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The Influence of Identifiable Personality Traits on Nurses' Intention to Use Wireless Implantable Medical Devices

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by

Vincent Molosky

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for the degree of Doctor of Philosophy
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We hereby certify that this dissertation, submitted by Vincent Molosky, conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirements for the degree of Doctor of Philosophy.

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An Abstract of a Dissertation Submitted to Nova Southeastern University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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Vincent J. Molosky
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Technically-driven medical devices such as wireless implantable medical devices (WIMD) have become ubiquitous within healthcare. The use of these devices has changed the way nurses administer patient care. Consequently, the nursing workforce is large and diverse, and with it comes an expected disparity in personalities. Research involving human factors and technology acceptance in healthcare is not new. Yet due to the changing variables in the manner of which patient care is being administered, both in person and in the mechanism of treatment, recent research suggests that individual human factors such as personality traits may hold unknown implications involving more successful adoption of emerging technologies for patient care.

The purpose of this research was to empirically investigate the influence of personality traits on a nurse's intention to use WIMDs for patient care. One hundred and two nurses from a tertiary teaching hospital in Michigan were surveyed to determine if their identifiable personality traits statistically related to their intention to use a WIMD. A predictive model was developed by combining constructs from the unified theory of acceptance and use of technology (UTAUT) model and the Five Factor personality trait model (FFM). The model used moderated multiple regression (MMR) to statistically identify if the personality traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism, moderated one or more statistically significant relationships between 1) performance expectancy (PE) and intention to use (IU), 2) effort expectancy (EE) and IU, 3) and social influence (SI) and IU. It was predicted that PE, EE, and SI would show statistical significance on a nurse's IU of a WIMD when moderated by one or more of the five personality traits. Results showed statistical significance between PE and IU, and EE and IU, but not between SI and IU, when moderated by extraversion. Results showed no statistical significance between PE and IU, EE and IU, or SI and IU when moderated by openness, conscientiousness, agreeableness, or neuroticism.

This research has contributed by conducting an investigation on individual human factors that may impact nurses' intention to use emerging technologies; and by providing statistical evidence that may help to better predict the role personality traits have on a nurse's adoption of WIMDs for patient care.

Acknowledgements

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I would also like to thank my family and friends for their continuous encouragement throughout this arduous process, especially to my wife Kimberly, and to my daughters Isabella and Sophia. Without their love and unwavering support I would have never considered such a goal possible. I am forever grateful to both my parents and in-laws for their tremendous support and encouragement throughout this process. Many thanks to my close friends and hockey buddies for pushing me just when I needed it.

Having a family of my own has instilled in me a level of endless motivation, certainly to provide for them, but also in becoming a role model, and in showing them what you can do regardless of the circumstances. I dedicate this dissertation with love to my daughters Isabella and Sophia, as an example of what hard work can allow you to accomplish.

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Chapter 1

Introduction

This research empirically investigated the influence of a nurse's identifiable personality traits and his or her intention to use wireless implantable medical devices (WIMD) for patient care. A conceptual framework was developed combining constructs from Venkatesh, Morris, Davis, and Davis's (2003) unified theory of acceptance and use of technology (UTAUT) model and the Five Factor personality trait model (FFM), based on McCrae and John's (1992), and Goldberg's (1999) five-dimension personality trait research. This framework was used to establish a predictive model to identify significant relationships between variables, to test the research hypotheses, and finally to answer the three questions that guided this research. In accordance with the current body of literature, a framework combining the FFM and UTAUT with focus on nurses and the use of WIMDs had yet to be applied within the healthcare domain. The results from this research has provided empirical data that may help lead to a better understanding as to the role and level of influence personality traits has on a nurse's adoption of emerging technologies for patient care.

This dissertation report consists of five chapters, and provides a narrative of this research, from an initial introduction, to the conclusion of results and future recommendations. Chapter 1 provides an overview of the investigation and describes both the purpose and main goal of this research. A description of the relevance and significance pertaining the research problem, and the supporting literature used to validate and develop the problem statement are presented. Chapter 1 introduces the FFM and the UTAUT constructs that were used to both develop the theoretical framework, and also to establish the three main questions that had guided this research. Chapter 1 also presented the current barriers and issues faced with solving the research problem, along with a description of the assumptions, limitations and delimitations that challenged this research.

Background

According to Khan et al. (2012), a wireless body area network (WBAN) is a communications system comprising of sensor nodes placed in or around the human body for real-time health monitoring. WBANs collect and transmit health data such as heart rate, skin temperature, and blood pressure to a remote destination such as to a workstation or mobile device. WBANs are often referred to as body area networks (BAN), body sensor networks (BSN), or personal area networks (PAN). Typical WBANs transfer patient health data using one of several wireless communication protocols such as ZigBee, radio frequency identification (RFID), or Bluetooth (Baig et al., 2017; Beretta, Rincon, & Khaled, 2012; Chan, Esteve, Fourniols, Escriba, & Campo, 2012). Implantable medical devices (IMD) have been in use for an extensive period of time and vary in size and complexity (Denning et al., 2010). In relation to this research an IMD is defined by Denning et al., as “electronic devices designed to treat abnormal physiological conditions within the body” (p. 917). Based on this definition and in combination with WBAN capabilities, a WIMD can therefore be defined as a medical system that uses a form of wireless technology to connect and administer patient care between implantable physical devices and remote end-user software applications. Devices such as pacemakers, implantable cardioverter-defibrillators (ICD), insulin pumps, and pain infusion pumps that are invasive and incorporate wireless functionality can be considered as WIMDs (Denning et al.).

Khan, et al. (2012) assert that recent breakthroughs in wireless communication protocols, reductions in sensor node power consumption, and improved computer chip capabilities have led to emerging technologies such as WIMDs for patient care. Day, Schoemaker, and Gunther (2000) define emerging technologies as "science-based innovations that have potential to create a new industry or transform an existing one; deriving from radical innovations; and formed by the convergence of previously separate research streams" (p. 2). Despite this, recent studies suggested that the growth and pervasiveness of IMDs, WBANs, and in relation WIMDs, generate more complex challenges involving administration, and initiate a greater resistance in the adoption phase by healthcare professionals (Chan, et al., 2012; Denning, et al., 2010; Hatz, Sonnenschein, & Blankart, 2017; Kumar, Lee, & Lee, 2011).

A literature review conducted by Li et al. (2013), showed that past research involving the adoption of technologies in healthcare more often than not targeted physicians as the healthcare professional. Out of 93 papers reviewed by Li et al., 68 focused solely on physicians, and 25 on a combination of other healthcare professionals including RNs, licensed practical nurses (LPN), and physician assistants (PA). A good example of this of a past and ongoing trend can be seen in Yarborough and Smith's (2007) literature review and research on technology acceptance among physicians. Yarbrough and Smith's study focused on the adoption of emerging technologies in the healthcare domain similar to this research stream, however, physicians were the only healthcare professionals considered. As reiterated by Li et al., this trend continues. While physicians will always be the principle caregiver and decision maker, nurses are an essential part of the process in administering quality patient care (Aldosari, Al-Mansour, Aldosari, & Alanazi, 2017; Hung, Tsai, & Chuang, 2014; Li et al.).

According to the Bureau of Labor Statistics (2017), Occupational Employment and Wages report there were over 3.5 million nurses employed nationally, and the largest share of healthcare jobs in the United States (US). This number consists of RNs, LPNs, nurse practitioners (NP), nurse midwives (NM), nurse anesthetists (NA), and clinical nurse specialists (CNS). Table 1 shows an employment comparison between these nursing professions and those of physicians, surgeons and physician assistants (PA). References within this report using the term ‘nurse’ and ‘nurses’, included all six of these nursing professions.

Table 1
Occupational Employment Statistics - National Estimates as of May, 2017

Occupation	*Number Employed (Individuals)*
Registered Nurse (RN) & Clinical Nurse Specialist (CNS)	2,687,310 (http://www.bls.gov/oes/current/oes291141.htm, 2017)
Licensed Practical Nurse (LPN)	695,610 (http://www.bls.gov/oes/current/oes292061.htm, 2017)
Nurse Practitioner (NP)	136,060 (http://www.bls.gov/oes/current/oes291171.htm, 2017)
Nurse Midwife (NM)	5,110 (http://www.bls.gov/oes/current/oes291161.htm, 2017)
Nurse Anesthetist (NA)	36,590 (http://www.bls.gov/oes/current/oes291151.htm, 2017)
Physicians and Surgeons	311,320 (http://www.bls.gov/oes/current/oes291069.htm, 2017)
Physician Assistants (PA)	91,670 (http://www.bls.gov/oes/current/oes291071.htm, 2017)

Note: NAs, NMs, and NPs are the Advanced Practice Registered Nurses (APRNs).

Researchers have recognized this gap between the nursing healthcare profession and the adoption of emerging technologies and have initiated new and exclusive research to help remedy this proven need. For example, Holtz and Krein (2011) conducted a study focusing solely on nurses, while excluding all other healthcare professionals. Holtz and Krein adopted the UTAUT model to predict a nurse's intention to use an electronic medical record (EMR) system, which at that time was an emerging technology in healthcare. Aldosari et al. (2017) conducted a study on nurse's acceptance of an EMR system using a variation of the technology acceptance model (TAM). Aldosari et al. included constructs representing the impact of top management and information technology (IT) support. Aldosari et al. found that there was a positive correlation between top management, perceived usefulness (PU), perceived ease of use (PEU) and their acceptance of the EMR system.

For many nurses their job duties continue to be critical in nature and the resulting consequences of failure great. Much success is dependent on their ability to effectively use the designated mechanism of treatment for patient care. This fundamental has not changed, but because of the continuing separation between traditional and technically-dependent methods of patient care many nurses have had their job duties altered, with no choice but to conform, and attempt to become more proficient in using emerging technologies such as WIMDs (Aldosari et al., 2017; Chang & Hsu, 2012). For the purpose of clarification, it is assumed that nurses are not the principle decision makers in the use of WIMDs and the likely result of inherently technical job responsibilities. Because of this, a nurse's intention to use does not infer direct choice but rather their perceptions, attitudes, and beliefs influenced by WIMDs and related technologies.

Problem Statement

The problem that this research addressed was a need to gain a better understanding of nurses' intention to use methods of patient care that utilize emerging technologies in the form of wireless and implantable medical devices and systems. Recent studies supported this and had demonstrated that many nurses were reluctant to adopt non-traditional methods of patient care that incorporate tasks involving emerging technology (Ifinedo, 2012; Karsh et al., 2009; Li et al., 2013). Hwabamungu and Williams (2010) reinforced this problem and asserted that successful adoption and sustainability of such technologies are not solely based on the capability or effectiveness of the device or system, but the intention to use by the caregiver. In directly discussing wearable patient monitoring (WPM) devices, Baig et al. (2017) state that "the acceptance of any system in the healthcare domain depends on user-awareness, as well as clinician and patient acceptance" (p.7). According to Ifinedo, success or failure for a large percentage of technology-related projects in healthcare is dependent upon the healthcare professional's level of resistance, including nurses.

In support of this problem, de Veer, Fleuren, Bekkama, and Francke (2011) claimed that if innovative technology is not properly introduced into a nurse's workflow then the technology may not be used as intended, and in turn patient care stands less of a chance of being administered as effectively as possible. In an attempt to help solve this issue de Veer et al. developed a framework based on Rogers' (2003) Diffusion of Innovations (DOI) theory using categories of innovation determinants and innovation processes. de Veer et al.'s goal was "to gain a better understanding of the determinants influencing the success or failure of the innovation process of new technologies as perceived by nursing staff". (p. 3). In a survey administered by de Veer et al., approximately half of the nurses who recently had technology introduced into their workflow responded negatively. This included feedback on EMRs, remote healthcare, and various emerging technologies for patient care.

A literature review by Li et al. (2013) reported that as of 2013 there was still a significant need for research involving technology acceptance by healthcare professionals. Li et al. stated that "due to the complex contextual dynamics of healthcare settings, our work suggested that there would be potential to extend theories on information technology adoption" (p. 1). More recently Hung, Tsai, and Chuang (2014) conducted a study using theory of reasoned action (TRA) along with three additional constructs of implementation context (IMC), technological context (TC), and individual context (INC) to develop a new theoretical model. Hung et al.'s model predicted that trustworthiness (TW) and perceived usefulness (PU) had a positive relationship on a nurse's intention to use a specialized health information system. A unique aspect of Hung et al.'s study, which was conducted in a Taiwanese hospital, was that nurses were not required to use the new system. Each individual nurse had the option to continue to utilize the old system without penalty. Hung, et al. concluded that a nurse's failure to adopt may be due to a lack of effective policies and procedures, inadequate training applications, and too short periods of learning; each having the potential to negatively affect current patient care, and even hinder future developments in patient care. Baig et al. (2017) also conduct a literature review pertaining to wearable monitoring systems and the importance on the acceptance of such devices by healthcare professional and patient alike. Baig, et al., believe that due to the dependency and affordability, that inevitability patient care will come to fully rely on such technology. This will ensure that nurses will need to adapt and adopt, and the importance of organizational training and procedures.

The circumstances involved, within the context of this combination of nurse and advanced technologies, shows that there has been a multitude of predictors and theoretical models applied in an attempt at solving this problem. The common variable is the increasing complexity in the mechanism and process of treatment used for patient care. This means that the evolution of the problem can essentially be traced to the proliferation of emerging technologies and a nurse's lack of familiarity to them. There seems to be little evidence that the current methods of diffusion are effective enough, as significant challenges involving nurses' intention to use remains (Bautista, Rosenthal, Lin, & Theng, 2018; Bennani & Oumlil, 2013; Li, et al., 2013; Vitari & Ologeanu-Taddei, 2018).

Dissertation Goal

The main goal of this research was to empirically investigate the influence of identifiable personality traits on a nurse's intention to use WIMDs for patient care. The secondary goal of this research was to enrich the current body of knowledge (BOK) by contributing new data, and by demonstrating the impact of identifiable personality traits on a nurse's intention to use emerging technologies in the form of wireless and implantable devices for patient care. To accomplish this, a conceptual model was developed combining the UTAUT model and FFM to create a foundation of research constructs (see Figure 1).

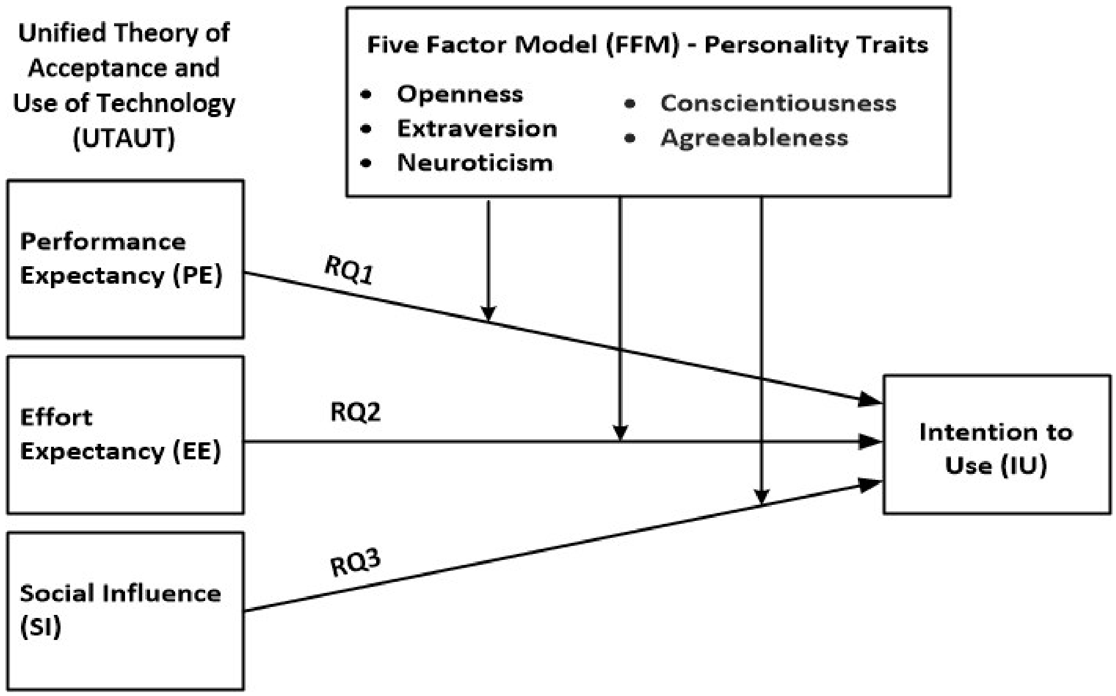


Figure 1. Conceptual Model: UTAUT with inclusion of FFM

The results of this research showed implications for future studies and provided new insight on other possible avenues of research pertaining to individual human behavioral factors and their role in successful adoption of emerging technologies for use throughout the healthcare domain. The resulting data from this research may be used directly or indirectly to help healthcare institutions, vendors, and practitioners alike.

Research Questions

The main question that guided this research is: Does a nurse's identifiable personality traits influence his or her intention to use emerging technologies in the form of WIMD systems for patient care? By applying the conceptual model this main question was then broken down into three distinct research questions. Each of these questions incorporated one of Venkatesh, et al.'s (2003) UTAUT predictors of behavior in the form of intention to use (IU), represented by constructs of performance expectancy (PE), effort expectancy (EE), social influences (SI).

Each of the three research questions also incorporated five individual moderators. This set of moderating constructs constituted the five FFM personality traits. This included openness, conscientiousness, extraversion, agreeableness, and neuroticism (McCrae & John, 1992). Supporting data in the form of demographics that are typically included in the UTAUT framework were collected to offer additional characteristics. These were age, gender, and technology work experience (TWE). TWE derives from Venkatesh, et al.'s (2003) UTAUT construct of work experience (WE) and represents the level of technology within a nurse's workflow in terms of WIMD exposure. TWE was collected to add to the descriptive data, with an option to control for the different groups of nurses, those with and without WIMD experience. More in-depth descriptions of these construct's operational measures follow this section. Based on these defined constructs, the research questions that were used to drive the research are as follows:

Research Question 1 (RQ1)

Will performance expectancy (PE) influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs), and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

Research Question 2 (RQ2)

Will effort expectancy (EE) influence a nurse's IU WIMDs, and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

Research Question 3 (RQ3)

Will social influence (SI) influence a nurse’s IU WIMDs, and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

UTAUT Constructs

Venkatesh et al., (2003) established four foundational concepts of PE, EE, SI, and FC to predict either behavioral intentions or actual behavior. These four constructs are the theoretical underpinnings of the UTAUT model. In their own words, Venkatesh et al. state that “future research should focus on identifying constructs that can add to the prediction of intention and behavior over and above what is already known and understood" (pg. 471). Therefore, in review of the research goal and guided by the research questions, PE, EE, and SI were implemented into the theoretical model and used as the three main constructs in predicting nurses’ intention to use WIMDs.

