0.168	0.267	0.125	0.167	0.182	-0.236	-0.252	-0.258	0.742	.861[a]	0.782	0.480	0.236	0.070	0.152	0.179	-0.034	0.044	-0.092	0.052
	PC3	0.158	0.187	0.265	0.374	0.220	0.292	0.281	-0.357	-0.315	-0.331	0.632	0.782	.812[a]	0.412	0.326	0.051	0.274	0.232	-0.017	0.072	-0.041	0.134
	PC4	-0.006	0.028	0.065	0.166	0.075	0.092	0.119	-0.049	-0.092	-0.089	0.427	0.480	0.412	.286[a]	0.142	0.086	0.085	0.114	0.011	0.039	-0.003	0.009
	FC1	0.292	0.259	0.371	0.445	0.410	0.482	0.456	0.087	0.051	0.079	0.126	0.236	0.326	0.142	.476[a]	0.354	0.489	0.314	0.109	0.157	0.270	0.221
	FC2	0.072	0.068	0.140	0.187	0.293	0.232	0.255	0.323	0.208	0.271	0.048	0.070	0.051	0.086	0.354	.513[a]	0.412	0.323	0.108	0.191	0.259	0.221
	FC3	0.288	0.262	0.363	0.381	0.409	0.435	0.416	0.048	0.038	0.069	0.048	0.152	0.274	0.085	0.489	0.412	.561[a]	0.381	0.103	0.214	0.282	0.324
	FC4	0.059	0.072	0.144	0.213	0.222	0.184	0.224	0.010	-0.011	0.006	0.129	0.179	0.232	0.114	0.314	0.323	0.381	.329[a]	0.090	0.209	0.217	0.255
	Att1	0.000	-0.006	0.042	0.148	0.080	0.103	0.143	0.126	0.082	0.082	-0.032	-0.034	-0.017	0.011	0.109	0.108	0.103	0.090	.101[a]	0.079	0.202	0.022
	Att2	0.055	0.083	0.099	0.091	0.074	0.052	0.110	0.031	0.021	0.016	0.026	0.044	0.072	0.039	0.157	0.191	0.214	0.209	0.079	.173[a]	0.203	0.178
	Att3	0.187	0.185	0.242	0.309	0.183	0.261	0.334	0.268	0.199	0.190	-0.116	-0.092	-0.041	-0.003	0.270	0.259	0.282	0.217	0.202	0.203	.463[a]	0.125
	Att4	0.165	0.183	0.189	0.078	0.146	0.110	0.119	-0.085	-0.042	-0.038	-0.001	0.052	0.134	0.009	0.221	0.221	0.324	0.255	0.022	0.178	0.125	.285[a]

Notes. Extraction Method: Principal Components Analysis
a. Reproduced Communalities

The residuals were computed between the observed and the reproduced correlations and the extraction method applied was the Principal Components Analysis (see Table 11).

Table 11

Reproduced Correlations: Residuals

Reproduced Correlations																							
		BI1	BI2	BI3	PE1	PE2	PE3	PE4	SI2	SI3	SI4	PC1	PC2	PC3	PC4	FC1	FC2	FC3	FC4	Att1	Att2	Att3	Att4
Residual[b]	BI1		0.002	0.006	0.001	-0.006	-0.013	0.019	0.009	-0.028	0.007	-0.012	-0.009	-0.011	0.036	0.002	-0.001	-0.004	0.008	0.016	-0.011	-0.017	0.008
	BI2	0.002		0.001	0.004	0.007	-0.012	0.011	-0.022	0.017	-0.014	0.011	-0.018	-0.008	0.012	0.023	0.025	-0.019	-0.029	-0.010	0.029	-0.006	-0.010
	BI3	0.006	0.001		0.015	0.011	0.001	-0.044	0.025	-0.011	0.008	0.013	0.020	0.009	-0.069	0.003	-0.027	0.005	0.050	-0.019	0.000	0.011	-0.030
	PE1	0.001	0.004	0.015		0.044	-0.068	0.044	0.001	0.014	-0.038	0.037	-0.009	-0.006	-0.045	-0.015	0.023	0.002	0.001	-0.009	-0.042	0.016	-0.014
	PE2	-0.006	0.007	0.011	0.044		0.025	-0.083	0.011	0.026	-0.055	-0.028	-0.001	0.004	-0.001	0.034	0.035	-0.014	-0.015	-0.024	0.101	-0.030	-0.070
	PE3	-0.013	-0.012	0.001	-0.068	0.025		0.047	-0.013	0.014	0.017	-0.039	0.041	0.005	0.032	-0.016	-0.031	0.024	-0.049	0.034	######	0.015	0.034
	PE4	0.019	0.011	-0.044	0.044	-0.083	0.047		-0.007	-0.029	0.038	0.008	-0.041	0.002	0.033	-0.012	0.016	-0.010	0.048	-0.042	-0.014	-0.013	0.011
	SI2	0.009	-0.022	0.025	0.001	0.011	-0.013	-0.007		0.050	-0.015	-0.010	0.006	0.004	0.007	-0.030	-0.030	0.038	0.035	0.012	0.021	-0.027	-0.034
	SI3	-0.028	0.017	-0.011	0.014	0.026	0.014	-0.029	0.050		-0.018	-0.005	0.043	0.004	-0.039	-0.024	-0.031	0.006	-0.039	0.019	-0.029	0.017	0.087
	SI4	0.007	-0.014	0.008	-0.038	-0.055	0.017	0.038	-0.015	-0.018		0.003	-0.030	0.014	0.018	0.020	0.038	-0.015	0.012	-0.005	-0.053	0.019	-0.007
	PC1	-0.012	0.011	0.013	0.037	-0.028	-0.039	0.008	-0.010	-0.005	0.003		0.029	-0.021	-0.048	0.010	0.022	0.012	0.027	-0.014	-0.053	0.003	-0.020
	PC2	-0.009	-0.018	0.020	-0.009	-0.001	0.041	-0.041	0.006	0.043	-0.030	0.029		-0.011	0.000	-0.024	-0.023	0.042	-0.021	0.000	-0.004	0.017	0.020
	PC3	-0.011	-0.008	0.009	-0.006	0.004	0.005	0.002	0.004	0.004	0.014	-0.021	-0.011		0.061	0.004	-0.033	-0.010	0.011	-0.034	-0.011	0.011	0.033
	PC4	0.036	0.012	-0.069	-0.045	-0.001	0.032	0.033	0.007	-0.039	0.018	-0.048	0.000	0.061		0.008	0.036	-0.050	-0.049	0.077	0.084	-0.037	-0.002
	FC1	0.002	0.023	0.003	-0.015	0.034	-0.016	-0.012	-0.030	-0.024	0.020	0.010	-0.024	0.004	0.008		0.024	-0.014	0.023	0.051	-0.010	-0.001	-0.049
	FC2	-0.001	0.025	-0.027	0.023	0.035	-0.031	0.016	-0.030	-0.031	0.038	0.022	-0.023	-0.033	0.036	0.024		-0.030	-0.009	-0.068	0.013	0.026	0.002
	FC3	-0.004	-0.019	0.005	0.002	-0.014	0.024	-0.010	0.038	0.006	-0.015	0.012	0.042	-0.010	-0.050	-0.014	-0.030		-0.002	0.014	-0.062	0.020	0.086
	FC4	0.008	-0.029	0.050	0.001	-0.015	-0.049	0.048	0.035	-0.039	0.012	0.027	-0.021	0.011	-0.049	0.023	-0.009	-0.002		0.046	0.046	-0.067	-0.018
	Att1	0.016	-0.010	-0.019	-0.009	-0.024	0.034	-0.042	0.012	0.019	-0.005	-0.014	0.000	-0.034	0.077	0.051	-0.068	0.014	0.046		-0.034	0.002	0.025
	Att2	-0.011	0.029	0.000	-0.042	0.101	######	-0.014	0.021	-0.029	-0.053	-0.053	-0.004	-0.011	0.084	-0.010	0.013	-0.062	0.046	-0.034		0.038	-0.036
	Att3	-0.017	-0.006	0.011	0.016	-0.030	0.015	-0.013	-0.027	0.017	0.019	0.003	0.017	0.011	-0.037	-0.001	0.026	0.020	-0.067	0.002	0.038		0.002
	Att4	0.008	-0.010	-0.030	-0.014	-0.070	0.034	0.011	-0.034	0.087	-0.007	-0.020	0.020	0.033	-0.002	-0.049	0.002	0.086	-0.018	0.025	-0.036	0.002	

Notes. Extraction Method: Principal Components Analysis
b. Residuals were computed between observed and reproduced correlations.

Six factors were extracted, having initial eigenvalues of 5.352, 3.340, 1.949, 1.450, 1.266, and 1.077, during the analysis. These eigenvalues accounted for 62.76% of the total variance explained (see Table 12). Each group of items loaded significantly to one single factor.

Table 12

Total Variance Explained

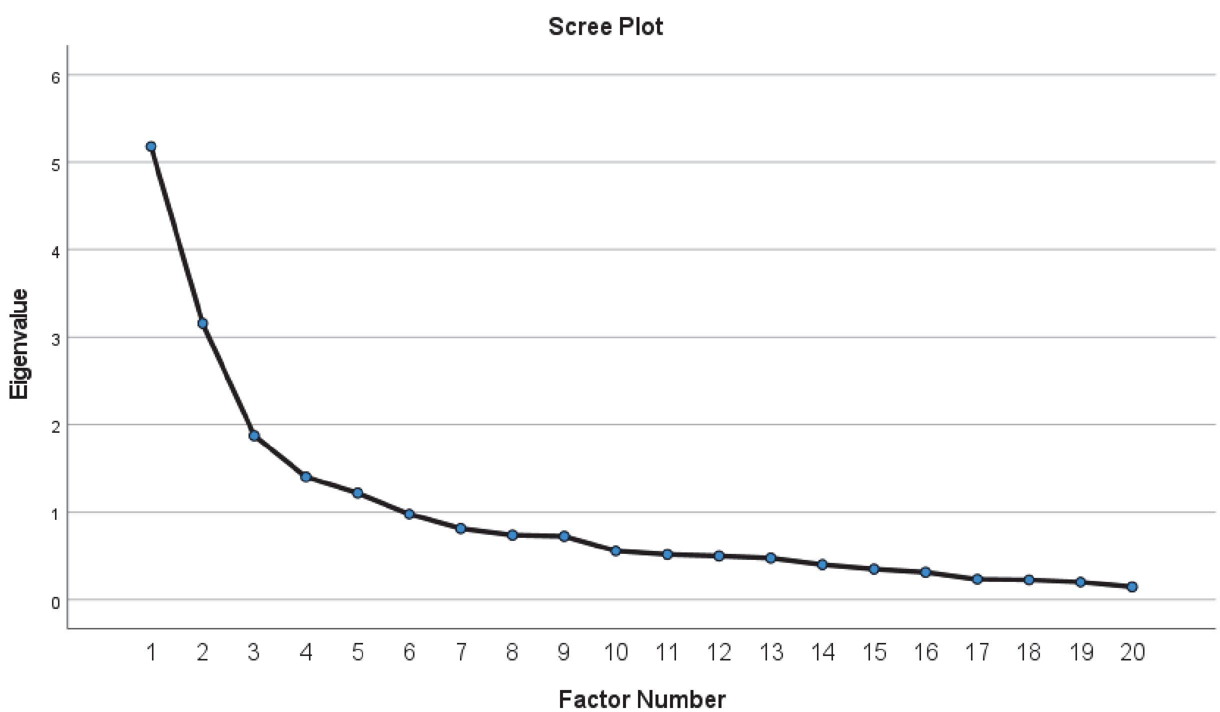
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	5.352	23.271	23.271	4.929	21.432	21.432	4.370
2	3.340	14.521	37.792	2.972	12.922	34.354	3.082
3	1.949	8.475	46.267	1.576	6.853	41.207	3.207
4	1.450	6.306	52.573	.932	4.051	45.258	2.351
5	1.266	5.506	58.079	.748	3.252	48.509	2.846
6	1.077	4.684	62.763	.513	2.231	50.741	1.145
7	.970	4.219	66.982				
8	.937	4.075	71.057				
9	.812	3.530	74.587				
10	.794	3.454	78.040				
11	.685	2.980	81.021				
12	.606	2.634	83.655				
13	.515	2.240	85.895				
14	.509	2.213	88.108				
15	.473	2.058	90.166				
16	.429	1.864	92.030				
17	.396	1.721	93.751				
18	.348	1.512	95.263				
19	.300	1.303	96.566				
20	.229	.996	97.562				
21	.219	.952	98.515				
22	.199	.865	99.379				
23	.143	.621	100.000				

Note. Extraction Method: Principal Axis Factoring.
[a.] When factors are correlated, sums of squared loadings are not added to obtain total variance.

Communalities values also ranged from 0.131 to 0.771. Giordano et al. (2020), advocated that communality values that range from 0.40 to 0.70 are considered satisfactory; however, values less than 0.4 may signify additional constructs measured by other items, which could be studied in additional investigations. Even though SI, SI3, and SI4 showed low communalities values, these items were reserved for supplementary examination due to their significance in measuring SI, as emphasized in the literature review segment of this study. By means of using a cut-off value of 0.5 for factor loading, four items Att1, Att2, Att3, and Att4 were excluded, reducing the items to 19. The sixth factor, Att, was excluded because none of the items measured loaded higher than 0.5 to this factor. Following Purwanto and Sudargini's (2021) recommendations, examination of the scree plot supported retaining the five factors as well. This is because at the sixth factor, the curve began to flatten out (see Figure 5).

Figure 5

Scree Plot of Eigen Values



Verification of convergent validity was completed by ensuring that, survey items measuring a specific variable loaded distinctly in that variable, and by confirming that the average variance extracted (AVE) was higher than .5 (Luo et al., 2019; Roberts et al., 2019). Convergent validity was also established by ensuring that the composite reliability was larger than .7, as depicted in Table 13 (Purwanto & Sudargini, 2021), with the exception of FC and Att, which had an AVE value of 0.22 and 0.19, respectively. Nevertheless, the FC AVE score was considered satisfactory because the composite reliability for this construct was greater than .6 (Colman et al., 2019), as depicted in Table 13. However, the composite reliability for Att was less than 0.60, at 0.53, and adds to the justification for eliminating the Att variable.

Table 13

Convergent Validity, Composite Reliability, and Cronbach's Reliability

Constructs	Number of factor Loadings	Average Variance Extracted (AVE)	Composite Reliability	Cronbach's Reliability Coefficient
PE	4	0.50	0.80	0.785
PC	4	0.63	0.92	0.850
SI	4	0.46	0.84	0.708
FC	4	0.22	0.61	0.705
Att	4	0.19	0.53	0.377

Cronbach's alpha coefficients were greater than 0.70 (α = .79, α = .85, α= .71, α= .71), an indication of high internal reliability (Roberts et al., 2019), for all but one variable. Content validity (Hong et al., 2019) was supported through the literature review in this study. Lastly, discriminant validity was also confirmed by checking to ensure survey items did not cross load significantly onto other factors. Discriminant validity was also satisfied by verifying that the square root of AVE of each factor was greater than the inter-factor correlation as depicted in Table 14 (Purwanto & Sudargini, 2021).

Table 14

Factor Correlation Matrix and AVE Scores

Factor	AVE	√AVE (in bold)[a] and Pearson correlation (non-bold)[b]				
		PE	BI	PC	SI	FC
PE	0.50	**0.71**				
BI	0.70	0.48	**0.84**			
PC	0.63	0.25	0.18	**0.79**		
SI	0.46	0.17	0.13	0.29	**0.68**	
FC	0.22	0.56	0.29	0.28	0.21	**0.47**

[a] Square roots of AVE are shown in bold diagonally.
[b] The inter-factor Pearson correlations are shown in non-bold off-diagonally.

After confirming which constructs had an influential impact on a group of responses, CFA was then conducted to evaluate the fitness of the parsimonious measurement model, as well as to evaluate the causative correlations amongst the dependent and independent variables (Purwanto & Sudargini, 2021). According to Qin et al. (2020), high correlations between the latent exogenous variables otherwise referred to as multicollinearity, is a probable issue that scholars may contend with in the utilization of SEM. Consequently, a Pearson correlation coefficient (r), variance inflation factor (VIF), and tolerance assessments were utilized in examining relations between constructs to establish the existence of multicollinearity.

The values for all items assessing a specific construct were added together and then divided by the number of items measuring that construct to determine an average score to ensure every construct item was consistently weighted as a variable in the multicollinearity tests. The results of the bivariate correlation method depicted the absolute values of Pearson Correlations among variables lower than 0.9, which indicated that collinearity issues were less likely to exist. Armstrong (2019) advocated that a Pearson correlation coefficient greater than 0.9 is a sign of the presence of substantial collinearity. A tolerance value higher than 0.10 and a VIF value smaller than 10 is also an indication of the absence of multicollinearity issues. (Martynova et al., 2018; Reyes-Fournier et al., 2020). Since all variables had tolerance scores larger than 0.10 and VIF scores less than 10 (see Table 15), this outcome pointed to no multicollinearity issues in the study.

Table 15

Multicollinearity Diagnostics

Pearson Collinearity (N = 246)							Collinearity Statistics Coefficients[a]	
	PE	PC	SI	FC	Att	BI	Tolerance	VIF
Performance Expectancy	1	0.254	0.171	0.562	0.311	0.475	0.651	1.536
Perceived Credibility	0.254[b]	1	0.293	0.227	0.003	0.107	0.791	1.265
Social Influence (SI)	0.171[c]	0.293[b]	1	0.213	0.224	0.126	0.809	1.236
Facilitating Conditions	0.562[b]	0.227[b]	0.213[b]	1	0.451	0.289	0.575	1.740
Attitude (Att)	0.311[b]	0.003[b]	0.224[c]	0.451[b]	1	0.206	0.771	1.298
Behavioral Intent (BI)	0.475[b]	0.107[b]	0.126[c]	0.289[b]	0.206[b]	1	-	-

Note. [a] Dependent Variable: Behavioral Intent
[b] Correlation is significant at the 0.01 level (2-tailed)
[c] Correlation is significant at the 0.05 level (2-tailed)

Confirmatory Factor Analysis and SEM

The SEM and CFA models were completed utilizing the MLE. MLE is often used in SEM modeling (Maydeu-Olivares, 2017). According to Wulandari et al. (2021), univariate normal distribution does not guarantee the occurrence of multivariate normal distribution, hence the need to extend the assessment of univariate normal distribution into multivariate methods. Proposed by Mardia (1970), one such extended method is skewness and kurtosis (Wulandari et al., 2021). All variables utilized in this investigation were assessed for normality utilizing skewness and kurtosis values. This decision was taken because MLE of SEM statistical analysis techniques hinge on multivariate normality assumptions (Maydeu-Olivares, 2017).

Table 16 demonstrates the skewness and kurtosis results for each latent construct indicator. Multivariate normality for the latent construct indicator measures is required when implementing covariance-based structural equation modeling (Hair et al., 2017; Qin et al., 2020; Scherer & Teo, 2020). According to Kline (2018), a normal distribution assumption can be made when the research data exhibits absolute skewness and kurtosis statistics of less than 3 and 10, respectively. None of the measurement kurtosis and skewness statistic values exceeded these levels. Therefore, it was assumed the research data exhibited multivariate normality, facilitating the use of covariance-based SEM for data analyses. This situation denotes high data normality, as depicted in Table 16.

Table 16

Assessment of Data Normality for SEM

Variable indicator	min	max	skewness	kurtosis	Normality assumption
Perceived Credibility					
PC1	1.000	5.000	-.237	-.854	Yes
PC2	1.000	5.000	-.510	-.733	Yes
PC3	1.000	5.000	-.905	-.367	Yes
PC4	1.000	5.000	-.214	-.620	Yes
Performance Expectancy					
PE1	1.000	5.000	-1.331	1.375	Yes
PE2	1.000	5.000	-.623	-.629	Yes
PE3	1.000	5.000	-1.334	1.220	Yes
PE4	1.000	5.000	-1.341	1.656	Yes
Social Influence					
SI1	1.000	5.000	-.733	-.185	Yes
SI2	1.000	5.000	.537	-.710	Yes
SI3	1.000	5.000	-.120	-1.019	Yes

Variable indicator	min	max	skewness	kurtosis	Normality assumption
Perceived Credibility					
SI4	1.000	5.000	.063	-1.087	Yes
Facilitating Conditions					
FC1	1.000	5.000	-1.223	.846	Yes
FC2	1.000	5.000	-.228	-1.129	Yes
FC3	1.000	5.000	-1.745	2.348	Yes
FC4	1.000	5.000	-1.328	1.437	Yes
Attitude					
Att1	1.000	5.000	-.670	-.672	Yes
Att2	1.000	5.000	-0.323	0.315	Yes
Att3	1.000	5.000	-.358	-.554	Yes
Att4	1.000	5.000	-1.807	2.345	Yes
Behavioral Intent					
BI3	1.000	5.000	-1.998	3.172	Yes
BI2	1.000	5.000	-1.600	1.823	Yes
BI1	1.000	5.000	-1.857	2.655	Yes

Seven indices were well-thought-out in the CFA in order to ascertain a good fit of the measurement model in the SEM analysis. The target values or benchmark values for the selected indices were determined based on the fact that a large sample size was obtained, i.e., the sample size of 246. The indices selected assisted in evaluating the SEM model. These seven indices included: a Relative Fit Index (RFI) of at least 0.8 (Schumacker & Lomax, 2015), an Incremental Fit Index (IFI) with a minimum of .90 (Kline, 2018), a Normed Fit Index (NFI) of at least .9 (Byrne & Byrne, 2013), a Tucker Lewis Index (TLI) higher than .9 (Schumacker & Lomax, 2015), a Root Mean Square Error of Approximation (RMSEA) value less than .10 (Purwanto & Sudargini, 2021), a Comparative Fit Index (CFI) score greater than .90 (Fan et al., 1999), and a ratio of the model Chi-squared to degrees of freedom (X^2/df) less than 3, with p-value > .05 (Purwanto & Sudargini, 2021).

A model with five or more indices meeting the threshold or benchmark value would be considered a good fit model (Kline, 2018). It is worth noting that the p-value is sensitive to sample size, and therefore, a good-fit model may find its p-value less than 0.05 (Byrne & Byrne, 2013). Gathering from the results, the CFA measurement model exhibited a poor goodness-of-fit (the ratio of $\chi 2/df = 2.02$, $p < .001$; CFI = .925; RMSEA = .07; TLI = .910; NFI = .864; RFI = .836; IFI = 0.926).

The usual method for improving a model's fit in SEM is to examine the model modification indices for any suggested correlations between the construct's items' residual errors (Flora, 2020). However, a vital assumption on reliability, underlying SEM utilization is that the exogenic variables are measured free of error (Deng et al., 2018; Scherer & Teo, 2020). Violation of this assumption could result in bias, which will further prejudice the path estimates for exogenic variables and, eventually, the study outcome (Deng et al., 2018; Scherer & Teo, 2020). Additionally, correlating measurement errors to improve model fit may also have a negative effect on the path estimate and therefore conceal the true model (Flora, 2020). According to Grace and Steiner (2021), the correlation of errors should not happen with the exclusive objective of model fit enhancement. Instead, correlation errors should be performed and substantiated based on theoretical concepts or past studies.

In the CFA, the measurement instrument indicated a poor fit. However, a satisfactory output was observed in the model obtained in the EFA. The properties of reliability, validity, and statistical significance of the measurement instrument of this study were examined in the EFA. It was confirmed that the configuration of modeled relationships was specified as intended. Residuals and modification indices (MIs) were then examined to continue evaluating the adequacy of the measurement instrument. According to Reyes-Fournier et al. (2020) MIs calculate approximately the projected variation in the structural model Chi-square if a parameter constrained to zero is unconstrained.

The arrangement of each survey item was examined because the model fit can also be affected by the wording of the items on the measurement scale (Grace & Steiner, 2021). Residuals and MIs pointed out that it was necessary to add error covariance between the PE factor's items. It was also required to correlate errors between the SI factor's indicators. The suggested correlations in MIs may reflect an item linked with the wording of the indicators that are perceptually closely connected (Grace & Steiner, 2021).

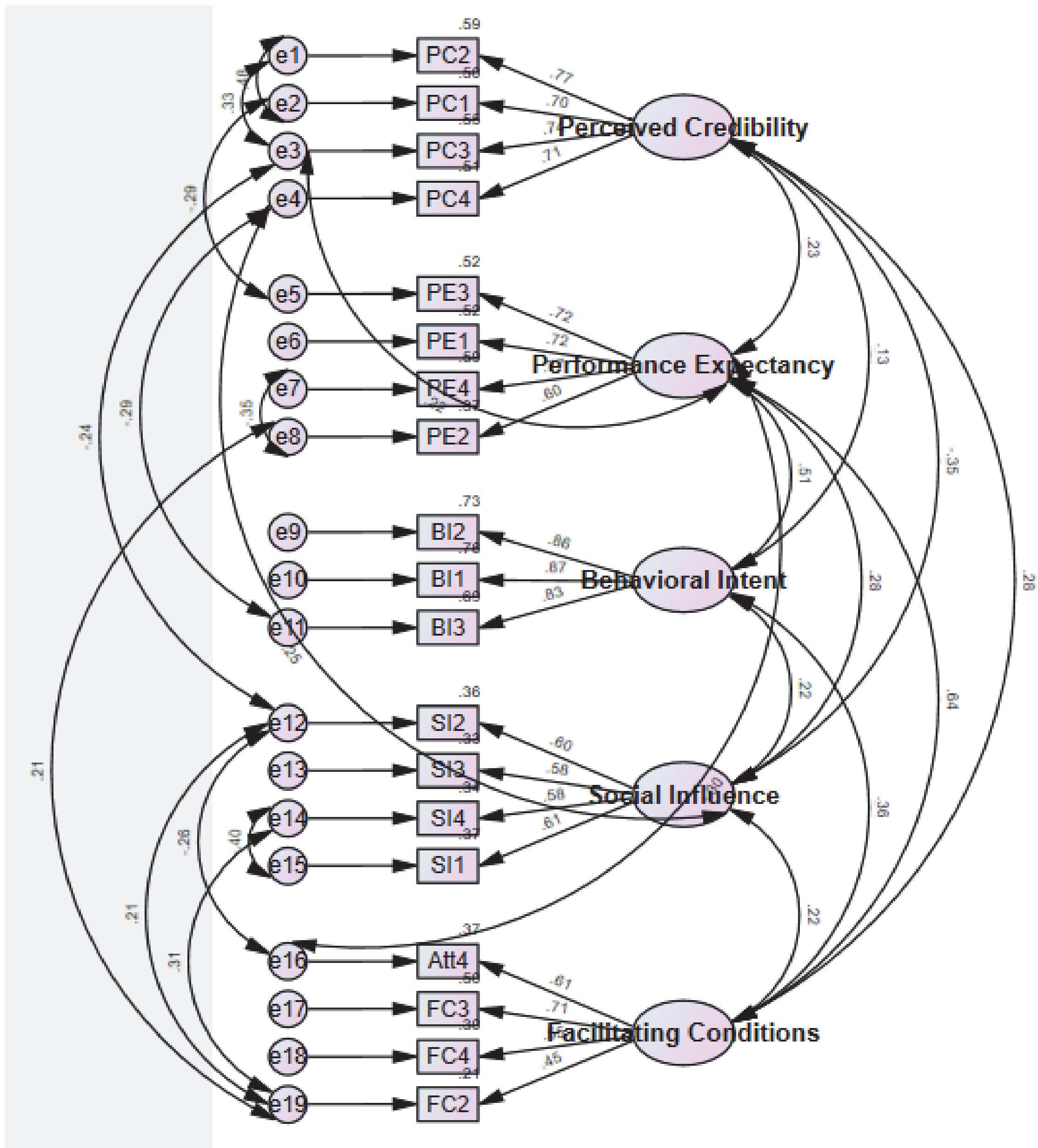
After modification of the model based on MIs, by adding covariances between the construct's items residual errors (Scherer & Teo, 2020), a satisfactory model fit was attained (the ratio of $\chi 2/df = 2.02$, $p < .001$; CFI = .925; RMSEA = .065; TLI = .910; NFI = .864; IFI = 0.926; RFI = 0.836). For the PE factor, the MI pointed to the addition of covariance between the residual errors for the following items: PE4 and PE2; PE3 and PC1. For the SI factor, the MI indicated the addition of covariance among residual errors for its items: SI1 and SI4; SI2 and Att4; SI2 and FC2. For PC, the MI suggested covarying the following PC items' residual errors: PC1 and PC2; PC1 and PC3, PC3 and SI2; PC4 and BI3).

A non-zero covariance between the residual errors for the above-mentioned items was possible because these measures have similar wordings (Song et al., 2020). In the CFA original model, FC1 loaded to the PE factor and not the FC factor as expected; therefore, it was removed. Att1 also loaded to the PE factor and was removed., Att2, and Att3 also loaded to the SI factor with very low factor loadings and therefore were removed from the model. Deleting FC1, Att1, Att2, and Att3 from the analysis ensured a good fit between the model and the data.

Figure 6 and Figure 7 explain the modified measurement model with standardized and non-standardized estimates respectively, extracted after adding covariances and FC1 removal. By way of confirming that the calculated AVE value was higher than .5, convergent validity of the measurement model was established (Luo et al., 2019; Roberts et al., 2019). Convergent validity was also established by checking that the composite reliability calculated was larger than 0.7 for all of the factors, as shown in Table 13 (Purwanto & Sudargini, 2021), except for FC, which had an AVE value of 0.41. However, the FC AVE score was considered satisfactory. This is because the composite reliability for this construct was greater than 0.6 (Colman et al., 2019), as shown in Table 13. These results were in accordance with the EFA outcome. Figure 7 depicts a parsimonious model with unstandardized path coefficients and the coefficient of determination, R^2 values.

Figure 6

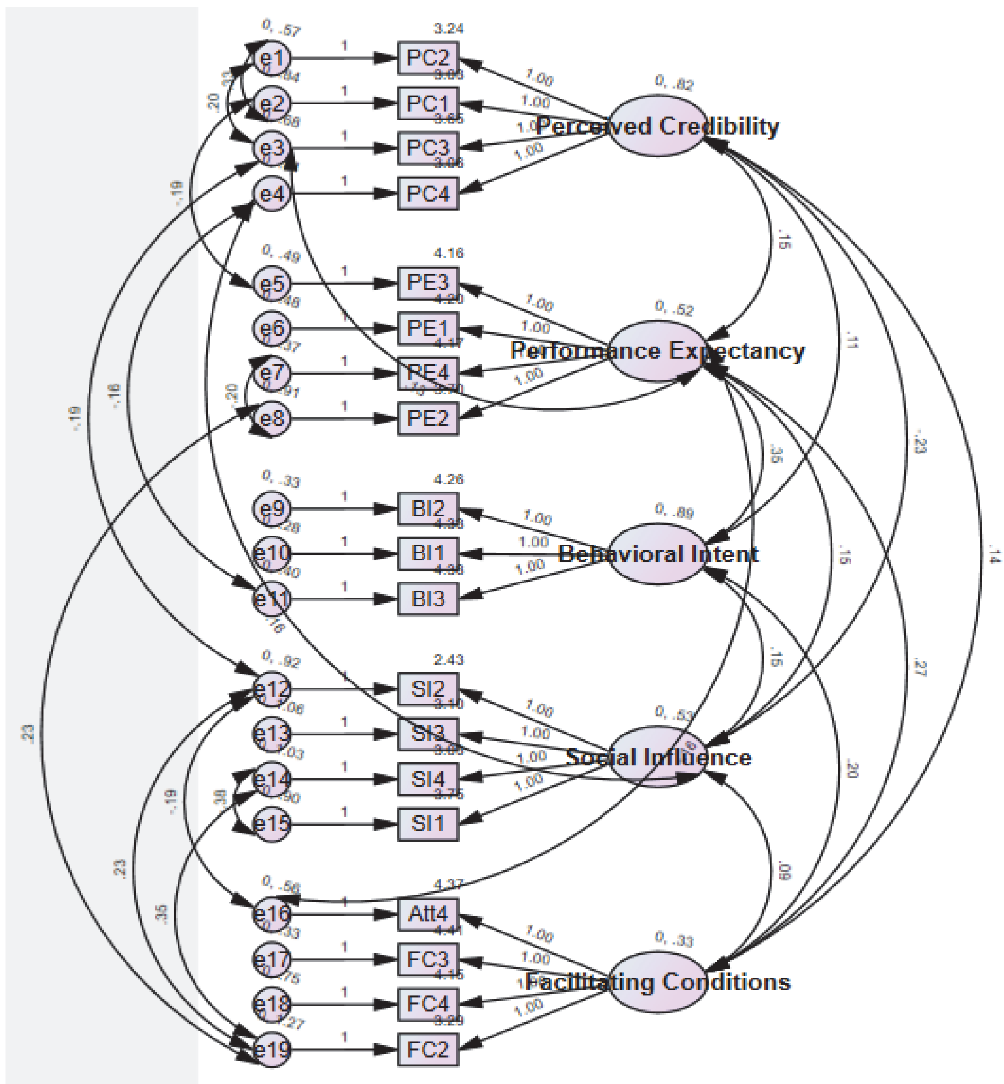
Measurement Model: Factor Loadings, Covariance between the Residual Errors, Latent Variable Covariances, R^2 Values, and Standardized Path Estimates



Note. Tests of model fit using maximum likelihood (ML) estimation (ratio of $\chi 2/df$ = 2.02, $p < .001$; CFI = .925; RMSEA = 0.065; TLI = .910; NFI = .8640.

Figure 7

Measurement Model: Factor Loadings, the Covariance between the Residual Errors, Latent Variable Covariances, R^2 Values, and Unstandardized Path Estimates



Note. Tests of model fit using maximum likelihood (ML) estimation (N = 246): The ratio of $\chi 2/df = 2.02$, $p < .001$; CFI = .925; RMSEA = .065; TLI = .910; NFI = .864.

Table 17 presents the standardized and unstandardized path loadings along with the corresponding significance levels.

Table 17

Measurement Model Indicator Statistics

Measurement Model Indicator	Unstandardized Indicator Loading	Standardized Indicator Loading	Standard Error	Critical Ratio	*p*-value
Perceived Credibility					
PC1	1.000	0.704	0.082	36.79	< 0.001
PC2	1.000	0.768	0.076	42.88	< 0.001
PC3	1.000	0.741	0.078	46.66	< 0.001
PC4	1.000	0.711	0.082	37.49	< 0.001
Performance Expectation					
PE1	1.000	0.723	0.064	65.54	< 0.001
PE2	1.000	0.605	0.077	48.40	< 0.001
PE3	1.000	0.719	0.064	64.69	< 0.001
PE4	1.000	0.768	0.060	69.18	< 0.001
Social Influence					
SI1	1.000	0.608	0.076	49.14	< 0.001
SI2	1.000	0.603	0.077	31.65	< 0.001
SI3	1.000	0.575	0.081	38.49	< 0.001
SI4	1.000	0.581	0.080	38.01	< 0.001
Facilitating Conditions					
FC2	1.000	0.454	0.081	40.71	< 0.001
FC3	1.000	0.707	0.052	84.84	< 0.001
FC4	1.000	0.552	0.067	62.34	< 0.001
Attitude					
Att4	1.000	0.608	0.060	72.40	< 0.001

Measurement Model Indicator	Unstandardized Indicator Loading	Standardized Indicator Loading	Standard Error	Critical Ratio	*p*-value
Behavioral Intent					
BI3	1.000	0.830	0.072	60.47	< 0.001
BI2	1.000	0.855	0.070	60.52	< 0.001
BI1	1.000	0.873	0.069	62.83	< 0.001

SEM Parsimonious Model and Results

After the measurement model was established through the CFA, it became necessary to reexamine the assumptions of multicollinearity. The variance inflation factor (VIF) and tolerance were employed to check relations between factors for the determination of multicollinearity. With a tolerance value higher than .10 and a VIF value less than 10, the absence of multicollinearity can be ascertained (Martynova et al., 2018; Reyes-Fournier et al., 2020). Because all the variables have tolerance scores greater than 0.10 and VIF scores less than 10 (see Table 18), it is therefore confirmed that no multicollinearity issues existed in this study.

Table 18

SEM Parsimonious Model Multicollinearity Diagnostics

	Unstandardized Coefficients		Standardized Coefficients		95.0% Confidence Interval for β			Collinearity Statistics	
Model	β	Std. Error	β	T	Sig	Lower Bound	Upper Bound	Tolerance	VIF
1 (Constant)	1.639	0.449		3.655	<.001	0.756	2.523		
Perfomance Expectancy	0.537	0.084	0.448	6.387	<.001	0.371	0.703	0.651	1.54
Social Influence	0.041	0.070	0.036	0.580	0.563	-0.098	0.179	0.809	1.24
Perceived Credibility	0.003	0.061	0.003	0.042	0.966	-0.118	0.124	0.791	1.27
Facilitating Conditions	0.004	0.099	0.003	0.044	0.965	-0.190	0.199	0.575	1.74
Attitude	.092	0.104	0.057	0.881	0.379	-0.113	0.297	0.771	1.30

Per the measurement model presenting evidence of validity and reliability in the CFA (see Table 18), a path analysis for the SEM parsimonious model was performed (Purwanto & Sudargini, 2021) to assess the hypotheses formulated in the conceptual research framework. Results of the SEM parsimonious model BI, PC, FC, SI, and PE demonstrated acceptable fit indices (ratio of $\chi 2/df = 1.438$, $p < .001$; CFI = 0.964; IFI = 0.966; RMSEA = .042; TLI = 0.949; NFI = 0.895; RMSR = 0.077; RFI = 0.849; GFI = 0.922; PRatio = 0.696; PCFI = 0.671; PNFI = 0.623 (see Appendix P). A compilation of the structural model goodness of fit statistics such as fitness indices, fitness acceptance criteria, and this study's fitness index estimates can be found in Table 19.

Table 19

Structural Model Goodness-of-Fit Statistics

Fitness Index	Fitness Acceptance Criteria	Fitness Index Estimates	Goodness-of-fit verdict
Absolute			
GFI	> 0.90	0.922	Satisfactory
RMSEA	> 0.08	0.042	Satisfactory
SRMR	> 0.10	0.077	Satisfactory
Incremental			
AGFI	> 0.80	0.878	Satisfactory
CFI	> 0.90	0.964	Satisfactory
IFI	> 0.90	0.966	Satisfactory
NFI	> 0.90	0.895	Satisfactory
TLI	> 0.90	0.949	Satisfactory
Parsimony Adjusted Measures			
X^2	Non-significant at the $p < 0.05$ level	253	Satisfactory
$\chi 2$ / df	< 5, preferably < 3	1.44	Satisfactory
PCFI	> 0.60	0.671	Satisfactory
PNFI	> 0.60	0.623	Satisfactory
PRatio	> 0.60	0.696	Satisfactory

Structural Model. There are two main methods for analyzing structural models, namely, Partial Least Squares Structural Equation Modeling (PLS-SEM) and covariance-based SEM (CB-SEM). PLS-SEM is a multivariate statistical technique that helps examine complex relationships among a number of variables (Kono & Sato, 2022; Zhou et al., 2022). To the extent that the conceptual structural model in this study has only one mediation analysis, it cannot be classified as complex, to warrant PLS-SEM analysis. Therefore, CB-SEM was applied for the analysis.

SPSS AMOS 26 was used by the researcher in compiling the graphic-oriented covariance-based SEM structural model. Figure 8 depicts the structural model, also known as the SEM parsimonious model, with standardized path estimates. Adjacent to the paths between the latent unobserved constructs are numerical values representing the model's path loadings. Table 20 presents the standardized and unstandardized path loadings along with the corresponding significance levels for the structural model's paths.

Table 20

Research Model CB-SEM Path Statistics

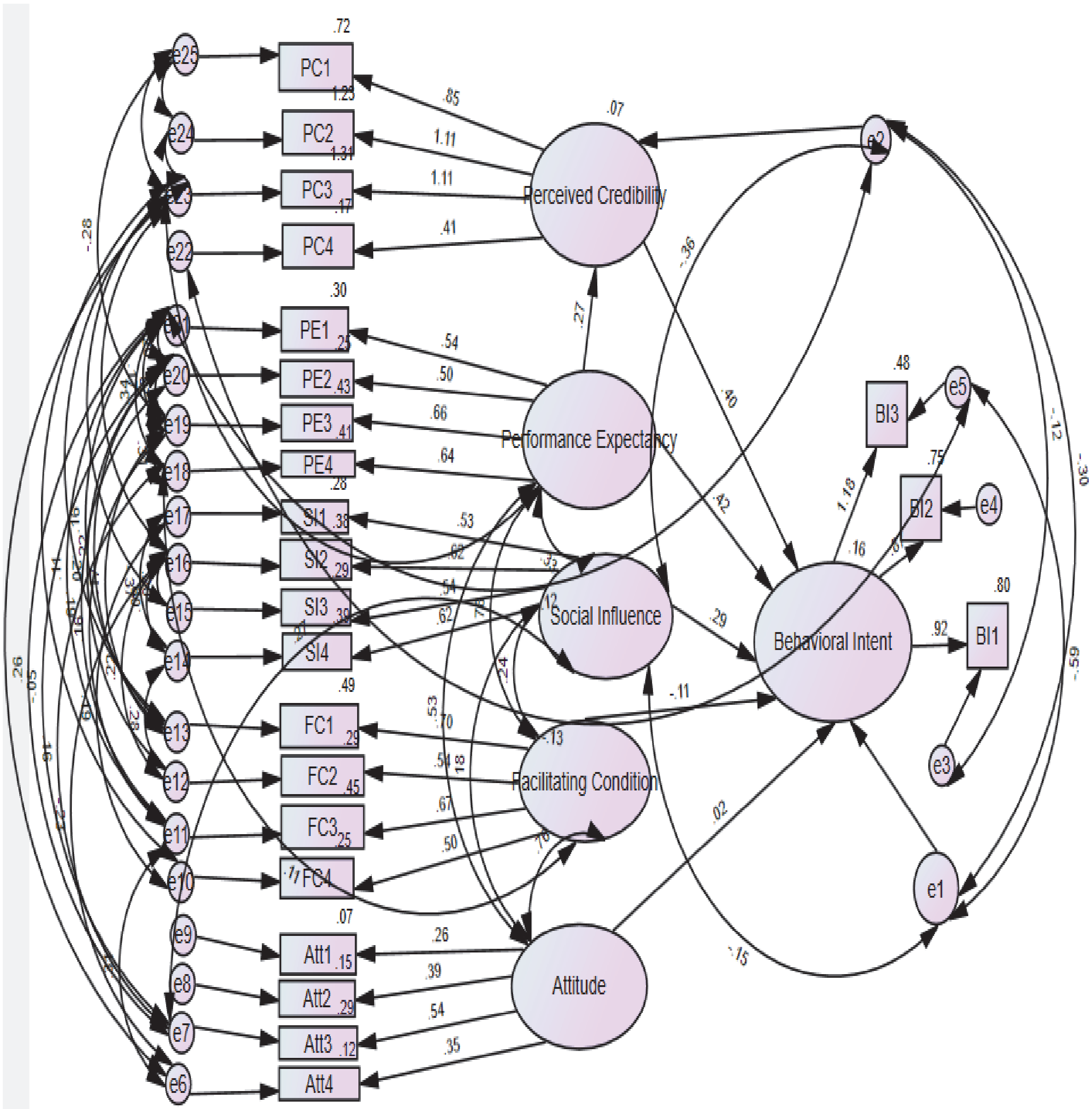
Structural model path	Unstandardized path loading	Standardized path loading	Standard error	Critical Ratio	*p*-value
Att → BI	0.06	0.02	0.616	0.09	.93
PE → BI	0.81	0.42	0.421	1.91	*** [a]
FC → BI	-0.16	-0.11	0.338	-0.47	.64
SI → BI	0.49	0.29	0.423	1.17	*** [a]
PC → BI	0.38	0.40	0.420	0.90	*** [a]
PE → PC	0.53	0.27	0.153	3.47	***[a]

Note. [a] significant at the $p < 0.001$ level

In Figure 8, the PC-BI, PE-BI, and SI-BI paths were found to be statistically significant, with standardized loadings of 0.40, 0.42, and 0.29, respectively. The FC-BI and Att-BI paths were not statistically significant, with standardized loadings of -0.11 and 0.02, respectively. The variance in PC and BI attributable to the predictor constructs were 0.07 (7%) and 0.16 (16%), respectively. The PE-PC path was also found to be statistically significant with standardized loading of 0.27.

Figure 8

Research Parsimonious Model: R^2 Values, Covariance Values, and Standardized Path Estimates

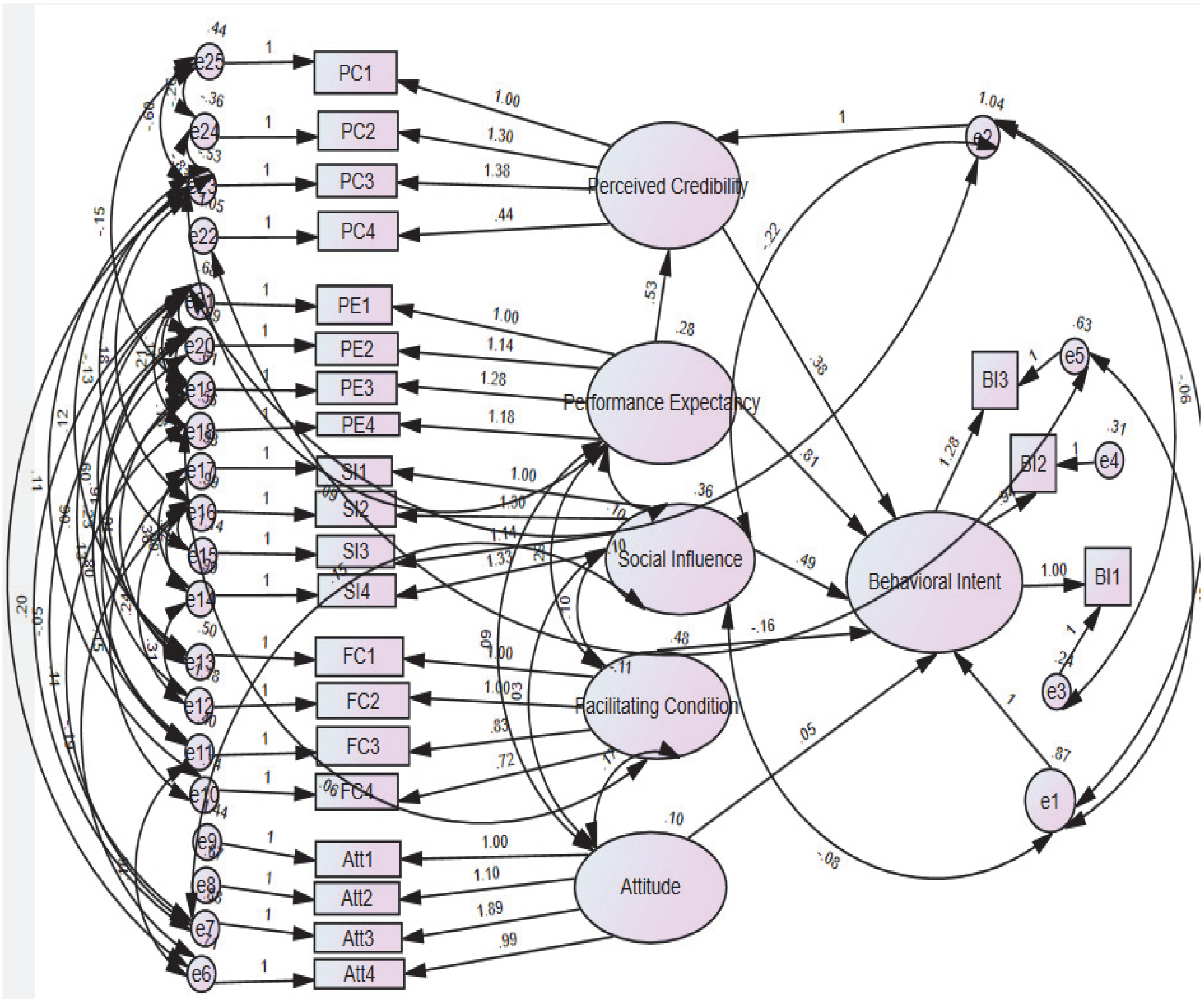


Note. $p < 0.05$ level, The ratio of $\chi2/\text{df} = 1.438$, $p < .033$; CFI = .96482; IFI = 0.966; RMSEA = .042; TLI = 0.949; NFI = 0.90; RMSR = 0.08; GFI = 0.922; AGFI = 0.878; PCFI = 0.671; PNFI = 0.623; TLI = .87; NFI = .976; RFI = 0.823.

In Figure 9, the PC-BI, PE-BI, and SI-BI paths were found to be statistically significant, with unstandardized loadings of 0.38, 0.81, and 0.49, respectively. The FC-BI and Att-BI paths were not statistically significant with unstandardized loadings of -0.16 and 0.06, respectively. The variance in PC and BI attributable to the predictor constructs were 0.07 (7%) and 0.16 (16%), respectively. The PE-PC path was also found to be statistically significant with unstandardized loading of 0.53.

Figure 9

Research Parsimonious Model: R2 Values, Covariance, and Unstandardized Path Estimates

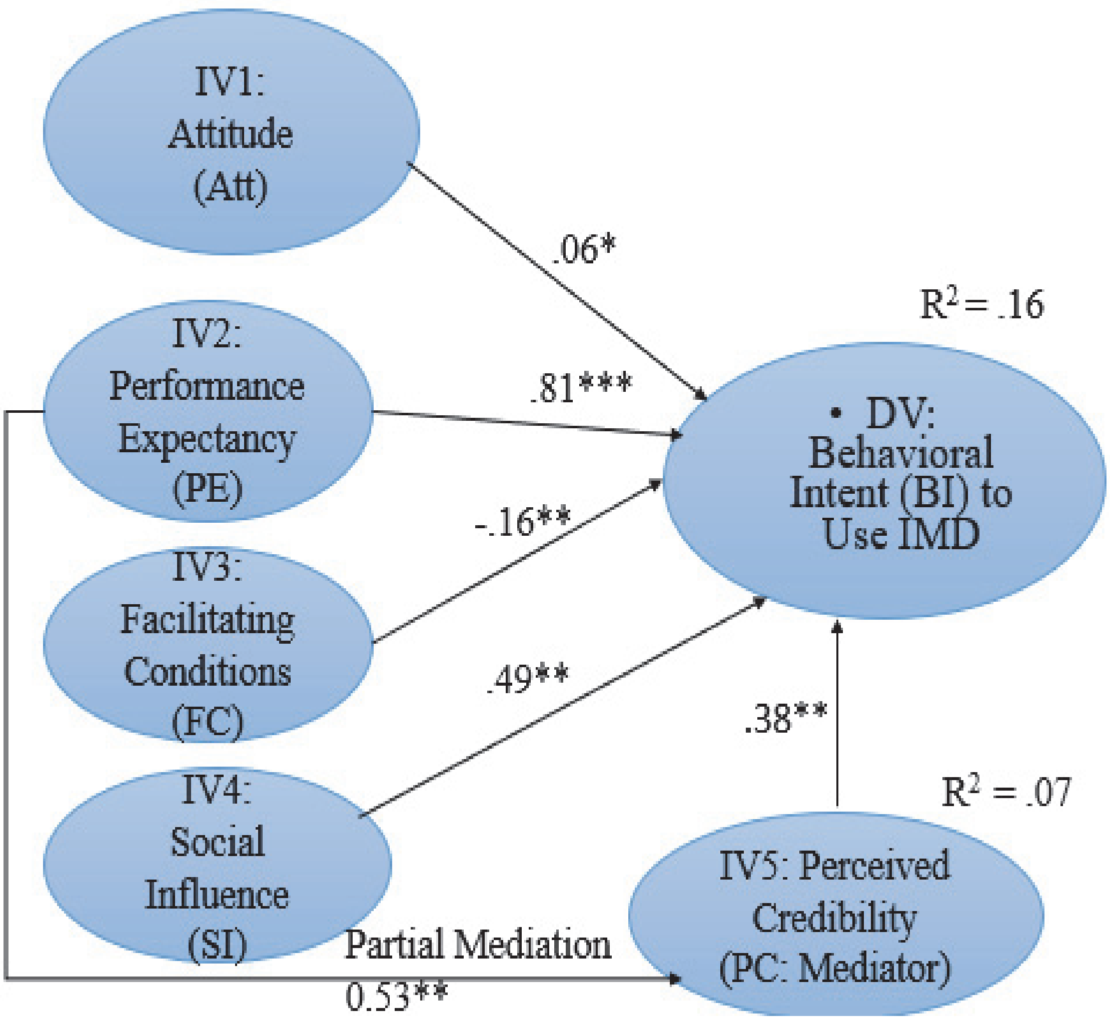


Note. *p < .001 level, The ratio of χ2/df = 1.438, *p* < .001; CFI = .965; IFI = 0.966; RMSEA = .042; TLI = 0.949; NFI = 0.895; RMSR = 0.077; GFI = 0.922; PRatio = 0.696; PCFI = 0.671; PNFI = 0.623; RFI = 0.849.

In Figure 10, the simplified version of the SEM Structural Model of the independent and dependent variables with corresponding unstandardized estimates, the direction of mediation, the mediating variable, and R^2 values are depicted.

Figure 10

Simplified SEM Parsimonious Model with Unstandardized Estimates and R^2 Values



*Note. *p < 0.05 level, **p <0.01 level, and *** p < 0.001 level*, The ratio of $\chi 2/\mathrm{df} = 1.438$, $p < .001$; CFI = .965; IFI = 0.966; RMSEA = 0.042; TLI = 0.949; NFI = 0.90; RMSR = 0.077; GFI = 0.922; PRatio = 0.696; PCFI = 0.671; PNFI = 0.623; RFI = 0.849.

Research Question 1 / Hypothesis 1

What is the degree of relationship, if any, between Attitude and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H1a) hypothesis:

***H1*a:** Attitude is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

Four items (Att1, Att2, Att3, and Att4) measured the Att independent variable adapted from Yeow et al. (2013) using a five-point Likert-scale response format. Att1 measured the item, "I had / will have my doctor solely prescribe my device instead of personally choosing my own treatment options.", using a five-point Likert-scale response format (see Table 21).