In predicting IU, PE can be defined as the degree to which a nurse believes that using a WIMD will better assist him or her in job performance in the form of patient care. Empirically PE has shown to be a strong predictor and of positive correlation to IU (Holtz & Krein, 2011; Hung, et al., 2014; Venkatesh, et al., 2011). In predicting IU, EE can be defined as the degree to which a nurse believes a certain level of effort is necessary in using a WIMD for patient care. Officially defined as “ease associated with the use of the system” (Venkatesh, et al., 2003, p.450), EE has empirically shown to be negatively correlated with IU in some instances (Venkatesh, et al., 2011). In predicting IU, SI can be defined as a nurse’s perceived social pressure or social status achieved from using a WIMD for patient care. As with PE, SI has empirically shown to typically have a positive correlation with IU (Venkatesh, et al.).

Lastly, FC can be defined as the degree to which a nurse believes that an organizational and technical infrastructure are purposely in place to support the use of a “system” (WIMD) and to assist for patient care (Venkatesh, et al., 2003). Venkatesh, et al.’s conceptual development and theoretical underpinnings of FC is partly based on Thompson’s (1991) model of PC utilization (MPCU). Empirical testing completed by Venkatesh, et al. has shown that in this context IU is already captured by EE, and any testing for significance between FC and IU while EE is in place will result in a likely overlap. Because of this, the UTAUT FC is not applied with the purpose to predict IU; though FC is used as a predictor for studies that do measure actual use as a criterion or dependent variable (Venkatesh, et al., Venkateshet al., 2011)

FFM Constructs

To capture and study personality traits various trait theories have been developed over many decades. From Woodsworth’s Personal Data Sheet, published in 1917, to the current FFM domains (Goldberg, 1999; Uffen & Breitner, 2014, Rosellini & Brown, 2017). According to McRae and John (1992) the FFM was developed using non-experimental factor analysis to create a hierarchy of descriptors based on the organization of personality traits in terms of five basic dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Uffen & Breitner).

Korzaan and Bozwell (2008) define a trait as “dimensions of individual differences in tendencies to show consistent patterns of thoughts, feelings and actions” (p.16). Korzaan and Bozwell contend that the more an individual has of a specific trait, the more they will likely exhibit behaviors associated with that trait; and that by studying traits, an individual’s personality can be discovered. McElroy, Hendrickson, Townsend, and DeMarie (2007), define a personality as “a stable set of characteristics and tendencies that determine peoples’ commonalities and differences in thoughts, feelings, and actions” (p.810). Thus, a personality trait can be considered as a representation of an individual’s disposition leading to patterns of attitudes and behaviors that are found to be stable and sustained across a person’s lifespan (McRae & Costa, 1987; Junglas, Johnson, & Spitzmuller, 2008).

Relevance and Significance

Much of the research involving a nurse’s intention to use has examined technologies that have been widely dispersed and already in use for a lengthy period of time. As referenced throughout this report, EMR systems and more generalized information communication technologies (ICTs) were two examples commonly studied (Aldosari et al., 2017; Bautista et al., 2018). Confirmation of this was also found in Li et al.’s (2013) literature review in which 57 out of 93 papers examined EMR’s technology adoption by healthcare professionals. In reviewing the literature the research stream comprising of individual behavior associated with the adoption of emerging technologies was inconsistent at best. Studies using constructs in the form of personality traits involved with the adoption of emerging technologies within the healthcare domain were scarce, showing little contribution to this specific field of study. Prior to this research, this current body of literature showed no empirical research combining the FFM and UTAUT together for use within the healthcare domain. While the reason for an overall lack of research in this context might have been due to how personality traits focus on the individual, it was also an important factor as to why this model and research provides valid insight and helps to contribute to the current BOK. Cocosila (2013) provides an explanation and states that “these traits could make individuals behave differently even if they are exposed to the same context” (p.15). The addition of the UTAUT compiles past technology acceptance models and brings another level of comprehensiveness to this research stream.

There is growing research that points to personality traits impacting behavioral intentions in the IS field. An early example can be seen from Korzaan and Boswell’s (2008) study that used the FFM to predict individual concerns regarding information privacy, computer anxiety, and in relation to this research, behavioral intentions. Korzaan and Boswell reiterate that a deeper understanding is needed to identify the impact personality traits have on an individual’s choices in areas of IS. Junglas, Johnson, and Spitzmuller (2008) conducted similar research using the FFM’s Big Five personality traits and the concern for privacy (CFP) in an attempt to measure an emerging technology in the form of location-based services (LBS).

More recently Barnett et al. (2015) utilized constructs from the UTAUT and the FFM to form a theoretical model as a way to predict both perceived and actual use of technology. The results Barnett et al.’s study showed that three personality traits were significant predictors of perceived and actual use. Kennedy, Curtis, and Waters (2014) administered a personality test in Australia using Costa and McCrae’s (2010) NEO-PI-3 personality trait (neuroticism, extraversion, openness, and personality inventory version 3) to 72 emergency room (ER) nurses. Kennedy et al.’s goal was to try and identify how personality influences nurses’ decision making in the context of the ER setting, by comparing their results to those of a similar number from the general population.

Kennedy et al. found ER nurses to show higher significance in extraversion, openness and agreeableness. The NEO-PI-3 and its personality trait facets used to collect data derive directly from the FFM and its five personality domains used for this research.

In closer relation to this research's theoretical framework, Devaraj, Easley, and Crant's (2008) model combines the TAM, the FFM, and the construct's subjective norms (SN) and computer self-efficacy (CSE) (Figure 2).

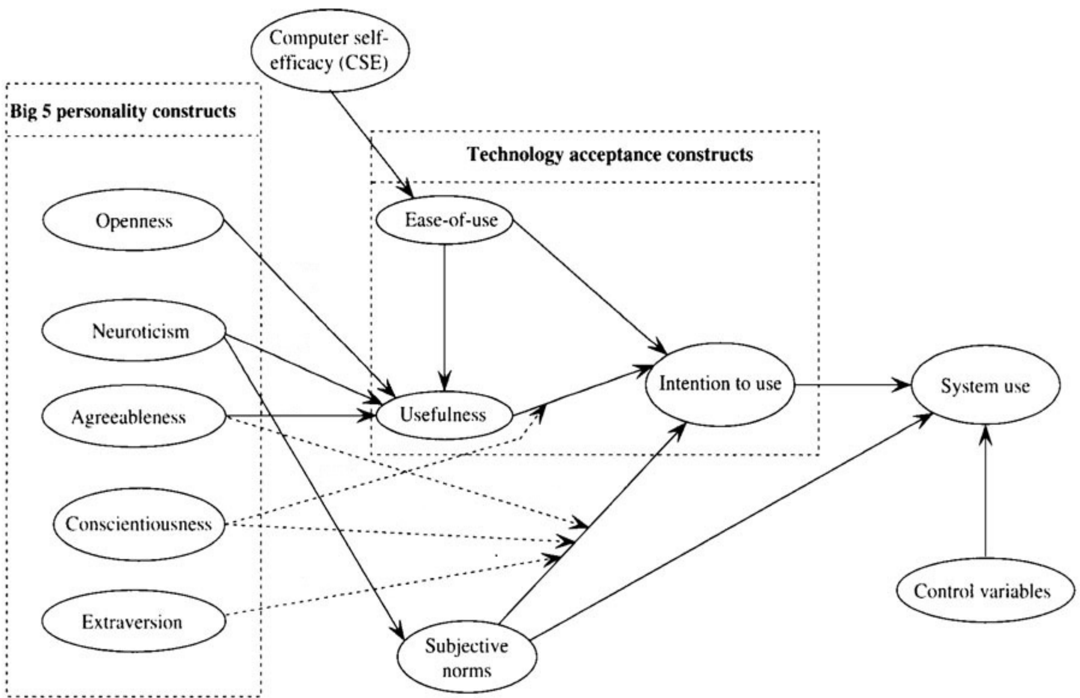


Figure 2. Devaraj, et al.'s (2008) Research Model

The results of Devaraj, et al.'s study displayed statistically significant relationships between several FFM constructs and both CSE and TAM constructs. Although Devaraj, et al.'s study is within the academic domain and not healthcare, Devaraj, et al. does conclude that the five FFM constructs would be predictive moderators for particular technologies and the intention to use. Maier (2011) who builds upon Devaraj, et al.'s study, developed a loose research diagram that combines constructs from the TAM, the

UTAUT, FFM, and other individual related constructs. Maier's proposed research focuses on organizations in general, giving flexibility to modify the research domain (Figure 3).

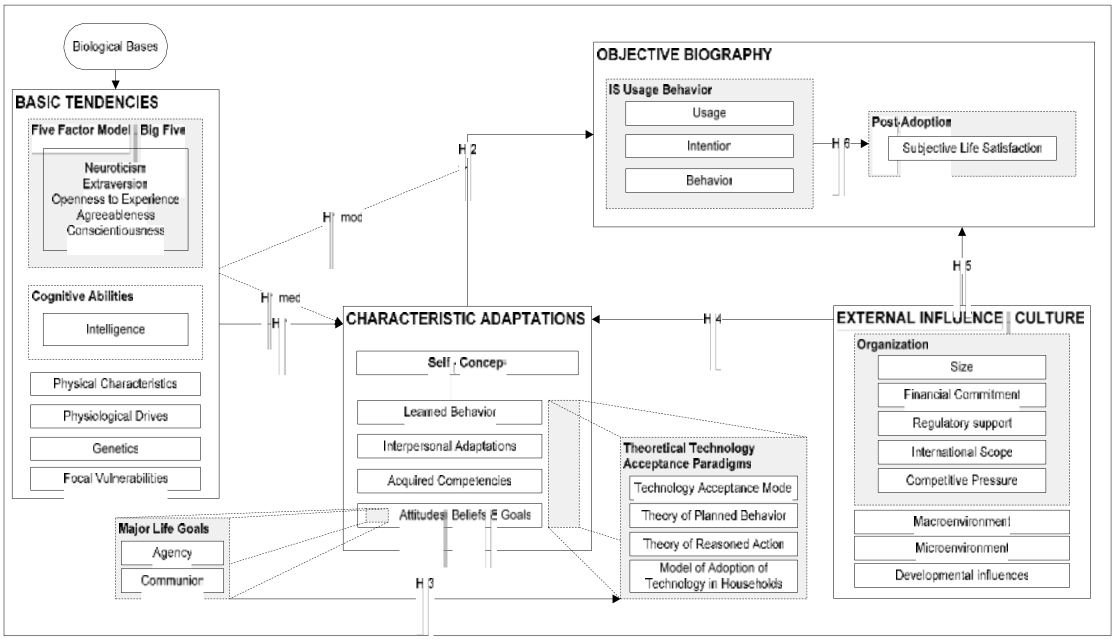


Figure 3. Maier's (2011), integrating technology adoption models and the FFM

Other studies involving the FFM have used personality traits as predictors for either user acceptance or user attitude but have not integrated the UTAUT model as a whole (Barnett et al., 2015). For example, Clark, Karau, and Michalisin (2012) used the FFM's Big Five to identify relationships between user attitudes and personality traits in order to predict workers who may be more receptive to the technical methods necessary for telecommuting. Zhou and Lou (2011) used the Big Five as predictors of user acceptance for mobile commerce. In similar fashion, De Oliveira, Cherubini, and Oliver (2013) used personality traits, actual usage, and perceived usability to measure the level of customer satisfaction for mobile phone services.

WIMDs are unique in the sense that they have yet to be widely deployed but continue to be extensively developed for patient care (Baig et al., 2017; Chan et al., 2012). Once a WIMD is implanted into a patient, the level of physical invasiveness combined with required technical interaction results in a shift in traditional nursing responsibilities and is one of the more significant challenges nurses face in administering quality patient care. Just recently the first wirelessly administered micro-sized pacemaker was implanted into a female patient at the Cleveland Clinic. This device has been aptly named the Nanotism and was developed at St. Jude Medical in Minnesota. The Nanotism is approximately the size of an AAA battery and about 90% smaller than a traditional sized pacemaker (Cleveland.com, 2014).

Another device, just gaining Food and Drug Administration (FDA) approval in mid-2014, is St. Jude Medical's neurostimulation system called the Protégé IPG. This rechargeable WIMD system administers spinal cord stimulation for pain and will enable a patient to receive state of the art treatment methods as they are approved. The Protégé is able to accomplish this by applying software upgrades wirelessly and without the typical need to surgically replace. St. Jude Medical states that "Chronic pain sufferers implanted with this new device can access innovative therapies, stimulation modes, diagnostics, or other features once approved through future software upgrades — without the need to surgically replace their medical device" (St. Jude Medical, 2015, p.1). These two WIMDs offer good examples of what current emerging technologies for patient care represent. The differences between WIMDs and older devices used to administer similar treatment look to be revolutionary. For example, the level of invasiveness, the technology itself, and methods of treatment are all vastly different from what was applied in research even ten years ago.

Based on the unfamiliarity of WIMDs, this rapid diffusion of technology may lead to such things as a lack in policy and procedures and inadequate sources of training; both of which may be essential for successful adoption of WIMDs by nurses (Holtz & Krein, 2011, Vitari & Ologeanu-Taddei, 2018). More complications may evolve when nurses charged with WIMD-related job duties may not have a choice but to carry them out, regardless if they are qualified to do so, perceived or actual. Nurses choosing not to communicate these types of limitations to their supervisor so as to not jeopardize their position may be common. A study conducted by Walter and Lopez (2008) used professional autonomy as a construct in accordance with the TAM. The results of Walter and Lopez's research found that perceived threats to professional autonomy have a negative impact on both IU and PU involving clinical information technology (CIT). An example of a perceived threat might be in the introduction of a new WIMD that improves upon the speed and efficiency of a nurse's workflow. This may also result in unknown or undetected issues involving the quality of patient care being administered (Holtz & Krein).

Taking these factors into consideration a claim can be made that for a nurse to effectively perform his or her duties using WIMDs for patient care, each must have the skill, confidence, and willingness to use (Aldosari et al., 2017; Hwabamungu & Williams, 2010; Ifinedo, 2012). A nurse's resistance to use WIMDs may result in improper use, and ultimately deficiencies in patient care with a variation of consequences, including death (Chang & Hsu, 2012; Li, et al., 2013). Byrd, Byrd, Madariaga, and Mbarika (2011) conducted a study focusing on the safety and quality of healthcare in the United States and reported that medical errors result in costs up to 29 billion dollars annually, and also are the eighth leading cause of death in the U.S. Other obscure issues are also present. For example, a failure in patient care due to human error but blamed intentionally or accidentally on the technology or the medical device can also have serious consequences. By not properly identifying human error as the root cause, a viable and promising method of patient care may be falsely rendered irrelevant or even harmful (de Veer et al., 2011; Ifinedo, 2012).

Having the ability to better understand what influences a nurse's intention to use WIMDs or other emerging technologies on an individual level, an overall improvement in patient care now and in the future is likely. The potential benefits are many and may allow healthcare institutions to more accurately predict adoption factors, to formulate more effective implementation strategies, and to improve upon staff training and education; all inevitably to ensure safe, reliable, and cost-effective methods of patient care (Baig et al., 2017; Bautista et al., 2018; Beretta et al., 2012; de Veer et al., 2011, Vitari & Ologeanu-Taddei, 2018).

Barriers and Issues

There were several barriers to overcome in conducting this research. One barrier was due to unintended restrictions in sample size and diversity. The sample of nurses, which are the unit of analysis, are from a 378-bed tertiary teaching hospital located in southeast Michigan. The hospital currently employs various types of full and part-time nurses. The sample group and location were chosen based on the geographical location and ease of access. Due to this, a non-random sampling method was applied, resulting in some risk for systematic sampling bias, and less representation of the overall population of nurses.

To help overcome this barrier and to get as many nurses within this sample frame to participate, the researcher met with the hospital's Chief Nursing Officer (CNO) and established multiple methods to ensure distribution of the questionnaire. This included a crafted email sent by the CNO to his nurse manager subordinates, and then forwarded on to their nursing subordinates. After initial distribution of this email, another follow-up reminder email was also sent out. In support, 200 printed cards were physically distributed to various departments within the hospital where nurses were employed. The printed cards included a short summary of the research, instructions on how to access and complete the questionnaire, and the secure web uniform resource locator (URL) to the questionnaire. Emphasis was put on the anonymity and voluntariness in participating, along with an opportunity to contribute to valid research involving their profession. These extra measures were taken to mitigate possible reluctance due to voluntary participation and help to increase the number of final submissions.

Another barrier that faced this research was the constant changes and the rapid diffusion of technology into and throughout the healthcare domain. To overcome this barrier, this research focused exclusively on WIMDs that would have been actively in use at the hospital. Example WIMDs would include wireless iterations of pacemakers, implantable cardioverter-defibrillators (ICD), insulin pumps, and pain infusion pumps. This likely allowed for a better chance of recognition by the participating nurses that chose to complete and submit the questionnaire in its entirety. While having the inclusion of nurses with WIMD experience will allow for specific data, those without experience using WIMDs also hold valid data.

Other barriers that this research was faced with were issues of individual bias. For example nurse's attitudes based on their perception of security and privacy concerns, cultural and religious beliefs, self-image, as well as safety concerns pertaining to the invasiveness of WIMDs may influence a nurse's decision to participate (Denning et al., 2010). In an attempt to overcome this barrier the researcher notated that the purpose of this research is to gain a better understanding as to the adoption factors of emerging technologies for nurses and in turn patient care.

Another issue may have resulted from the rapid change in the type and number of patients being cared for by an individual nurse. Unique patient characteristics such as personality, physical presence and diagnosis may have impacted the level of treatment received, such as in the form of accuracy, effectiveness, timeliness, and overall quality (de Veer, et al., 2011). This issue will likely be more prominent for nurses who work in certain types of departments within the hospital. For example, a nurse working in the emergency department will certainly be exposed to more diverse types of patients on a daily basis, due to both the nature of the department and in most cases the type of the care given. In comparison, a nurse working in a long-term care department would not have as many variables impacting the level of care being administered to each patient. According to Tiberio, Mitzner, Kemp, and Rogers (2013), personal robots taking the place of healthcare providers, including nurses, may help to remedy such issues, at least in mitigating the fluctuation in the level of care being provided on a patient to patient basis. Tiberio et al. are quick to admit however, that interactions involving robots would also be relegated to specific types of patients, treatments as well as institutions.

Although the survey for this research was anonymous, due to the inclusion of human subjects a last barrier was in the requirement for Institutional Review Board (IRB) approval. In specific, because nurses are the sample participants, both the college and the hospital required the approval procedure. Under this research the IRB reviewed the risk involving exposure or wellbeing that might have occurred to the participating human subjects. The IRB also confirmed that the research followed institutional protocols set for these actions through policy and consent forms.

Assumptions, Limitations and Delimitations

Assumptions

Several assumptions were established for this research. First, it was assumed that the intended sample participants provided accurate representation of the larger population of nurses that work at the hospital. A second assumption was that the institution of focus provided an accurate representation of a general hospital setting across the United States. It was assumed that questionnaire submissions were anonymous, and therefore a third assumption was that participating nurses answered the questions honestly and to the best of their ability. Lastly, it was assumed that the instruments established for this research have been sufficiently tested for reliability and validity, and therefore were used with assurance.

Limitations

There were several limitations facing this research. One limitation was due to the sample group of nurses being drawn from a single location. This resulted to some extent, in an imbalance in nurse characteristics, such as demographics of race, age and gender; as well as identifiable personality traits. Thus an inadequate representation of the remaining nursing population may have affected the overall generalizability of the research. Another possible limitation was due to the accuracy in sample responses due to the large size and number of items on the questionnaire. Lastly, having an uneven amount of nurses with or without TWE may have also added an imbalance.

Delimitations

A delimitation of this proposed research will result from allowing all nurses employed at the target institution to participate in answering the questionnaire. As mentioned in the Limitations section, this means that there likely will be two types of participating nurses, ones that have or do not have experience using WIMDs. While each perspective, based on the TWE construct, may provide valid data, this separation of two groups may eventually be evaluated and potentially controlled for in future research. Lastly, a majority of the participating nurses likely do not decide on the usability of WIMDs which may have helped limit any biased answers, and helped to get an even more accurate reflection of a nurse's perception, attitude and beliefs, due to that this research was independent from their place of employment, potentially removing any remaining bias.

Definitions of Terms

The following terms pertain only to the scope of this research. Each definition is in the context of information systems, technology and the medical field of study. These terms may hold separate meaning in other research domains.

Agreeableness (A) **–** Is one of the five global FFM personality domains used in research to describe human personalities. When used in research A can be broken down into more explicit traits or primary factors such as compliance, submissive, modesty and trustful, among others (McCrae & John, 1992).

Conscientiousness (C) – Is one of the five global FFM personality domains used in research to describe human personalities. When used in research C can be broken down into more explicit traits or primary factors such as dutifulness, reliable, competence and ethical, among others (McCrae & John, 1992).

Effort Expectancy (EE) – One of four UTAUT constructs and defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003, p. 450).

Extraversion (E) – Is one of the five global FFM personality domains used in research to describe human personalities. When used in research E can be broken down into more explicit traits or primary factors such as outgoing, assertive, social and enthusiastic, among others (McCrae & John, 1992).

Facilitating Conditions (FC) – The second UTAUT construct, defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003, p. 453).

Five Factor Model (FFM) – A personality trait model consisting of five main personality dimensions of openness, conscientiousness, extraversion, agreeableness and neuroticism; sometimes referred to as the ‘Big Five’, and developed by McCrae and John (1992), and Goldberg (1992) (Goldberg, 1993).

Implantable Medical Devices (IMD) – Defined as “electronic devices designed to treat abnormal physiological conditions within the body” (Denning et al., 2010, p.917).

International Personality Item Pool (IPIP) – A public domain website providing multiple instances of personality measures (Goldberg, et al., 2006).

Neuroticism (N) – Is one of the five global FFM personality domains used in research to describe human personalities. When used in research N can be broken down into more explicit traits or primary factors such as anxiety, self-conscious, sensitive, unstable and depressed, among others (McCrae & John, 1992).

Nurse(s) – For the scope of this research any instance of ‘nurse’ or ‘nurses’ within this report will be one the following: clinical nurse specialist (CNS), licensed practical nurse (LPN), nurse anesthetist (NA), nurse midwives (NM), nurse practitioner (NP), or registered nurse (RN) (Bureau of Labor Statistics, 2017).

Openness (O) – Is one of the five global FFM personality domains used in research to describe human personalities. When used in research O, also referred to as openness to experience, can be broken down into more explicit traits or primary factors such as fantasy, ideas, emotions, curiosity and imaginative, among others (McCrae & John, 1992).

Performance Expectancy (PE) – The third UTAUT construct, and defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447).

Social Influence (SI) – The fourth UTAUT construct, and defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003, p. 451).

Technology Acceptance Model (TAM) – A seminal model extended from the theory of reasoned action (TRA) that studies the acceptance of technology by users (Davis, 1989).

Trait Theory – The study of human personality based on individual characteristics, identified by repetition or habitual behavior, feelings, emotions, and thoughts. Gordon

Allport and following, Raymond Cattell developed the current day trait theory foundation (Kassin, 2004).

Technology Work Experience (TWE) – A construct unique to this research model that represents a nurse’s use of a WIMD. TWE holds a dichotomous value represented by either a yes or a no.

Unified Theory of Acceptance and Use of Technology (UTAUT) – A technology acceptance model developed by Venkatesh, Morris, Davis, and Davis (2003). The UTAUT combines eight previous conceptual research models involving usage behavior and technology acceptance (Venkatesh et al., 2003).

Wireless body area network (WBAN) – Any wireless based device that is on the person. Sometimes referred to, or the same as a body area network (BAN), wireless personal area network (WPAN), amongst several other disambiguations (Khan et al., 2012).

Wireless implantable medical device (WIMD) – A medical device that combines the characteristics of both an IMD and a WBAN. An example may be a wirelessly administered pain infusion pump that is physically installed under the human skin (Denning, et al., 2010; Khan, et al., 2012).

Summary

This chapter explained the development and implementation of emerging technologies that have permanently altered the way patient care is administered. Integration and use of technology, in the form of WIMDs continues to become more ubiquitous within the healthcare domain and into a nurse’s workflow. This has resulted in many new challenges, including successful adoption of emerging technologies such as

WIMDs for patient care (Khan, et al., 2012; Li et al., 2013).

This chapter introduced the main research components, including an explanation of WIMDs, and the theoretical underpinnings of the conceptual model. A summary of the background and origins of the investigation, and also the literature validating the need for this research, and in defining the problem statement, were each described. Also included in this chapter was a description of each of the research constructs derived from the FFM and UTAUT model, and how each were conceptually applied to the research framework. This chapter also defined the overall research goal, and the three research questions that guided it. Lastly, the initial challenges in the form of barriers, delimitations, limitations, and assumptions linked to this research were discussed.

Chapter 2 provides a literature review of the framework's core components that make up the theoretical model and the foundation of the research. The UTAUT model is reviewed, and its growing use within the healthcare domain to help define implementation strategies for new, pervasive, and technically advanced medical devices. The FFM is also reviewed, and the increased attention that individual human factors are now receiving related to the adoption of new technologies. The impact of other valid models that have long played a role in technology acceptance and in identifying individual personality traits, such as the TAM and the Myers Briggs Type Indicator (MBTI) are briefly related. Chapter 2 also reviews the technically-driven medical devices that have initiated new research strategies, and methods to ensure acceptance of use for devices such as WIMDs for patient care.

Chapter 3 presents an overview of the research methodology and design, and the tools and statistical analyses that were used to carry out the research. The steps taken in conducting the active research, from distribution of the questionnaire to the collection of the sample data are each described. The required steps taken to ensure compliance through the institutional IRBs is also summarized in Chapter 3. The components that validated this research's theoretical model are explained, including the construct measures, the internal and external validity, and the internal and external threats. Chapter 3 concludes with a narrative of how the data analysis process was conducted, including the steps of linear regression, testing the null and alternative hypotheses, and in answering the main research questions.

Chapter 4 presents the results and complete details of the final statistical analyses. Post collection tasks, including the pre-analysis screening, identification of outliers, and determining the levels of reliability, normality and assumptions of the data are included. Characteristics of the sample data in the form of demographic and descriptive statistics are also presented. The results of the MLR and MMR analyses, from testing the predictive model to calculating the weight and moderating effects of the variable coefficients on IU, are statistically defined in Chapter 4, including the rejection or failure to reject the null and alternative hypotheses.

In Chapter 5, conclusions are drawn from the results of the statistical analyses and are used to answer each of the three research questions. Implications from this research, as well as recommendations for future research are also described. Chapter 5 concludes with a final summary review of the completed research and its contribution to the current body of knowledge. The Appendices and References sections conclude this report.

Chapter 2

Review of Literature

Overview

Hwabamungu and Williams (2010) reiterate that the adoption and the sustainability of technically-driven medical devices are not solely dependent upon the capability or effectiveness of a device but in addition to the “willingness and capability to incur any technological adoption and continuous use costs” (p. 123). This statement has, and likely will continue to be, accurate. Many questions are asked when discussing technology acceptance but one which is ever present: why do some humans accept certain technologies while others do not?

Researchers have begun to delve deeper into this human-technology conundrum within the healthcare domain and are attempting to overcome the difficult challenges in the acceptance of emerging technologies in the form of advanced technology-driven medical devices. de Veer, et al. (2011), reflect upon two distinct areas in need of study, those being acceptance of use by patients, and acceptance of use by nurses and other caregivers. In all likelihood one will not be successful without the other; meaning that a patient cannot fully embrace a possible medical solution if their caregiver has not done so themselves (Ifinedo, 2012).

WBANs, IMDs and WIMDs

A WBAN is a telecommunications system comprising of hardware that is installed inside, worn outside, or around the human body (Khan, et al., 2012). WBANs gather and transmit human health data to a remote destination using networking protocols such as ZigBee, RFID, and Bluetooth. In a basic sense WBANs are very simplistic electronic devices which combine established wireless and sensor technologies together (Beretta, Rincon, & Khaled, 2012; Ellouze, et al., 2013). An example of a typical WBAN in use today would be an externally attached heart rate monitoring device that transmits data using a wireless network. An IMD is a medical device that is physically implanted into the human body and used to treat current physiological conditions or to help prevent future abnormalities (Denning, et al., 2010). IMDs are invasive and many times require complex medical procedures for installation. Examples of popular IMDs would be ICDs, artificial pacemakers, and pain infusion pumps. A WIMD combines IMD and WBAN functions and can be considered a medical system, consisting of one or more physically implanted medical devices that uses a wireless network to connect to an external point of origin, such as a software application or information system.

These emerging technologies have gained a solid foundation in the healthcare domain and continue to garner a high level of significance both within patient care and in medical research (Kumar, et al., 2011). Maha and Hussein (2011) state that "the potential of using a body area network with several sensors to monitor vital functions of a human body can only be tapped if we achieve the ease of use and the ease of configuration" (p. 1). Because of their intrusiveness WIMDs and similar devices introduce new dynamics and possible relationships to human computer interaction (HCI), many of which are yet to be fully understood. Recent research has been conducted involving theories pertaining to human cognition, behavioral intentions and personality traits to better understand these relationships (Maier, 2011).

Technology Acceptance

Currently within the healthcare domain, technology has become pervasive in almost every facet of patient care, and has made the concept of adopting technology integral (Maier, 2011). While many research streams have exhausted technology acceptance, recent studies have proven that it yet remains relevant within the healthcare domain and specifically for patient care (Li, et al., 2013; Rasmussen, 2012). In relation to this research Holtz (2010) conducted a study using the UTAUT and created a framework in an attempt to measure a nurse's acceptance of an EMR system. Holtz reiterates the importance of successful implementation of not only information management systems (IMS) but all technology, which is continually infused into healthcare. Holtz also reflects on the increased amount of pressure put on healthcare professionals by their healthcare institutions to ensure effective integration of these systems and devices. Holtz's work is just one of many others that provides valid data regarding the adoption of technology into a nurse's workflow, and which gave affirmation as to why this research was valid and necessary.

There are several driving factors behind the push of technology into healthcare. The obvious is simply for better patient care, but profitability, reputation, and competition are stimulants as well. Dillon and Lending (2010) look to national policy as a main catalyst for the immediate and full integration of health information technologies. Dillon and Lending, who have also conducted research involving healthcare professionals and technology acceptance, provide empirical data supporting a perceived level of accuracy as a critical factor in successful adoption of patient-care information systems (IS). Although Dillon and Lending's study was completed in 2010 it still displays the upward trend in research involving the healthcare professional's role in the adoption of technology in healthcare. A simple example can be seen in research conducted by Rasmussen (2012), looking at the effect of a hospital's changeover from a traditional physical whiteboard system to an electronic whiteboard system for communication between healthcare professionals involved with the administration patient care in an emergency setting. These studies are just a few that help to validate the influence of human behavior in relation to the successful adoption of technology for patient care. WIMD and related devices have only opened more questions involving technology acceptance, especially as they become more dependent for life and death conditions. (Carr et al., 2010; Li, et al., 2013)

Technology Acceptance Model (TAM)

With the integration of technology into industry, Davis (1989) proposed a theoretical model specific to the acceptance of technology by users. This popular model, referred to as TAM has become the foundation for many other technology acceptance models. However, Davis's early research on technology acceptance was based on the human behavioral sciences Theory of Reasoned Action (TRA) model (Bagozzi, Davis, & Warshaw, 1992). TRA was used extensively within social and psychological fields of study and was developed by Ajzen and Fishbein in 1975 (Davis, Bagozzi, & Warshaw, 1989). Figure 4 shows the original TAM.

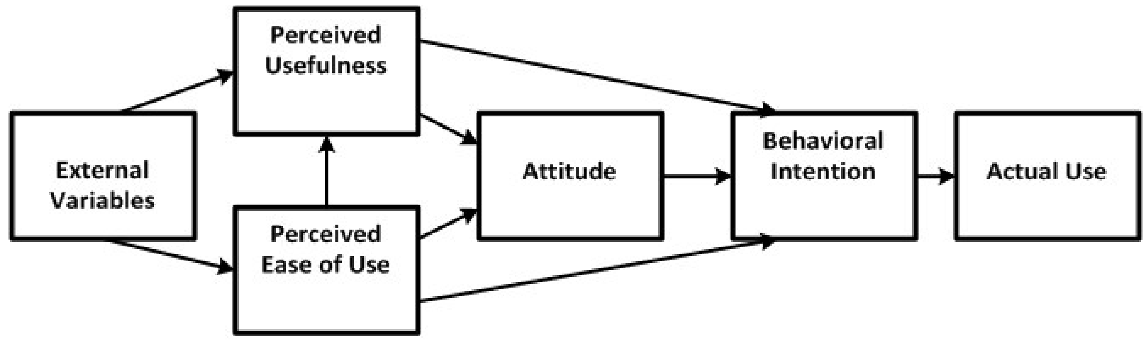


Figure 4. Original Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989).

Since its inception, the TAM has been used not only in its traditional form but has had countless modifications with, and to, its constructs to create alternative theoretical models for ongoing technology acceptance research. For example, Mei (2009) utilized the TAM in collaboration with constructs from two other standard models, that of Ajzen's (1991) theory of planned behavior (TPB), and Roger's (2003) Diffusion of Innovations (DOI) theory. Mei combined these constructs to formulate a conceptual model with the purpose to measure motivations and intentions of users who are influential in adopting technology in organizations.

An original example can be found in Yarbrough and Smith's (2007) study that focuses on the barriers physicians were faced with when dealing with emerging technologies designed to improve quality healthcare. In an attempt to identify these barriers, Yarbrough and Smith developed a modified TAM that targeted a physician's perception of implementation barriers. Figure 5 displays Yarbrough and Smith's modification of the TAM.

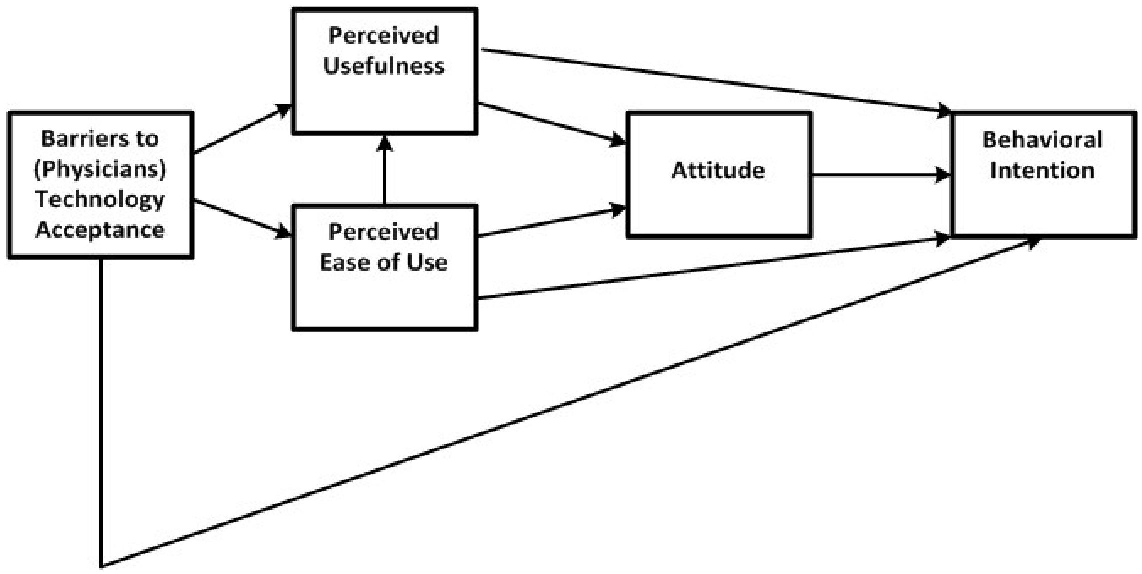


Figure 5. Modified TAM, with barriers to physicians (Yarbrough & Smith, 2007).