Table 21

Att1 Frequency Table

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	15	6.1	6.1	6.1
	Disagree	37	15.0	15.0	21.1
	Neither agree nor disagree	35	14.2	14.2	35.3
	Agree	77	31.3	31.3	66.6
	Strongly agree	82	33.4	33.4	100.0
	Total	246	100.0	100.0	

In Table 21 two-thirds of respondents had a positive opinion about having their doctor solely prescribe their device instead of personally choosing their own treatment options. Only one-fifth of the participants had a negative opinion about having their doctor solely prescribe their device instead of personally choosing their own treatment. Att2 measured the item "IMDs are available at both government and private health facilities for the treatment and management of disease conditions" using a five-point Likert-scale response format (see Table 22).

Table 22

Item Att2 Frequencies

		Frequency	%	Valid %	Cumulative %
Responses	Strongly disagree	6	2.4	2.4	2.4
	Disagree	4	1.6	1.6	4.0
	Neither agree nor disagree	99	40.2	40.2	44.2
	Agree	87	35.4	35.4	79.6
	Strongly agree	50	20.4	20.4	100.0
	Total	246	100.0	100.0	

In Table 22, 55.8% of the respondents are of the view that government and private health facilities provide IMD services for treatment and management of disease conditions. Only 4% of respondents had a negative view of the availability of IMDs at government and private health facilities. Forty percent of respondents were not sure whether IMDs were available at both government and private health facilities. Att3 measured the item "I would always adopt an IMD if I could choose my treatment options" using a five-point Likert-scale response format (see Table 23).

Table 23

Item Att3 Frequencies

		Frequency	%	Valid %	Cumulative %
Responses	Strongly disagree	11	4.5	4.5	4.5
	Disagree	25	10.2	10.2	14.7
	Neither agree nor disagree	83	33.7	33.7	48.4
	Agree	63	25.6	25.6	74.0
	Strongly agree	64	26.0	26.0	100.0
	Total	246	100.0	100.0	

In the above table, one-half of the participants were of the view that they would always adopt an IMD if given the opportunity to select their treatment options. A third of the participants were undecided as to whether they would adopt an IMD if given a choice. One-sixth disagreed they would adopt an IMD if given the opportunity to choose. Att4 measured the item "I discussed / will discuss my treatment option with my physician before using an IMD." using a five-point Likert-scale response format (see Table 24).

In Table 24, nine out of every 10 participants agree to discuss treatment options with their physician before IMD use. Only 6% of participants disagreed they would discuss their treatment option with their physician before use. The final 4.5% were not definite on whether to discuss their treatment options with their physician or not.

Table 24

Item Att4 Frequencies

		Frequency	Percent (%)	Valid %	Cumulative %
Response	Strongly disagree	5	2.0	2.0	2.0
	Disagree	10	4.1	4.1	6.1
	Neither agree nor disagree	11	4.5	4.5	10.6
	Agree	82	33.3	33.3	43.9
	Strongly agree	138	56.1	56.1	100.0
	Total	246	100.0	100.0	

Table 25, listing the statistical analysis for the Att construct, displayed no missing values. The means for the Att items was in the range of 3.59 to 4.37, indicating an overall positive outlook for the items measured in the Att variable.

Table 25

Statistical Analysis of Attitude Construct

		Att1	Att2	Att3	Att4	Att construct
N	Valid	246	246	246	246	246
	Missing	0	0	0	0	0
Mean		3.71	3.70	3.59	4.37	3.45
Std. Deviation		1.244	0.895	1.113	0.903	0.903
Cronbach's Alpha						
Skewness		-0.674	-0.325	-0.360	-1.818	-1.818
Kurtosis		-0.662	0.346	-0.540	3.439	3.439

The standard deviation for the Att variable indicators ranged from 0.895 to 1.244. This indicates a limited spread of values around the mean. Further assessment of the kurtosis and skewness values, which ranged from -0.662 to 3.439 and -1.818 to -0.325, respectively, is an indication that the data was multivariate normal since indices ranged beyond -2 and +2, the acceptable range for univariate normality (Smith, 2018).

Additionally, the Cronbach's α-score for Att assessed by four items Att1, Att2, Att3, and Att4 ($\alpha = 0.377$) depicted non-reasonable internal consistency reliability with an alpha coefficient (α) lesser than the acceptable benchmark values of ($0.6 < \alpha < 0.7$) (Sinclair et al., 2022; Taber, 2018). As demonstrated in Table 26, the outcomes of the SEM parsimonious model analysis revealed that the alternative hypothesis (H1a), which anticipated that Att would be a statistically significant predictor of the U.S. public's BI to use IMD, was not supported ($\beta = .057$, $p < .001$).

Table 26

Test of Attitude Effects

Path	Path coefficient	Standard error	Beta	C.R.	p-value
Att predictor of BI	0.09	0.102	0.057	0.897	0.370[a]

Note. [a]Not significant at the .05 level

Thus, the null hypothesis ($H1_o$) that anticipated that Att would not be a statistically significant predictor of the U.S. public's BI to use IMD was supported. Therefore, Attitude is not a significant predictor of the BI to use an IMD.

Research Question 2/Hypothesis 2

What is the degree of relationship, if any, between performance expectancy and the U.S. patients' behavioral intent to use an IMD?

The following alternative (H2a) hypothesis was derived from the research question.

H2$_a$: Performance Expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use IMD.

The performance expectancy construct was measured in the survey instrument adapted from Yeow et al. (2013) using four items (PE1, PE2, PE3, and PE4), and also measured with a five-point Likert scale format. In Table 27, PE1 measured the item "I am confident my device will work when I need it to."

Table 27

Item PE1 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	6	2.4	2.4	2.4
	Disagree	13	5.3	5.3	7.7
	Neither agree nor disagree	26	10.6	10.6	18.3
	Agree	83	33.7	33.7	52.0
	Strongly agree	118	48.0	48.0	100.0
	Total	246	100.0	100.0	

In Table 27, 81.7% of participants were confident that their devices would work when required. Only 8.7% did not believe that their devices would function when required. About 10% were neutral as to whether their devices would function or not. In Table 28 frequencies for item "I have / will have fewer disease symptoms because of my device" are shown.

Table 28

Item PE2 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	14	5.7	5.7	5.7
	Disagree	32	13.0	13.0	18.7
	Neither agree nor disagree	48	19.5	19.5	38.2
	Agree	71	28.9	28.9	67.1
	Strongly agree	81	32.9	32.9	100.0
	Total	246	100.0	100.0	

In Table 28, about two-thirds of respondents are of the view they will exhibit fewer disease symptoms due to their devices. One-fifth are not of the view that they will exhibit fewer symptoms due to their devices. The remaining one-fifth of respondents also are neutral as to whether they will exhibit fewer symptoms or not. Table 29 depicts the frequency analysis for item PE3, “My device is / will be the most effective treatment option”.

Table 29

Item PE3 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	10	4.1	4.1	4.1
	Disagree	10	4.1	4.1	8.2
	Neither agree nor disagree	33	13.3	13.3	21.5
	Agree	70	28.5	28.5	50.0
	Strongly agree	123	50.0	50.0	100.0
	Total	246	100.0	100.0	

In Table 29, 78.5% of participants believe their devices will be the most effective treatment option. On the contrary, 8.2% do not believe their device will be their most effective treatment option. 13.3% have a neutral opinion. In Table 30, frequencies for the item PE4, “I am sure my device functions / will function the way it is supposed to” are depicted.

Table 30

Item PE4 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	8	3.3	3.3	3.3
	Disagree	7	2.8	2.8	6.1
	Neither agree nor disagree	33	13.4	13.4	19.5
	Agree	85	34.6	34.6	54.1
	Strongly agree	113	45.9	45.9	100.0
	Total	246	100.0	100.0	

In Table 30, 80.5% of respondents are of the perception their devices will work the way it is supposed to. However, 6.1% are of a divergent view that their devices will not function the way they are supposed to. Another 13.4% are undecided as to whether their devices will function as expected. Before SEM analysis was conducted, the raw data was examined for missing values (see Table 31).

Table 31

Statistical Analysis of Performance Expectancy

		PE1	PE2	PE3	PE4	PE construct
N	Valid	246	246	246	246	246
	Missing	0	0	0	0	0
Mean		4.2	3.70	4.16	4.17	4.02
Std. Deviation		0.991	1.214	1.068	0.987	0.834
Cronbach's Alpha						0.785
Skewness		-1.339	-0.627	-1.342	-1.349	-1.287
Kurtosis		1.428	-0.617	1.270	1.715	1.922

Relevant assumptions underlining SEM utilization include unstandardized constructs, normally distributed data, the unprocessed data has no missing values, and the observations for all measurement scales are unrelated (Deng et al., 2018; Scherer & Teo, 2020). Utilizing skewness values and multivariate kurtosis, the sampling distribution of the mean was checked for normality (Deng et al., 2018; Scherer & Teo, 2020). There were no missing values in the statistical analysis presented for the PE construct in Table 31. The analysis also demonstrated that the means for the PE indicators ranged from 3.70 to 4.20, which suggested an overall positive outlook of the items measured in the PE variable.

The standard deviations for the PE indicators had a range from 0.987 to 1.214. These standard deviation values suggested a thin spread of values around the mean. The skewness and kurtosis values, ranging from -1.349 to -0.627 and 1.270 to 1.715, respectively, is an indication that the data was univariately normal. Values ranging between -2 and +2 are considered univariately normal (Smith, 2018). Furthermore, the Cronbach's α score for PE evaluated by four items (α = 0.785) demonstrated strong internal reliability with an alpha coefficient greater than the acceptable benchmark values of ($0.6 < \alpha < 0.7$) (Sinclair et al., 2022; Taber, 2018).

Hypothesis 2 Testing. This research question was tested by assessing its alternative and null hypotheses. As demonstrated in Table 32, the outcomes of this finding revealed that the alternative hypothesis (H1a), which anticipated that PE would be a statistically significant predictor of the U.S. public's BI to use IMD, was supported ($\beta = .448$, $p < .001$).

Table 32

Test of Performance Expectancy Effects

Path	Path coefficient	Standard error	Beta	C.R.	p-value
PE predictor of BI	0.54	0.084	0.448	6.398	***[a]

Note. [a] Significant at the .001 level.

Thus, the null hypothesis ($H1_o$) that anticipated PE would not be a statistically significant predictor of the U.S. public's BI to use IMD was not supported. PE is, therefore, a significant predictor of the BI to use an IMD.

Research Question 3/Hypothesis 3

What is the degree of relationship, if any, between facilitating conditions and U.S. patients' behavioral intent to use an IMD? This question presented the following alternative (H3a) hypothesis. ***$H3_a$:*** Facilitating Conditions is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD. The FC construct was assessed in the survey instrument adapted from Yeow et al. (2013) by four items (FC1, FC2, FC3, and FC4). The measurements were taken using a five-point Likert scale format. FC1 measured the item "My device enhances / will enhance my standard of living " using a five-point Likert-scale response format in Table 33.

Table 33

Facilitating Conditions Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	4	1.6	1.6	1.6
	Disagree	18	7.3	7.3	8.9
	Neither agree nor disagree	25	10.2	10.2	19.1
	Agree	80	32.5	32.5	51.6
	Strongly agree	119	48.4	48.4	100.0
	Total	246	100.0	100.0	

In Table 33, 80.9% of the respondents believe that an IMD will enhance their standard of living. Contrarily, 8.9% do not believe that an IMD will improve their standard of living. The remaining 10.2% are neutral as to IMDs improving their standard of living. In Table 34, item FC2 "I have / will have fewer doctor visits per year, reducing my healthcare costs, leading to efficient health management after I began/begin using my device than before receiving my device(s)." was analyzed.

Table 34

Item FC2 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	24	9.8	9.8	9.8
	Disagree	55	22.4	22.4	32.2
	Neither agree nor disagree	45	18.3	18.3	50.5
	Agree	69	28.0	28.0	78.5
	Strongly agree	53	21.5	21.5	100.0
	Total	246	100.0	100.0	

In Table 34, one-half of the respondents are of the perception that IMDs will reduce their hospital visits leading to efficient health management. One-third, however, are of the view that the IMDs will not reduce their hospital visits and lead to efficient healthcare management. The final one-fifth remain undecided as to whether IMDs will reduce their hospital visits. In Table

35, FC3 measured the item "I feel that the use of an IMD for treatment and disease condition management is beneficial." using a five-point Likert-scale response format.

Table 35

Item FC3 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	4	1.6	1.6	1.6
	Disagree	6	2.4	2.4	4.0
	Neither agree nor disagree	18	7.3	7.3	11.3
	Agree	76	30.9	30.9	42.2
	Strongly agree	142	57.8	57.8	100.0
	Total	246	100.0	100.0	

In Table 35, 88.7% of participants were of the view that IMD use is beneficial. Only 3.9% of participants held a contrary view. The remaining 7.3% were undecided as to whether an IMD was beneficial. In Table 36, FC4 measured the item FC4, "My health insurance covers / will cover my use of an IMD." using a five-point Likert-scale format.

Table 36

Item FC4 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	7	2.8	2.8	2.8
	Disagree	14	5.7	5.7	8.5
	Neither agree nor disagree	23	9.3	9.3	17.8
	Agree	94	38.3	38.3	56.1
	Strongly agree	108	43.9	43.9	100.0
	Total	246	100.0	100.0	

In Table 36, 82.2% of the respondents are of the view that their health insurance will cover their IMD expenses. However, 8.5% are of a contrary view. The remaining 9.3% are neutral. A frequency distribution table was created to simplify and systematize the data gathered for this question. An overview of how many participants were in every survey item on the scale of measurement can be found in Table 37.

Table 37

Statistical Analysis of Facilitating Conditions

		FC1	FC2	FC3	FC4	FC construct
N	Valid	246	246	246	246	246
	Missing	0	0	0	0	0
Mean		4.19	3.29	4.41	4.15	4.008
Std. Deviation		0.997	1.295	0.856	0.999	0.757
Cronbach's Alpha						0.693
Skewness		-1.231	-0.229	-1.756	-1.336	-0.930
Kurtosis		0.888	-1.127	3.442	1.491	0.906

In Table 37, the statistical analysis for the FC construct displayed no missing values. The means for the FC items were in the range of 3.29 to 4.41, indicating an overall positive outlook for the items measured in the FC variable. The standard deviation for the FC variable indicators ranged from 0.856 to 1.295. This indicates a limited spread of values around the mean. Further assessment of the kurtosis and skewness values, which ranged from -1.127 to -3.442 and -1.756 to -0.229, respectively, is an indication that the data was univariate normal since indices ranged between -2 and +2, the acceptable range. (Kalkbrenner, 2021). Additionally, the Cronbach's α-score for FC assessed by four items FC1, FC2, FC3, and FC4 ($\alpha = 0.693$) depicted reasonable internal consistency reliability with an alpha coefficient (α) within the acceptable benchmark values of ($0.6 < \alpha < 0.7$) (Adriani et al., 2020; Taber, 2018). The test of the effects of FC on BI to use an IMD is depicted in Table 38.

Table 38

Test of Facilitating Conditions Effects

Path	Path coefficient	Standard error	Beta	C.R.	p-value
FC predictor of BI	-0.11	0.097	0.003	0.45	0.964[a]

Note. [a] Not significant at the .05 level.

Analysis of Hypothesis 3. As shown in Table 38, the SEM analysis of this question's null and alternative hypotheses found that there is no significant relationship between FC and BI ($\beta = -0.11$, $p > .05$). Thus, the null hypothesis ($H3_0$), that FC is not a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD, was supported.

Research Question 4 / Hypothesis 4

What is the degree of relationship, if any, between social influence and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H4a) hypothesis. $H4_a$. Social Influence is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD. The social influence construct was assessed in the survey instrument adapted from Yeow et al. (2013) by four items (SI1, SI2, SI3, and SI4). SI1 measured the item "Those I consider important to me influence my intention to use an IMD" using a five-point Likert-scale response format (see Table 39).

Table 39

Item SI1 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	13	5.3	5.3	5.3
	Disagree	22	8.9	8.9	14.2
	Neither agree nor disagree	53	21.6	21.6	35.8
	Agree	84	34.1	34.1	69.9
	Strongly agree	74	30.1	30.1	100.0
	Total	246	100.0	100.0	

In Table 39, 64.2% of respondents are of the perception that those that are important in their lives influence them to use an IMD. 14.2% are of a contrary view. The remaining 21.6% are neutral on the subject. In Table 40, frequency analysis for SI2 "The United States government encouragement influences my intention to use an IMD" is shown.

Table 40

Item SI2 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	79	9.0	32.1	32.1
	Disagree	52	24.1	21.1	53.2
	Neither agree nor disagree	70	46.9	28.5	81.7
	Agree	19	7.7	7.7	89.4
	Strongly agree	26	10.6	10.6	100.0
	Total	246	100.0	100.0	

In Table 40, 18.3% of respondents are of the view that the U.S. government's encouragement influences their intention to use an IMD. Another 33.1% are of a contrary view. The remaining 46.9% are undecided on the subject. In Table 41, item SI3 "Patients I know who are using IMDs, including those in my Facebook Support Group influence my intention to use an IMD" was analyzed.

Table 41

Item SI3 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	34	13.8	13.8	13.8
	Disagree	47	19.1	19.1	32.9
	Neither agree nor disagree	65	26.4	26.4	59.3
	Agree	60	24.4	24.4	83.7
	Strongly agree	40	16.3	16.3	100.0
	Total	246	100.0	100.0	

In Table 41, 40.7% of respondents are of the view that their social circle is influential in their decision to use an IMD. Another 32.9% are of the contrary view. The remaining 26.4% hold a neutral opinion. In Table 42, SI4 measured the item "Achieving IMD compliance is the sole responsibility of those in charge of regulatory compliance and not the patient." using a five-point Likert-scale response format. A frequency distribution table was created, to simplify and systematize the data gathered for this question.

Table 42

Item SI4 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	33	13.4	13.4	13.4
	Disagree	60	24.4	24.4	37.8
	Neither agree nor disagree	63	25.6	25.6	63.4
	Agree	46	18.7	18.7	82.1
	Strongly agree	44	17.9	17.9	100.0
	Total	246	100.0	100.0	

In Table 42, 36.6% of the respondents believe that IMD compliance lies in the hands of those in charge of regulatory compliance. However, 37.8% of respondents were of the contrary view that IMD compliance is not the sole responsibility of those in charge of regulatory compliance. The final 25.6% of respondents remained undecided. In Table 43 the statistical analysis for the SI construct displayed no missing values.

Table 43

Statistical Analysis of Social Influence

		SI1	SI2	SI3	SI4	SI construct
N	Valid	246	246	246	246	246
	Missing	0	0	0	0	0
Mean		3.75	2.43	3.10	3.03	3.08
Std. Deviation		1.136	1.298	1.278	1.30	0.895
Cronbach's Alpha						0.678
Kurtosis		-0.164	-0.700	-1.016	-1.085	-0.545

The means for the SI items were in the range of 2.43 to 3.75, with an average of 3.09, indicating an overall neutral outlook (neither agree nor disagree) for the items measured in the SI variable. The standard deviation for the SI variable indicators ranged from 1.136 to 1.300. This indicates a limited spread of values around the mean. Further assessment of the kurtosis and skewness values, which ranged from -1.085 to -0.164 and -0.737 to 0.540 respectively, is an indication that the data is univariate normal since indices ranged between -2 and +2, the acceptable range. (Smith, 2018).

Pertinent assumptions underlying SEM utilization of SEM include: the unprocessed data having no missing values, being normally distributed data, constructs being unstandardized constructs, and the observations for all measurement scales being unrelated (Deng et al., 2018; Scherer & Teo, 2020). Consequently, prior to performing the SEM analysis, the raw data was examined for any missing values. The sampling distribution of the mean was also checked for normality using the skewness values and multivariate kurtosis values (Deng et al., 2018; Scherer & Teo, 2020).

Hypothesis 4 Testing. Question 4 was tested by assessing its null and alternative hypotheses. As shown in Table 44, the findings of this investigation depicted that SI positively affects BI ($\beta = 0.29$, $p > .01$).

Table 44

Test of Social Influence Effects

Path	Path coefficient	Standard error	Beta	C.R.	p value
SI predictor of BI	0.494	0.423	0.29	1.167	***[a]

Note. [a] Significant at the .001 level.

Hence the alternative hypothesis (H4a), that SI is a statistically significant predictor of the U.S. public's BI to use IMD, is supported and the null hypothesis is rejected. SI is, therefore, a significant prognosticator of the BI to use an IMD.

Research Question 5 / Hypothesis 5

What is the degree of relationship, if any, between perceived credibility and U.S. patients' behavioral intent to use an IMD? This question presented the following alternative

(H5a) hypothesis: $H5_{a.}$ Perceived credibility is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

The PC construct was assessed in the survey instrument adapted from Kohnke et al. (2014) by four items (PC1, PC2, PC3, and PC4). The measurements were taken using a five-point Likert scale format (see Table 45). A frequency distribution table was created, to simplify and systematize the data gathered for this question. An overview of how many participants were in every survey item on the scale of measurement can be found in the following tables. In Table 45, frequencies for the item PC1 can be found.

Table 45

Item PC1 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	44	17.9	17.9	17.9
	Disagree	26	10.6	10.6	28.5
	Neither agree nor disagree	84	34.1	34.1	62.6
	Agree	62	25.2	25.2	87.8
	Strongly agree	30	12.2	12.2	100.0
	Total	246	100.0	100.0	

In Table 45, 37.4% believe that their devices will be difficult to hack. Contrarily 28.5% believe that criminals can hack their devices. The remaining 34.1% are neutral about device hackability. In Table 46 item PC2 was evaluated.

Table 46

Item PC2 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	38	15.4	15.4	15.4
	Disagree	22	8.9	8.9	24.3
	Neither agree nor disagree	63	25.6	25.6	49.9
	Agree	89	36.3	36.3	86.2
	Strongly agree	34	13.8	13.8	100.0
	Total	246	100.0	100.0	

In Table 46, one-half of the participants believe that IMDs are secure. One-quarter of the participants do not believe that their devices are secure. The remaining one-quarter are indifferent as to the security of IMDs. In Table 47, item PC3 “I feel safe / will feel safe using my device” was analyzed.

Table 47

Item PC3 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	38	2.1	2.1	2.1
	Disagree	22	6.9	6.9	9.0
	Neither agree nor disagree	63	39.3	39.3	48.3
	Agree	89	45.5	45.5	93.8
	Strongly agree	34	6.2	6.2	100.0
	Total	246	100.0	100.0	

In Table 47, 51.7% of participants believe that they feel safe using their devices. On the other hand, 9% of participants do not feel safe using their devices. The remaining 39.3% of participants are undecided on how they feel about the safety of their device. In Table 48, item PC4 “IMD limits / will limit unwarranted access to my personal information and health data.” was analyzed.

Table 48

Item PC4 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	29	11.8	11.8	11.8
	Disagree	40	16.3	16.3	28.1
	Neither agree nor disagree	88	35.8	35.8	63.9
	Agree	66	26.8	26.8	90.7
	Strongly agree	23	9.3	9.3	100.0
	Total	246	100.0	100.0	

In Table 48 36.1% of the respondents are of the view IMDs will limit unwarranted access to their personal information and health data. On the other hand, 28.1% of respondents do not believe IMDs will limit access to their personal information. The remaining 35% are not decisive on whether IMDs will limit unwarranted access. In Table 49, a statistical analysis of the PC variable is presented.

Table 49

Statistical Analysis of Perceived Credibility

		PC1	PC2	PC3	PC4	PC construct
N	Valid	246	246	246	246	246
	Missing	0	0	0	0	0
Mean		3.03	3.24	3.65	3.06	3.246
Std. Deviation		1.252	1.253	1.349	1.131	1.037
Cronbach's Alpha						0.850
Skewness		-0.238	-0.513	-0.911	-0.215	-0.690
Kurtosis		-0.847	-0.724	-0.349	-0.608	-0.145

Pertinent assumptions underlying SEM utilization of SEM include: the unprocessed data having no missing values, normally distributed data, constructs being unstandardized constructs, and the observations for all measurement scales being unrelated (Deng et al., 2018; Scherer & Teo, 2020). Consequently, prior to performing the SEM analysis, the raw data was examined for any missing values. The statistical analysis for the PC construct is displayed with no missing values. The sampling distribution of the mean was also checked for normality using the skewness values and multivariate kurtosis values (Deng et al., 2018; Scherer & Teo, 2020). The means for the PC items were in the range of 3.03 to 3.65, indicating an overall positive outlook for the items measured in the PC variable. The standard deviation for the PC variable indicators ranged from 1.131 to 1.349. This indicates a limited spread of values around the mean.

Further assessment of the kurtosis and skewness values, which ranged from -0.847 to -0.349 and -0.911 to -0.215, respectively, is an indication that the data was univariate normal, since indices ranged between -2 and +2, the acceptable range. (Kalkbrenner, 2021). Additionally, the Cronbach's α-score for PC assessed by four items PC1, PC2, PC3, and PC4 ($\alpha = 0.850$) depicted robust internal reliability with an alpha coefficient (α) larger than the acceptable benchmark values of ($0.6 < \alpha < 0.7$) (Sinclair et al., 2022; Taber, 2018).

Hypothesis 5 Testing. After testing the null and alternative hypotheses, it was found that the alternative hypothesis (H5a), which anticipated that PC would be a statistically important prognosticator of the U.S. patient's BI to use an IMD, was supported (β=.40, p <.001), as shown in Table 50.

Table 50

Test of Perceived Credibility Effects

Path	Path coefficient	Standard error	Beta	C.R.	p-value
PC predictor of BI	0.380	0.420	0.40	0.904	***[a]

Note. [a] Significant at the .001 level.

The findings of this analysis suggested a direct effect of the PC factor on the BI to use, the dependent variable. Therefore, the alternative hypothesis (H2a), which predicted that PC is a statistically significant predictor of the U.S. patient's BI to use IMD, was accepted.

Consequentially, the null hypothesis ($H5_o$), which forecasts that PC is not a statistically significant predictor of the U.S. public's BI to use IMD, was not supported.

Research Question 6/Hypothesis 6

What is the degree of relationship, if any, between performance expectancy and U.S. patients' behavioral intent to use an IMD when accounting for perceived credibility? Presented by the following alternative (H6a) hypothesis: ***H6*a.** Performance expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD when mediated by perceived credibility. PE was also measured by the items PE1, PE2, PE3, and PE4, as was included in the PE scale in the second research question.

Lastly, the scale for the dependent variable BI to use was adapted from Yeow et al. (2013). The scale included three items, BI1, BI2, and BI3, measuring the extent to which participants use IMD for treating and managing disease conditions. In Table 51, item BI1 "I intend to use an IMD for treatment and management of a disease condition that a doctor would usually prescribe an IMD" was analyzed.

Table 51

Item BI1 Frequencies

		Frequency	%	Valid %	Cumulative %
Valid	Strongly disagree	15	6.1	6.1	6.1
	Disagree	6	2.4	2.4	8.5
	Neither agree nor disagree	16	6.5	6.5	15.0
	Agree	55	22.4	22.4	37.4
	Strongly agree	154	62.6	62.6	100.0
	Total	246	100.0	100.0	

In Table 51, 85% of respondents intend to use an IMD. On the contrary, 8.5% do not intend using an IMD. The remaining 6.5% are undecided on IMD use. In Table 52 item BI2 "I predict I would use IMD for treatment and management of a disease condition that a doctor would usually prescribe an IMD" was analyzed.

Table 52

Item BI2 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	13	5.3	5.3	5.3
	Disagree	8	3.3	3.3	8.6
	Neither agree nor disagree	25	10.1	10.1	18.7
	Agree	57	23.2	23.2	41.9
	Strongly agree	143	58.1	58.1	100.0
	Total	246	100.0	100.0	

In Table 52, 81.3% of participants predict they would use an IMD. On the other hand, 8.6% of participants did not predict they would use an IMD. The remaining 10.1% were undecided on predicting IMD use. In Table 53, item BI3 "I plan to continue using an IMD in the future for treatment and management of a disease condition that a doctor would usually prescribe an IMD" was analyzed.