Yet another example is Devaraj et al. (2008), who conducted research by combining cross-model constructs from the Big Five personality trait model and the TAM, while also adding CSE and SN in order to better predict intention to use technology in an academic setting. The results of Devaraj et al.'s empirical investigation displayed statistical significance in several relationships between the Big Five as moderators and several TAM constructs in predicting IU. Devaraj et al.'s model can be seen in Figure 2.

TAM has also been used extensively throughout the healthcare domain. This is reflected in a literature review conducted by Li et al. (2013). Li et al.'s paper shows that a majority of the 93 studies reviewed used the TAM to predict healthcare professionals' adoption behaviors. While the TAM is one of the most reliable models in the IS field, this study looked to a more comprehensive technology acceptance model to supply the necessary constructs in conducting the research.

Unified Theory of Acceptance and Use of Technology (UTAUT)

Since its creation there have been many variations of the TAM introduced to various degrees of success. One of the more prominent and successful models is the UTAUT (Venkatesh, Sykes, & Zhang, 2011; Whitten et al., 2010). According to Venkatesh, et al. (2003), the UTAUT was developed with the purpose to create a technology acceptance model that improved upon all other past and present, in order to predict technology acceptance more accurately. The UTAUT consists of eight theoretical models established in multiple fields of study. These include the TRA, TPB, TAM, model of PC utilization (MPCU), social cognitive theory (SCT), IDT, motivational model (MM), and the combined TAM and TPB (C-TAM-TPB) model (Holtz, 2010; Venkatesh et al.). A visual representation of the UTAUT can be seen in Figure 6.

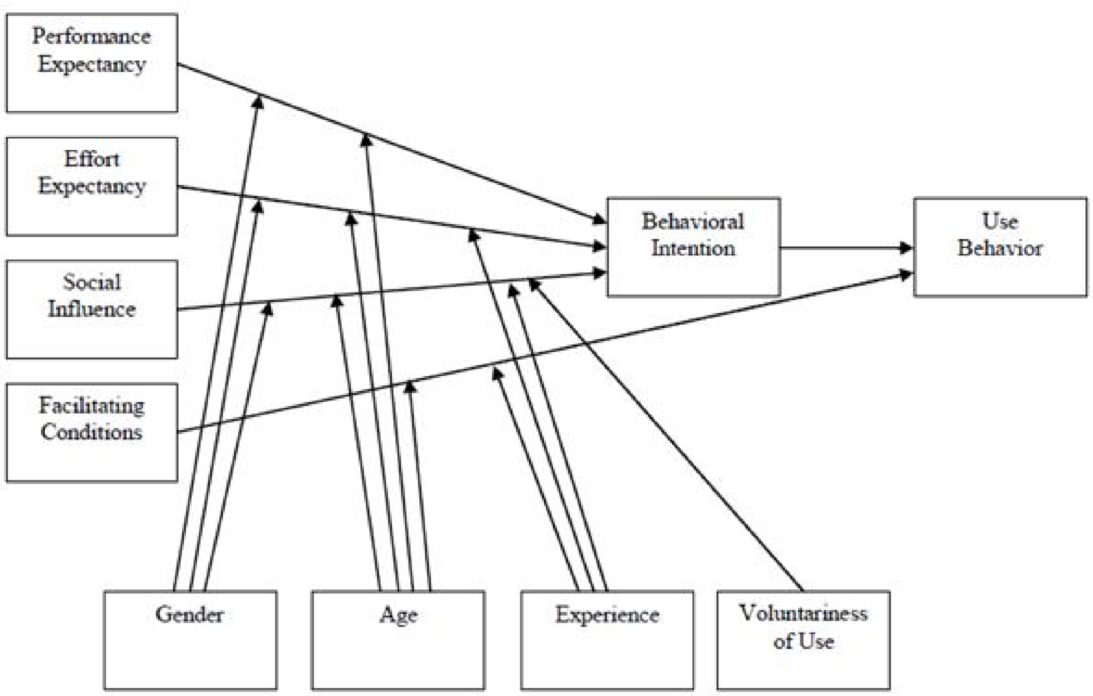


Figure 6. Original UTAUT model (Venkatesh et al., 2003).

Through the last decade the UTAUT model has become one of the more prominent technology acceptance models in various research domains, including healthcare (Infendo, 2012; Whitten, 2010). For example, Venkatesh et al. (2011) conducted a follow-up study involving the UTAUT model and the acceptance of an EMR healthcare system by physicians. Venkatesh et al. builds on his original UTAUT model created in 2003 and found that a moderator (age) was the most significant driver in predicting a physician's intention to use. Venkatesh et al. added that "future research should thus attempt to integrate different other theories to enrich UTAUT and its applicability to this content" (p.8). Whitten et al. (2010) utilized the UTAUT model as an application in structuring telemedicine programs; doing so by focusing on preparation instead of outcomes. Wills, El-Gayar, and Bennett (2008) conducted research by using the UTAUT model to examine a group of healthcare professional's intention to adopt an EMR system. This group excluded all physicians and considered only RNs, LPNs, and PAs. In proximity to Wills et al.'s research, Holtz and Krein (2011) also conducted research using the UTAUT but to predict only nurses' intention to use a newly implemented EMR system. Holtz and Krein's data collection consisted of 113 responding RNs or LPNs with a majority being female between the ages of 30 and 39. Based on their findings, Holtz and Krein concluded that the UTAUT is reliable and provides a solid framework for predicting a nurse's intention to use emerging technologies in healthcare. The UTAUT model has proven to be a robust, effective, and adaptable technology acceptance model when applied within the healthcare domain.

Definitions of Constructs

In Table 2 the four main UTAUT constructs are listed. Each entry provides the name, definition, and a breakout of established research constructs and their corresponding theoretical model each UTAUT construct originated from.

Table 2

Definitions of Constructs: UTAUT

Name	*Definition*	*Originated From* *Constructs*	*Model*
Performance Expectancy (PE)	Defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447, Venkatesh et al., 2003).	perceived usefulness	Technology Acceptance Model (TAM)
		relative advantage	Innovation Diffusion Theory (IDT)
		outcome expectations	Social Cognitive Theory (SCT)
		extrinsic motivation	Motivational Model (MM)
		job-fit	Model of PC Utilization (MPCU)
Effort Expectancy (EE)	Defined as "the degree of ease associated with the use of the system" (p. 450, Venkatesh et al., 2003).	perceived ease of use	TAM
		complexity	MPCU
		ease of use	IDT
Social Influence (SI)	Defined as "the degree to which an individual believes that important others believe he or she should use the new sysem" (p. 451, Venkatesh et al., 2003)	social norm	Theory of Reasoned Action (TRA)
		social factors	MPCU
		image	IDT
Facilitating Conditions (FC)	Defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (p. 453, Venkatesh et al., 2003)	perceived behavioral control	TPB
		facilitating conditions	MPCU
		conpatability	IDT

Personality Traits

The influence of individual characteristics on human behavior has been a part of research in the social sciences for many decades. Allport and Odbert (1936) developed an initial framework that identified close to 4,000 personality traits. Due to the difficulty in conducting viable research with such a large amount of individual traits, various researchers such as Cattell (1965) began the process of elimination by grouping similar traits into categories using factor analysis. At this point once personality traits were validated as identifiable and measureable, multiple research streams began to propagate throughout the field of psychology (McCrae & John, 1992; Goldberg, 1990; Goldberg, 1992; Chapman & Goldberg, 2017). While there are currently several reliable and well-established personality trait theories, only the three most relevant to the nature and scope of this research were considered.

16 Personality Factors Model

One popular personality trait model that has been used extensively, is Cattell's 16 Personality Factors model and its Sixteen Personality Factor Questionnaire (16PF) (Cattell & Cattell, 1995; Akin, Guclu, Ruya, Sevcan, & Yusuf, 2010). This model was originally developed by Raymond Cattell in 1949 and focused on three distinct personality variables. These were defined as: 1) natural life data, 2) experimental / behavioral data, and 3) questionnaire / responsive data (Cattell & Cattell). Cattell's model has proven to be an effective tool in personality trait research, and has been a critical reference in the development of trait theory and a valid template for many more research models. However, due to the nature of this research other more viable models were considered.

Myers Briggs Type Indicator (MBTI)

Another valid personality assessment model used in various fields of study is the Myers Briggs Type Indicator (MBTI). The MBTI was released in 1962 by Katharine Cook Briggs and Isabel Briggs Myers. The foundation for the MBTI derives from Carl Jung's 1921 book *Psychological Types* which defines principle psychological functions (Bayne, 1995). The theory behind the MBTI is based on a combination of 16 psychological pairings composed of extraversion and introversion (I—E), sensing and intuition (S—I), thinking and feeling (T—F), and lastly, judging and perceiving (J—P) (Bayne). According to McEloy, Hendrickson, Townsend, and DeMarie (2007), MBTI continues to be used extensively within organizational studies. Although MBTI was not used in thisresearch, it is referenced in this report to show an example of the diversity in personality trait models.

Five Factor Model of Personality (FFM)

The third personality trait model examined is the FFM. McRae and John (1992) define the FFM as "a hierarchical organization of personality traits in terms of five basic dimensions: Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to experience" (p. 175). These are designated as the Big Five traits, sometimes referred to as OCEAN, and represent the human personality (Goldberg, 1992; Korzaan & Boswell, 2008; Salleh, Mendes, Grundy, & Burch, 2009). The FFM has a long history of diverse research streams, evaluations, criticisms, validations, and analysis from many different researchers. Along with McRea, John and Costa, Goldberg has been essential to the past and present development of the FFM (Goldberg, 1992; Goldberg, 1993; Goldberg, 1999; Chapman & Goldberg, 2017).

FFM and Technology Acceptance

Research relating to the behavioral sciences, including that of psychology, sociology, and cognition has been involved with technology acceptance for many years (Barnett, et al., 2015; Devaraj, et al., 2008; Ozbek et al., 2014; Nov & Ye, 2008; Rosellini & Brown, 2017; Svendsen, et al., 2013). With psychology in particular, theoretical models have been developed in an effort to help determine human behavior's interaction with technology. Still today, older technology-related theoretical models which were previously considered out of date are still used in collaboration with social and psychological theories (Maier, 2011). Ajzen (1988), who developed the TRA, one of the foundational models that the TAM originated from, considered personality traits as external factors. Based on the TRA, personality traits combined with other external variables would determine one's faith and motivation and dictate one's attitude and subjective norms; the base constructs of the model (Ajzen; Wang & Yang, 2005).

Studies combining personality traits and technology acceptance have recently re-gained this recognition and have been seen in diverse research domains including education, business, and traditional IS sectors; though with mixed results (Maier, 2011). In relation to this research, Korzaan and Boswell (2008) created a conceptual model based on the FFM and considered how the Big Five impacted theoretical constructs within a general IS setting. Korzaan and Boswell focused on how the FFM constructs potentially impacted privacy concerns, computer anxiety, and behavioral intentions. In related research, Devaraj et al. (2008) combined the FFM, the TAM, and two additional constructs of subjective norms and computer self-efficacy to conduct an empirical study involving the acceptance and use of technology by master's level college students.

Devaraj et al. (2008) discovered in their research that individual differences, in the form of personality variables impacted student's intention to use a collaborative technology system. Salleh, et al. (2009) applied the FFM in research in an attempt to measure the influence of personality traits on the adoption of paired programming in academics. Salleh, et al. found that differences in personality traits did not affect student's academic performance in the context of paired programming. In another example of the FFM being used in the IS field, Cullen and Morse (2011) used the FFM's Big Five to create a conceptual model to measure the level of influence personality traits have on participation of online communities, involving both type and level. Cullen and Morse's results showed variations between individual personality traits and motivating factors for participation of online communities.

More recently, Barnett et al. (2015), conducted research that utilized constructs from both the UTAUT as well as the FFM to form a theoretical model in an attempt to predict perceived and actual use of technology in a web based classroom environment. Barnett et al.'s study used the FFM's five personality traits as predictive constructs much in the same way as the UTAUT constructs, to empirically measure associations between variables. The results Barnett et al.'s study showed that three personality traits showed significance in predicting perceived and actual use. Specifically conscientiousness displayed a positive relationship and neuroticism showed a negative relationship, both as expected. One surprise of Barnett et al.'s results was that extraversion also showed significance, but in a negative direction and not positive as expected.

These examples of recent studies involving technology acceptance show the significance individual characteristics in the form of personality traits can have on attitudes, perceptions, intended behavior, and actual use. However, these types of studies are far and few between. The current body of literature has yet to establish a solid foundation of research that validates the combination of personality trait theory and technology acceptance; such as with the FFM and UTAUT and within the healthcare domain. In providing insight in the development of this research, a study conducted by Barnett et al. (2015), Karzaan and Boswell (2008), Devaraj et al. (2008), McElroy et al. (2007), and Svendsen et al. (2013) distinguish viable theoretical links between the FFM and technology acceptance model constructs. Each study also validated the need for future research to extend the current technology acceptance models with individual factors as external and moderating variables. Venkatesh (2003) puts it best and state that “future research should focus on identifying constructs that can add to the prediction of intention and behavior over and above what is already known and understood" (pg. 471).

Definitions of Constructs

Table 3 categorizes each FFM construct by a broad or global factor name, these being Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A), and Neuroticism (N). Also shown are groups of primary trait facets, Q-sort listings, and general adjectives for each of the FFM constructs of (Block, 1961).

Table 3

Definitions of Constructs: FFM

Factor (broad sense / global capacity)	*Trait facets (primary factors) (Costa, McCrae, & Dye, 1991)*	*Q-sorts (McCrae, Costa, & Busch, 1986)*	*Supplemental Adjectives (John, 1989)*
Openness	Ideas, Fantasy, Actions, Feelings, Aesthetics, Values, Emotions	values intellectual matters, vast ranging interests, unusual thought processes; aesthetically, emotionally reactive, unconventionalities, wide array of experiences, Introspective	Artistic, Imaginative, Curious, Insightful, Emotional, Original
Conscientiousness	Deliberation, Self-discipline, Striving to Achieve, Dutifulness, Competence, Dependability	ethical behavior, achieves self-discipline, high aspirations, productive, responsible, dependable, not self-indulgent, can delay gratification, very organized	Reliable, Responsible, Organized, Efficient, Thorough, Planful
Extraversion	Assertiveness, Warmth, Positive emotions, Gregariousness, High activity, Stimulation	behaves assertively, talkative, skilled in humor, gregarious, high personal energy, socially active	Assertive, Talkative, Outgoing, Social, Active, Energetic, Enthusiastic
Agreeableness	Compliance, Modesty, Tender, Unselfishness, Straightforward, Cooperativeness	generally trustful, sympathetic and considerate, warm and compassionate, giving behavior	Sympathetic, Trusting, Appreciative, Generous, Kind, Forgiving, Submissive
Neuroticism	Anxiety, Vulnerability, Instability, Depression, Hostility, Self-Consciousness, Impulsiveness	basically anxious, Insecure, Self-depreciating, thin-skinned, fluctuation of moods, delicate ego, feelings of inadequacy,	Anxious, Tense, Worrying, Angry, Sensitive, Touchy, Self-pitying, Unstable

Summary

This chapter presented a literature review of the past and current research involving the theoretical origins of this research's framework. A review was conducted of the known and valid technology acceptance theoretical models, including the TAM and the UTAUT. The development of the original TAM and the creation of the UTAUT were also described (Davis, 1989; Venkatesth, et al., 2003; Venkatesh et al., 2011). Seminal studies of technology acceptance research were referenced, including such as well-known writings by Ajzen and Fishbein (1975), Ajzen (1991), Davis (1989), Davis, Bogazzi, and Warsaw (1989), Venkatesh, et al., (2003), and Venkatesh, et al. (2011). Past and recent studies were reviewed involving the UTAUT within the healthcare domain. This included the original development of the UTAUT and its constructs of which have been proven valid and reliable (Barnett et al., 2015; Svendsen et al., 2013; Venkatesh, et al.).

The chapter also reviewed the known personality trait theories that have commonly been used in the technology acceptance field of study, within the healthcare domain, and valid to the development of this research's conceptual framework. Three models were reviewed and considered as viable options. These were the FFM, the MBTI, and Cattell's 16 Personality Factor Model. The FFM was reviewed more in-depth, including its origins and continued development, its validation and reliability, and its fit within this research's framework.

Based on a review of the literature, this research extended Barnett et al.'s, (2015), McElroy, et al.'s (2007), Devaraj et al.'s (2008), and Svendsen et al.'s (2013) previous studies by combining constructs from the valid and reliable FFM and UTAUT model to form a conceptual framework. This framework was used to develop an operational predictive model that was used to investigate the connection between personality traits and technology acceptance.

Chapter 3

Methodology

Overview

This chapter introduces the methodology and related strategies used to carry out this research and to help answer if a nurse's identifiable personality traits influence his or her intention to use wireless implantable medical devices (WIMDs). This chapter explains the type of research design and how the investigation was to be conducted, including the research methods applied to answer the research questions. The framework's construct measures are conceptually and operationally defined, including instrument development and established levels of validity, along with the proposed testing for reliability. Threats to internal and external validity, and the methods of mitigation for each are also explained. All characteristics of the proposed sample and the sample population are described. A description of how the collected data was to be analyzed and applied within the research framework was also provided. Also included in this chapter is an explanation of the Institutional Review Board (IRB) processes and documentation required for each participating institution. Chapter 3 ends with a summary of all steps taken to conduct the active research and to prepare for the statistical analysis phase.

Research Methods and Approach

The main question that guided this research was: Does a nurse's identifiable personality traits influence his or her intention to use a WIMD for patient care? To operationalize, model constructs were applied to create the three research questions as follows:

Research Question One (RQ1)

Will performance expectancy (PE) influence a nurse’s intention to use (IU) wireless implantable medical devices (WIMDs), and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

Research Question Two (RQ2)

Will effort expectancy (EE) influence a nurse’s IU WIMDs, and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

Research Question Three (RQ3)

Will social influence (SI) influence a nurse’s IU WIMDs, and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

Based on the conceptual model, the research questions, and the positivistic nature of the research, a deductive approach was used to develop and test the following null and alternative hypotheses:

Null Hypothesis One ($H1_0$): Performance expectancy (PE) will not significantly influence a nurse’s intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by a personality trait of Five Factor Model (FFM).

Alternative Hypothesis One ($H1_1$): Performance Expectancy (PE) will significantly influence a nurse’s intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by a personality trait of Five Factor Model (FFM).

Null Hypothesis Two ($H2_0$): Effort Expectancy (EE) will not significantly influence a nurse's intention to use (IU) WIMDs when moderated by a personality trait of Five Factor Model (FFM).

Alternative Hypothesis Two ($H2_1$): Effort Expectancy (EE) will significantly influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by a personality trait of Five Factor Model (FFM).

Null Hypothesis Three ($H3_0$): Social Influence (SI) will not significantly influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by a personality trait of Five Factor Model (FFM).

Alternative Hypothesis Three ($H3_1$): Social Influence (SI) will significantly influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by a personality trait of Five Factor Model (FFM).

In following this research paradigm, a quantitative research method was adopted. A survey methodology was used to collect empirical data from a sample population. The collected data was analyzed in the form of descriptive and inferential statistics, with the purpose to investigate possible relationships between the moderating variables of openness, conscientiousness, extraversion, agreeableness, neuroticism, the independent (predictive) variables PE, EE, SI, and the dependent variable IU.

Research Design

The goal of this research was to empirically investigate the influence of identifiable personality traits on a nurse's intention to use WIMDs for patient care. Past studies in the context of this exploratory research stream have confirmed the existence of relationships beyond simple correlation, however they were far and few between. (McElroy, et al., 2007; Devraj, et al., 2008; Salleh, et al., 2009; Cullen & Morse, 2011; Hung, et al., 2014). In following with a quantitative survey design, multiple instruments were used to form a questionnaire that was deployed to collect the sample data under investigation for this research. Each instrument was also developed based on the operational framework and construct measures (Figure 7), while adhering to viable levels of validity and reliability (Straub, 1989).

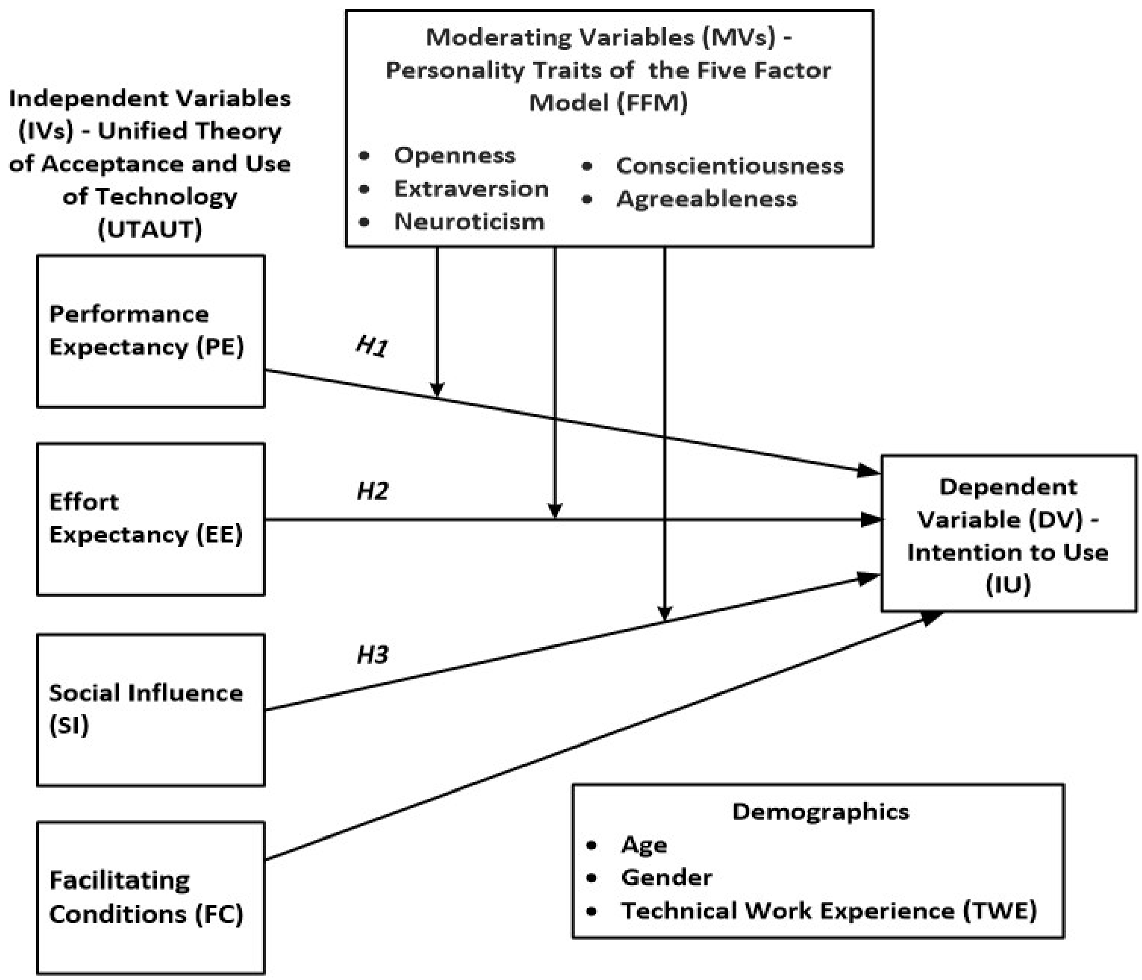


Figure 7. Operational Model: UTAUT with the inclusion of FFM

The operational constructs were grouped into three main categories based on their positions in the research. The first category of constructs of PE, EE, and SI derived from the contributing part of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, and operationally represented the predictors, or independent variables (IV) of this framework. The second category included the construct of intention to use (IU) and operationally represented the single dependent variable (DV) of the framework. The third category of constructs, those of openness, conscientiousness, extraversion, agreeableness, and neuroticism derived from the Five Factor personality trait Model (FFM) and operationally represented the focal set of moderating variables. Additional demographical data in the form of age, gender, and technology work experience (TWE), was also collected for descriptive purposes and helped to form a profile of the participating nurses.

As for FC, Venkatesh, et al. (2011) had shown that in this context of research IU is already captured by EE, and any testing for significance between facilitating conditions (FC) and IU while EE is in place would have resulted in a likely overlap. Additionally, FC was developed to be used as the single predictor of actual use, and not normally applied with the purpose to predict intention. Since this research was not longitudinal in nature, and with no data being collected pertaining to actual use, FC was not used to develop a fourth hypothesis. However, since moderators have shown significant influence on FC, data collection in the form of an additional four questions remained in place (Venkatesh, et al.). In Table 4 all variables are broken out and listed by type, model and name.

Table 4

Variable Description: Type of Variable, Model of Origin, Construct Name

Type of variable:	Independent Variables (IV)	Dependent Variable (DV)	Moderating Variables (MV)	Demographics
Model:	UTAUT	UTAUT	FFM	
Construct Name:	Performance Expectancy (PE)	Intention to Use (IU)	Openness	Technology Work Experience (TWE)
	Effort Expectancy (EE)		Conscientiousness	
			Extraversion	Age
	Social Influence (SI)		Agreeableness	Gender
	Facilitating Conditions (FC)		Neuroticism	

Data Collection

A survey instrument in the form of a questionnaire was used to gather data. The questionnaire collected data from participants in a cross-sectional manner. The questionnaire consisted of three sections and was structured using a funnel approach, starting with general questions and funneling down to those more specific in nature (Grover & Vriens, 2006). All questions were closed-ended, with a limited number of answer choices. The questionnaire is shown in Appendix A.

The questionnaire was distributed through an online method. The hospital's chief nursing officer (CNO) helped to distribute to each admissible nurse under his supervision through an institutional email system. Satellite locations of the hospital group were considered to extend the sample frame if submissions were lacking enough to significantly affect the analysis for a quantitative study. Since IRB approval for the hospital was institutional-wide and not location-based, additional IRB validation would not have been required if the sample frame was extended. Completed questionnaire submissions comprised of 72 answers representing data sets for factors of intention to use WIMDs, general demographics, and moderators in the form of personality traits.

The first section of the questionnaire labeled Section I consisted of three total questions. The first two questions were used to collect general demographics of age and gender. The third question was used to collect data representing TWE. Each question was labeled by its construct name or abbreviation. The first question, for age, was labeled ‘1. Age’. The second question, representing gender, was labeled ‘2. Gender’. Whereas the third and last question, representing the technology-work experience, was labeled ‘3. TWE’.

Section II of the questionnaire consisted of 50 total questions. This section represented the conceptual framework’s FFM constructs of openness, consciousness, extroversion, agreeableness, and neuroticism. This group of questions incorporated a known personality trait scale, referred to as the International Personality Item Pool (IPIP) and was adopted from Goldberg (1992), and Costa and McRae (1992). The use of the IPIP for research was free and without the requirement to obtain permission to use (International Personality Item Pool.org, 2018). Each question for the FFM constructs was also ordered by a combination of the representing construct’s first letter abbreviation and a sequential number, as explained for Section II. For example the first question was labeled ‘E01’, whereas the last question was labeled ‘O50’.

Section III of the questionnaire consisted of 19 total questions. Each question represented a single scale item for one of the constructs of PE, EE, SI, FC, and IU. This section was developed based on Venkatesh, et al.’s (2003) original UTAUT model. Each question was ordered by a combination of the construct's abbreviation conjoined with a sequential number. The purpose of this identification method was to use the question's unique label to link it both to the conceptual construct, and to its corresponding operational variable that was used to represent its data for analysis. For example the first question was labeled 'PE01', whereas the last question was labeled 'IU03'. In the next section each instrument is described more in depth, including the measurement of scale and validation.

Instrument Development

In order to conduct the active research, the transformation of constructs from their conceptual state to a measurable statistical variable was completed. In doing so, a 72-item multi-section instrument was developed and modified to fit this theoretical research model. The instrument was adopted from previously validated instruments and scales, with the exception of the items that were used to collect the measures of age, gender, and TWE. Characteristics of these instruments, including the measurement scales, location, and corresponding item identification codes as related to the UTAUT and FFM variables of PE, EE, SI, FC, IU, openness, conscientiousness, extraversion, agreeableness, and neuroticism, are shown in Table 5.

Table 5

Questionnaire Measurement Scales / Section and Instrument

Name	*Measurement*
Section II: Instrument 4 Performance Expectancy (PE) (Venkatesh et al., 2003)	PE01: I would find the WIMD useful in my job. PE02: Using the WIMD enables me to accomplish tasks more quickly. PE03: Using the WIMD increases my productivity. PE04: If I use the WIMD, I will increase my chances of getting a raise.
Section II: Instrument 5 Effort Expectancy (EE) (Venkatesh et al., 2003)	EE05: My interaction with the WIMD would be clear and understandable. EE06: It would be easy for me to become skillful at using the WIMD. EE07: I would find the WIMD easy to use. EE08: Learning to operate the WIMD is easy for me.
Section II: Instrument 6 Social Influence (SI) (Venkatesh et al., 2003)	SI09: People who influence my behavior think that I should use the WIMD. SI10: People who are important to me think that I should use the WIMD. SI11: The senior management of this hospital has been helpful in the use of the WIMD. SI12: In general, the hospital has supported the use of the WIMD.
Section II: Instrument 7 Facilitating Conditions (FC) (Venkatesh et al., 2003)	FC13: I have the resources necessary to use the WIMD. FC14: I have knowledge necessary to use the WIMD. FC15: The WIMD is not compatible with other devices I use.

	FC16: A specific person (or group) is available for assistance with WIMD difficulties.
Section II: Instrument 8 Intention to Use (IU) (Venkatesh et al., 2003)	IU17: I intend to use the WIMD in the next 3 months. IU18: I predict I would use the WIMD in the next 3 months. IU19: I plan to use the WIMD in the next 3 months.
Section III: Instrument 9 Extraversion (Goldberg, 1992)	E01: I am the life of the party. E06: I don't talk a lot. E11: I feel comfortable around people. E16: I keep in the background. E21: I start conversations. E26: I have little to say. E31: I talk to a lot of different people at parties. E36: I don't like to draw attention to myself. E41: I don't mind being the center of attention. E46: I am quiet around strangers.
Section III: Instrument 10 Agreeableness (Goldberg, 1992)	A02: I fee little concern for others. A07: I am interested in people. A12: I insult people. A17: I sympathize with others' feelings. A22: I am not interested in other people's problems. A27: I have a soft heart. A32: I am not really interested in others. A37: I take time out for others. A42: I feel others' emotions.

	A47: I make people feel at ease.
Section III: Instrument 11 Conscientiousness (Goldberg, 1992)	C03: I am always prepared. C08: I have my belongings around. C13: I pay attention to details. C18: I make a mess of things. C23: I get chores done right away. C28: I often forget to put things back in their proper place. C33: I like order. C38: I avoid my duties. C43: I follow a schedule. C48: I am exacting in my work.
Section III: Instrument 12 Neuroticism (Goldberg, 1992)	N04: I get stressed out easily. N09: I am relaxed most of the time. N14: I worry about things. N19: I seldom feel blue. N24: I am easily disturbed. N29: I get upset easily. N34: I change my mood a lot. N39: I have frequent mood swings. N44: I get irritated easily. N49: I often feel blue.
Section III: Instrument 13 Openness (Goldberg, 1992)	O05: I have a rich vocabulary. O10: I have difficulty understanding abstract ideas. O15: I have a vivid imagination. O20: I am not interested in abstract ideas.

O25: I have excellent ideas.

O30: I do not have a good imagination.

O35: I am quick to understand things.

O40: I use difficult words.

O45: I spend time reflecting on things

O50: I am full of ideas.

Demographic Measures

The three instruments in Section I of the questionnaire were the framework's demographic variables of gender, age, and TWE. The first instrument consisted of a single item and represented age. Data for this item was collected using an interval scale and held a continuous value. The second instrument also consisted of a single item and represented gender. Data was collected using a nominal scale of measure and held a dichotomous value as a categorical variable. The third instrument also consisted of one item and represented TWE. Data for TWE was collected using a nominal scale and also held a dichotomous value as a categorical variable, represented by either a yes or a no. An extensive definition of a WIMD was also included in this section of the questionnaire; intended to be read prior to answering the third question of TWE.

UTAUT Measures

Data for the four UTAUT IV constructs of PE, EE, SI, FC, and the single DV construct of IU was gathered using a total of five instruments consisting of 19 separate items in the form of questions. Specifically, the PE, EE, SI, and FC constructs were measured using separate four-item instruments, whereas the IU construct was measured using a three-item instrument (Venkatesh, et al., 2003). All 19 items were measured using identical seven-point Likert scales that ranged from “Completely Disagree” to “Completely Agree”. Table 5 distinguishes each of these five construct instruments, including their corresponding items, identification codes, and their final placement on the questionnaire.

FFM Measures

Section III consisted of five instruments and 50 items, 10 for each of the FFM personality trait variables of openness, conscientiousness, extraversion, agreeableness, and neuroticism. This group of items incorporated a known personality trait scale, referred to as the 50-item International Personality Item Pool (IPIP) and is adopted from Goldberg’s (1992) Big Five Markers, and Costa and McCrae’s (1992) NEO-PI-R Domains. This version of the IPIP inventory deployed a 5-point Likert scale, ranging from very inaccurate to very accurate. The use of the IPIP for research was free and without the requirement to obtain permission to use (International Personality Item Pool.org, 2018).

Reliability and Validity

Reliability

According to Sekaran and Bougie (2010), reliability “is a test of how consistently a measuring instrument measures whatever concept it is measuring” (p. 157). Straub (1989) refers to reliability as representing construct stability, with high levels of consistency and accuracy across repeated observation. Instrument reliability can be confirmed using a calculated value in the form of internal consistency. Internal consistency can be measured using several statistical formulas. Depending on the data type being collected, such as whether the instrument items are categorical, or continuous for example, will typically determine which formula best fits.

Two formulas were considered to measure instrument reliability for this research including Cronbach's alpha, published in 1951 (Cronbach, 1951) and the Kuder-Richardson Formula, published in 1937 (Sekaran & Bougie, 2010). Cronbach's alpha is a reliability coefficient indicating the positive level of correlation between a set of items measuring a concept (Sekaran & Bougie). Cronbach's alpha has been widely used across multiple research domains and proven to be an effective way to test for instrument reliability. The Kuder-Richardson Formula also measures internal consistency for instrument reliability, but does so when dichotomous data is collected, such as with a nominal scale (Sekaran & Bougie). Another related option considered was the Spearman-Brown prophesy formula, which is also used to calculate the reliability coefficient under certain conditions (Terrell, 2015).

The goal when testing for the reliability coefficient is to achieve a calculated score as close to 1.0 as possible. Current coefficient guidelines reflect that scores of less than .60 likely require some form of remedial action, whereas scores above .70 are acceptable levels and scores above .80 very good to excellent (Sekaran & Bougie, 2010). If reliability coefficient scores are between .60 and .70, remedial actions may or may not be taken, depending on the type and desired integrity of the instrument (Sekaran & Bougie). The multiple instruments that were distributed and used to conduct this research have been thoroughly and repeatedly tested for reliability.

Each of the UTAUT instrument items have been extensively checked for reliability. Initial research conducted by Venkatesh et al., (2003), indicated all internal consistency reliability scores greater than .70. Testing was conducted over a seven month period, with re-testing on three separate occasions across multiple business domains. This exact process was repeated by Venkatesh, Sykes, and Zhang (2011) eight years later specifically for the purpose of testing within the healthcare domain. Reliability scores for all UTAUT instruments were again all greater than .70.

Iterations of the IPIP have been widely used in studies in various domains pertaining to personality traits, including the 50-item IPIP that was used in the data collection phase of this research (Goldberg, et al., 2006). The IPIP's shared constructs have been used in various research domains over a period of 30 years, and have been extensively tested for reliability. Coefficient alpha scores for all FFM construct measures prior to being used in this research were all greater than .70 including .87 for extraversion, .82 for agreeableness, .79 for conscientiousness, .86 for neuroticism, and .84 for openness. Other iterations, including a lexical 44-item, and a 100-item version of the 50-item IPIP have shown high internal consistencies, and test-retest reliability as well (Goldberg, 1999; Lim & Ployhart, 2006; Boudreaux & Ozer, 2015).