Table 53

Item BI3 Frequencies

		Frequency	%	Valid %	Cumulative %
Response	Strongly disagree	15	6.1	6.1	6.1
	Disagree	5	2.0	2.0	8.1
	Neither agree nor disagree	14	5.7	5.7	13.8
	Agree	49	19.9	19.9	33.7
	Strongly agree	163	66.3	66.3	100.0
	Total	246	100.0	100.0	

In Table 53, 86% of respondents plan to continue using an IMD in the future. Contrarily, 8.1% do not plan to use an IMD in the future. The remaining 5.7% are undecided on future IMD use. Statistical analysis of the dependent variable, Behavioral Intent to use an IMD, is presented in Table 54.

Table 54

Statistical Analysis of Behavioral Intent to use an IMD

		BI1	BI2	BI3	BI Construct
N	Valid	246	246	246	246
	Missing	0	0	0	0
Mean		4.33	4.26	4.38	3.26
Std. Deviation		1.111	1.108	1.099	0.88
Cronbach's Alpha					0.900
Skewness		-1.869	-1.610	-2.011	-0.48
Kurtosis		2.735	1.886	3.263	0.71

In Table 54, the statistical analysis for the BI construct displayed no missing values. The means for the BI items were in the range of 4.26 to 4.38, indicating an overall positive outlook for the items measured in the BI variable. The standard deviation for the BI variable indicators ranged from 1.099 to 1.111. This indicates a limited spread of values around the mean.

Further assessment of the kurtosis and skewness values, which ranged from 1.886 to -3.263 and -2.011 to -1.610, respectively, is an indication that the data was multivariate normal since indices ranged beyond -2 and +2, the acceptable range for univariate normality (Kalkbrenner, 2021). Additionally, the Cronbach's α-score for BI assessed by three items BI1, BI2, and BI3 ($\alpha = 0.887$) depicted reasonable internal consistency reliability with an alpha coefficient (α) larger than the acceptable benchmark values of ($0.6 < \alpha < 0.7$) (Adriani et al., 2020; Taber, 2018).

Pertinent assumptions underlying utilization of SEM include: the unprocessed data having no missing values, normally distributed data, constructs being unstandardized constructs, and the observations for all measurement scales being unrelated (Deng et al., 2018; Scherer &

Teo, 2020). Consequently, prior to performing the SEM analysis, the raw data was examined for any missing values. The sampling distribution of the mean was also checked for normality using the skewness values and multivariate kurtosis values (Deng et al., 2018; Scherer & Teo, 2020).

Statistical Analysis for all Variables

In the above statistical analyses for each research question and variables, the results depicted that the means for the variables ranged from a low value for SI (M = 3.08) to a high for BI (M = 4.32). This is an indication of an overall positive outlook for the variables measured in the study. PE (M = 4.06) was the second most important factor for the U.S. patient's BI to use an IMD, followed by PC (M = 4.01). The standard deviations ranged from .856 to 1.349. This indicates a limited spread of values around the mean. Further assessment of the kurtosis and skewness values, which ranged from 3.439 to -1.127 and -2.011 to 0.540 respectively, is an indication that the data was multivariate normal. (Smith, 2018). Additionally, as depicted in Table 55, the Cronbach's α-score indicated that all 23 items assessing the dependent and independent variables depicted strong internal reliability with an alpha coefficient (α) of .805, larger than the acceptable benchmark values of ($0.6 < \alpha < 0.7$) (Sinclair et al., 2022; Taber, 2018). In Table 55, a summary of statistical analysis for all variables is found.

Table 55

Summary of Statistical Analysis for all Variables

N = 246	Mean	Standard Deviation	Cronbach's Reliability Coefficient
All Variables	3.73	0.493	0.805

Pertinent assumptions underlying SEM utilization for Parsimonious Model generation include: the unprocessed data having no missing values, normally distributed data, constructs being unstandardized constructs, and the observations for all measurement scales being unrelated (Deng et al., 2018; Scherer & Teo, 2020). Consequently, prior to performing the SEM analysis, the raw data was examined for any missing values. The sampling distribution of the mean was also checked for normality using the skewness values and multivariate kurtosis values (Deng et al., 2018; Scherer & Teo, 2020). SEM Analysis of the mediating effects of PC on PE is shown in Table 56.

Table 56

Mediating Effects of Perceived Credibility on Performance Expectancy

	Path	Path Coefficient	Std. Error	Beta	C.R.	p-value
SEM Analysis	PE mediated by PC1	0.53	0.397	0.23	6.455	***[a]
	PE mediated by PC2	0.69	0.936	0.30	3.704	***[a]
	PE mediated by PC3	0.73	0.096	0.30	6.219	***[a]
	PE mediated by PC4	0.24	0.086	0.11	2.338	**[b]
Linear Regression	PE mediated by PC	0.5733	0.070	0.48[c]	8.20[d]	***[a]

Note. [a] Significant at the .001 level.
[b] Significant at the 0.05 level.
[c] Standardized regression coefficient from linear regression.
[d] T-statistic coefficient.

Hypothesis 6 Testing

This question's null and alternative hypotheses were assessed using linear regression and SEM. The sixth hypothesis (H6) revealed that PC did explain variance of the BI factor. PC was also extracted as a mediator of PE as well as a predictor of BI. As depicted in Table 57, the findings of this analysis disclosed that PC serves an intermediary role in describing the variances of BI ($\beta = .48$, $p < .001$).

Thus, the alternative hypothesis (H6a) that predicts that PE is statistically mediated by PC is supported, and the null hypothesis ($H6_0$) is rejected. Figure 8 depicts the SEM parsimonious model with the coefficient of determination (R^2) value and standardized path coefficients. Conclusions of the SEM parsimonious model demonstrated that the extended UTAUT model justified 16% of the variance for BI to use IMD ($R^2 = 0.16$). The complete and summarized results of hypotheses testing are demonstrated in Table 57, where the supported hypotheses are underlined.

Table 57

Summary of Hypothesis Testing

Hypotheses	Path	Remarks
H10.	Att is not a predictor of BI	Supported
H1a.	Att is a predictor of BI	Not supported
H20.	PE is not a predictor of BI	Not supported
H2a.	PE is a predictor of BI	<u>Supported</u>
H30.	FC is not a predictor of BI	Supported
H3a.	FC is a predictor of BI	Not supported
H40.	SI is not a predictor of BI	Not supported
H4a.	SI is a predictor of BI	<u>Supported</u>
H50.	PC is not a predictor of BI	Not supported
H5a.	PC is a predictor of BI	<u>Supported</u>
H60.	PE is not mediated by PC	Not supported
H6a.	PE is mediated by PC	Supported

Evaluation of the Findings

The aim of this investigation was to provide a further understanding of the issues surrounding the U.S. patient's intention to adopt and use IMDs for efficient healthcare management. In determining the factors shaping the U.S. public's acceptance of IMDs, the investigation framework used Yeow et al.'s (2013) extension of UTAUT to include FC, SI, PC, and PE constructs, and expanded the model to include Att. The impact of each independent variable on the U.S. patient's BI to use an IMD was examined. In addition, the extent to which the predictions of the variable PE were mediated by the construct of PC was also explored. The results of the study found both empirical and theoretical support for the capability of the UTAUT framework to offer an improved understanding of the factors influencing user acceptance of IMD technologies. The following are explanations of the findings of each of the research questions addressed in this study.

Research Question 1 / Hypothesis 1

What is the degree of relationship, if any, between Attitude and U.S. patients' behavioral intent to use an IMD? This question presented the following alternative (H1a) hypotheses: ***H1*a.** Attitude is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD.

Interestingly, in answering this research question, it was found that the patient's attitude to IMD technology did not affect the BI to use an IMD. In other words, the Att factor was not able to explain any variance of the BI to use an IMD. Thus, the null hypothesis ($H1_0$) was maintained. This is an indicator to the point that the U.S. patient's negative or positive attitude toward IMD is not key to their adoption and intention to use an IMD. This discovery may be due to the decision to use an IMD being made together with their physician instead of individually as observed in the responses to item 29 on the survey "I discussed / will discuss my treatment option with my physician before using an IMD.", where 89.4% agreed to discuss their option with the physician before IMD use.

This contradicts Seyal and Turner's (2013) conclusions that users' attitudes are a significant predictor of the acceptance and intention to use a specific technology. Similarly, this finding contradicts Thomas et al.'s (2020), assertion that Att is the strongest determinant of BI to adopt and use mobile learning. Chen and Lin (2018), during their research on healthcare wearable devices, discovered that changing attitudes towards healthcare influence the actual use of healthcare wearable devices.

Research Question 2 / Hypothesis 2

What is the degree of relationship, if any, between performance expectancy and the U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H2a) hypotheses: $H2_a$: Performance Expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use IMD. In researching this question, it was found that the patient's expectation of the device to perform its duties does affect the BI to use an IMD. In other words, the PE factor explained the variance of the BI to use an IMD. Thus, the null hypothesis ($H1_0$) was rejected, and the alternative hypothesis was accepted. This result is in consonance with previous investigations that observed a significant relationship between the PE and BI factors where other attributes were studied in dissimilar settings (Nikolopoulou et al., 2021; Sabas & Kiwango, 2021; Shaikh et al., 2021; Sołtysik-Piorunkiewicz & Zdonek, 2021).

Sołtysik-Piorunkiewicz and Zdonek (2021) discovered that performance expectancy was a significant factor in influencing Society 5.0 and Industry 4.0 to use open data. Nikolopoulou et al. (2021) also discovered that performance expectancy was an influencing factor in the determination of teachers' intention to use mobile internet. Similarly, Shaikh et al. (2021) discovered that performance expectancy was a significant predictor of mobile banking adoption. In another instance, Cimperman et al. (2016), researching healthcare, also discovered that the higher the expected performance for devices the higher the intention to use the device continuously. Also, Chen and Lin (2018), in their research on healthcare wearable devices, discovered a positive relationship between performance expectancy and actual use of healthcare wearable devices.

The findings are in contrast to studies that found out PE was not a predictor of BI, such as Hino (2015), Yeow et al. (2013), and Mtebe and Raisamo (2014). A different study on the adoption of mobile electronic medical records discovered a substantial impact of PE on Att but not on BI (Hwang et al., 2019). The justification for these contrasts might rest in the fact that these studies were conducted under different scenarios where other features were examined. For instance, Hwang et al. (2019) investigated the acceptance of systems having other technological capabilities, including mobile accessibility, in contrast to this study which examined the adoption of an IMD for efficient healthcare management.

Research Question 3 / Hypothesis 3

What is the degree of relationship, if any, between facilitating conditions and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H3a) hypotheses: Facilitating Conditions is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD. The outcomes of H3 suggested that there was no significant effect of FC on BI; hence the null hypothesis was maintained. Results of the SEM analysis discovered a negative effect of FC on the U.S. patient's behavioral intent to use an IMD, and thus the null hypothesis was accepted, and the alternative rejected. It was also observed that there was a negative correlation between FC and BI to use. This observation suggests that when technological and administrative infrastructure are emphasized, it reduces the edge to use an IMD, as the patient relies on the infrastructure put in place to help manage their disease condition effectively.

This outcome suggests that neither an administrative nor technological infrastructure is required to facilitate IMD use and acceptance. This result does not support previous findings in studies such as Catherine et al. (2018), Onaolapo and Oyewole (2018) and Vanduhe et al. (2020), where FC was found to have significant effect on BI. However, it is in consonance with Bilgihan et al. (2017), and Utomo et al. (2021), where it was discovered that FC does not have any effect on BI.

Research Question 4 / Hypothesis 4

What is the degree of relationship, if any, between social influence and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H4a) hypotheses: ***$H4_a$.*** Social Influence is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD. This result aligns with the alternative hypothesis estimation that the U.S. patient's intention to use an IMD is directly influenced by the motivations and views of other individuals or group that hold a meaningful position in their lives. Chen and Lin (2018) also discovered that SI was a significant prognosticator of device use.

According to Chen and Lin (2018) when inpatients have a positive experience with healthcare wearable devices, there is the tendency of sharing their experiences with society and recommending others to use the devices. This research contradicts Venkatesh et al.'s (2003) findings suggesting that SI is not a relevant determinant of an individual's intention to use technology especially when the acceptance of the specific technology is voluntary. Other researchers such as Al-Adwan et al. (2022) and Cokins et al. (2020) that have examined the effect of SI on BI in different voluntary settings also reported similar contradictory results.

Research Question 5 / Hypothesis 5

What is the degree of relationship, if any, between perceived credibility and U.S. patients' behavioral intent to use an IMD? This question presented the following alternative (H5a) hypotheses: H5a. Perceived credibility is a statistically significant predictor of the U.S. patient's behavioral intent to use an IMD.

Grounded on the SEM analysis results, the null hypothesis was rejected because PC directly explained the variance of the BI factor. This finding indicates that the safety and security levels of an IMD system do influence the U.S. patient's intention to use an IMD. This result is consistent with Colman et al. (2019), Yeow et al. (2013), and Hino (2015). A possible theoretical reason is that with the wide variety of advanced technologies in artificial intelligence (AI), machine learning (ML), deep learning (DL) and cybersecurity with high orders of encryption (Garzotto et al., 2020; Iacopino et al., 2021; Maschmeyer et al., 2021), the U.S. patient perceives device hacking and patient's identity theft no more as challenging behaviors which cannot be dealt with (Piro et al., 2020; Simovic et al., 2022). Hence, U.S. patients perceive PC (safety and security) as a relevant factor influencing their intention to use IMD technology. This finding indicates U.S. patients believe that using an IMD is safe from hackers and secures their health information from theft and therefore influences their intention to use an IMD.

Research Question 6 / Hypothesis 6

What is the degree of relationship, if any, between performance expectancy and U.S. patients' behavioral intent to use an IMD when accounting for perceived credibility? This question presented the following alternative (H6a) hypotheses: ***H6*a.** Performance expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD when mediated by perceived credibility.

Apart from establishing PC as a significant predictor of BI to use an IMD, within the SEM analysis, the PC factor was discovered as a mediating variable between PE and BI and did explain the changes of the BI variable; hence the alternative hypothesis H6a was supported, and null rejected. This result is consistent with the findings of hypothesis H5 where PC is a predictor of BI to use an IMD. This outcome is also similar to that which Yeow et al. (2013) reported. Another observation in this research, is a positive relationship between PE and PC, whilst PE also explained the changes in variance in the mediating PC variable. Yeow et al. (2013), also discovered a positive relationship between PE and PC. Because device hacking and theft of personal identifying information is a challenge to tackle (Zhou et al., 2019) U.S. patients perceive an IMD as a reliable system for effectively preventing device hackers, which explains why PC has a positive impact on BI to use an IMD.

Summary

The researcher adapted from Yeow et al.'s (2013) original questionnaire, and the research instrument items were adapted from instruments developed by Yeow et al. (2013), Kohnke et al. (2014), and Morosan (2016). The survey was distributed through Qualtrics.com, amongst Facebook IMD Support Group members. Of the 363 responses downloaded from Qualtrics, only 246 responses qualified for further analysis. The minimum estimated sample size, obtained by the power analysis, was 226, and therefore the amount of 246 responses was adequate for use.

In determining the factors shaping the U.S. patients' acceptance of IMD, the investigative framework made use of Yeow et al.'s (2013) extension of UTAUT to include FC, SI, PE, and PC as independent variables, and included Att as another independent variable, to expand the model. The survey results were initially processed and examined using SPSS 28 with principal axis factoring (PAF) as the parameter estimation method, during the exploratory factor analysis. For confirmatory factor analysis and path analysis, SEM and SPSS AMOS version 26 software were used.

In the above statistical analyses for each research question and variables, the results depicted that the means for the variables ranged from a low value for SI (M = 3.08) to a high for BI (M = 4.32). This is an indication of an overall positive outlook for the variables measured in the study. PE (M = 4.06) was the second most important factor for the U.S. patient's BI to use an IMD, followed by PC (M = 4.01). The standard deviations ranged from .856 to 1.349. This indicates a limited spread of values around the mean.

The EFA analysis showed that only five independent factors (FC, SI, Att, PE, and PC) underlined the conducted survey. After the assessment of multicollinearity issues and examining the reliability and validity of the EFA parsimonious measurement model, a CFA was subsequently conducted to assess model fitness. The SEM and the CFA model were performed using the MLE. Resultant measurements suggested that the EFA measurement model revealed a poor goodness-of-fit. After the establishment of the measurement model via CFA, SEM multicollinearity assumptions were reexamined, and the model's reliability and validity were verified. The SEM parsimonious model found that Att, SI, PE, FC, BI, and PC exhibited satisfactory fit indices (The ratio of $\chi 2/df = 1.438$, $p < .001$; CFI = 0.964; RMSEA = 0.042; TLI = .949; IFI = 0.966; NFI =.895; RFI = 0.849; GFI = 0.922; RMSR = 0.077; PRatio = 0.696; PNFI = 0.623; PCFI = 0.671).

Results derived from the first research question found that Att did not affect the dependent variable BI to use. This discovery suggests that the U.S. patient's attitude to IMD technology does not influence their intention to use an IMD. The findings of the second research question suggested that PE did explain the variance of the BI factor, and therefore was extracted as an influential factor in the SEM analysis. This finding suggests that when IMDs perform to the expectation of patients, more people will be influenced to use IMDs. The results of the third research question demonstrated that there was no substantial effect of FC on BI. This result also supports the revelation that the U.S. patient's intent to use an IMD does not hinge on the existence of administrative, technological, or specialized infrastructure to facilitate the adoption and use of IMDs.

The findings of the fourth research question revealed a positive effect of SI on the U.S. patient's intention to use an IMD. This finding suggests that the U.S. patient's use of an IMD is influenced by the motivations and views of individuals or groups that hold a meaningful position in the patient's life. Device recommendations by peers and social media groups play an important role in the decision to use an IMD.

The conclusion of the fifth research question revealed that PC is a strong predictor of the U.S. patient's intent to use an IMD. Knowing that their devices are secure and personal information is safe will encourage patients to use IMDs. The results of the sixth and final research question revealed that PC is a significant mediating variable between PE and BI, and also helps in explaining the variations of the PE factor. In conclusion, the SEM parsimonious model indicated that the extended UTAUT model clarified 16% of the variance for behavioral intention to use IMD ($R^2 = 0.16$). The study implications, limitations, specific contributions to the field and industry, recommendations for practice and future IMD research are included in Chapter 5.

Chapter 5: Implications, Recommendations, Conclusions

A summary of the study, its implications, limitations, ethical considerations, and recommendations to academia and practice is presented in this chapter. The problem addressed in this study is that, while IMDs are largely accessible, well over 60% of U.S. patients who could have benefitted from IMD usage are not interested in taking advantage of this life-saving technology for varied reasons (Banerjee et al., 2019; Longras et al., 2020). The reasons influencing the behavioral intent to use an IMD may include patients' attitudes, social influence, facilitating conditions, perceived credibility, and performance expectancy (Loughlin et al., 2021; Sabas & Kiwango, 2021; Sołtysik-Piorunkiewicz & Zdonek, 2021). The purpose of this study was the examination of the relationship between the independent variables of PE, PC, SI, FC, and Att on their effect on the dependent variable of the U.S. patient's behavioral intention (BI) to use an IMD for efficient healthcare management. This investigation, conducted using online surveys, also examined the degree to which the PC variable mediated the predictions of PE.

The chapter begins with a discussion of the research findings and ultimate implications for IMD technology research, education, and IMD adoption practices. In the segment on recommendations for practice, recommendations are discussed on how the study can be applied to both practice and theory. In recommendations for future research, what future IMD researchers can do to improve upon this study, is discussed. In the conclusions, the meaning of the research results in the context of the previous research and theory, was emphasized.

In determining the factors shaping the U.S. patient's acceptance of IMDs for efficient healthcare management, this investigative framework made use of Yeow et al.'s (2013) extension of Venkatesh et al.'s (2003) UTAUT model. Venkatesh et al.'s (2003) model posited that perceived credibility (PC) mediates performance expectancy (PE), and suggested that PC, PE, facilitating conditions (FC) and social influence (SI), and facilitating conditions (FC) as determinants of technology acceptance and adoption. The Attitude factor was added as a determinant to expand the model.

Venkatesh et al. (2003) recommended that when effort expectancy (EE) and PE are omitted from the UTAUT framework, the Att effect should be taken into consideration. In this study, the EE factor was omitted because the use of an IMD is simplified as it is embedded subcutaneously and requires no effort from the user. Hence, Att was introduced as a replacement for EE. This study applied a quantitative, nonexperimental, correlational approach because the research constructs were investigated in their original form without manipulation (Cokins et al., 2020; Salloum & Shaalan, 2019). This quantitative correlational study was based on six research questions emanating from the research purpose and the conceptual framework of the UTAUT model.

Using an online survey on Qualtrics.com, the data was gathered to evaluate the perspectives of the respondents. According to Natarajan et al. (2017), using an online survey tool was the best choice because it is the most robust of survey tools and also prominent in scholarly investigations. Moreover, the online survey enhanced the ability of each respondent to respond to survey items at their own convenience. The respondents also participated in a low-pressure context, skipping any question, or ending their participation at any time without prejudgment or penalty (Story & Tait, 2019).

The survey format used in this study was adapted from Yeow et al.'s (2013) original survey questionnaire, and instrument items were adapted with approval from the instrument developers; Yeow et al. (2013), Kohnke et al. (2014), and Morosan (2016). Both the survey and research instrument items were slightly modified to suit this study context (see Appendix A).

The online questionnaire was administered by Qualtrics.com to as many Facebook IMD Support Group members residing within the US, minus territories, and provinces, who voluntarily opted to participate.

A total of 363 individuals consented to participate in the survey. The 363 responses were downloaded as both SPSS 28 (.sav) and Excel 2022 (.xls) files from Qualtrics.com. Within the Microsoft Excel 2022 spreadsheet program, the downloaded data was examined for discrepancies, missing values, and errors. As a result, 117 surveys were discarded for not meeting the 5% or less missing data rule or giving the same answer to all questions, which is a sign of disengagement from the survey. Only 246 participants answered more than 95% of the questions and were also not disengaged from the survey.

Considering that the minimum estimated sample size calculated during the power analysis was 226, the value of 246 fully completed questionnaires was considered appropriate for further analysis. Another justification of adequacy for factor analysis was that it is recommended for each question or survey item to have at least ten responses for factor analysis to take place (Plonsky & Ghanbar, 2018). With 23 items to be analyzed during factor analysis, which would amount to a minimum of 230 respondents and therefore, the amount of 246 totally completed surveys met the minimum number of respondents requirement for factor analysis and subsequent SEM and path analysis.

As related earlier, all research results were initially evaluated and analyzed using the SPSS 28, then SPSS AMOS 26 software, and finally SEM technique. The mediation of PE predictability of the DV BI to use an IMD, by the PC construct was also evaluated, using SPSS linear regression and SEM parsimonious model techniques. According to Aneiros et al. (2022), a regression analysis is appropriate when evaluating the strength of the relationship between constructs. In addition, an exploratory factor analysis, followed by confirmatory factor analysis was conducted to analyze the underlying relationships within the model. EFA and CFA helped in assessing the fit of the postulated measurement model (Gomes et al., 2020). Causative correlations amongst the independent and dependent variables were also examined. The SPSS AMOS 26 statistical software was selected because its syntax and drawing features are easy to use, allowing the researcher to perform SEM examinations (Martynova et al., 2018; Reyes-Fournier et al., 2020).

Just as in most research studies, limitations of the research must be taken into consideration. Some important limitations pertaining to the internal and external validity of the study included selection treatment interaction, experimental effects, maturation effects, and sampling bias. The limitation of selection treatment interaction limitation encompasses the generalizability of the research results to other demographic segments or groups of individuals (Tran et al., 2021; Wang et al., 2020). In mitigating the effect of selection treatment on external validity, a subsection representative of the entire U.S. population was selected to conduct the investigation, i.e., Facebook IMD Support group members, and then the research outcomes were generalized to the target U.S. population.

This research required that the Facebook IMD groups consist of members residing in any of the 50 U.S. states, less provinces, and territories. Eventually, 49 states were represented in the survey with North Dakota being the only state without representation. Therefore, it can be concluded that the limitation of selection treatment interaction was catered to because the sample was reasonably representative of the target population, i.e., individuals residing within the 50 U.S. states.

The second type of limitation, known in research circles as experimental effects, is in reference to various ways in which participants react. The reactions may be based on their perceptions of individual participation in an investigation, which in turn may threaten both the external and internal validity of research findings (Goette & Tripodi, 2020; Kim & Song, 2020). Maturation effects, the third limitation, relates to the changes in the behavior of the survey participants due to issues such as stress, fatigue, and other challenges which can occur within a short span of time (Flannelly et al., 2018). With regards to the second limitation, participants' responses might be different for reasons such as apprehensions about being in a research study or the eagerness with which they approach the research survey only to meet what was not expected.

On the contrary, in the third limitation, participants' responses may differ for reasons such as fatigue, stress, or mindset at the time of actively participating in the survey. The reliability of the survey and authenticity of the study depended to a large extent on the respondents offering sincere answers to survey items and on respondents' commitment to complete the entire questionnaire online. Simovic et al. (2022) explicated that when an instrument collects deep-seated demographic data, respondents may become apprehensible that their responses may not be confidential, leading to a situation of either no-response or false answers. In addition, the variation of mood and conduct during the period when the survey is taken may imperil the internal validity of the research (Flannelly et al., 2018; Lesko et al., 2020). This is because the way and manner in which participants responded may explain variations in the IVs instead of the DV (Lesko et al., 2020).

In the same vein, participants' alternating conduct during survey-taking may become perilous to external validity because the research findings may not be generalizable since respondents' answers may inadequately reflect the style in which the target population would usually respond to online surveys (Story & Tait, 2019). In an attempt to address the limitations of maturation and experimental effects, participants were provided an informed consent form (Tse et al., 2021). A survey introductory letter was omitted because a digital flyer had already been advertised on the relevant Facebook IMD Support group walls. The informed consent form (see Appendix E), delivered together with the questionnaire, explained the study purpose and extra measures implemented to ensure anonymity. Furthermore, all the scales in the measuring instrument were combined and modified slightly to suite the U.S. context. The measurement scales were adapted from questionnaires that were previously validated and have been proven to be reliable and valid for the assessment of users' acceptance and behavioral intentions to use other technologies in other jurisdictions (Kohnke et al., 2014; Morosan, 2016; Yeow et al., 2013).

An important limitation on the internal and external validity of this research was maturation effects. About halfway through the data collection process, I stopped the data collection due to low response rates based on the low number of responses per week. I increased the number of eligible Facebook IMD Support groups from five to twelve by obtaining permissions from their respective group administrators. Permission was sought from the NCU IRB to effect the modification of the sample population by way of adding more permission letters from group administrators. After IRB approval of the additions, the survey was reopened for further data collection from group members. This change tremendously increased the survey response rate.

At the very beginning of the survey-taking process, participants were furnished with the informed consent form (see Appendix E). Based on the respondent's response to the consent form, participants would either progress with the main survey or be booted out automatically for non-consent. The purpose of the consent form was to explain in detail the aim of the investigation and the extra measures taken to maintain the participant's anonymity. According to Story and Tait (2019), when a long questionnaire is utilized, a low response rate should be anticipated. In addressing this limitation, a survey introductory letter was not applied with the aim of abridging the questionnaire without tampering with the validity and reliability of the investigation (Perrotta et al., 2021). The tactic applied to moderate the maturation effect threat resulted in a higher response rate.

To avoid the limitation of sampling bias (Gondauri et al., 2020), respondents were randomly selected from Facebook IMD support groups. In addition, the information gathered was only generalizable to U.S. patients living in any of the 50 states, but not territories or provinces. Furthermore, the demographic information was only limited to producing a profile of the respondents and not for assessing variations in the study variables. After acquiring approval from NCU IRB, the survey was opened, on Qualtrics.com, to Facebook IMD support group members.

All participants were greeted with an informed consent form (see Appendix E), which explained the study purpose, confidentiality, and anonymity measures taken to protect participants' data. The voluntary participation of respondents was also clarified. Per the explanations in the informed consent form, participants' data collected has been safely stored, password-protected, and will be destroyed after a period of three years. The measuring instrument put no participants at risk, in addition to keeping participants' personal data confidential by way of not collecting personally identifying data such as names, phone numbers, or email addresses.

Implications

The use of IMDs is a concept that has been evaluated and described in several ways. This includes concerns over patient privacy (Gondauri et al., 2020), uses for disease condition management (Aileni et al., 2020), responses to user behavior and perceptions (Reich-Stiebert et al., 2020), and benefits as an effective component of an efficient healthcare system (Liu et al., 2018). Furthermore, extensive investigations on the IMD discussion have concentrated on either IMD technology in mandatory settings (Piro et al., 2020; Simovic et al., 2022) or user perceptions toward IMD technology (Pycroft & Aziz, 2018; Wong & Wong, 2021). However, research on the adoption of IMDs for disease condition management in voluntary settings is very limited (Banerjee et al., 2019; Gagliardi et al., 2017). Thus, the pivot of this study rests on offering a better understanding of the important determinants influencing the U.S. patient's behavioral intent to adopt an IMD for efficient healthcare management.

Comprehending the important determinants connected with IMD adoptability for efficient healthcare management would assist IMD manufacturers and healthcare policymakers to develop and devise wide-ranging policies, strategies, and procedures warranting efficient and effective implementation leading to higher IMD adoption rates. The study results have important practical and theoretical implications. From a theoretical point of view, it is empirically evidenced in this study that the UTAUT model is suitable for studying the factors of IMD adoption and use, as the extended-UTAUT model applied in this study accounted for 16% of the variance in BI to use an IMD. From a practical standpoint, the results of this investigation offer academics and practitioners significant insight into understanding the U.S. patient's acceptance of IMDs, potentially improving the delivery of efficient healthcare within the United States.

Since the inception of the UTAUT model, academicians have illustrated that it is a reliable method of establishing the factors influencing individuals to accept and adopt new technologies, such as healthcare wearable devices (Chang, 2020; Chen & Lin, 2018; Lee & Lee, 2020), mobile electronic medical records (Shin et al., 2017), and mobile learning technologies (Onaolapo & Oyewole, 2018). In this study, the constructs investigated in the expanded UTAUT framework demonstrated a significant level of reliability and validity throughout the investigation, as indices were within the acceptable ranges, such as Cronbach's alpha coefficient benchmark of ($0.6 < \alpha < 0.7$) (Sinclair et al., 2022; Taber, 2018); composite reliability greater than .7 (Purwanto & Sudargini, 2021), AVE higher than .5 (Luo et al., 2019; Roberts et al., 2019); a ratio of Chi-square to degrees of freedom (X^2/df) less than 5 (Taber, 2018); an RMSEA value less than .08 (Sinclair et al., 2022); a CFI score greater than .90 (Purwanto & Sudargini, 2021); an NFI of at least 0.90 (Purwanto & Sudargini, 2021); GFI of at least 0.90; RMSR of at least 0.6 (Hair et al., 2017; RFI of at least 0.9 (Roberts et al., 2019); IFI of at least 0.95 (Taber, 2018); a TLI higher than 0.90 (Hair et al., 2017). Therefore, this investigation added empirical evidence to the literature by studying the reliability and competence of the UTAUT framework, which was established in a workplace setting (Venkatesh et al., 2003) to explain the U.S. patient's intentions to use an IMD in a voluntary context throughout the 50 U.S. states.

This investigation focused on six research questions created to decipher participants' perceptions of UTAUT factors in relation to the acceptability of IMD for efficient healthcare management. The research findings draw attention to the following five key issues: (1) U.S. patients are not only self-motivated but also by others or the larger society, in the acceptance and adoption of IMDs for efficient healthcare management. (2) Improving the performance and effectiveness of IMDs would positively affect patients' intentions to adopt an IMD. (3) The U.S.

public's perception of security, robustness, and reliability of IMDs does influence their decision to use an IMD for efficient healthcare management. (4) Enabling environments, infrastructure, and components do not add to the patient's motivation to adopt and use IMDs. (5) Patients' attitudes to IMD technology, do not influence their decision to use an IMD for efficient healthcare management. The following are explanations of the research findings and theoretical and practical implications of each research question.

Research Question 1. What is the degree of relationship, if any, between Attitude and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H1a) hypotheses: Attitude is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD. In hypotheses testing it was discovered that Att was the weakest predictor of the U.S. patient's intention to use an IMD, and therefore the null hypothesis was maintained, and the alternative was rejected. This is an indication that the U.S. patient's positive or negative attitudes toward IMDs are not relevant in their decision to adopt and use an IMD.

This finding is akin to Venkatesh et al. (2003), where it was discovered that in the presence of performance expectancy and effort expectancy, attitude is not a significant predictor of BI. According to Venkatesh et al. (2003), the effect of attitude on behavioral intent is spurious and is only evident in the absence of effort expectancy and performance expectancy. With the presence of performance expectancy in this study model, the effect of Att on the BI to use an IMD was spurious, as expected. This finding is also in agreement with de Cosmo et al. (2021) where it was discovered that attitude toward mobile advertising does not have a direct effect on the behavioral intent to use chatbot but is rather mediated by one's attitude toward chatbots.

This study's finding contradicts assertions made by Seyal and Turner (2013) that users' attitudes toward a specific technology, to a large extent, predicts the intent to make use of the technology. This finding is also in contradiction with Thomas et al. (2020), who discovered that Att is the strongest predictor of BI to use mobile learning technology. The reasons for these contradictions may include the dissimilar settings under which the research was performed and the examination of many other different factors or attributes. In Seyal and Turner (2013) the study was about executives' use of biometrics. In Thomas et al. (2020), the study revolved around the use of the UTAUT model in explaining mobile learning adoption in higher education in the Caribbean. This study's focus is about IMD adoption for efficient healthcare management.

A non-hypothesized discovery from this research is the positive influence of facilitating conditions on the patient's attitude towards IMD adoption and use. Deducing from the investigations' results, U.S. patients will display a positive attitude toward IMD use when they have the perception that the appropriate infrastructure are in place. This result is in consonance with Chatterjee (2021) where facilitating conditions positively influenced users' attitudes towards IoT usage. In a study on attitudes toward mobile banking, Angelia et al. (2021) also discovered that facilitating conditions positively influenced the user's attitude towards mobile banking. In another study in Tunisia, Nasri (2021) discovered that facilitating conditions positively impacted the user's attitude to accept internet banking in Tunisian banks. The inter-factor correlation between FC and Att in the SEM results of this study, makes the relationship a strong candidate for future research.

Another non-hypothesized discovery from this study is the positive influence of social influence on attitude. Deduced from the SEM results of this study, inter-factor correlations between SI and Att, showed a positive correlation in the direction of Att. This discovery suggests that when influenced by individuals, online support groups, or organizations they consider important, patients will develop a positive attitude towards IMD adoption and use, which will result in increased patronage for devices. This revelation is in consonance with Tiwari et al. (2020) where it was discovered that social influence is a strong prognosticator of positive attitudes towards online class adoption during the COVID-19 era.

According to Tiong Tan and Chua (1986), consumers are more vulnerable to advice from friends, neighbors, and family members. These groups can all be classified as the important people in the individual's life and therefore can have an impact on their attitudes and decisions. In agreement with the non-hypothesized finding, Izuma (2013) in a study on the neural basis of social influence and attitude change, stated that attitude change in itself is a particular type of social influence. Izuma (2013) further emphasized that human preferences and attitudes are modulated by social influence. This makes the relationship between SI and attitude towards technology a viable option for future research.

Research Question 2. What is the degree of relationship, if any, between performance expectancy and the U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative hypothesis: Performance expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use IMD.

It was discovered in this study that PE does affect BI, i.e., the PE factor explained the variance in the BI dependent variable. Thus, the null hypothesis (H1o) was rejected.

This finding indicates U.S. patients are of the view that their devices will perform as expected and therefore using an IMD will help them manage their health conditions more efficiently. This result is in tandem with previous studies that discovered significant positive relationships between the PE and the BI factors (Nasri, 2021; Sabas & Kiwango, 2021). Sołtysik-

Piorunkiewicz and Zdonek (2021) discovered that performance expectancy was a significant factor in influencing Society 5.0 and Industry 4.0 to use open data. Nikolopoulou et al. (2021) also discovered that performance expectancy was an influencing factor in the determination of teachers' intention to use mobile internet. Similarly, Shaikh et al. (2021) discovered that performance expectancy was a significant predictor of mobile banking adoption.

Even though prior research has identified PE as an important predictor of BI, there are some studies contradicting this assertion of PE positively influencing BI, including Miraz et al. (2022) where PE was found as not a significant predictor of the behavioral intent to adopt cryptocurrency for use in digital transactions in Malaysia. In another example in Indonesia, Utomo et al. (2021), did not find PE as a significant prognosticator of the BI to use the mobile healthcare application, named Si Pandai Kemas Tangsel. Also, Lutfie and Marcelino (2020) did not find PE as a significant prognosticator of the BI of Facebook customers to purchase from Facebook using the Advert Feature. The reasons for these contradictions may include the dissimilar settings under which the research was performed and the examination of many other different factors or attributes.

Research Question 3. What is the degree of relationship, if any, between facilitating conditions and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H3a) hypothesis: Facilitating Conditions is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD. SEM analysis resulted in discovering a negative effect of FC on the U.S. patient's intent to use an IMD and therefore the alternative hypothesis was rejected, and the null hypothesis was accepted. This finding suggests that the U.S. patient does not depend on the existence of an adequate administrative, specialized, and technological structure in order to decide on adopting and using an IMD.

This result is in resonance with Utomo et al. (2021) where it was discovered that FC was not a significant predictor of BI to use the mobile health application in Indonesia. In sharp contrast to the above finding, Zhou et al. (2019) discovered that FC and SI had the strongest influence on BI, serving as mediator, of use behavior to adopt and use hospital electronic information management system among the nurses in Ghanaian hospitals. This contradicting result may be due to the other factors under study such as professional experience and voluntariness, in addition to the BI variable serving a dual purpose of dependent variable for FC and SI, and also acting as a mediator between the independent variables of SI and FC, and the dependent variable of, use behavior.

The positive correlation between FC and Att (see Table 18) gives an indication that the U.S. patients' attitudes towards IMD adoption and use, revolve around the existence of facilitating conditions such as adequate IMD infrastructure. Even though not postulated in this study's conceptual research framework, this discovery is in line with others, such as Williams et al. (2015). In another study involving telepresence robots in an educational setting, it was discovered that FC was a significant determinant of the decision to use telepresence robots. Contrarily, Bilgihan et al. (2017) argued that FC has no effect on Att. However, in the same research findings, PC was discovered as a positive influencer of attitude towards technology use. The reasons for this contrast may be the varying contexts under which the different studies were conducted, as well as the other factors that were investigated concurrently. For instance, Bilgihan et al. (2017) studied the adoption of mobile accessibility systems that have other technological capabilities, whilst this study investigated IMD adoption for efficient healthcare management.

Research Question 4. What is the degree of relationship, if any, between social influence and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H4a) hypothesis: Social influence is a statistically significant predictor of the U.S. patient's behavioral intent to use an IMD. The results for the fourth hypothesis depicted that SI had a significant effect on BI to use, and hence the null hypothesis was rejected. This discovery supports the assessment that U.S. patients' intention to use an IMD for efficient healthcare management is influenced by the opinions and motivations of individuals and groups that hold a significant position in their lives.

This finding is in dissonance with Venkatesh et al.'s (2003) discovery, which suggested that SI is not a significant prognosticator of BI to use technology. Kim et al. (2020b) and Varshneya et al. (2017) also contradict this study by reporting that SI had no effect on BI. The reasons for these contrasts may include the varying contexts under which the different studies were conducted, as well as the other factors that were investigated concurrently.

Research Question 5. What is the degree of relationship, if any, between perceived credibility and U.S. patients' behavioral intent to use an IMD?

This question presented the following alternative (H5a) hypotheses: Perceived credibility is a statistically significant predictor of the U.S. patient's behavioral intent to use an IMD. Based on the SEM analysis results, the null hypothesis was rejected because PC contributed to explaining the variance of the BI factor. This indicated that the security and safety guarantee of IMDs does significantly influence the U.S. patient's intent to use an IMD. This result is consistent with Kim and Song (2020) in a study on purchase intentions via competence and authenticity, discovered that PC was a significant determinant of the BI to purchase. Thanigan et al. (2021) also discovered that PC was a significant predictor of BI to use technology. A plausible reason is that with the plethora of technologies such as Artificial Intelligence (AI) used by hackers to steal people's PII (Bachtiger et al., 2020; Siontis et al., 2021), the public views the PC (safety and security) of their devices, as an important determining factor in their decision to use IMDs (Manrai et al., 2021).

Research Question 6. What is the degree of relationship, if any, between performance expectancy and U.S. patients' behavioral intent to use an IMD when accounting for perceived credibility?

This question presented the following alternative (H6a) hypotheses: Performance expectancy is a statistically significant predictor of the U.S. patients' behavioral intent to use an IMD when mediated by perceived credibility.

As well as being a significant predictor of BI, PC in the SEM analysis was discovered to be a significant mediating variable, between PE and PC, in effect explaining the changes of the PE factor, hence in support of H6a, the alternative hypothesis. Yeow et al. (2013) also reported similar outcomes, where a positive relationship between PC and PE was observed. Because hacking and PII theft may seem a challenging vice that may endanger devices (Bachtiger et al., 2020; Siontis et al., 2021), it is reasonable that the U.S. patient perceives an IMD as a safe and secure system, which would perform its duties as expected, and therefore PC and PE do have a positive influence on BI to use an IMD.

Research in the sphere of IMD adoption and use is non-existent in comparison to the adoption of other technological innovations (Gagliardi et al., 2018). Inferences derived from the UTAUT's extended version used in this study suggested that PE, PC, and SI are direct determinants of BI, whilst PC plays a mediating role between PE and BI. The research findings also point to the fact that U.S. patients are more influenced by institutions of authority, groups, or highly esteemed individuals' recommendations or views, and less influenced by their personal views, or perceptions of IMD adoption for efficient healthcare management, which could lead to a more positive attitude towards IMD adoption and use. Lastly, the research results suggest that levitating awareness of IMD's security, privacy, and safety features, infrastructure, and available support may help U.S. patients acclimatize with the manifold benefits of IMD implementation and how it can help to improve healthcare management.

This study adds to the understanding of why people adopt technology, which could lead to improved-systems development for design, construction, and implementation of IMDs in a manner that will help boost the prospects of user acceptance. Moreover, understanding the key factors influencing the U.S. patients' adoption of IMDs would provide valuable insights that might empower policymakers, healthcare institutions, IMD manufacturers, hospitals, and physicians to offer suitable IMD adoption solutions to minimize the cost of healthcare to include the costs of frequent hospital visits.

Recommendations for Practice

This study's findings offer both practitioners and scholars significant insights into understanding the U.S. patient's perspectives on IMD adoption for efficient healthcare management. Grasping the salient factors that influence patient acceptance of IMD would enable policymakers, IMD manufacturers, health institutions, hospitals, etc., to provide future innovations and policy targets to maximize IMD patronage for efficient healthcare management. Per the findings of this study, PE, PC, and SI have a positive impact on the BI to use an IMD. These findings suggest that the patient's expectations of the IMD's performance, the IMD's safety and security levels, and the impact of the user's source of inspiration are important limitations to successful IMD implementation. The direct and positive association between performance expectancy and the BI to use an IMD, found in this study, drew support from previous studies which highlighted the importance of performance expectancy for the explanation of IT-innovations acceptance (Catherine et al., 2018; Chua et al., 2018; Hamzat & Mabawonku, 2018; Sair & Danish, 2018).

Onaolapo and Oyewole (2018), in a study on BI to use smartphones for mobile learning by postgraduate students of Nigeria discovered that performance expectancy positively influenced the BI to use smartphones. Catherine et al. (2018) in another study to assess the BI to use ATMs with fingerprint authentication in Ugandan banks, also discovered that PE is a significant prognosticator of BI to use ATMs. Hence, performance expectancy issues such as the patient's confidence in their device working as they need it to, the patient having fewer disease symptoms because of their device, the patient's device being their most effective treatment option, and the patient's surety that their device functions the way it is supposed to, should be addressed.

I recommend that IMD manufacturers and IMD network managers ensure the availability of the devices at all times, considering performance expectancy was discovered in this research as a significant prognosticator of IMD adoption and use. When implanted IMDs are always available, in terms of 24/7 device functionality, the IMD security triage of medical information confidentiality, device integrity, and device availability (Aljumaie et al., 2021; Alsuwaidi et al., 2020; Baranchuk et al., 2018; Brantly & Brantly, 2020) will be complete. Furthermore, IMD manufacturers, must ensure devices are state-of-the-art, providing improvements that make them the most effective devices for the specific disease condition considering performance expectancy was discovered as a significant predictor of IMD adoption and use. Also, device manufacturers must ensure device performance is consistent at all times because, as was deduced from the findings U.S. patients rely on the device's performance expectancy to decide the use of the specific IMD for efficient healthcare management. I also recommend that physicians and institutions of health, provide device hotlines where patients can report device functionality issues without apprehension of being penalized.

The positive influence of PC on BI to use an IMD discovered in this study draws support from several studies emphasizing the relevance of this prognosticator in the prediction of a novel system's adoption (Kim & Song, 2020; Malik, 2020; Manrai et al., 2021; Thanigan et al., 2021). In this study, PC was also found as a mediating variable between PE and BI and helped in explaining BI predictions measured by the PE determinant. Though not postulated in this study, there was also a positive relationship found between PE and PC. This finding suggests that while patients are expecting their devices to perform according to standards, they are concurrently perceiving the devices to be credible (i.e., safe and secure).

The above finding also suggests that, when an IMD is not performing to expectation, the patient does not perceive the IMD as safe to use and secured from vulnerabilities. Comparable results were reported in Colman et al. (2019) and Yeow et al. (2013), where a direct and positive association was observed between the PE and PC variables. In another study on medical education, Long et al. (2022) also discovered that the PE variable positively impacts the PC variable. Thus, policymakers, IMD manufacturers, and IMD network managers should also take into consideration PC issues in addressing IMD acceptability.

The PC factor in this study consisted of the following issues which need to be addressed: My IMD is / will be difficult to hack by criminals (PC1), using an IMD is / will be secure (PC2), I feel safe / will feel safe using my device (PC3), and IMD limits / will limit unwarranted access to my personal information and health data (PC4). Deducing from the research findings, IMD manufacturers are expected to provide hack-proof devices and ensure device designs incorporate robust security and safety features right at the beginning of device design. Policymakers must ensure the highest security and safety standards in the industry are met when it comes to the manufacture of IMDs. Hospitals, healthcare institutions, insurance firms, and physicians must also ensure unwarranted access to patients' PII and health data. U.S. patients feeling more safe and secure with IMD use will translate into higher interest in IMD adoption for efficient healthcare management.

Additionally, the government should advertise to the U.S. public that IMDs for disease condition management provide sturdy protection against exploitation and device alteration, robust data security, verified, and validated access (Cristina et al., 2021; Garzotto et al., 2020; Iacopino et al., 2021; Liu et al., 2018; Verfürth, 2021). The U.S. patient also needs to be informed of who will gain access to any information stored on the IMD and who will access information transmitted from the IMD to the hospital or healthcare institution.

The positive correlation between social influence and the BI to use an IMD, found in this study, drew support from previous studies which highlighted the importance of social influence for the explanation of IT-innovations acceptance (Andrews et al., 2021; Chua et al., 2018; Cokins et al., 2020; Singh et al., 2020; Twum et al., 2022; Widyanto et al., 2021; Zhou et al., 2019). Hence, SI issues such as: those I consider important to me influence my intention to use an IMD (SI1), the U.S. government encouragement influences my intention to use an IMD (SI2), patients I know who are using IMDs, including those in my Facebook Support Group influence my intention to use an IMD (SI3), and achieving IMD compliance is the sole responsibility of those in charge of regulatory compliance and not the patient (SI4), must be addressed.

It is therefore recommended that the U.S. government, healthcare regulatory bodies, IMD manufacturers, hospices, healthcare institutions, social media IMD support group administrators, and physicians, promote awareness regarding IMD features, objectives, available resources, impact, and advantages through the propagation of this information to the public. In the medical field, because social influence is a significant predictor of BI to use an IMD, physicians must endeavor to maintain a positive physician-patient relationship in terms of engaging patients in the IMD adoption decision-making process. To attract more IMD users, it is recommended that IMD manufacturers enhance the use of social media communities such as Twitter, Instagram, Facebook, Blogs, SMS messages through mobile phones, and e-mail as well as traditional media such as radio, television, and newspapers advertisements. This will consequentially affect customers' decision to adopt and accept the technology.

Physicians should also be encouraged to join relevant social media platforms where they can encourage current and prospective IMD users, seeking information, on the benefits of using an IMD. Providing U.S. patients with important information on IMDs will consequently result in more positive attitudes toward IMD adoption and use. In addition, IMD-related institutions and regulatory bodies should provide both online services and phone hotlines to address issues and concerns which relate to IMD implementation and device malfunctioning. These recommendation were derived from social influence having been discovered as a significant prognosticator of BI to use an IMD in this study. With the implementation of the above practical recommendations, increasing the probability of U.S. patients' IMD adoption for efficient healthcare management is more likely, and will lead to improved health outcomes for the entire nation.

Recommendations for Future Research

To improve the adoption and use of IMD, both the U.S. public and private sectors must have a broad understanding of the issues relating to the U.S. patients' intent to adopt IMDs for efficient healthcare management. This study required that Facebook IMD support groups for U.S. residents living within the 50 U.S. states, less provinces and territories be used as the research sites due to physical restrictions surrounding COVID-19, including social distancing protocols (Miller et al., 2021; Sujood et al., 2021; Tiwari et al., 2020). The study was therefore delimited to the sample that is representative of the target population, U.S. residents within the 50 states but not provinces and territories (Krug & Kulhavy, 1973). This sample is, therefore, a generalizable representation of the U.S. patients' behavioral intent to use an IMD.

Primarily, it is recommended that future research expands geographically beyond the U.S. to other countries on other continents to include Europe, Asia, Australia, South America, and Africa, where the IMD user population is much lower than in the US. This would help provide an improved understanding of those countries' patients' attitudes and perceptions of adopting IMDs for efficient healthcare management, whilst providing a global view of the phenomenon. It would also help us understand whether geography and culture mediate the impact of the determining factors on BI to use an IMD.

Secondly, this investigation's findings showed that SI is a determining factor of the U.S. patient's IMD adoption intent. This finding suggests that patients are influenced by the important people, groups, and organizations in their lives to adopt IMDs. Individuals' disposition to adopt and use IMD technology partially depends on whether they perceive that they have been adequately motivated by those they look up to for advice and support. Therefore, it would be valuable to expand the UTAUT model to test the influence of other IMD adoption determinants such as awareness and trust (Kaur & Arora, 2020; Nasri, 2021; Ng, 2020; Patil et al., 2020; Widyanto et al., 2021). This researcher also recommends that future research investigate the extent of patient attitudes towards IMD adoption when the SI factor is accounted for, because this study revealed a significant correlation between SI and Att, which finding, however was not postulated in this research.

Thirdly, a recommendable research direction includes investigating the moderating effects of the patient's age, patient's gender, their IMD familiarity levels, and whether the impact of these factors outweighs the negative effect of facilitating conditions on IMD adoption and use (Miraz et al., 2022; Utomo et al., 2021). A fourth recommendation would be to use qualitative research or mixed methods research (Hong et al., 2019). With qualitative interviews the open-ended form of answers will help provide a deeper understanding of the relevant factors as provided by the patients themselves. This recommendation will help to further improve the model accuracy and assist in finding more relevant and current influential factors. better understand the factors influencing patients' positive and negative perceptions of IMD adoption for efficient healthcare management.

With the current work only limited to IMDs such as ICDs, catheters, and defibrillators, it is recommended that future research may replicate the study using different and innovative technologies such as smart wearable technologies to find out how different the results might be from the current research. Examples of smart wearables technology include IoMWD and wSMDs. Examples of wSMDs include the Apple Watch series and the Fitbit Flex watch. Example functionalities of these state-of-the-art devices include body temperature monitoring, predicting ovulation, electrocardiography, heartrate monitoring, blood pressure levels monitoring, and oxygen saturation rate monitoring.

Other functionalities of the watches include providing electrocardiographs of the heart, irregular heart rate notification, fall detection and notification, sleep patterns, and calories expended in a specific activity such as walking, jogging, and running. These notifications can be sent to designated phone numbers such as physicians, healthcare providers, and guardians. Research into how the UTAUT factors of PE, SI, FC, EE, and PC impact the BI to use Apple Watch Ultra, for instance would help establish generalization whilst proving the usefulness of the research model and further establishing the model's external validity. The EE variable has been suggested because the patient involved will expect to expend some effort in enabling the device to function properly.

Furthermore, future research may extend this study to include other potential constructs of interest to the medical community and technology itself such as IMD affordability, IMD accessibility, and patient-physician relationship. IMD affordability would be akin to FC, IMD accessibility would be akin to PC, and patient-physician relationship, akin to SI. It would also be expedient to extrapolate future research in the direction of the two non-postulated findings in this study, first of which was the positive influence of FC on Att towards the use of a specific technology.

The second non-postulated finding, which is recommended for further research, is the positive influence of SI on Att towards IMD use. Further research on user perceptions of IMD system reliability, and design characteristics, would also be of interest to IMD manufacturers. By extension, further research could consider whether individual-level cultural variables have a direct effect on BI to adopt and use an IMD within the current extended-UTAUT research model or in other competing models such as TAM and Diffusion of Innovations theories.

A final recommendation is the research direction of BI to use an IMD serving the dual purpose of acting as the dependent variable for the five UTAUT independent variables of SI, FC, PE, EE, and PC, and the mediator between the five independent variables and the dependent variable of actual device use. This model should incorporate two extra hypotheses of EE and FC directly influencing the actual IMD use variable, apart from the two variables' hypothesized influence on BI to use. This is because in reality, intent to use a device may not result in actual device use, especially for external devices such as smart medical wearable devices where the user has the flexibility of deciding when and where not to wear the device, on a daily basis.

Conclusions

Medical implant technologies and other innovations such as telemedicine, wearable personal IoT devices for health management, and chatbots for diagnosis based on patients' identified symptoms have become prevalent. This phenomenon has led to a healthier, longer-living populace with lowered mortality rates (Iacopino et al., 2021; Simovic et al., 2022). IMDs are important components of providing efficient and effective healthcare management for many patients, and yet the important factors influencing the patient to adopt and use an IMD have not been completely explored.