To confirm that the instruments for this research were measuring how they were intended and with necessary consistency, all construct measures were tested for reliability as a preliminary research step conducted prior to data analysis. Specifically, upon collection of the sample data, Cronbach's alpha was applied in calculating the reliability (alpha) coefficient. Due to the historical standing of both UTAUT and FFM construct measures, results of the alpha scores were as expected to be, above .70. Cronbach's alpha was calculated and evaluated using The IBM Statistical Package for the Social Sciences (SPSS) version 25.0 software application. During this process secondary indicators of reliability, including an inter-item matrix, were also reviewed to confirm valid correlation across items.

Instrument Validity

According to Sekaran and Bougie (2010), validity "is a test of how well an instrument that is developed measures the particular concept it is intended to measure" (p. 157). Construct validity is "the degree to which a test measures what it claims to measure" (Terrell, 2015, p.86). There are two types of construct validity, convergent and discriminant. Convergent validity reflects on the positive correlation, or the similarities between construct measures; whereas discriminant validity does the opposite, and focuses on dissimilar concepts, or the negative correlation (Terrell).

The 19 combined construct measures that make up the UTAUT instruments have been extensively tested for validity within multiple research domains. Upon initial development the UTAUT was empirically tested for content and construct validity by Venkatesh et al. (2003). Venkatesh et al. conducted a longitudinal study with testing on three separate occasions over an eight month period of time, on IT usage, and across four different business related industries. Results were also cross-validated using data from two additional organizations (Venkatesh et al., 2003). Venkatesh et al.'s original testing included 48 separate validity tests, using partial least squares (PLS) to review both convergent and discriminant validity. As mentioned Venkatesh et al. (2011) conducted a follow-up study specifically for the purpose of testing the validity and reliability of UTAUT within the healthcare domain. As with the original testing the UTAUT was able to explain .70 of the variance in IT usage.

Many follow-up studies have substituted technology-based terminology in place of ‘system’ while maintaining the original levels of validity and reliability displayed by Venkatesh et al. (Holtz, 2010; Venkatesh, Sykes, & Zhang, 2011). According to Straub (1989) “researchers should use previously validated instruments wherever possible, being careful not to make significant alterations in the validated instruments without revalidating the instrument content, constructs, and reliability” (p.161). For this framework the only modification from the original UTAUT item measures was the replacement of “system” with “WIMD”. WIMD, defined in Chapter 1 as an encompassing technical system, remained consistent with the original levels for this research.

The 50-point IPIP measures that make up the FFM instrument have been extensively tested for validity over a wide variety of research domains (Barnett et al., 2015). The iteration of the FFM used for this research was empirically tested for content and construct validity, resulting in good indications of both convergent and discriminant validity (Chapman & Goldberg, 2017; Lim & Ployhart, 2006; Socha, Cooper, McCord, 2010). As Straub (1989) suggests, instrument validity is an integral part of the rigor necessary in creating a solid foundation for research methodology.

Internal Validity Threats

A threat to internal validity that was considered prior to conducting the research was in selection, based on variations in responses because of different levels of experience. A mitigating factor may be in that many job duties related to general nursing may be similar, in similar job positions. Therefore results being vastly different due to years of experience may not be likely. Another threat initially considered was due to having two possible distinct groups of respondents, nurses with and without WIMD experience, and which could have led to spurious relationships between an IV and the DV. The TWE construct may allow mitigation of this by collecting specific data whether a nurse did or did not have experience using a WIMD. Almost 80 percent of respondents reported as having experience using a WIMD, thus significantly reducing a possible variance in data due to a spurious relationship.

Another threat to internal validity was in maturation. Since the questionnaire was not distributed exactly the same for every nurse, variations in response results may have been influenced by individual and unique factors. For example one nurse having a higher level of fatigue over another. Or another factor might have been in a nurse's perception, based on the diversity of patients and conditions being treated, and then immediately participating in the study. Selection bias was another threat to internal validity, mainly due to the limited geographical representation of the nursing population. Bias may also have been present since neither the college nor the hospital IRB required mandatory participation, thus only data from those nurses who volunteered to participate were included. This may have resulted in a lack of representativeness of the sample population.

External Validity Threats

There seem to have been two main threats to external validity and the generalizability of the research. The first may have been present due to the experimenter effect (Terrell, 2015). In explaining this effect in this setting, distribution of the survey came down from one form of supervisor to the next. Therefore, nurses participating may both act and respond to the survey differently than they might in an independent scenario, for example outside of work, and without professional pressure. However, since participation was optional and entirely online, this threat to external validity was likely minimal.

The second threat to external validity pertained to selection-treatment interaction. Due to initial possibility of two distinct groups of participants, nurses who have experience with WIMDs and those who have not, the final analysis of the research many not have taken into account the differences between the two groups. The TWE construct and survey question helped to mitigate the need to do so by confirming that a majority of the participating nurses have had experience using WIMDs. Statistically controlling for the remaining small percentage of approximately 20 percent of nurses who did not report having experience using a WIMD could have been a secondary option. Obtaining data also from nurses without WIMD experience allowed for additional avenues of research to be considered.

Population and Sample

The sample population for this research was all professional nurses employed at a tertiary teaching hospital in the Midwest United States. This included all full and part time registered nurses (RN), licensed practical nurses (LPN), nurse practitioners (NP), nurse midwives (NM), nurse anesthetists (NA), and clinical nurse specialists (CNS). All other healthcare professionals were excluded based on the two following factors. In conducting a literature review, a majority of the literature showed that physicians were the predominant population targeted when investigating similar research, and with very little focus on nurses. Secondly, nurses have interacted with emerging technologies for patient care as frequently, and in certain circumstances more so than other healthcare professionals, including physicians (Aldosari, et al., 2017; Hung et al., 2014; Li et al., 2013).

Data was gathered from a 378-bed tertiary teaching hospital in southeast Michigan. At the time of distribution of the questionnaire, the hospital employed various types of nurses that were valid as participants. The location was chosen based on the researcher’s geographical region, the size and type of the hospital, and the ease of access to the sample group. Due to the nature of the research and the necessity to use specific nurse subjects, the sample was not randomly selected and consisted of convenience samples.

Distribution of the questionnaire through physical means was initially considered. Based on discussions with the hospital’s chief nursing officer (CNO), distribution of the questionnaire was approved through use of the online survey method. The CNO helped in the process by sending email messages to his subordinates, and them unto their subordinates and finally to the nursing employees. If there was a lack in respondents, other hospital satellite locations would have been considered. The satellite locations were within close proximity and considered within the same geographical region and therefore the sample group would have remained from the same sampling frame.

As stated in Chapter 1 the unit of analysis was all professional nurses employed by the participating hospital. These included RNs, LPNs, NPs, NMs, NAs, and CNSs. If the sample would have been expanded to include additional satellite hospitals the unit of analysis would have included any additional types of professional nurses employed by the hospital corporation. Additionally, no further IRB process would have been required, as IRB validation is administered on the institutional level for the hospital, and not by individual locations.

Data Analysis

In determining the best analysis tools for this quantitative exploratory research, several factors were first considered. The baseline plan in answering the research questions was to conduct empirical research to evaluate data collected from events that have already occurred, while using descriptive and inferential statistics without variable manipulation. Upon collection of the data, the process consisted of three general steps for analysis. The first was to filter and clean the data using a pre-analysis data screening process. The second step was to calculate and to analyze the descriptive data, such as the mean, frequencies, and standard deviations for each variable. The third step was to calculate and analyze the data using inferential statistics. Each of these three steps are explained below.

Pre-Analysis Data Screening

Prior to data analysis, a pre-analysis data screening process was conducted. The purpose of this screening process was to confirm that the collected data was accurate and retained integrity prior to analysis. Screening consisted of visual inspections of the returned online questionnaire submissions. Initially there were concerns about the large quantity of questions on the questionnaire and of missing data, repeated answers, as well as human error during the manual review and input processes. Many of these potential issues were avoided due to the survey software used to collect data having the ability to export into a compatible format that was then immediately imported into the software applications used to conduct statistical analysis. All without human processing; thus removing risks that can typically occur with manual manipulation of the data. IBM SPSS version 25.0 was used for statistical analysis of the data.

The final part in reviewing the data was to identify any data extremities in the form of outliers. Since outliers can cause significant inaccuracies in the statistical analysis results, steps were taken to remedy those identified. There are several methods to identify outliers, with some preferred based on type of research and the characteristics of the data. Because this research used regression models for analysis, the Mahalanobis Distance equation was used as the method to identify any outliers (Maesschalck, Jouan-Rimbaud, & Massart, 2000; Yu, et al., 2018).

Descriptive Statistics

Once all data was successfully filtered during the screening process, the next step was to analyze the collected sample data using descriptive statistics. Since a majority of the data being collected was through the use of ordinal scales, measures of central tendency, including the median and mode, in addition to the measures of variability and position, including the range, percentile, and the interquartile range were initially considered (Sekaran & Bougie, 2010). However, based on the initial review of the collected data, along with the quantitative goals of the research, parametric testing was used to administer data analysis. Thus the descriptive statistics used in the final data analysis were those of mean, variance and standard deviation. Graphical representations of the data including scatter plots, bar charts, p-plots, and histograms, were added for visual assistance and also to help determine frequency and distribution of the data.

Statistical Foundation

The data that was collected for both the IVs and DVs was through the use of ordinal scales. Based on current and past literature related to this area of research, researchers have used both non-parametric and parametric methods to statistically analyze the datasets collected through ordinal means. In many cases the decision in using one over another is through accumulative characteristics of the collected sample data, such as with its type, amount, and distribution properties. Prior to knowing the characteristics collected during this research, non-parametric testing was initially considered. To test the relationships described in the research hypotheses, the rank correlation coefficient using either the Mann-Whitney U test, or the Kruskal-Wallis one-way analysis of variance was considered, along with post hoc testing using the Bonferroni correction (Sekaran & Bougie, 2010). After collecting the data and reviewing its characteristics, parametric methods were then chosen with the purpose to establish a more powerful model in predicting nurse's intentions to use WIMDs.

Regression Analysis

To statistically investigate the moderating effects of the five MVs on the three relationships between each IV of PE, EE, and SI and the single DV of IU, multiple linear regression (MLR) and moderated multiple regression (MMR) methods of analysis were used (Hair et al., 2010; Hayes, 2018; Sekaran & Bougie, 2010). MLR was used to develop a predictive model by combining the three IVs of PE, EE, and SI as a method to measure their weight of statistical significance in contributing to predicting a nurse's IU WIMDs. Statistical significance reflecting the strength of each IV was determined by the calculated regression coefficient, which measured the change in variance of the DV while holding all other IVs constant. Whereas determination of each IVs directional influence of being either positive or negative to the DV, was based on the calculated coefficient as a positive or a negative number.

MMR was used to test whether any of the personality traits of openness, conscientiousness, extraversion agreeableness, and neuroticism significantly moderated one or more of the three possible significant relationships between the IVs of PE, EE, and SI, the DV IU. Similar to conducting hierarchical linear regression (HLR), variables were assigned aggregated measures based on a two-step loading process. Mean values were used to represent each MV, IV, and DV in all phases. Interaction terms (designated product of a single IV and a single MV) were assigned to each of the 15 IV-MV combinations that were loaded into the second step of the MMR model. As with MLR, the calculated MMR regression coefficient determined the statistical significance of the variable relationships. The MMR coefficient was calculated using an F-test and through the F-change statistic. The resulting p-value, if statistically significant ($p < .05$), confirmed if moderation was occurring, and provided a rejection or failure to reject the null and alternative hypotheses.

IRB

The components of this research's survey methodology, including the questionnaire was in compliance with the college and with the hospital's IRB protocol. Because of the nature of this research approval was required from both IRBs to ensure all possible risk involving the research subjects was removed. The college IRB process included several steps in order to reach compliance. Training and certification through the Collaborative Institutional Training Initiative (CITI) Program, submission of protocol and consent forms as required by the college IRB were met, and approved. Appendix C provides confirmation that all college requirements were successfully met. Exemption status was thus granted by the college IRB to proceed with this research under the exempt Category 2, as shown in Appendix C. Category 2 ensures that this research was conducted under an educational setting involving the use of a survey procedure that collects non-identifiable data from living adults, without interaction, and with the purpose to contribute to the generalizable knowledge (Health and Human Services.gov, 2019).

The hospital also required full IRB compliance due to the research involving human subjects. As with the college IRB, additional CITI training, along with protocol assurance and consent forms submitted by the researcher were required, as shown in Appendix D and G. Due to no affiliation between the college and hospital additional hospital IRB requirements were necessary. Per the hospital IRB policy, a research sponsor was required. The sponsor must have been employed by the hospital, was a qualified researcher, and willing to take accountability for the researcher and the research conducted Appendix F shows the agreement approved by the sponsor. Approval from the chief nursing officer (CNO) was also necessary, as shown in Appendix E. Appendix D provides confirmation that all requirements were successfully met; with exemption status granted by the hospital IRB to proceed with this research also under the exempt Category 2 (Health and Human Services.gov, 2019).

Summary

This chapter summarized the setup and procedures that were used to both prepare and conduct this quantitative research. Included was an overview of the research paradigm and in compliance, a description of the applied survey methodology. A breakdown of the questionnaire used to collect the sample data was given, including each instrument, section and group of questions. Specifically, data was gathered through 102 nurses employed at a hospital located in southeast Michigan. Characteristics of the sample, including the population, location, and participation specifications were described in this chapter. Also defined were the steps taken to test validity of the instruments and the reliability of the research framework's constructs (Straub, 1989). This included the UTAUT constructs of PE, EE, SI, and FC, and the FFM's five personality traits constructs of openness, conscientiousness, extraversion, agreeableness and neuroticism. Internal and external threats to validity and reliability, and how, if possible, each was mitigated.

This chapter described how the transformation of the theoretical model from conceptual to operational, and constructs to variables was to be conducted. Details involving the two types of regression analyses, followed by a description of procedures that would be used to test the research hypotheses were also summarized in this chapter. Lastly, a narrative of the individual IRB processes required by the hospital and school were defined, and of which resulted in the status of this research being exempt from further IRB review.

Chapter 4

Results

Overview

This chapter presents a summary of the applied research methods and the quantitative data analysis that was conducted to identify significant relationships between the three independent variables (IV) of performance expectancy (PE), effort expectancy (EE), and social influence (SI), the single dependent variable (DV) of intention to use (IU), and the five moderating variables (MV) of openness, conscientiousness, agreeableness, extraversion, and neuroticism. To start, the survey method and procedures from distribution to final collection are described. Next, the pre-analysis data screening and cleaning process is summarized. The collected data is then presented, starting with an outline of demographics and a summary of the descriptive characteristics. Next, reliability of the data is confirmed, followed by a review of the assumptions of the data, including correlation of variables. Lastly, the inferential analysis procedures are presented, including a summary of the multiple linear and moderated multiple regression models used to test the research hypotheses. This chapter concludes with a brief summary of the statistical results leading to the conclusion of this research.

Data Collection

A survey method was used to collect quantitative data using a 72-item questionnaire. The questionnaire, as shown in Appendix A, was used to collect multiple types of data using 13 different instruments that were separated into three sections. The first section consisted of three questions and three instruments, and collected demographic data. The second section related to the Five Factor Model (FFM) of personality traits and consisted of 50 total questions split into five instruments evenly. The final section related to the Unified Theory of Acceptance and Use of Technology (UTAUT) Model and consisted of 19 total questions, also split between five instruments.

The questionnaire was setup electronically online and hosted through a secure survey web service to provide online access for the respondents. This method of distribution was used for several reasons. First it ensured a high level of security, as the hosted website was secured through a secure socket layer (SSL) as well as using best practices for login and password requirements. The researcher was the only individual with access to the application and to the data. Additionally, this method ensured less probability of data entry errors due to all questions requiring an answer for successful submission. Specifically, if an answer to a question was not filled in, then an error message would direct the respondent to the location of any unanswered question. This method also allowed for a more streamlined approach in distributing the questionnaire using electronic mail (email); with a single instance of distribution potentially reaching all respondents simultaneously and with the same level of effectiveness.

As required by both the college and hospital IRBs an informed consent form was required to be presented to prospective participants prior to providing access to the questionnaire. The informed consent included specifications on participation, including the risks and benefits, the level of confidentiality as well as the participant’s right to withdraw from the research at any time. The form also explained that the survey is completely voluntary and that the survey does not collect personal or identifiable data. The informed consent form also served as part of the questionnaire's introduction page which was required to be clicked through in order to proceed to the first page of the questionnaire. The informed consent form is shown in Appendix B.

The actual distribution consisted of a solicitation email message that was forwarded from the hospital's Chief Nursing Officer (CNO) and out through the hospital's internal email system. The message would then reach the email inbox of the full and part-time registered nurses employed by the hospital. The CNO pointed out that, although recommended, it is not required to 'check' their hospital email on a frequent basis. He also pointed out that many do not, which will reduce those accessible. Another limitation was due to participation being entirely voluntary.

As an additional method to help distribution was 200 postcard-sized handouts that were given to the CNO, who then distributed to his direct subordinates, and then unto their subordinates and so on until reaching the majority of registered nurses employed at the hospital. The cards were three by five inches and consisted of identical criteria to what was in the email sent out to all nurses, including a link to the online questionnaire. Although used as supplemental method to increase participation, this secondary mechanism of distribution exposed this research to an added threat of external validity due to the experimenter effect (Terrell, 2015).

Setting

The research took place at a 378-bed tertiary hospital in southeast Michigan. The hospital is a subsidiary of a 14-location hospital corporation. The hospital provides a variety of services through multiple departments such as emergency, surgical, orthopedic, cardiac, neuroscience, and cancer treatment. As defined in the Methodology section, in order to conduct research using employees of this hospital, a separate and regimented internal review board (IRB) process was initiated and required to be completed by the researcher. At the time of this research the hospital employed full, part-time nursing employees that met the criteria for this research.

Data Collected

Altogether there were 102 completed and usable respondent submissions. Based on the accessible population, the response rate was calculated at 25 percent, while maintaining a 95 percent confidence level. To further validate, according to Hair et al. (2010), the results of a study can significantly increase in generalizability under certain conditions; specifically, when a regression-based model is used, and if valid and reliable predictor or independent variables (IVs) reside in the model. For example Venkatesh et al.'s (2011) UTAUT constructs of PE, EE, and SI; all of which are included within this research's theoretical model, are each considered highly reliable, valid, and extensively used with consistency. Hair et al. estimates that no less than 15-20 observations per IV will enable the results to maintain generalizability.

In taking these factors into consideration this helps to offset the low response rate and the 6.6 percent margin of error. The online survey software used to collect the data also had the capability to export data into a compatible file format specifically fitted for import into the IBM SPSS version 25.0 software package that was used for the data analysis. By deploying the questionnaire and collecting the data in this manner, and without the need for manual input processes, missing data, and repeated answers, human errors were much less of a concern. Nevertheless, a thorough and complete data screening process was administered.

Pre-Analysis Data Screening

Upon collecting all respondent data, a pre-analysis data screening process was conducted. As explained in the Methodology section, one purpose of this process was to confirm that the accuracy and the integrity of the data was retained as best as possible prior to conducting the analysis. The first step consisted of visually inspecting each of the 110 submitted datasets. Since all submissions required to be complete there were no missing answers identified. The survey software application worked by ensuring no incomplete submissions were included in the data collection. Accuracy of the data was also protected by the survey software as the choices were all selected by radio buttons.

Secondly, each dataset submission was visually screened for response-set issues. During this step a total of six submissions were identified with repeated answers across the instruments. Depending on the instrument scale and respondent dataset either all ‘7’s, ‘5’s or ‘1’s were found to be present. These respondent’s answers were viewed as potentially biased and therefore were removed from consideration for analysis.

Lastly, outliers were determined by calculating the Mahalanobis Distance, which can be used as a detection method for multivariate outliers. (Maesschalck, Jouan-Rimbaud, & Massart, 2000). The Mahalanobis Distance equation used to identify outliers for this research was:

$$D_M = \sqrt{\vec{x} - \vec{u})^T S^{-1} \ (\vec{x} - \vec{u})} \tag{1}$$

Where x is vector of the data, u is the vector of the mean values, and S is the covariance matrix. There were two instances identified as outliers. In dealing with these two cases, two options were available, either to winsorize or to remove entirely from consideration (Yu, et al., 2019). Due to the extremity of the high-end distance these outliers were removed from the main dataset prior to analysis. Table 6 displays the identified outliers and values of their Mahalanobis Distance scores. Overall there were eight individual respondent datasets removed from the data analysis portion of this research, leaving a total of 102 to form the full and valid dataset. This concluded the pre-analysis data screening process.

Table 6

Mahalanobis Distance Detected Outliers

Level Comparison		*Calculated Value*
High	(removed)	32.5039
	(removed)	30.1536
		23.8994
		22.8863
		22.4776
Low		4.3069
		4.3699
		4.5823
		4.7674
		5.0727

General Data Analysis

Demographic Data

The sample population for this research consisted of approximately 800 professional nurses, with likely half of that equivalent of the total population, including

RNs, LPNs, NPs, NMs, NAs, and CNSs employed full or part-time at a 378-bed tertiary hospital in Southeast Michigan. The three instruments in Section I of the questionnaire were used to collect data for three separate demographical characteristics of the sample respondents. These included age, gender, and technology work experience (TWE).

The first instrument consisted of a single question representing age. Data for this question was collected using an interval scale and held a continuous value. Values were split into five groups in the form of multiple choice answers, which were (a) 18-30, (b) 31-40, (c) 41-50, (d) 51-60, and (e) 60 or older. As shown Figure 8 the participating respondent nurse demographic dataset shows that the largest age group percentage was between the ages of 41 and 50, at 37.25%. The second largest group consisted of nurses between the ages of 31 and 40, equating to an overall percentage of 28.43%. This was followed up by those nurses between the ages of 18-30, with a percentage of 16.67%. The last two groups of nurses were between the ages of 51 and 60, at 13.73%, and ages 60 and over, at 3.92%. Overall the sample constituted 12.75 percent of the frame.

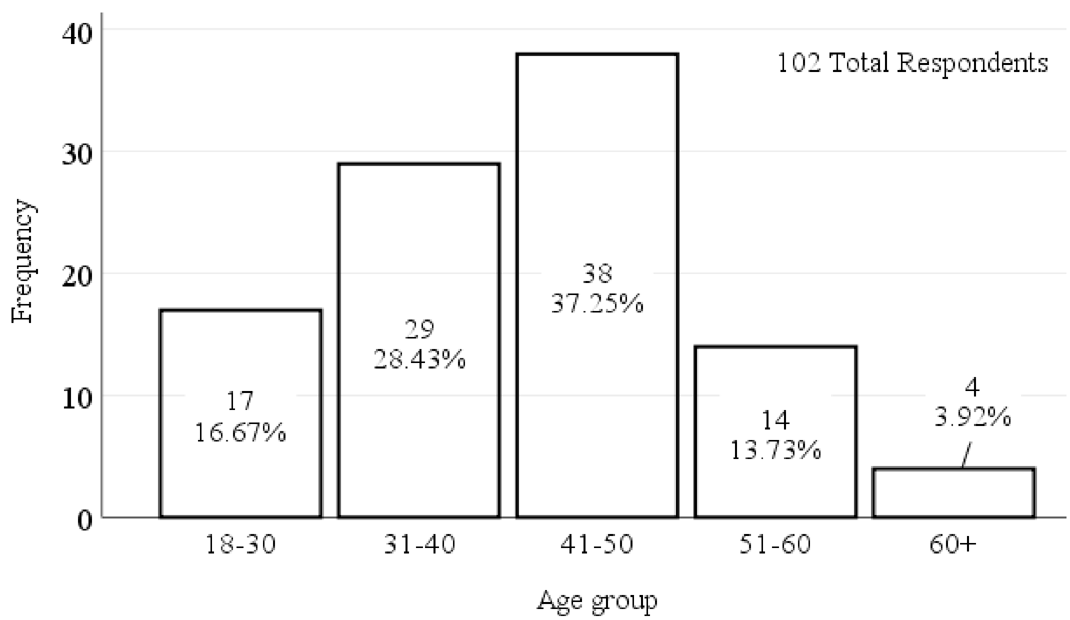


Figure 8. Demographic Data for Age of Participating Nurses

The second instrument consisted of a single question representing gender, with data being collected using a nominal scale with three category choices of male, female, or non-binary. Out of the total of 102 respondents 82 were represented as female, whereas 20 were male. There were zero non-binary respondents from the questionnaire. According to the Bureau of Labor and Statistics (2018), a national survey conducted in 2017 from the current population of all registered nurses showed that 90% are female. Figure 9 displays the results from the survey results.

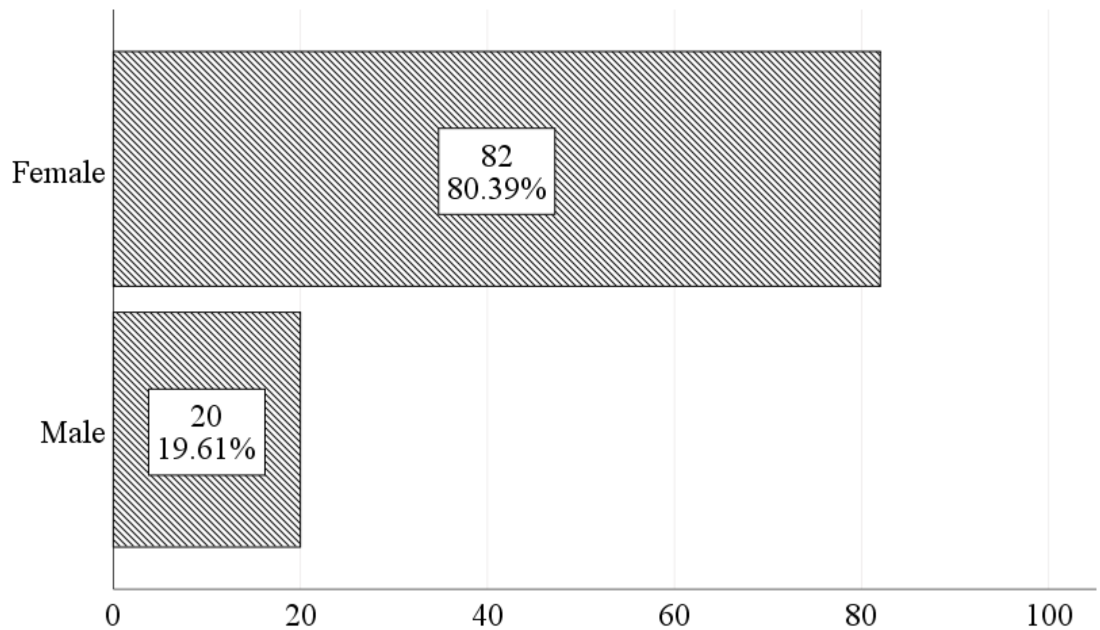


Figure 9. Demographic Data for Gender of Participating Nurses

The third instrument, representing TWE, used a nominal scale to collect dichotomous data in the form of yes or no values. As part of this question a brief paragraph defining WIMDs and their use for patient care was included. In addition, Pacemakers, implantable cardioverter-defibrillators (ICD), insulin pumps, and pain infusion pumps that incorporate wireless functionality were given as examples. Section 1 in Appendix A shows the TWE question and the instruction to read the WIMD explanation paragraph. Out of the 102 total respondents, 78 reported that they have had experience using WIMDs in their jobs, with 24 stating they have not. Figure 10 displays these responses as notated on the questionnaire as either a yes or no, along with their corresponding percentages of 76.47% and 23.53% respectively.

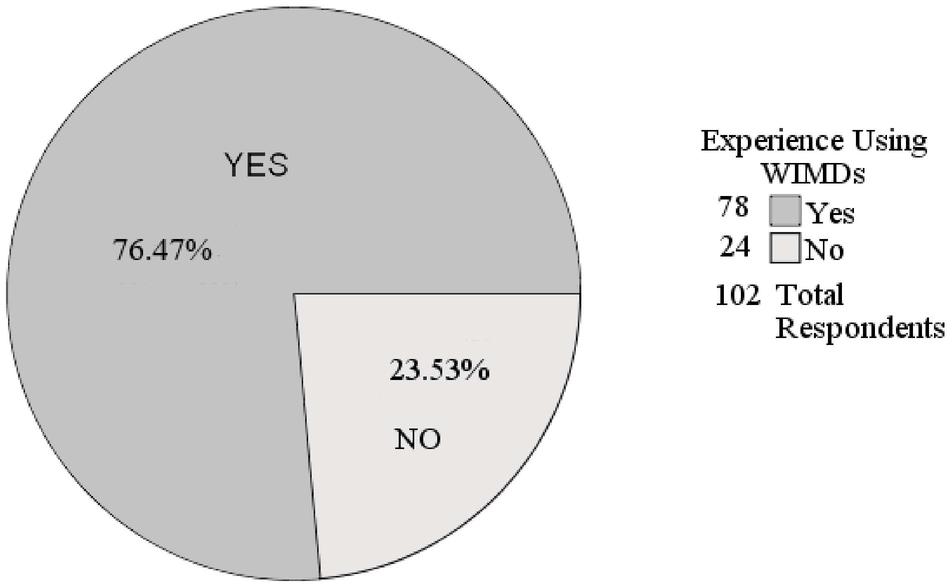


Figure 10. Demographic Data for TWE of Participating Nurses

Descriptive Data

There were a total of 10 variables that were included within the three research hypothesis. Five of the variables represented the UTAUT model and held aggregated values based on the collection of four 7-point Likert subscales for PE, EE, SI, and FC, and three 7-point Likert subscales for IU. The remaining five variables represented the FFM and held aggregated values based the collection of 10 5-point Likert subscales for openness, conscientiousness, extraversion, agreeableness, and neuroticism. Table 7 presents the base descriptive statistics for measures of frequency, dispersion and of central tendency.

Table 7

Descriptive Data

	Construct	*N*	*Minimum*	*Maximum*	*Mean*	*Standard Deviation (SD)*
UTAUT Item Scale 1 - 7	Intention to Use	102	2.00	6.67	4.5686	1.14474
	Performance Expectancy	102	2.50	7.00	5.1993	.97635
	Effort Expectancy	102	2.75	7.00	5.2108	.95294
	Social Influence	102	2.00	6.25	4.3137	.93322
	Facilitating Conditions	102	1.33	6.67	4.4346	1.19108
FFM Item Scale 1 - 5	Openness	102	2.40	5.00	3.7873	.51946
	Conscientiousness	102	2.10	5.00	4.0618	.57610
	Extraversion	102	1.60	4.90	3.2559	.72557
	Agreeableness	102	2.70	5.00	4.1824	.51941
	Neuroticism	102	1.20	4.30	2.5402	.62904

Reliability Analysis

Cronbach’s Alpha was administered to assess the internal consistency for the scale items of constructs PE, EE, SI, FC, IU, openness, conscientiousness, extraversion, agreeableness, and neuroticism. To ensure all survey items were of the same scale direction, a preliminary step was taken to reverse score those construct items that were inversely listed within the instruments. Listing various scale items in the opposite direction is used as a method to better focus the respondent’s attention, with the intent to improve response validity and strengthen correlation (Goldberg, 2006). For this research, 24 out of the 69 scale items were reversed scored prior to administering the reliability analysis. For example a “1” value in a subscale item from neuroticism would be reverse coded to a “5” in order to match the direction of all other instruments. When measuring internal consistency using Cronbach’s Alpha the calculated reliability coefficient should be as close to 1.0 as possible, with a minimum score of .70 ($\alpha \geq .70$) to achieve a sufficient level of reliability (Cronbach, 1951; Sekeran and Bougie, 2010). The Cronbach's alpha equation used to test the reliability for the 10 constructs was written as:

$$\alpha = \frac{k \times \bar{c}}{\bar{v} + (k-1)\bar{c}} \tag{2}$$

Where k is the number of scale items, $\bar{c}$ is the average of covariances between items, and $\bar{v}$ represents the average variance of the items. Table 8 presents the results, sorted by construct, the number of scale items, and the final Cronbach's alpha coefficient scores.

Table 8

Results of Internal Reliability Analysis

Construct	*Number of Items*	*Cronbach's Alpha (α)*
Intention to Use (IU)	3	.818
Performance Expectancy (PE)	3	.812
Effort Expectancy (EE)	4	.873
Social Influence (SI)	4	.739
Facilitating Conditions (FC)	3	.794
Openness	10	.793
Conscientiousness	10	.819
Extraversion	10	.893
Agreeableness	10	.808
Neuroticism	10	.839

The results of the reliability analysis using Cronbach's Alpha showed evidence that there was sufficient internal consistency, as each of the ten constructs tested had a coefficient alpha score greater than .70. Viable levels were expected and have been consistently reached with the UTAUT model (Venkatesh et al., 2011). The highest reliability coefficient reached was extraversion (α = .893), with the lowest being SI (α =.739). After reviewing the inter-item correlation matrix for the two constructs that were close to the threshold score (PE, FC), a single subscale item was identified as showing a slightly lower correlation than the other three subscales for each of PE and FC. The item-total-statistics matrix also showed a change in the coefficient alpha for both constructs if the subscale items in question were removed. For PE the "If I use the WIMD I will increase my chances of getting a raise" item had a corrected item-total correlation (α = .120), and when removed from the model the coefficient alpha had a positive change (α = .204), (α =.608, - α =.812). Due to this contrast and the lack of correlation of this question and the sample respondents, it was removed from the research model. As for FC, the "The WIMD is not compatible with other devices I use" item had a corrected item-total correlation (α =.149), and when removed the coefficient alpha increased (α = .076), (α =.758 - α = .794). However, FC was not part of the hypothesis testing due to its purpose as a measure to predict actual use and not intention to use, but was included as informative data related to the model (Venkatesh et al.). IBM SPSS version 25.0 was used to calculate the Cronbach's Alpha coefficient values.

Assumptions of the Data

Normal Distribution and Parametric Testing

The FFM and UTAUT construct instruments used Likert scales to collect ordinal data. Since ordinal data is not appropriately ranked between scale items, then best practices dictate that non-parametric statistical tests should be administered. However, parametric tests can be more powerful than those of their non-parametric counterparts. It has been suggested that some parametric tests are robust enough to provide valid analysis and with much more predictive power for ordinal data treated as ranked scale items, but with the stipulation that the sample data is normally distributed. According to Sekaran, and Bougie (2010), a sample that is normally distributed by being populated closer to the mean without a large number of extremes, will result in a reasonable level of accuracy in representing the population. Sekaran and Bougie, state that “when the properties of the population are not overrepresented or underrepresented in the sample, we will have a representative sample” (p.268). To determine if the data is normally distributed five methods that are commonly used for quantitative research were evaluated accumulatively.

The Shapiro-Wilk and the Kolmogorov-Smirnov tests are both valid methods frequently used to test for normality. The Shapiro-Wilk test has consistently been used in research to test for normality due to its predictive power, though more directed towards smaller sample sizes (Ghasemi & Zahediasl, 2012). The Kolmogorov-Smirnov test has been utilized in research since its inception over 60 years ago and continues to be, albeit with refinements (Ghasemi & Zahediasl; Hair et al., 2010). When using the Kolmogorov-Smirnov and Shapiro-Wilk tests for normality, if the p-value is greater than .05, representing no statistical significance in the value, then the null hypothesis will fail to be rejected. Conversely, if the p-value is less than or equal to .05 and thus showing statistical significance, then the null hypothesis will be rejected. Therefore confirming statistically, that the data is not normally distributed. The default assumption for the null hypothesis is that the data is normally distributed; then statistically tested to reject or failure to reject this assumption (Razali & Wah, 2011; Hair et al., 2010). The Shapiro-Wilk equation used for this research was:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{3}$$

Where x_i is the ordered sample values, a_i represents the constraints of the sample size, n. IBM SPSS version 25.0 was used to administer the Shapiro-Wilk and the Kolmogorov-Smirnov tests for normality. Constructs were assigned aggregated values based on each of the subscale items for PE, EE, SI, FC, IU, openness, conscientiousness, extraversion, agreeableness, and neuroticism. The values (N=102) were then ran through the two normality tests by calculating the level of significance for the differences from a normal distribution (Hair et al., 2010).