An academy of scholars has examined society's adoption and free will to use a specific technology and has recommended the validity and appropriateness of the UTAUT model in predicting BI in different settings across a wide variety of technologies (Alvi, 2021; Bu et al., 2021; Chen et al., 2022; Khan et al., 2022). This is the first research utilizing the extended UTAUT model predicting BI of IMD adoption and use. Furthermore, research scholars have contended that UTAUT provides a robust theoretical basis for the exploration of technology adoption and use (Kim & Lee, 2020; Wan et al., 2020). Also, in order to provide a better understanding of technology acceptance, the UTAUT model needs expansion (Bu et al., 2021; Khan et al., 2022).

This quantitative nonexperimental correlational study intended to investigate the factors influencing the U.S. patient's acceptance of IMDs for efficient healthcare management. To decipher IMD acceptance, the UTAUT model was expanded and used to test five determinant factors of Att, PE, FC, SI, and PC. Results of the SEM parsimonious model suggested that PE was the strongest predictor of the U.S. patient's intention to use an IMD. PC and SI in that order of strength were also discovered through SEM analysis as having positive effects on the U.S. patient's intent to use an IMD.

Finally, the research findings suggested a significant correlation between FC and Att, SI and Att, and also between PE and PC, which hypotheses were not originally included in this study. The correlations between FC and Att, suggest that with adequate IMD infrastructure, U.S. patients will develop a positive attitude towards IMD adoption. A positive correlation between SI and Att also suggests that society, the U.S. government, social media support groups, and those that patients believe to be important in their lives influence the patient's attitudes toward IMD adoption and use. Similarly, this study discovered that PC was a mediating factor between PE and BI in explaining the changes of the BI factor.

In addressing the determining factors for IMD adoption, this researcher recommended that the U.S. government, healthcare policymakers, IMD manufacturers, and health institutions that recommend IMDs to their patients should (1) prioritize spending on innovative IMD infrastructure setup, research-based device upgrades, device software updates, IMD hotlines, and device maintenance, to stimulate positive attitudes towards IMD adoption (2) increase public awareness, especially in the social media space, with specific references to the IMD features, positive impacts, resource-support availability, quality-of-life advantages of IMDs, and (3) provide device-tailored policy-enforcement for the authentication and validation of IMDs based on AI cybersecurity, to safeguard the device owner's information, and also provide inconsistency-alerts in the device-authentication process. In championing the IMD cause, future researchers are encouraged to expand the UTAUT model to test the influence of other determining factors of technology adoption, such as effort expectancy. Finally, the extent to which a patient's attitude toward the IMD adoption is mediated by the FC factor needs to be examined, as a significant correlation between FC and Att was discovered in this study.

There are several medical and disease conditions that would benefit from the use of an IMD, and yet the IMD adoption and usage rates remain low (Gowani et al., 2022; Tiwari et al., 2020). Several scholars have concluded that IMDs help to maintain a healthier society, especially in times of a health pandemic when movement restrictions are in place (Antonini et al., 2021; Fox et al., 2021). Other scholars have attested to the fact that IMDs are a means to a healthier society, especially in times of a health pandemic when movement restrictions are in place and patients may not be able to access healthcare facilities and services so easily (Antonini et al., 2021; Fox et al., 2021; Tiwari et al., 2020).

In order to enhance the probability of acceptance and IMD use, the U.S. patient, physicians, healthcare policymakers, IMD manufacturers, and other stakeholders need to have an improved understanding of the problems bordering the U.S. patient's intention to adopt an IMD for efficient healthcare management (Daley et al., 2020). However, until now, there is limited research on the determinants connected with the adoption and use of IMDs (Briggs et al., 2020; Ratna, 2020).

Research scholars have contended that UTAUT provides a robust theoretical basis for the exploration of technology adoption and use (Kim & Lee, 2020; Wan et al., 2020). Also, physicians, healthcare policymakers, IMD manufacturers, and other stakeholders need to have an improved understanding of the factors bordering the U.S. patient's intention to adopt an IMD for efficient healthcare management (Daley et al., 2020). However, until now, there has been limited research on the determinants connected with the adoption and use of IMDs (Khan et al., 2022; Ratna, 2020). Social influence, perceived credibility, and performance expectancy were discovered in this study as the significant determinants of IMD adoption and use.

This study's findings have both practical and theoretical implications. From a theoretical perspective, the empirical evidence of this research discovered that the original UTAUT model is suitable for investigating the determining factors of IMD adoption and use since the extended UTAUT model applied in this study was able to account for 16% of the variance in BI to use an IMD. From a practical standpoint, the results of this study offered both practitioners and scholars vital insights into understanding the U.S. patient's perspectives on the important factors influencing IMD adoption and use. An improved understanding of the influential factors influencing user acceptance of IMD for efficient healthcare management would enable healthcare policymakers, healthcare institutions, hospitals, physicians, financial institutions, and IMD manufacturers to develop appropriate future provisioning whilst crafting strategic policies to tackle health management challenges. Finally, providing the U.S. public with pertinent information on IMDs and the available IMD resources will lead to more positive attitudes toward IMD technology, which will translate into higher IMD usage rates for efficient healthcare management in the United States.

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Appendices

Appendix A

Implantable Medical Device Adoption Survey

The following survey questionnaire investigates the U.S. patients' perceptions of an Implantable Medical Device (IMD) for treatment and management of a disease condition that a physician would usually prescribe an IMD. The purpose of the survey is the assessment of the U.S. patients' behavioral intent to use an IMD for treating and managing disease conditions. Your cooperation in completing this questionnaire as accurately as possible is very much appreciated.

PART 1: Demographics Please check the number which best represents your personal description	
Q1: Gender	1. Male 2. Female 3. Prefer not to say 4. Non-binary/Third gender
Q2: Age Range	1. 18–27 years 2. 28–37 years 3. 38–47 years 4. 48–57 years 5. 58–67 years 6. 68 years or more
Q3: Educational Level	1. Some High School 2. High School Diploma 3. Trade or Vocational degree 4. Some College / Associates degree 5. College Graduate/ Bachelors' degree 6. Masters 7. Doctoral Degree / PhD
Q4: What best describes your familiarity with Implantable Medical Devices such as Pacemakers, Implantable Cardioverter Defibrillators (ICD), Implantable Arrhythmic Devices (IAD), Coronary	1. Not at all familiar 2. Somewhat familiar 3. Familiar 4. Very Familiar 5. Expert Familiarity

stents, cochlea implants etc. for treating, controlling, and managing disease conditions?					
Q5: Do you currently use an implantable medical device such as pacemaker, ICD, IAD, coronary stent, etc.? Check all that apply	1. Pacemaker 2. Implantable Cardiac Defibrillator 3. Implantable Arrythmia Device 4. Coronary Stent 5. Cochlea implant 6. Other 7. Not currently using an implant				
Q6. Current state of residence	1. Alabama 2. Alaska 3. Arizona 4. Arkansas 5. California 6. Colorado …….. to 50th state, excluding provinces and territories				
PART 2: Behavioral Intent to use an IMD. Please circle appropriate number indicating the best response describing your disagreement or agreement on the factors affecting your intention to use an IMD for treatment and management of a disease condition that a doctor would usually prescribe an IMD					
Q7: I intend to use an Implantable Medical Device (IMD) for treatment and management of a disease condition that a doctor would usually prescribe an IMD?	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
Q8: I predict I would use IMD for treatment and management of a disease condition that a doctor would	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree

usually prescribe an IMD					
Q9: I plan to continue using an IMD in the future for treatment and management of a disease condition that a doctor would usually prescribe an IMD	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
PART 3: Factors affecting intention to use an IMD: **PERFORMANCE EXPECTANCY** Survey Statement/Question	Strongly Disagree	Disagree	Neither disagree nor agree	Agree	Strongly Agree
Q10: I am confident my device will work when I need it to.					
Q11. I have / will have fewer disease symptoms because of my device.					
Q12: My device is / will be the most effective treatment option					
Q13: I am sure the device functions / will function the way it is supposed to.					

SOCIAL INFLUENCE Survey Statement/ Questions	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
Q14. Those I consider important to me influence my intention to use an IMD					

Q15. The United States government's encouragement influences my intention to use an IMD.					
Q16. Patients I know who are using IMDs, including those in my Facebook Support Group influence my intention to use an IMD.					
Q17. Achieving IMD compliance is the sole responsibility of those in charge of regulatory compliance and not the patient.					

PERCEIVED CREDIBILITY (PC): Security and Safety Survey Statement/Question	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Disagree
Q18. My IMD is/ will be difficult to be hacked by criminals.					
Q19. Using IMD is/ will be secure.					
Q20. I feel safe /will feel safe using my device.					
Q21. IMD limits/will limit access to my personal information and health data.					

Attitude (Att) Survey Statement/Question	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
Q22. My device enhances/will enhance my standard of living.					
Q23. I have/will have fewer doctor visits per					

year, reducing my healthcare costs, leading to efficient health management, after I began/begin using my device than before receiving my device.					
Q24. I feel that the use of an IMD for treatment and disease condition management is beneficial.					
25. My help insurance covers/will cover my use of an IMD.					
Facilitating Conditions (FC) Survey Statement / Question	Strongly Disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
Q26. I had / will have my doctor solely prescribe my device instead of personally choosing my own treatment options.					
Q27. IMDs are available at both government and private health facilities for treatment and management of disease conditions.					
Q28. I would always adopt an IMD if I could choose my treatment options.					
Q29. I discussed / will discuss my treatment option with my physician before using an IMD.					

Appendix B

Permission to use survey instruments – Yeow et al. (2013)

RE: Permission to adopt and modify survey questions from your study: Ergonomics issues in national identity card for homeland security

Inbox

Paul Yeow xxx.xxxx@rmit.edu.vn via ncuonline.onmicrosoft.com   Fri, Aug 13, 4:32 AM (3 days ago)

to Emmanuel

Dear Emmanuel,

Yes, you have our permission to use our instrument. Let me know if you need any help in your research. I am in the editorial board of Applied Ergonomics and reviewer in Ergonomics. I think these two journals will be interested in your research.

The survey instrument is included in the paper at that appendix section.

Wishing you all the best.

Regards,

Paul

Sent from Mail for Windows

From: Emmanuel Ameh
Sent: Thursday, 12 August, 2021 7:10 PM
To: **xxxx**@yahoo.com; Paul Yeow; xxxxxxx@iputra.edu.my; xxx@gmail.com
Subject: Permission to adopt and modify survey questions from your study: Ergonomics issues in national identity card for homeland security

Good Morning Dr. Yeow, Dr. Loo, and Dr. Yuen,

I am currently pursuing a PhD in Technology and Innovation Management with a concentration in Cybersecurity at the Northcentral University, in San Diego, California. As part of the requirements of this degree, I am conducting quantitative dissertation research focusing on examining the issues surrounding the United States patients' intention to adopt an Implantable Medical Device as an alternative to current forms of treatment for efficient health management. My dissertation research topic is: A Factor Analysis of Implantable Medical Devices for Efficient Healthcare Management in the United States.

For this research, I need to compile an online survey instrument to be administered on the Qualtrics website. I would therefore like to request your permission to adopt and modify survey questions from your study: Ergonomics issues in national identity card for Homeland Security.

It is my hope that your research will be one of the bases for my dissertation to apply the theory to a different situation in the context of the United States, modifying some of the variables in the instrument and duplicating the findings in the context of the United States. The theory in my research has slightly been changed, adding the attitude construct, and removing the anxiety variable to determine whether this new variable has any role in my research study.

I look forward to receiving your approval to use and modify your above-mentioned instrument for my dissertation.

I can assure you adequate reference to your work in my dissertation will be provided.

I can be contacted at E.Ameh1065@o365.ncu.edu

Thank you in advance for your cooperation.

Best Regards,

Emmanuel Ameh

Doctoral Candidate

Northcentral University, CA

USA

E.Ameh1065@o365.ncu.edu

Emmanuel Ameh <xxxx.xxxx@gmail.com>   Fri, Aug 13, 8:04 AM (3 days ago)

to Emmanuel, Paul

Dear Dr. Yeow,

Thank you for your prompt response to my email. The goodwill and consent are very much appreciated. I look forward to publishing my research and the two recommended journals will definitely be considered. Thank you once again for your cooperation.

With Best Regards,

Emmanuel Ameh

Emmanuel Esem Ameh,

Doctoral Candidate

Northcentral University
Email: xxxxxxxxx@gmail.com
Phone: (XXX)XXX-XXXX

"Students First - Service and Excellence"

Paul Yeow Fri, Aug 13, 8:50 PM (3 days ago)

to me, Emmanuel

Dear Emmanuel,

You are most welcome 😊.

Regards,

Paul

Appendix C

Permission to use survey instrument – Kohnke et al. (2014)

RE: Permission to adopt and modify survey questions from your study: Incorporating UTAUT predictors for understanding home care and clinician's acceptance of healthcare telemedicine equipment

Inbox

Anne Kohnke xxxxxxx@udmercy.edu via ncuonline.onmicrosoft.com | Aug 13, 2021, 4:56 AM (3 days ago)

to Emmanuel

Good Morning,

I am happy to provide permission to adopt and modify the attached survey instrument for your research. I wish you all the best.

Kindest regards,

Anne Kohnke, Ph.D.

Associate Professor

Cybersecurity & Information Systems Department (C&IS)

Principal Investigator of the NSA/DHS Center of Academic Excellence in Cyber Defense (CAE-CD)

University of Detroit Mercy

4001 McNichols Road

Detroit, MI 48221

Briggs Building, 2nd Floor Office, Rm 211

Center for Cyber, Security & Intelligence Studies

From: Emmanuel Ameh <xxxxxxxx@o365.ncu.edu>
Sent: Thursday, August 12, 2021 7:58 AM
To: akohnke <xxxxxx@conkeyss.com>; Anne Kohnke <xxxxxxxx@udmercy.edu>; xxxxx@conkeyss.com
Subject: Permission to adopt and modify survey questions from your study: Incorporating UTAUT predictors for understanding home care and clinician's acceptance of healthcare telemedicine equipment

Good morning Dr. Kohnke, Dr. Bush, and Dr. Cole,

I am currently pursuing a PhD in Technology and Innovation Management with a concentration in Cybersecurity at the Northcentral University in San Diego, California. As part of the requirements of this degree, I am conducting a quantitative dissertation research focusing on examining the issues surrounding the United States patients' behavioral intention to adopt an Implantable Medical Device as an alternative treatment option for efficient healthcare management. My research topic is: A Factor Analysis of Implantable Medical Devices for Efficient Healthcare Management in the United States.

For this research, I need to compile an online survey instrument that will be administered on the Qualtrics website. I would therefore like to request your permission to adopt and modify the demographic survey questions from your study: Incorporating UTAUT predictors for understanding home care and clinician's acceptance of healthcare telemedicine equipment.

I look forward to your approval to use and modify your research instrument for my research.

Adequate referencing will be provided for your work in my dissertation.

I can be contacted at: E.Ameh1065@o365.ncu.edu.

Thank you in advance for your cooperation.

Best Regards,

Emmanuel Ameh

Doctoral Candidate

Northcentral University

San Diego, California

USA

xxxxxxxx@o365.ncu.edu

Emmanuel Ameh <xxxxxxxxxx@gmail.com> Aug 13, 2021, 9:47 AM (3 days ago)

to Emmanuel, Anne

Dear Dr. Kohnke,

Thank you for your prompt response and for sending me the attached copy of your questionnaire. The good wishes and consent are very much appreciated. Adequate reference to your work will be provided in my dissertation. Thank you once more for your permission.

Sincerely,

Emmanuel Ameh

Doctoral Candidate

Northcentral University

Email: xxxxxx@o365.ncu.edu
Phone: (xxx)xxx-xxxx

Appendix D

Permission to use survey instruments – Morosan (2016)

Re: Subject: Permission to adopt and modify survey questions from your study: An empirical examination of U.S. travelers’ intentions to use bio-metric e-gates in airports

Inbox

Morosan, Cristian <xxxxxxx@central.uh.edu> Tue, Aug 3, 10:04 AM (13 days ago)

to Emmanuel

Hi Emmanuel,

Please feel free to use any scales from any publications where I am an author. Best of luck with your research.

Sincerely,
Cristian

From: Emmanuel Ameh <xxxxxxxx@o365.ncu.edu>
Sent: Friday, July 30, 2021 2:32 AM
To: Morosan, Cristian <xxxxxxx@Central.UH.EDU>
Subject: Subject: Permission to adopt and modify survey questions from your study: An empirical examination of U.S. travelers’ intentions to use bio-metric e-gates in airports

Good Morning Dr. Morosan,

I am currently pursuing a PhD in Technology and Innovation Management with a concentration in Cybersecurity at the Northcentral University in San Diego, California. As part of the requirements of this degree, I am conducting quantitative dissertation research focusing on examining the issues surrounding the United States patients’ behavioral intention to adopt an Implantable Medical Device as an alternative treatment option for efficient healthcare management. My research topic is: A Factor Analysis of Implantable Medical Devices for Efficient Healthcare Management in the United States.

For this research, I need to compile an online survey instrument that will be administered on the Qualtrics website. I would therefore like to request your permission to adopt and modify the demographic survey questions from your study: An empirical examination of U.S. travelers’ intentions to use biometric e-gates in airports. It is my hope that your demographic questions will assist in producing a profile of my survey respondents.

I look forward to your approval to use and modify your research instrument for my dissertation research.

Adequate referencing will be provided for your work in my dissertation.

I can be contacted at: xxxxxxxxxxxxx@o365.ncu.edu.

Thank you in advance for your cooperation.

Best Regards,

Emmanuel Ameh

Doctoral Candidate

Northcentral University

San Diego, California

USA

xxxxxxxxxxxxx@o365.ncu.edu

Emmanuel Ameh <xxxxxxxx@gmail.com> Tue, Aug 3, 8:49 PM (13 days ago)

to Cristian, Emmanuel

Dear Dr. Morosan,

Thank you for your email. I appreciate your express consent and goodwill gesture to use your instrument and scales. Thank you once again for your cooperation.

Yours Sincerely,

Emmanuel Esem Ameh,

PhD Candidate

Northcentral University

San Diego, CA

Appendix E

Consent Letter

Introduction

My name is Emmanuel Ameh, and I am a doctoral student at Northcentral University (NCU). I am conducting a research study to investigate the relationship between the factors that influence the behavioral intent to use an Implantable Medical Device. The name of this research study is "Factor Analysis of Implantable Medical Devices for Efficient Healthcare Management in the United States." I am seeking your consent to participate in this study.

Please read this document to learn more about this study and determine if you would like to participate. Your participation is completely voluntary, and I will address your questions or concerns at any point before or during the study.

Eligibility

You are eligible to participate in this study if:

1. You are age 18 or older
2. You are using or have used an Implantable Medical Device in the past
3. An Implantable Medical Device was recommended to you, but you declined to use one
4. You live in any of the 50 states within the United States, excluding territories and provinces

I hope to include 300 people in this research.

Activity

If you decide to participate in this study, you will be asked to complete this online survey on Qualtrics.com for 15 – 20 minutes

During these activities, you will be asked questions about:

- Your perceptions of the influential factors of social influence, performance expectancy of device, device user attitudes, perceived credibility of device, facilitating condition of device.
- Your perceptions on Behavioral intent to use an Implantable Medical Device
- Your age, gender, educational level, income level, current state of residence, familiarity with Implantable Medical Devices and specific Implantable Medical Device currently used.

All activities and questions are optional: you may skip any part of this study that you do not wish to complete and may stop at any time.

If you need to complete the activities above in a different way than I have described, please let me know, and I will attempt to make other arrangements.

Risks

There are no foreseeable risks or discomforts associated with this study. You can still skip any question you do not wish to answer, skip any activity, or stop participation at any time.

Benefits

If you participate, there are no direct benefits to you. This research may increase the body of knowledge in the subject area of this study.

Privacy and Data Protection

I will take reasonable measures to protect the security of all your personal information, but I cannot guarantee confidentiality of your research data. In addition to me, the following people and offices will have access to your data:

- My NCU dissertation committee and any appropriate NCU support or leadership staff
- The NCU Institutional Review Board

This data could be used for future research studies or distributed to other investigators for future research studies without additional informed consent from you or your legally authorized representative.

I will securely store your data for 3 years. Then, I will delete electronic data and destroy paper data.

How the Results Will Be Used

I will publish the results in my dissertation. I may also share the results in a presentation or publication. Participants will not be identified in the results.

Contact Information

If you have questions, you can contact me at: xxxxxxxxxx@o365.ncu.edu

My dissertation chair's name is Dr. David Hildebrandt. He works at Northcentral University and is supervising me on the research. You can contact him at: dhildebrandt@ncu.edu.

If you have questions about your rights in the research or if a problem or injury has occurred during your participation, please contact the NCU Institutional Review Board at irb@ncu.edu or 1-888-327-2877 ext. 8014.

Voluntary Participation

If you decide not to participate, or if you stop participation after you start, there will be no penalty to you: you will not lose any benefit to which you are otherwise entitled.

Appendix F

Models and Theories of Individual Acceptance

Models and Theories	Constructs
Theory of reasoned action (TRA) by Fishbein and Ajzen (1975), derived from psychology to measure behavioral intention and performance.	Attitude Subjective norm
Technology acceptance model (TAM) by Davis (1989) included a new scale with two specific variables to determine user acceptance of technology.	Perceived usefulness Perceived ease of use
Technology acceptance model 2 (TAM2) by Venkatesh and Davis (2000) is adapted from TAM and includes more variables.	Subjective norm,[a] experience,[a] voluntariness,[a] image,[a] job relevance,[a] output quality,[a] and result demonstrability[a]
Motivational model (MM) also stemmed from psychology to explain behavior. Davis et al. (1992) applied this model to technology adoption and use.	Extrinsic motivation Intrinsic motivation
Theory of planned behavior (TPB) by Ajzen (1991) extended TRA by including one more variable to determine intention and behavior.	Attitude Subjective norm Perceived behavioral control
Combined TAM and TPB (C-TAM-TPB) by Taylor and Todd (1995).	Perceived usefulness, perceived ease of use, attitude, subjective norm, and perceived behavioral control
Model of PC utilization (MPCU) by Thompson et al. (1991) represented an adjustment from the theory of attitudes and behavior by Triandis (1980) to predict PC usage behavior.	Social factors, affect, perceived consequences (complexity, job-fit, long-term consequences of use), facilitating conditions, and habits
Innovation diffusion theory (IDT) by Rogers (1962) who adapted the theory to include the information systems innovations of Moore and Benbasat (1991), who identified five attributes from Rogers' model and two additional constructs.	Relative advantage,[b] compatibility,[b] complexity,[b] observability,[b] and trialability.[b] image and voluntariness of use
Social cognitive theory (SCT) by Bandura (1986) applies to information systems by Compeau and Higgins (1995) to determine usage.	Encouragement by others, others' use, support, self-efficacy, performance outcome expectations, personal outcome expectations, affect, and anxiety.
Unified theory of acceptance and use of technology model (UTAUT) by Venkatesh et al. (2003) integrated the above theories and models to measure user intention and usage on technology	Performance expectancy, effort expectancy, attitude toward using technology, social influence, facilitating conditions, self-efficacy, and anxiety.

Note. This table outlines the concept of the UTAUT system and the notions of the eight theories/models that Davis et al. (2003) studied to formulate this system. Adapted from Sundaravej (2009, pp. 3-4).
[a] Indicates TAM2 only.
[b] Indicates Roger's constructs.

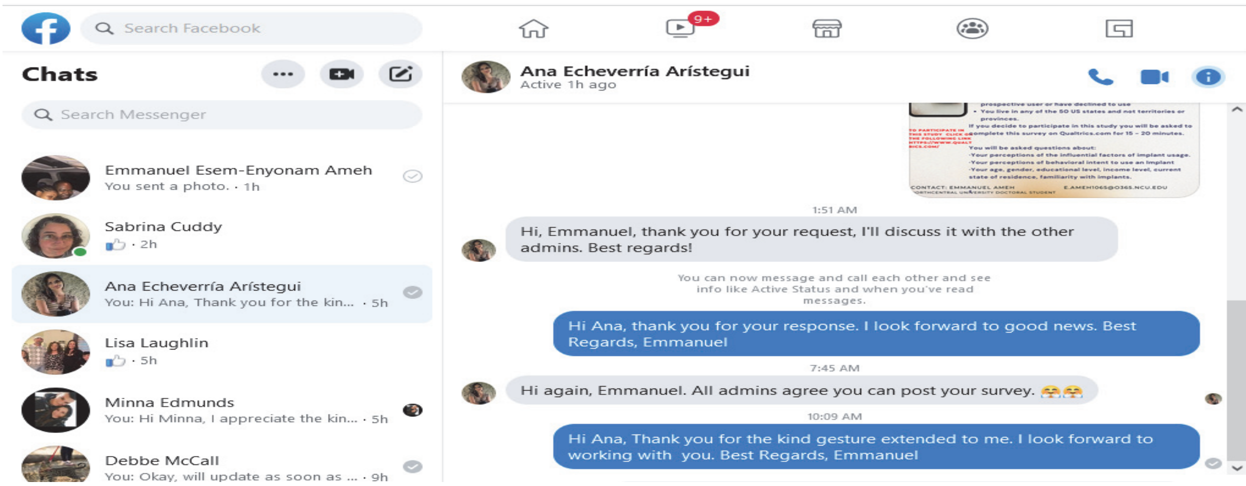
Appendix G

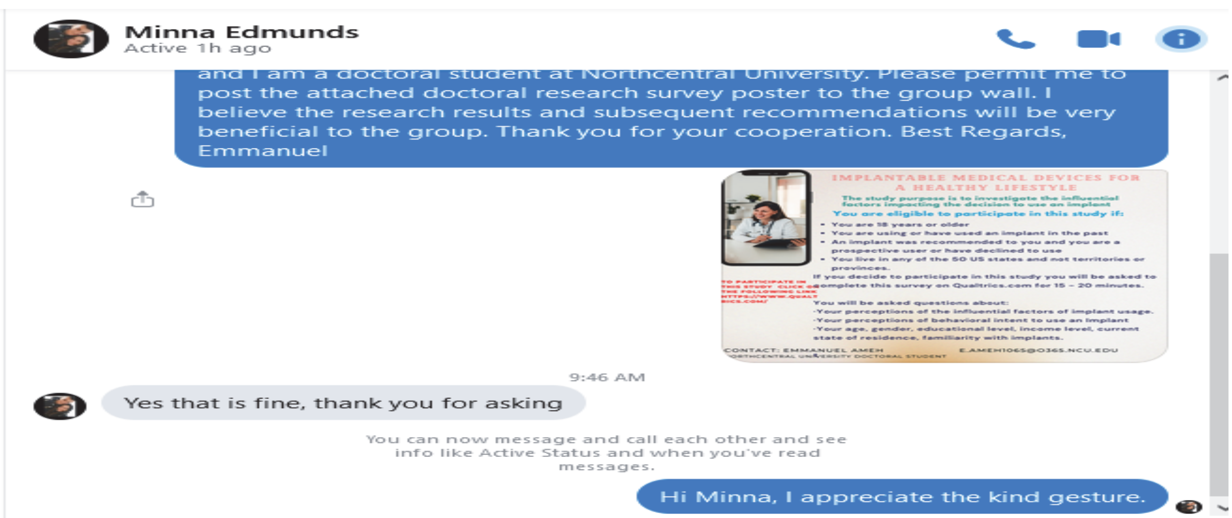
Constructs and Corresponding Survey Items

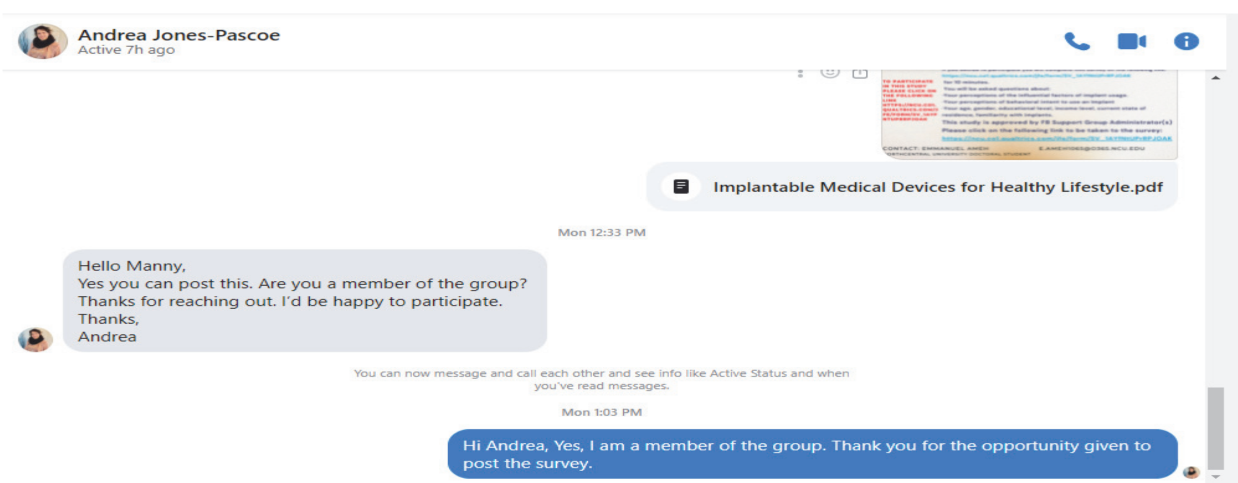
Factor	Name	Corresponding Survey Items
ATT-IV	Att	1. My device enhances/will enhance my standard of living 2. I have/will have fewer doctor visits per year, reducing my healthcare costs, leading to efficient health management, after I began/begin using my device than before receiving my device. 3. I feel that the use of an IMD for treatment and disease condition management is beneficial 4. My health insurance covers/will cover my use of an IMD
FC-IV	FC	1. I had / will have my doctor solely prescribe my device instead of personally choosing my own treatment options. 2. IMDs are available at both government and private health facilities for treatment and management of disease conditions. 3. I would always adopt an IMD if I could choose my treatment options. 4. I discussed / will discuss my treatment option with my physician before using an IMD.
PC-IV	PC	1. My IMD is/ will be difficult to be hacked by criminals. 2. Using IMD is/ will be secure. 3. I feel safe /will feel safe using my device. 4. IMD limits/will limit access to my personal information and health data.
PE-IV	PE	1: I am confident my device will work when I need it to. 2. I have / will have fewer disease symptoms because of my device. 3: My device is / will be the most effective treatment option 4: I am sure the device functions / will function the way it is supposed to.
SI-IV	SI	1. Those I consider important to me influence my intention to use an IMD 2. The United States government's encouragement influences my intention to use an IMD. 3. Patients I know who are using IMDs, including those in my Facebook Support Group influence my intention to use an IMD. 4. Achieving IMD compliance is the sole responsibility of those in charge of regulatory compliance and not the patient.
BI-DV	BI to use IMD	1. I intend to use an Implantable Medical Device (IMD) for treatment and management of a disease condition that a doctor would usually prescribe an IMD? 2. I predict I would use IMD for treatment and management of a disease condition that a doctor would usually prescribe an IMD 3. I plan to continue using an IMD in the future for treatment and management of a disease condition that a doctor would usually prescribe an IMD.

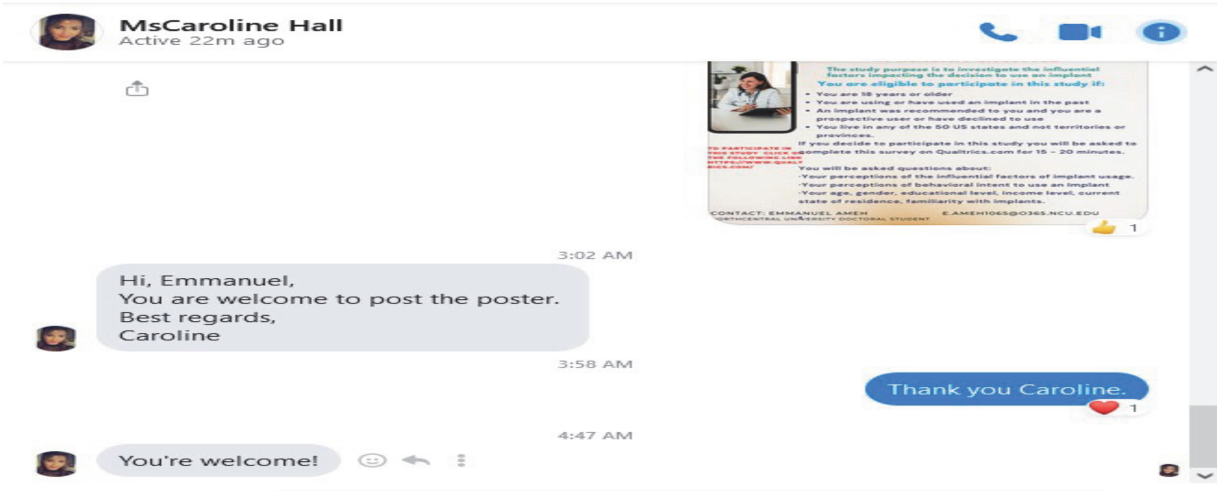
Appendix H

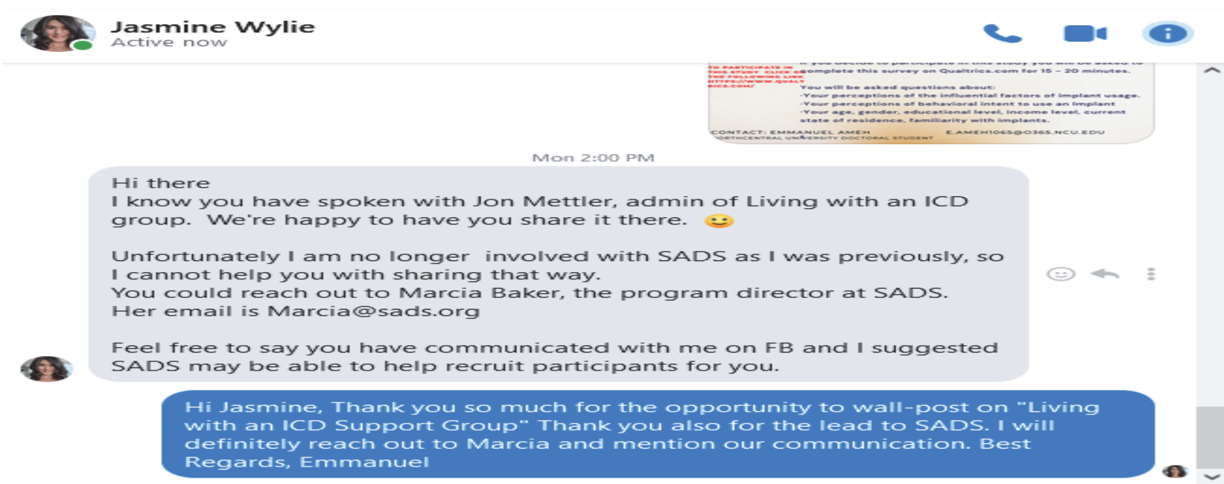
Facebook IMD Support Groups – Administrator Permissions

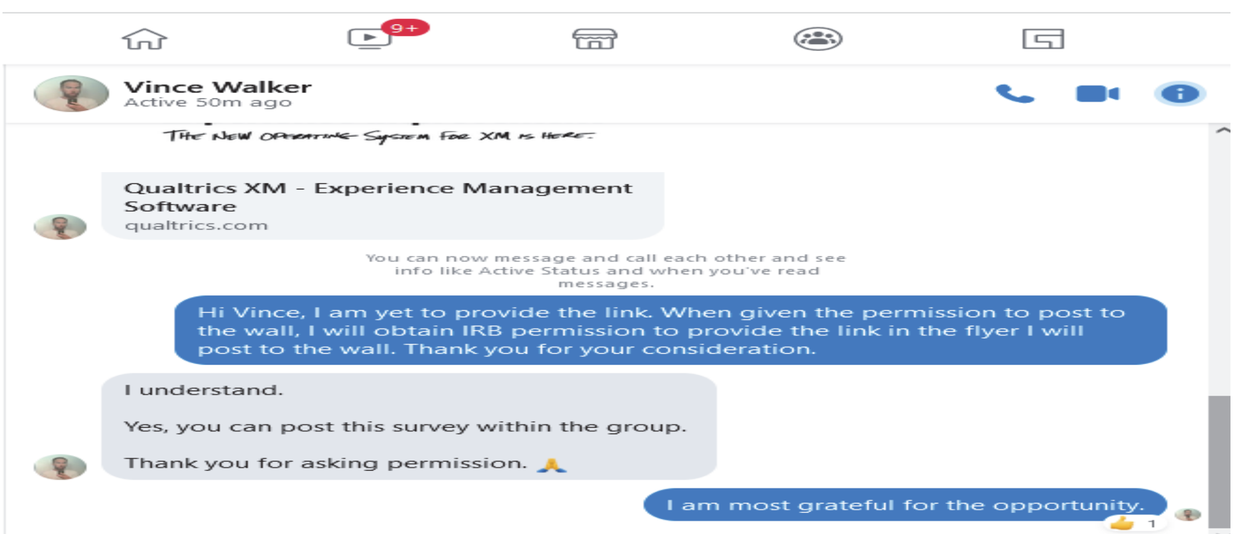




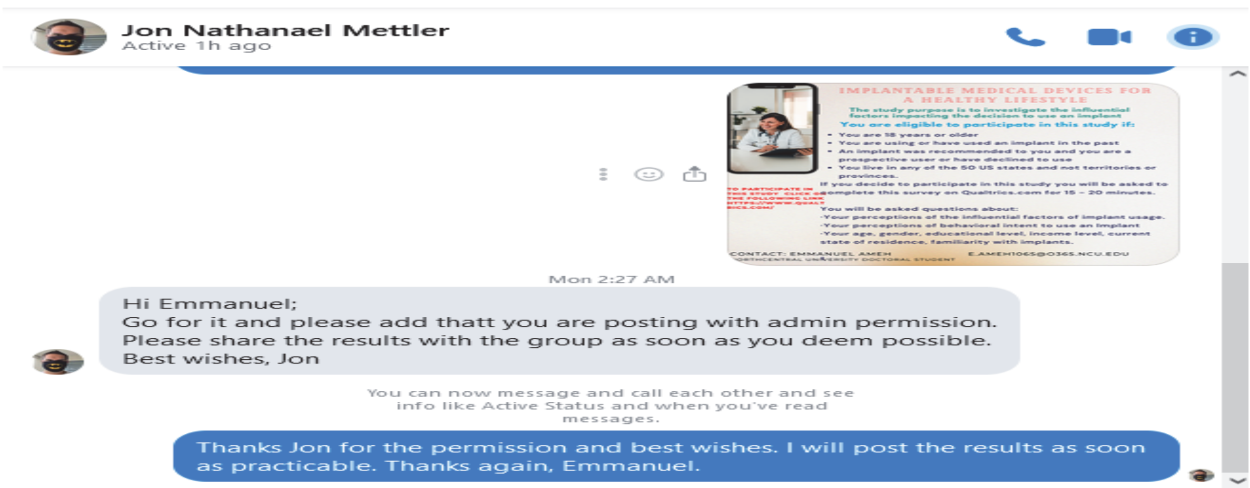


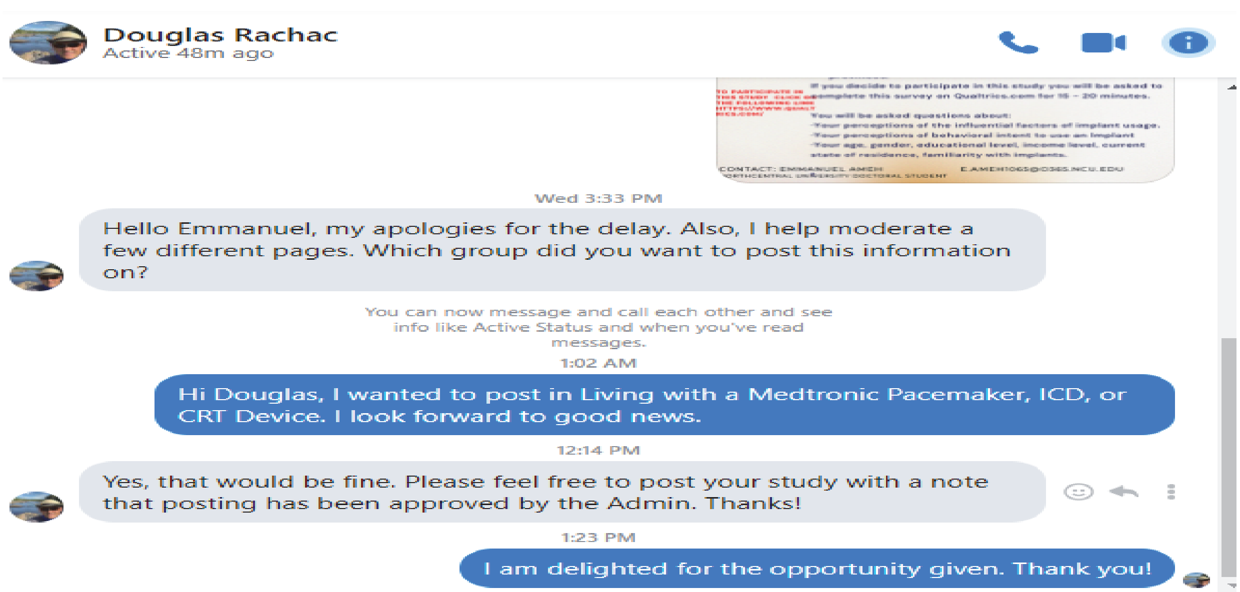

MsCaroline Hall
Active 22m ago
3:02 AM
Hi, Emmanuel,
You are welcome to post the poster.
Best regards,
Caroline
3:58 AM
Thank you Caroline.
4:47 AM
You're welcome!

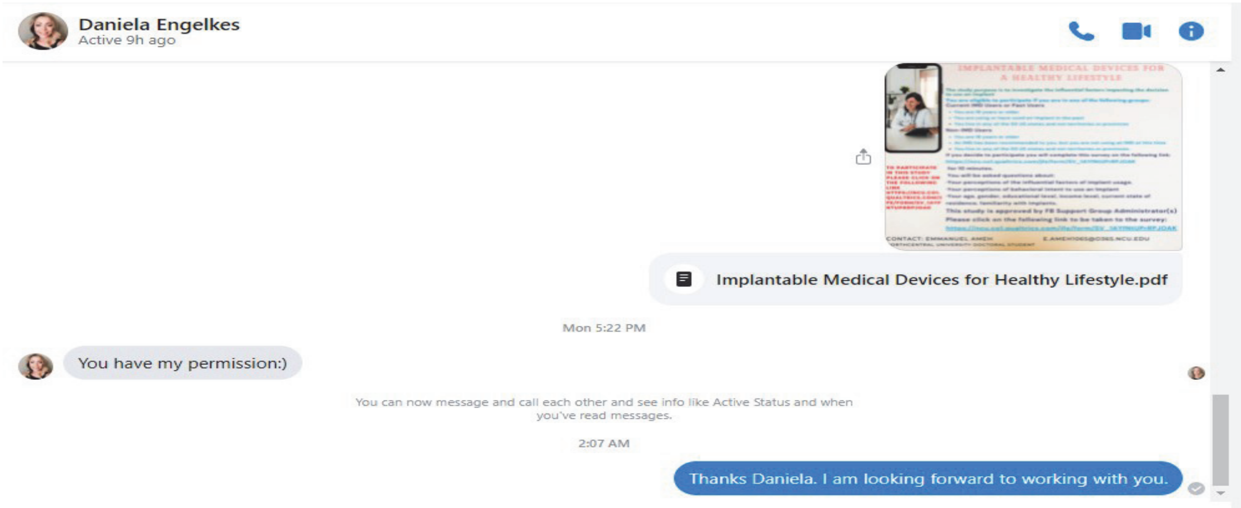

Jasmine Wylie
Active now
Mon 2:00 PM
Hi there
I know you have spoken with Jon Mettler, admin of Living with an ICD group. We're happy to have you share it there.
Unfortunately I am no longer involved with SADS as I was previously, so I cannot help you with sharing that way.
You could reach out to Marcia Baker, the program director at SADS.
Her email is Marcia@sads.org
Feel free to say you have communicated with me on FB and I suggested SADS may be able to help recruit participants for you.
Hi Jasmine, Thank you so much for the opportunity to wall-post on "Living with an ICD Support Group" Thank you also for the lead to SADS. I will definitely reach out to Marcia and mention our communication. Best Regards, Emmanuel

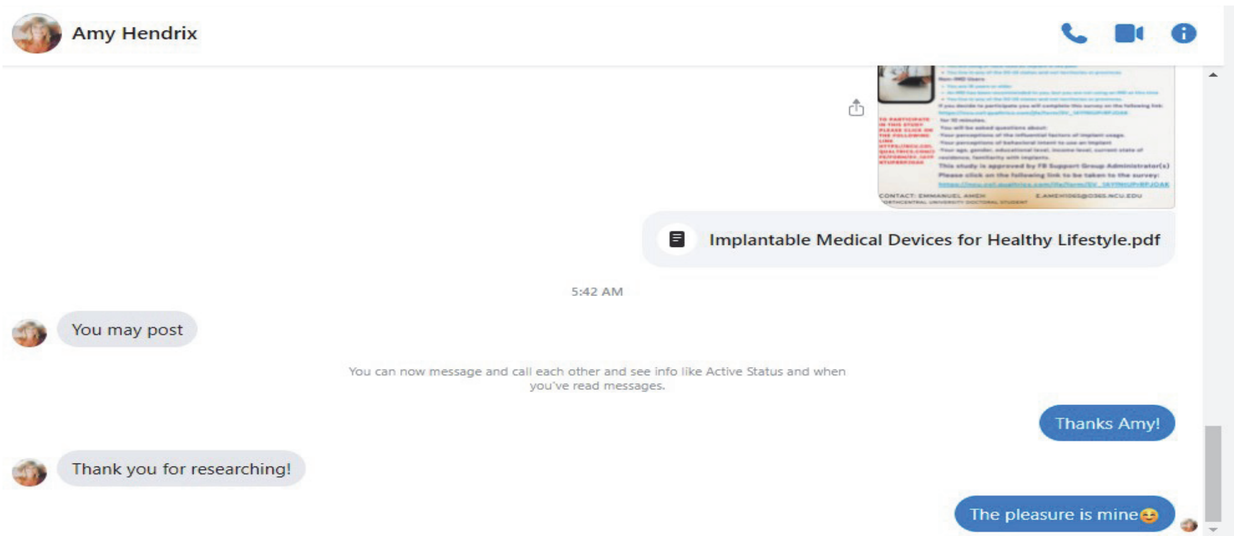

9+
Vince Walker
Active 50m ago
THE NEW OPERATING SYSTEM FOR XM IS HERE.
Qualtrics XM - Experience Management Software
qualtrics.com
You can now message and call each other and see info like Active Status and when you've read messages.
Hi Vince, I am yet to provide the link. When given the permission to post to the wall, I will obtain IRB permission to provide the link in the flyer I will post to the wall. Thank you for your consideration.
I understand.
Yes, you can post this survey within the group.
Thank you for asking permission.
I am most grateful for the opportunity.

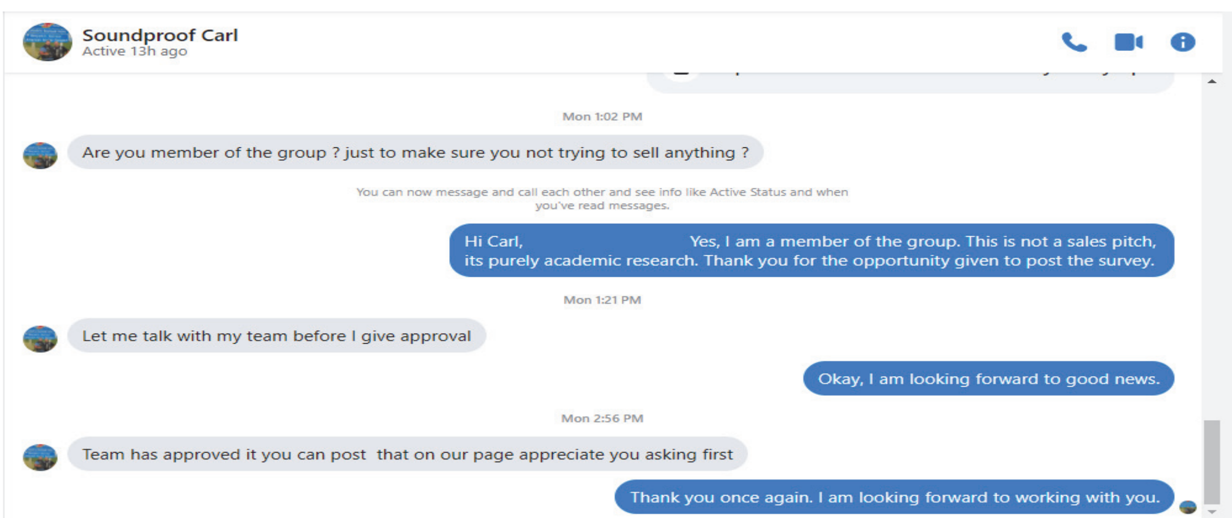

Claudia Fox Reppen
Mon 8:06 AM
Hi Emmanuel!
Yes, please feel free to post your survey in the group (you can mention in the post that the admin approved the post). You can encourage group members to contact you with any questions. Best of luck with your studies!
Claudia
You can now message and call each other and see info like Active Status and when you've read messages.
Mon 8:57 AM
Thanks Claudia.
9+
2


Jon Nathanael Mettler
Active 1h ago
IMPLANTABLE MEDICAL DEVICES FOR A HEALTHY LIFESTYLE
Mon 2:27 AM
Hi Emmanuel;
Go for it and please add thatt you are posting with admin permission.
Please share the results with the group as soon as you deem possible.
Best wishes, Jon
You can now message and call each other and see info like Active Status and when you've read messages.
Thanks Jon for the permission and best wishes. I will post the results as soon as practicable. Thanks again, Emmanuel.


Douglas Rachac
Active 48m ago
Wed 3:33 PM
Hello Emmanuel, my apologies for the delay. Also, I help moderate a few different pages. Which group did you want to post this information on?
You can now message and call each other and see info like Active Status and when you've read messages.
1:02 AM
Hi Douglas, I wanted to post in Living with a Medtronic Pacemaker, ICD, or CRT Device. I look forward to good news.
12:14 PM
Yes, that would be fine. Please feel free to post your study with a note that posting has been approved by the Admin. Thanks!
1:23 PM
I am delighted for the opportunity given. Thank you!

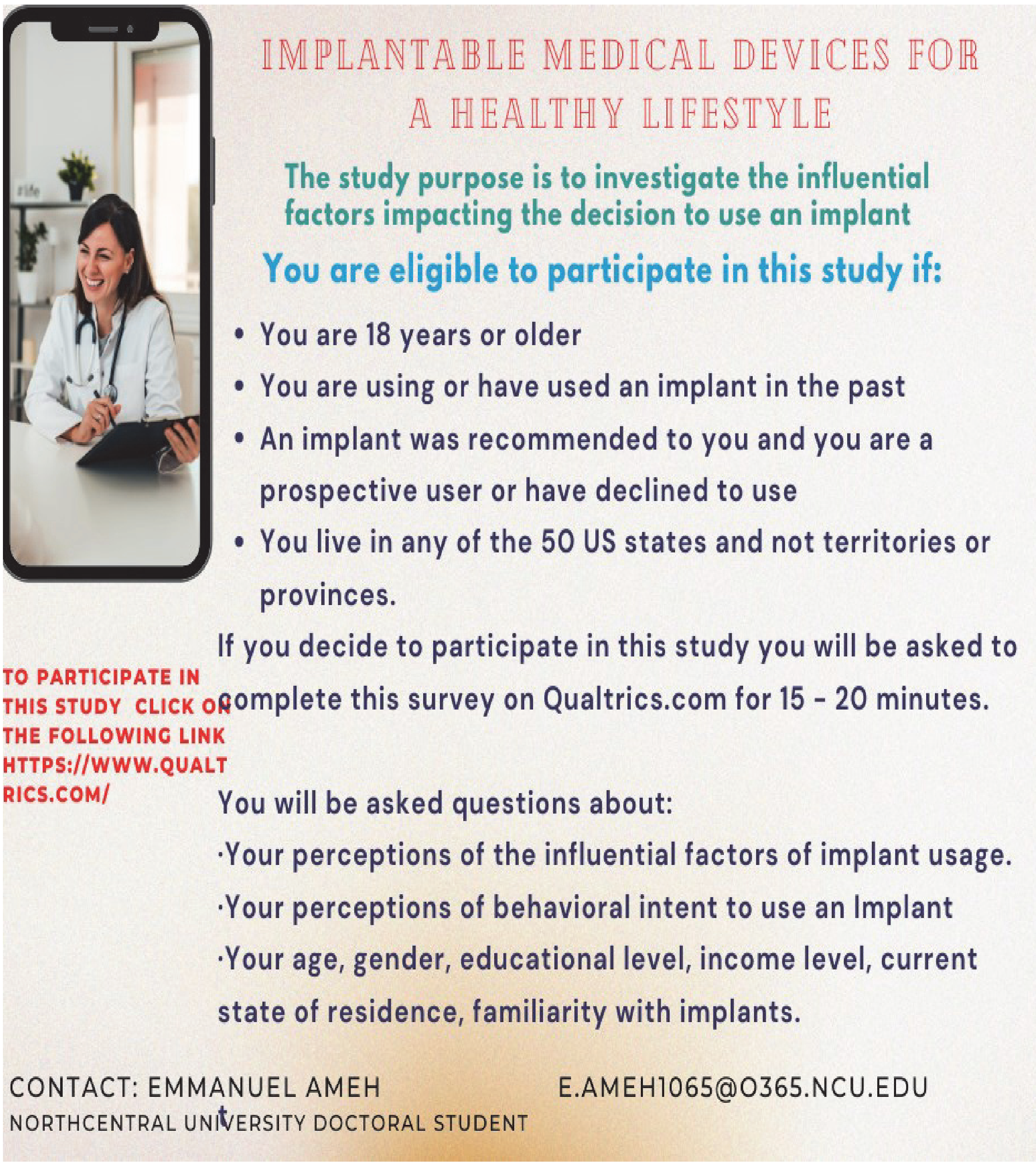

Daniela Engelkes
Active 9h ago
Implantable Medical Devices for Healthy Lifestyle.pdf
Mon 5:22 PM
You have my permission:)
You can now message and call each other and see info like Active Status and when you've read messages.
2:07 AM
Thanks Daniela. I am looking forward to working with you.


Amy Hendrix
Implantable Medical Devices for Healthy Lifestyle.pdf
5:42 AM
You may post
You can now message and call each other and see info like Active Status and when you've read messages.
Thanks Amy!
Thank you for researching!
The pleasure is mine😊


Soundproof Carl
Active 13h ago
Mon 1:02 PM
Are you member of the group ? just to make sure you not trying to sell anything ?
You can now message and call each other and see info like Active Status and when you've read messages.
Hi Carl, Yes, I am a member of the group. This is not a sales pitch, its purely academic research. Thank you for the opportunity given to post the survey.
Mon 1:21 PM
Let me talk with my team before I give approval
Okay, I am looking forward to good news.
Mon 2:56 PM
Team has approved it you can post that on our page appreciate you asking first
Thank you once again. I am looking forward to working with you.

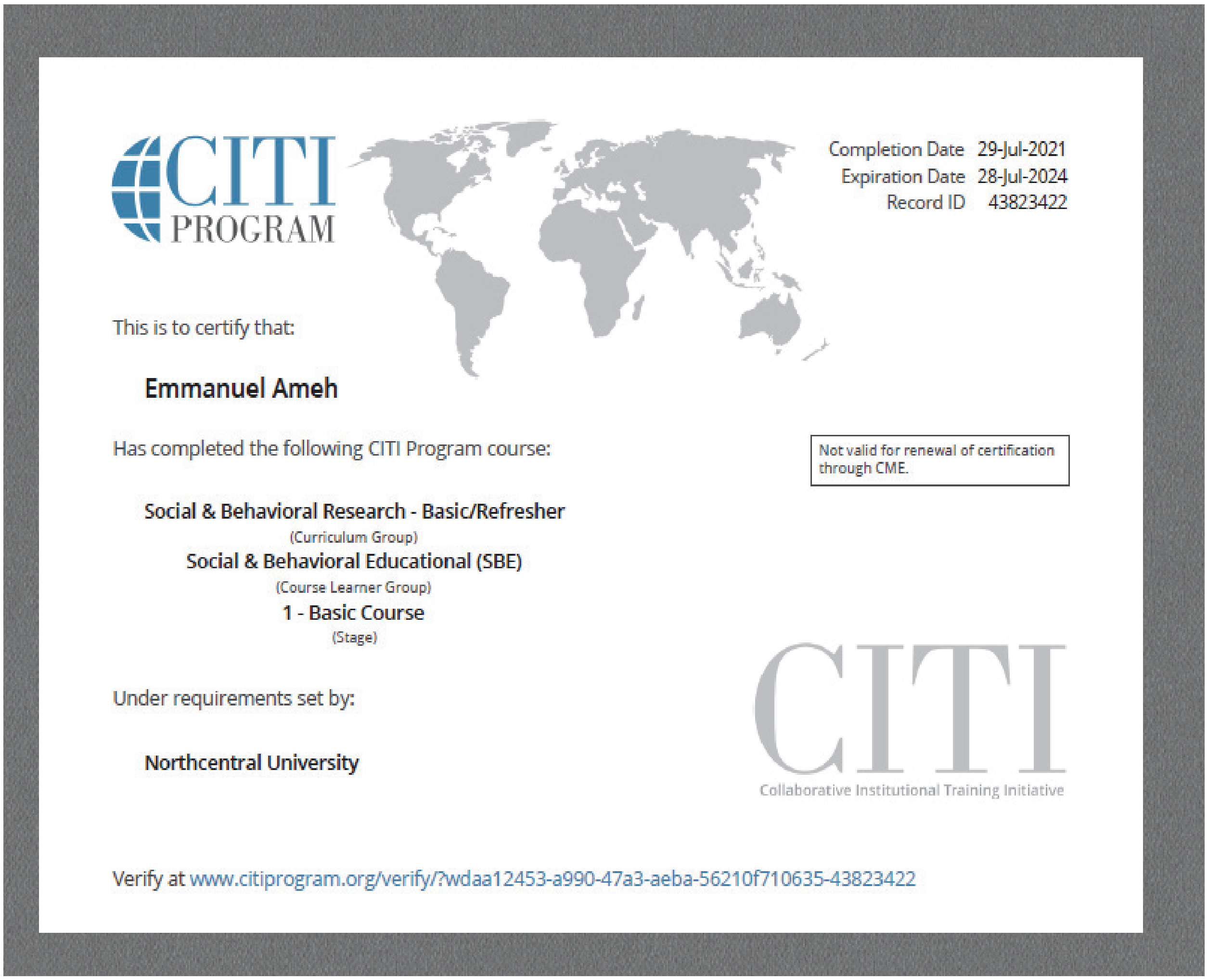
Appendix I

Survey Recruitment Flyer



Appendix J

Collaborative Institutional Training Initiative Program Certificate



CITI PROGRAM

Completion Date 29-Jul-2021
Expiration Date 28-Jul-2024
Record ID 43823422

This is to certify that:

Emmanuel Ameh

Has completed the following CITI Program course:

Not valid for renewal of certification through CME.

Social & Behavioral Research - Basic/Refresher
(Curriculum Group)
Social & Behavioral Educational (SBE)
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Northcentral University

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?wdaa12453-a990-47a3-aeba-56210f710635-43823422

Appendix K

IRB Approval Letter

NORTHCENTRAL UNIVERSITY

11355 N. Torrey Pines Road
La Jolla, CA 92037

Date: February 01, 2022
PI Name: Emmanuel Ameh
Chair Name (if applicable): David Hildebrandt
Application Type: Initial Submission
Review Level: Exempt - Category 2
Study Title: Factor Analysis of Implantable Medical Devices for Efficient Healthcare Management in the United States.

Approval Date: February 01, 2022

Dear Emmanuel:

Congratulations! Your IRB application has been approved. Your responsibilities include the following:

1. Follow the protocol as approved. If you need to make changes with your population, recruitment, or consent, please submit a modification form.
2. If there is a consent process in your research, you must use the consent form approved with your final application. Please make sure all participants receive a copy of the consent form.
3. **If there are any injuries, problems, or complaints from participants (adverse events), you must notify the IRB at IRB@ncu.edu within 24 hours.**
4. IRB audit of procedures may occur. The IRB will notify you if your study will be audited.
5. When data are collected and de-identified, please submit a study closure form to the IRB. See the IRBManager instructions on our website.
6. You must maintain current CITI certification until you have submitted a study closure form.
7. If you are a student, please be aware that you must be enrolled in an active dissertation course with NCU in order to collect data.

Best wishes as you conduct your research!

Respectfully,

Northcentral University Institutional Review Board
Email: irb@ncu.edu

NCU.edu

Appendix L

SPSS 28 Syntax

```
GET
  FILE='C:\Users\Manny\Emmanuel\Desktop\DIS-9904A\DataSet1 05-
21-2022.sav'.
DATASET NAME DataSet1 WINDOW=FRONT.
FREQUENCIES VARIABLES=BI1 BI2 BI3 PE1 PE2 PE3 PE4 SI1 SI2 SI3
SI4 PC1 PC2 PC3 PC4 FC1 FC2 FC3 FC4 Att1 Att2 Att3 Att4
  /STATISTICS=STDDEV VARIANCE RANGE MINIMUM MAXIMUM SEMEAN MEAN
MEDIAN MODE SUM SKEWNESS SESKEW
    KURTOSIS SEKURT
  /PIECHART PERCENT
  /ORDER=ANALYSIS.


///Reliabilities for all Independent and Dependent variables

RELIABILITY
  /VARIABLES=Attitude SocInf PerCred FaciCond PerfExp BehInt
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.


///Reliability Statistics for Attitude Variable

RELIABILITY
  /VARIABLES=Att1 Att2 Att3 Att4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=TOTAL MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.

///Reliability Statistics for Social Influence Variable

RELIABILITY
  /VARIABLES=SI1 SI2 SI3 SI4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=TOTAL MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.
```

```
///Reliability Statistics for Perceived Credibility Variable

RELIABILITY
  /VARIABLES=PC1 PC2 PC3 PC4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=TOTAL MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.

///Reliability Statistics for Facilitated Conditions Variable

RELIABILITY
  /VARIABLES=FC1 FC2 FC3 FC4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=TOTAL MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.

///Reliability Statistics for Performance Expectancy Variable

RELIABILITY
  /VARIABLES=PE1 PE2 PE3 PE4
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=TOTAL MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.

///Reliability Statistics for Behavioral Intent Variable

RELIABILITY
  /VARIABLES=BI1 BI2 BI3
  /SCALE('ALL VARIABLES') ALL
  /MODEL=ALPHA
  /STATISTICS=DESCRIPTIVE SCALE HOTELLING CORR COV TUKEY
  /SUMMARY=TOTAL MEANS VARIANCE COV CORR
  /ICC=MODEL(MIXED) TYPE(CONSISTENCY) CIN=95 TESTVAL=0.

///Exploratory Factor Analysis with Principal Axis Factoring
(PAF)Extraction Method

FACTOR
  /VARIABLES BI1 BI2 BI3 PE1 PE2 PE3 PE4 SI1 SI2 SI3 SI4 PC1 PC2
PC3 PC4 FC1 FC2 FC3 FC4 Att1 Att2
    Att3 Att4
  /MISSING LISTWISE
```

```
  /ANALYSIS BI1 BI2 BI3 PE1 PE2 PE3 PE4 SI1 SI2 SI3 SI4 PC1 PC2
PC3 PC4 FC1 FC2 FC3 FC4 Att1 Att2
    Att3 Att4
  /PRINT UNIVARIATE INITIAL CORRELATION SIG DET KMO REPR AIC
COVARIANCE EXTRACTION ROTATION
  /FORMAT SORT
  /PLOT EIGEN
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PAF
  /CRITERIA ITERATE(25)
  /ROTATION PROMAX(4)
  /METHOD=CORRELATION.

///Exploratory Factor Analysis with Principal Components (PC)
Extraction Method

FACTOR
  /VARIABLES BI1 BI2 BI3 PE1 PE2 PE3 PE4 SI1 SI2 SI3 SI4 PC1 PC2
PC3 PC4 FC1 FC2 FC3 FC4 Att1 Att2
    Att3 Att4
  /MISSING LISTWISE
  /ANALYSIS BI1 BI2 BI3 PE1 PE2 PE3 PE4 SI1 SI2 SI3 SI4 PC1 PC2
PC3 PC4 FC1 FC2 FC3 FC4 Att1 Att2
    Att3 Att4
  /PRINT UNIVARIATE INITIAL CORRELATION SIG DET KMO REPR AIC
COVARIANCE EXTRACTION ROTATION FSCORE
  /FORMAT SORT
  /PLOT EIGEN
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PC
  /CRITERIA ITERATE(25)
  /ROTATION VARIMAX
  /METHOD=CORRELATION.

///Bootstrapping for Linear Regression

BOOTSTRAP
  /SAMPLING METHOD=SIMPLE
  /VARIABLES TARGET=BehInt INPUT=  Attitude SocInf PerCred
FaciCond PerfExp
  /CRITERIA CILEVEL=95 CITYPE=PERCENTILE  NSAMPLES=1000
  /MISSING USERMISSING=EXCLUDE.
```

```
///Linear Regression Analysis

REGRESSION
  /DESCRIPTIVES MEAN STDDEV CORR SIG N
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS CI(95) BCOV R ANOVA COLLIN TOL CHANGE
ZPP
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT BehInt
  /METHOD=ENTER Attitude SocInf PerCred FaciCond PerfExp
  /SCATTERPLOT=(BehInt ,*ZPRED)
  /RESIDUALS DURBIN HISTOGRAM(ZRESID) NORMPROB(ZRESID).

///End of SPSS Analysis
```

Appendix M

AMOS 26 Syntax for SEM Parsimonious Model

```
Att1 = (1) Attitude_ + (1) e9
Att2 = Attitude_ + (1) e8
Att3 = Attitude_ + (1) e7
Att4 = Attitude_ + (1) e6
Beh_Int = Attitude_ + Faci_Cond + Per_Cred + Perf_Exp + (1) e1 + Soc_Inf
BI1 = (1) Beh_Int + (1) e3
BI2 = Beh_Int + (1) e4
BI3 = Beh_Int + (1) e5
FC1 = (1) Faci_Cond + (1) e13
FC2 = Faci_Cond + (1) e12
FC3 = (1) e11 + Faci_Cond
FC4 = Faci_Cond + (1) e10
PC1 = (1) Per_Cred + (1) e25
PC2 = (1) e24 + Per_Cred
PC3 = (1) e23 + Per_Cred
PC4 = (1) e22 + Per_Cred
PE1 = (1) e21 + (1) Perf_Exp
PE2 = Perf_Exp + (1) e20
PE3 = Perf_Exp + (1) e19
PE4 = Perf_Exp + (1) e18
Per_Cred = Perf_Exp + (1) e2
SI1 = (1) Soc_Inf + (1) e17
SI2 = Soc_Inf + (1) e16
SI3 = Soc_Inf + (1) e15
SI4 = Soc_Inf + (1) e14
e24 <> e25
e19 <> e25
e18 <> e19
e16 <> e23
e14 <> e17
e14 <> e16
e13 <> e23
e13 <> e19
e12 <> e16
e12 <> e14
e11 <> e19
e10 <> e17
e6 <> e11
e6 <> e23
e23 <> e24
e7 <> e18
e7 <> e21
```

e6 <> e16
e10 <> e23
e11 <> e21
e12 <> e20
e13 <> e20
e13 <> e21
e19 <> e21
e20 <> e21
e23 <> e25
e2 <> e3
e5 <> e1
e2 <> e1
e11 <> e20
e15 <> e16
e19 <> e20
e18 <> e21
e15 <> e23
Faci_Cond <> e18
e1 <> Soc_Inf
Soc_Inf <> e2
Attitude_ <> Faci_Cond
e7 <> Soc_Inf
Perf_Exp <> e23
Soc_Inf <> Perf_Exp
Faci_Cond <> Perf_Exp
Attitude_ <> Perf_Exp
Faci_Cond <> Soc_Inf
Attitude_ <> Soc_Inf
e7 <> e20
e5 <> e22
e2 <> e21

Appendix N

Measures of Sampling Adequacy: Anti-image Covariance

Anti-image Matrices

		BI1	BI2	BI3	PE1	PE2	PE3	PE4	SI2	SI3	SI4	PC1	PC2	PC3	PC4	FC1	FC2	FC3	FC4	Att1	Att2	Att3	Att4
Anti-image Covariance	BI1	0.310	-0.178	-0.102	-0.008	-0.009	-0.020	-0.038	-0.015	0.032	-0.015	0.037	-0.004	0.014	-0.034	-0.004	0.028	-0.008	0.008	0.002	0.043	0.029	-0.032
	BI2	-0.178	0.331	-0.111	0.028	0.025	0.011	-0.018	0.040	-0.061	0.022	-0.022	0.010	-0.005	-0.007	-0.020	-0.028	0.011	0.057	0.016	-0.059	-0.008	-0.012
	BI3	-0.102	-0.111	0.354	-0.050	-0.007	-0.056	0.036	-0.036	0.016	-0.023	0.015	-0.024	-0.027	0.081	-0.017	0.032	-0.019	-0.067	0.023	-0.006	-0.043	0.018
	PE1	-0.008	0.028	-0.050	0.497	-0.123	-0.005	-0.164	-0.007	-0.020	0.062	-0.032	0.006	-0.042	0.031	-0.025	-0.004	-0.021	0.021	-0.060	0.058	-0.111	0.051
	PE2	-0.009	0.025	-0.007	-0.123	0.585	-0.134	0.072	-0.019	-0.044	0.033	0.026	0.020	-0.038	0.017	-0.089	-0.112	-0.059	-0.004	0.031	-0.102	0.090	0.072
	PE3	-0.020	0.011	-0.056	-0.005	-0.134	0.408	-0.164	0.007	-0.019	-0.049	0.078	-0.057	-0.013	-0.003	-0.043	0.031	-0.061	0.079	-0.055	0.043	-0.019	0.003
	PE4	-0.038	-0.018	0.036	-0.164	0.072	-0.164	0.452	-0.028	0.009	-0.033	-0.029	0.048	-0.033	-0.038	-0.030	-0.025	-0.019	-0.081	0.039	-0.012	-0.034	0.013
	SI2	-0.015	0.040	-0.036	-0.007	-0.019	0.007	-0.028	0.551	-0.210	-0.150	-0.010	-0.010	0.081	-0.068	0.027	-0.067	-0.039	-0.028	-0.033	-0.023	-0.031	0.112
	SI3	0.032	-0.061	0.016	-0.020	-0.044	-0.019	0.009	-0.210	0.672	-0.065	0.028	-0.035	0.056	0.033	0.004	-0.001	0.037	0.032	-0.019	0.047	-0.058	-0.099
	SI4	-0.015	0.022	-0.023	0.062	0.033	-0.049	-0.033	-0.150	-0.065	0.643	-0.024	0.048	0.028	-0.035	-0.034	-0.126	0.022	0.000	0.009	0.075	-0.041	0.028
	PC1	0.037	-0.022	0.015	-0.032	0.026	0.078	-0.029	-0.010	0.028	-0.024	0.336	-0.166	-0.029	0.014	-0.017	-0.048	0.024	-0.029	-0.003	0.050	0.018	0.040
	PC2	-0.004	0.010	-0.024	0.006	0.020	-0.057	0.048	-0.010	-0.035	0.048	-0.166	0.229	-0.106	-0.067	0.021	-0.008	-0.034	0.021	0.001	-0.022	0.016	0.012
	PC3	0.014	-0.005	-0.027	-0.042	-0.038	-0.013	-0.033	0.081	0.056	0.028	-0.029	-0.106	0.261	-0.108	-0.048	0.059	-0.003	-0.052	0.057	0.019	0.000	-0.058
	PC4	-0.034	-0.007	0.081	0.031	0.017	-0.003	-0.038	-0.068	0.033	-0.035	0.014	-0.067	-0.108	0.636	-0.004	-0.081	0.063	0.058	-0.114	-0.094	0.035	0.026
	FC1	-0.004	-0.020	-0.017	-0.025	-0.089	-0.043	-0.030	0.027	0.004	-0.034	-0.017	0.021	-0.048	-0.004	0.558	-0.101	-0.076	-0.065	-0.079	-0.002	-0.028	0.032
	FC2	0.028	-0.028	0.032	-0.004	-0.112	0.031	-0.025	-0.067	-0.001	-0.126	-0.048	-0.008	0.059	-0.081	-0.101	0.590	-0.077	-0.089	0.089	-0.040	-0.071	-0.108
	FC3	-0.008	0.011	-0.019	-0.021	-0.059	-0.061	-0.019	-0.039	0.037	0.022	0.024	-0.034	-0.003	0.063	-0.076	-0.077	0.516	-0.092	-0.012	0.019	-0.057	-0.194
	FC4	0.008	0.057	-0.067	0.021	-0.004	0.079	-0.081	-0.028	0.032	0.000	-0.029	0.021	-0.052	0.058	-0.065	-0.089	-0.092	0.685	-0.100	-0.141	0.037	-0.059
	Att1	0.002	0.016	0.023	-0.060	0.031	-0.055	0.039	-0.033	-0.019	0.009	-0.003	0.001	0.057	-0.114	-0.079	0.089	-0.012	-0.100	0.870	0.019	-0.102	-0.033
	Att2	0.043	-0.059	-0.006	0.058	-0.102	0.043	-0.012	-0.023	0.047	0.075	0.050	-0.022	0.019	-0.094	-0.002	-0.040	0.019	-0.141	0.019	0.807	-0.165	-0.045
	Att3	0.029	-0.008	-0.043	-0.111	0.090	-0.019	-0.034	-0.031	-0.058	-0.041	0.018	0.016	0.000	0.035	-0.028	-0.071	-0.057	0.037	-0.102	-0.165	0.688	-0.005
	Att4	-0.032	-0.012	0.018	0.051	0.072	0.003	0.013	0.112	-0.099	0.028	0.040	0.012	-0.058	0.026	0.032	-0.108	-0.194	-0.059	-0.033	-0.045	-0.005	0.719

Appendix O

Measures of Sampling Adequacy: Anti-image Correlation Matrices

Anti-image Matrices																							
		BI1	BI2	BI3	PE1	PE2	PE3	PE4	SI2	SI3	SI4	PC1	PC2	PC3	PC4	FC1	FC2	FC3	FC4	Att1	Att2	Att3	Att4
Anti-image Correlation	BI1	.800[a]	-0.556	-0.308	-0.019	-0.021	-0.056	-0.101	-0.035	0.071	-0.033	0.115	-0.015	0.049	-0.076	-0.009	0.067	-0.019	0.017	0.003	0.086	0.062	-0.069
	BI2	-0.556	.774[a]	-0.323	0.069	0.056	0.029	-0.047	0.093	-0.129	0.047	-0.066	0.036	-0.018	-0.016	-0.048	-0.062	0.027	0.121	0.030	-0.114	-0.016	-0.025
	BI3	-0.308	-0.323	.866[a]	-0.118	-0.016	-0.146	0.090	-0.082	0.033	-0.048	0.042	-0.083	-0.090	0.171	-0.037	0.071	-0.044	-0.135	0.041	-0.011	-0.087	0.036
	PE1	-0.019	0.069	-0.118	.865[a]	-0.229	-0.010	-0.347	-0.014	-0.035	0.109	-0.079	0.018	-0.117	0.055	-0.047	-0.008	-0.042	0.036	-0.091	0.091	-0.190	0.086
	PE2	-0.021	0.056	-0.016	-0.229	.818[a]	-0.275	0.141	-0.034	-0.070	0.054	0.059	0.056	-0.097	0.029	-0.155	-0.191	-0.107	-0.007	0.043	-0.148	0.141	0.111
	PE3	-0.056	0.029	-0.146	-0.010	-0.275	.846[a]	-0.382	0.014	-0.036	-0.095	0.211	-0.185	-0.040	-0.007	-0.091	0.063	-0.133	0.149	-0.092	0.074	-0.036	0.005
	PE4	-0.101	-0.047	0.090	-0.347	0.141	-0.382	.839[a]	-0.056	0.016	-0.062	-0.075	0.151	-0.097	-0.071	-0.060	-0.048	-0.039	-0.145	0.061	-0.020	-0.061	0.022
	SI2	-0.035	0.093	-0.082	-0.014	-0.034	0.014	-0.056	.740[a]	-0.346	-0.253	-0.023	-0.029	0.214	-0.114	0.049	-0.118	-0.073	-0.046	-0.048	-0.035	-0.050	0.178
	SI3	0.071	-0.129	0.033	-0.035	-0.070	-0.036	0.016	-0.346	.753[a]	-0.099	0.059	-0.090	0.135	0.051	0.006	-0.001	0.064	0.046	-0.025	0.063	-0.085	-0.142
	SI4	-0.033	0.047	-0.048	0.109	0.054	-0.095	-0.062	-0.253	-0.099	.803[a]	-0.051	0.126	0.068	-0.054	-0.056	-0.205	0.039	0.000	0.012	0.104	-0.061	0.041
	PC1	0.115	-0.066	0.042	-0.079	0.059	0.211	-0.075	-0.023	0.059	-0.051	.735[a]	-0.598	-0.099	0.031	-0.039	-0.107	0.057	-0.061	-0.006	0.095	0.037	0.081
	PC2	-0.015	0.036	-0.083	0.018	0.056	-0.185	0.151	-0.029	-0.090	0.126	-0.598	.734[a]	-0.435	-0.176	0.058	-0.022	-0.098	0.052	0.003	-0.051	0.041	0.030
	PC3	0.049	-0.018	-0.090	-0.117	-0.097	-0.040	-0.097	0.214	0.135	0.068	-0.099	-0.435	.828[a]	-0.266	-0.126	0.151	-0.008	-0.124	0.120	0.041	0.001	-0.133
	PC4	-0.076	-0.016	0.171	0.055	0.029	-0.007	-0.071	-0.114	0.051	-0.054	0.031	-0.176	-0.266	.752[a]	-0.006	-0.133	0.110	0.087	-0.153	-0.131	0.053	0.038
	FC1	-0.009	-0.048	-0.037	-0.047	-0.155	-0.091	-0.060	0.049	0.006	-0.056	-0.039	0.058	-0.126	-0.006	.929[a]	-0.176	-0.141	-0.105	-0.114	-0.003	-0.044	0.050
	FC2	0.067	-0.062	0.071	-0.008	-0.191	0.063	-0.048	-0.118	-0.001	-0.205	-0.107	-0.022	0.151	-0.133	-0.176	.788[a]	-0.140	-0.140	0.125	-0.058	-0.111	-0.167
	FC3	-0.019	0.027	-0.044	-0.042	-0.107	-0.133	-0.039	-0.073	0.064	0.039	0.057	-0.098	-0.008	0.110	-0.141	-0.140	.885[a]	-0.155	-0.017	0.030	-0.096	-0.319
	FC4	0.017	0.121	-0.135	0.036	-0.007	0.149	-0.145	-0.046	0.046	0.000	-0.061	0.052	-0.124	0.087	-0.105	-0.140	-0.155	.790[a]	-0.129	-0.189	0.054	-0.084
	Att1	0.003	0.030	0.041	-0.091	0.043	-0.092	0.061	-0.048	-0.025	0.012	-0.006	0.003	0.120	-0.153	-0.114	0.125	-0.017	-0.129	.611[a]	0.023	-0.132	-0.042
	Att2	0.086	-0.114	-0.011	0.091	-0.148	0.074	-0.020	-0.035	0.063	0.104	0.095	-0.051	0.041	-0.131	-0.003	-0.058	0.030	-0.189	0.023	.624[a]	-0.221	-0.060
	Att3	0.062	-0.016	-0.087	-0.190	0.141	-0.036	-0.061	-0.050	-0.085	-0.061	0.037	0.041	0.001	0.053	-0.044	-0.111	-0.096	0.054	-0.132	-0.221	.842[a]	-0.008
	Att4	-0.069	-0.025	0.036	0.086	0.111	0.005	0.022	0.178	-0.142	0.041	0.081	0.030	-0.133	0.038	0.050	-0.167	-0.319	-0.084	-0.042	-0.060	-0.008	.677[a]

a. Measures of Sampling Adequacy(MSA)

Appendix P

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	100	253.092	176	.000	1.438
Saturated model	276	.000	0		
Independence model	23	2414.191	253	.000	9.542

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	.077	.922	.878	.588
Saturated model	.000	1.000		
Independence model	.303	.427	.375	.391

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.895	.849	.966	.949	.964
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.696	.623	.671
Saturated model	.000	.000	.000

Model	PRATIO	PNFI	PCFI
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	77.092	38.784	123.411
Saturated model	.000	.000	.000
Independence model	2161.191	2007.487	2322.285

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1.033	.315	.158	.504
Saturated model	.000	.000	.000	.000
Independence model	9.854	8.821	8.194	9.479

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.042	.030	.053	.865
Independence model	.187	.180	.194	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	453.092	474.811	803.625	903.625
Saturated model	552.000	611.946	1519.472	1795.472
Independence model	2460.191	2465.187	2540.814	2563.814

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	1.849	1.693	2.038	1.938
Saturated model	2.253	2.253	2.253	2.498
Independence model	10.042	9.414	10.699	10.062

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	202	216
Independence model	30	32

Execution time summary

Minimization: .141

Miscellaneous: 1.680

Bootstrap: .000

Total: 1.821