The results showed variation between the resulting p-values for each of the test types. The Shapiro-Wilk, the more recent of the two tests, calculated eight out of the ten constructs to be statistically significant. Openness showed the highest level of significance (p = .728), while Conscientiousness the lowest (p = .040), though above the threshold under Kolmogorov-Smirnov (p = .063). The Kolmogorov-Smirnov results showed five constructs having p-values greater than .05, with two more near the threshold (p = .40, p = .047), though each were statistically significant under their Shapiro-Wilk scores (p = .265, p = .050). The Kolmogorov-Smirnov equation used was:

$$D_n = \sup_x |F_n(x) - F(x)| \tag{4}$$

Where $\sup_x$ is the supremum, or least upper bound, set of distances, and $F_n(x)$ is the cumulative distribution function, and $F(x)$ the empirical distribution function. In addition to using the Kolmogorov-Smirnov and Shapiro-Wilk tests, histograms, boxplots, and normal quantile-quantile (Q-Q) plots were visually inspected for normality. The levels of skewness and kurtosis were scored and reviewed for acceptable levels based on their statistic, standard error, and z-values. Appendix H and I provide the statistical test results and corresponding histograms and Q-Q plots.

Skewness and kurtosis represent horizontal-type characteristics of the distribution described in the form of shape. Skewness helps to describe the balance of the data, from one side of the middle, or mean, compared to the other side. Data can be either positively skewed: consisting of more values to the left of middle, and displayed by the peak of the curve being off-center to the left. Or data can be negatively skewed: consisting of more values to the right of middle, displaying the peak of the curve off-center to the right (Hair et al., 2010; Terrell, 2015).

Kurtosis helps to describe the vertical characteristics of the distribution of data in the form of the curve being flat or peaked. Data that has more values distributed away negatively, or away from the center showing a lower, flat curve, has platykurtosis. Whereas data that has more positive values will be bunched up in the middle showing a high-peaked curve, has leptokurtosis (Hair et al., 2010; Terrell, 2015). The variable of openness shows a bell-shaped curve reflective of a normal distribution with minimal skewness and kurtosis. As an example, openness has a skewness statistic of -.180, a standard error of .239, and a z-value of -.753. Openness has a lower kurtosis statistic of -.101, a standard error of .474, and a z-value of -.213. From the UTAUT, EE has a skewness statistic of -.203, a standard error of .239, a z-value of -.849, and a high kurtosis statistic of -1.380, a standard error of .474, and a z-value of -.713. Four of the 10 variables are slightly positively skewed, while all hold a negative kurtosis statistic, or are slightly-to-moderately platykurtotic.

An accumulative evaluation of normality showed that a good portion of the constructs in this research pass both visual inspection and statistical testing, including the examination of histograms, levels of skewness and kurtosis, as well as the Shapiro-Wilk and Kolmogorov-Smironov test statistics. Therefore, the sample data can be considered approximately normally distributed (Doane & Seward, 2011; Razali & Wah, 2011). Statistical test results, histograms, and Q-Q plots are shown in Appendices H and I.

Correlation

Prior to applying regression a bivariate correlation analysis was conducted using Person's Correlation Coefficient test. All variables were loaded into a matrix that displayed the Pearson correlation coefficient (Pearson's *r*) along with the corresponding 2-tailed p-value represented by "Sig. (2-tailed)". The equation used for Pearson's *r*:

$$r = \frac{1}{n-1}\sum \frac{(x_i - \overline{X})(y_i - \overline{Y})}{s_x s_y} \qquad (5)$$

Where *n* is the sample size, x_{i} and y_{i} are sample points, and s_{x} and s_{y} are the sample standard deviations. IBM SPSS version 25.0 was used to calculate the Pearson's *r* value for each individual variable, including the five UTAUT variables of PE, EE, SI, FC, and, IU, and the five FFM variables of openness, conscientiousness, extraversion, agreeableness, and neuroticism. Pearson's *r* values that were flagged (*) if the calculated p-value was statistically significant ($p < .05$) either positive or negative. The results of all Pearson's *r* tests are presented in the correlation matrix displayed in Table 9.

Table 9

Pearson's Correlation Coefficient (r) - Matrix for FFM and UTAUT variables

Variable		PE	EE	SI	FC	IU	O	C	E	A
EE	Correlation Coefficient	.344**								
	Sig. (2-tailed)	.000								
SI	Correlation Coefficient	.400**	.144							
	Sig. (2-tailed)	.000	.148							
FC	Correlation Coefficient	.368**	.467**	.548**						
	Sig. (2-tailed)	.000	.000	.000						
IU	Correlation Coefficient	.382**	.476**	.451**	.467**					
	Sig. (2-tailed)	.000	.000	.000	.000					
O	Correlation Coefficient	.144	.094	-.021	.085	-.026				
	Sig. (2-tailed)	.148	.347	.836	.397	.795				
C	Correlation Coefficient	.014	-.091	.003	.052	-.138	.297**			
	Sig. (2-tailed)	.891	.365	.978	.605	.166	.002			
E	Correlation Coefficient	.010	.140	.083	.300**	.151	.425**	.018		
	Sig. (2-tailed)	.923	.161	.406	.002	.131	.000	.858		
A	Correlation Coefficient	.049	.056	.112	.071	.028	.210*	.470**	.189	
	Sig. (2-tailed)	.623	.575	.264	.480	.779	.034	.000	.058	
N	Correlation Coefficient	-.076	-.085	-.072	-.139	-.081	-.211*	-.260**	-.197*	-.038
	Sig. (2-tailed)	.451	.394	.470	.165	.420	.034	.008	.047	.706

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The correlation matrix notates values that show statistical significance between variables. In noting the highest positive correlation of significant for the IVs used in this research, PE and SI show a moderate to strong correlation (r = .400). Whereas the lowest (also positive) correlation of significance was between PE and EE (r = .344). Pearson's r also showed that the personality trait of extraversion had a moderate positive correlation with the personality trait of openness (r = .425). Conversely, Pearson's r revealed the lowest negative correlation between that of the personality traits of neuroticism and extraversion (r = -.197). Since regression is an extension of correlation some of the data in the matrix is redundant, as the significant results pertaining to the IVs and DV are presented in the regression analysis section of this report.

Assumptions for Regression

Prior to assessing the results from linear regression analysis and the final hypotheses testing, specific characteristics of the data were assumed to be present. To ensure these assumptions were met, supplemental pre and post regression tests were administered consisting of statistical analyses and visual inspections through graphical representations of the data. Table 10 shows the assumptions of linear regression that were tested pre and post analysis.

Table 10

Assumptions of Linear Regression

Assumption	*Description of Assumption*	*Validation Method*
Linear Relationship	Do each of the independent variables of PE, EE, and SI have a linear relationship with the dependent variable of IU?	Creation of three scatter plot graphs with the DV (IU) as Y (intercept), and each IV's (PE, EE, SI) as X (slope).
Independence of Observations	Is there an insignificant correlation between residuals?	Conduct statistical analysis using the Durbin-Watson test.
Outliers	Are there data values that reside at extreme points?	Conduct statistical analysis using the Mahalanobis distance.
Homoscedasticity	Do residuals show equivalence? Or is heteroscedasticity present?	Conduct statistical analysis using the Breucsh-Pagan and Koenker tests.
Collinearity / Multi-collinearity	Is there a significantly (too) strong linear relationship between variable(s)?	Conducted statistical analyses: Reviewed correlation matrix (Pearson's r). Reviewed Tolerance and Variation Inflation Factor (VIF)
Normality of Residuals	Are the residuals approximately normally distributed?	Creation of visual inspection of scatterplot and histogram graphs.

A straight, or linear alignment between two variables is the basic requirement to analyze data using linear regression (Sekaran & Bougie, 2010). To confirm that linear relationships exist between each of the IV and DV variable combinations as defined in the hypotheses, scatterplots were created by positioning the DV as the intercept on the y-axis and the IV representing the slope on the x-axis. Visual inspection for each combination was then completed to verify if linearity was present. Appendix J contains the inspected scatterplots for PE, EE, SI, and the single DV, IU.

To test for independence of observations between the IV's and the DV, a Durbin-Watson test was conducted for each of the variable combinations defined within the three research hypotheses: *H1*:PE-IU, *H2*:EE-IU, and *H3*:SI-IU. The Durbin-Watson test determines if autocorrelation is present between the observation's residual values. Scores can vary from zero to four, with values at approximately two indicating an independence of observations between variables (Durbin & Watson, 1971). The equation used to calculate for Durbin-Watson statistic:

$$\frac{\sum_{t=2}^{T}(e_{t-}\ e_{t-}1)^2}{\sum_{t=1}^{T} e_t^2} \tag{6}$$

Where *T* is the number of observations, and *e* represents the residuals. The results of the Durbin-Watson test to determine if independence of observations exist between these research variables are presented in Table 11 and are individually summarized in each of the results presented in the regression analysis in this chapter.

Table 11

Durbin-Watson (D-W) Test Results for Independence of Observations

Independent Variable (IV)	*Dependent Variable (DV)*	*D-W statistic*
Performance Expectancy (PE)	Intention to Use (IU)	1.984
Effort Expectancy (EE)	IU	2.004
Social Influence (SI)	IU	1.876

A check for the assumption of homoscedasticity was conducted using three methods. The first was a visual inspection of scatterplots that represent the linear variable combination for each hypothesis, with the DV stationed on the y-axis (intercept), and the IV on the x-axis (slope). These are shown in Appendix J. A secondary method was by calculating the level of statistical significance through a variation of chi-squared. The Breusch-Pagan test calculates a statistic that, if statistically significant ($p < .05$), rejects the default null hypothesis (H0: homoscedasticity) and results in heteroscedasticity (Breusch & Pagan, 1979; Koenker, & Bassett, 1982). Table 12 shows the results for the test of heteroscedasticity for the IVs.

Table 12

Breusch-Pagan Test Results for Heteroscedasticity

Variable	*B-K statistic*	*p-value*
Performance Expectancy (PE)	.626	.429
Effort Expectancy (EE)	1.245	.264
Social Influence (SI)	1.446	.229

$^{*}p < .05$

Having two or more IVs with abnormally high correlations can result in collinearity (two variables) and multicollinearity (more than two variables) and inaccurate statistical results when administering simple and multiple linear regression (Kock & Lynn, 2012). To test this assumption data was analyzed based on three factors. After running the regression analysis, the correlation matrix was inspected to ensure that collinearity was not present in any of the bivariate correlations ($r < .90$). The coefficient matrix was also reviewed to ensure both the tolerance (T) statistic as well as the variance inflation factor (VIF) were at sufficient levels. According to Kock and Lynn, the T value should be less than 1.0, and VIF should be less than 3.3. The correlation matrix is shown in Table 9. Table 13 shows the each of the T and VIF values for the IVs.

Table 13

Test Results for Multicollinearity

Variable	*Tolerance*	*Variance Inflation Factor (VIF)*
Performance Expectancy (PE)	.757	1.322
Effort Expectancy (EE)	.882	1.134
Social Influence (SI)	.840	1.190

To check that the residuals of the regression line established from the regression analyses were approximately normally distributed, the standardized values were used to create histograms and P-P plots. Assessment of normality was then conducted through visual inspection. Appendix K and L display the P-P plots and histogram representing the standardized residuals for the regression models.

Multiple Linear Regression

Multiple linear regression (MLR) was used to analyze the goodness of fit of the overall model in predicting nurses' intention to use WIMDs. In using MLR, a predictive model was developed through the combination of the three IVs of PE, EE, and SI, and by measuring their contribution in the form of statistical significance in predicting the single DV of IU. For this research, the MLR equation used was:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + e \tag{7}$$

Where Y is the DV of IU; β_0 is the constant or intercept value; $\beta_1 X_1$ represents the regression coefficient of the IV PE; $\beta_2 X_2$ represents EE; $\beta_3 X_3$ represents the third and last IV of SI; and where *e* is the residual. In administering MLR, an aggregated mean value was calculated for each of the variables, including PE, EE, SI, and IU. These values were then loaded together using MLR to test the predictive model. The model confirmed statistical significance: $F(3,98) = 20.407$, $p < .001$, and explained 38.5% ($R^2 = .385$) of the variance, thus showing it being a good fit for predicting IU. Table 14 summarizes the MLR model values.

Table 14

Multiple Linear Regression Model (MLR) Fit

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.620	.385	.366	.91173

Table 15 shows a summary of the model's coefficient values. The results showed that the two of three IVs, those of EE and SI were statistically significant ($p < .05$) in contributing to the prediction of IU. All variables were positively related to the DV; meaning as EE and SI increased so did IU. The regression model showed that EE was statistically significant as a predictor of IU ($p < .001$), followed closely by SI ($p < .001$). PE was not statistically significant in predicting IU when loaded into this model using MLR ($p = .240$).

Table 15

Multiple Linear Regression (MLR) Coefficients

Model		*Unstandardized Coefficients*		*Standardized Coefficients*		
		B	Std. Error	Beta	T	Sig.
1	(Constant)	-.380	.652		-.583	.561
	PE	.126	.107	.108	1.183	.240
	EE	.466	.101	.388	4.600	.000**
	SI	..431	.106	.352	4.068	. 000**

**$p < .001$; *$p < .05$

Moderated Multiple Regression

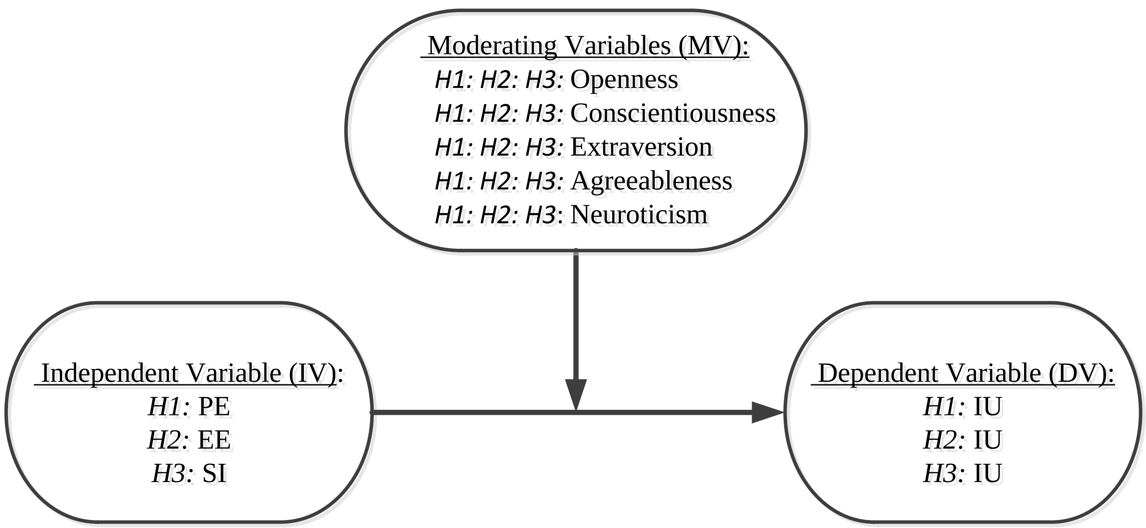
The second method of analysis was a moderated multiple regression (MMR) used specifically to take into consideration moderator variables. MMR was used to test whether the personality trait MV's of openness, conscientiousness, extraversion, agreeableness, and neuroticism significantly moderated one or more of the three possible significant relationships between the IVs of PE, EE, and SI, the DV IU, as defined in the research hypotheses. IBM SPSS version 25.0 was used to conduct the MM analysis, and does so in a similar multiple-step process to that of a hierarchal linear regression (HLR) model. Prior to conducting the MMR analyses, aggregated measures were applied to the necessary moderating, dependent, and independent variables. This included calculating the mean, and the interaction term values, of which were transformed into variables by calculating the product of the 15 individual MV – IV combinations as defined within the research hypotheses. Based on this configuration, five separate MMR analysis were conducted in order to test each set of null and alternative hypotheses that guided this research. The MMR equation used to test this hypotheses was:

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3 XM + e \tag{8}$$

Where Y is the DV of IU; β_0 is the constant or intercept value; $\beta_1 X$ represents the regression coefficient of one of the three IV's of PE, EE, or SI; $\beta_2 M$ represents the regression coefficient for one of the five MVs or openness, conscientiousness, extraversion, agreeableness, or neuroticism; $\beta_3 XM$ represents the regression coefficient for one of the 15 interaction term variables; and where e is the residual.

In executing each of the three MMR analysis, a two-step variable loading process was administered. During the first step three variables were loaded in as the first regression model (model 1). This included IU designated as the DV, PE (*H1* test), EE (*H2* test), or SI (*H3* test) designated as the individual IV, and one of five personality trait

MVs of openness, conscientiousness, extraversion, agreeableness, or neuroticism. With the second step, two variables were loaded in as the moderated regression model (model 2); with IU remaining as the single DV, and one of 15 interaction term variables loaded in as the designated IV. As defined, the interaction term variable is the product of one of three IVs and one of five MV's. Figure 11 displays all variables applied in the MMR analysis.



H1:
Test 1: PE → O → PE*O → IU
Test 2: PE → C → PE*C → IU
Test 3: PE → E → PE*E → IU
Test 4: PE → A → PE*A → IU
Test 5: PE → N → PE*N → IU

H2:
Test 1: EE → O → EE*O → IU
Test 2: EE → C → EE*C → IU
Test 3: EE → E → EE*E → IU
Test 4: EE → A → EE*A → IU
Test 5: EE → N → EE*N → IU

H3:
Test 1: SI → O → SI*O → IU
Test 2: SI → C → SI*C → IU
Test 3: SI → E → SI*E → IU
Test 4: SI → A → SI*A → IU
Test 5: SI → N → SI*N → IU

Figure 11: MMR with Moderators

The analysis of the results consisted of review of each of the regression output model's critical statistics including F, F-change, and the significance of F-change, along with R-squared, adjusted R-squared, and R-squared change, and finally the degrees of freedom, the standardized coefficient (*Beta*), and the unstandardized coefficient (*b*) and standard error. In reviewing the MMR output, rejection of the null hypothesis was dependent upon whether the regression model's p-value was statistically significant at a value of less than .05 ($p < .05$). This value was based on the change in the variance in predicting IU when adding the interaction term variable (moderation) to the regression model. It was calculated using an F-test and incorporated the F-change statistic to output a ratio measuring the level of significance of the model. If significant ($p < .05$) the null hypothesis ($H1_0$, $H2_0$, $H3_0$) was rejected, while the alternative hypothesis ($H1_1$, $H2_1$, $H3_1$) failed to be rejected. The results for each of the three separate MMR analysis, based on the three research hypotheses and corresponding research questions are presented in the following three sections.

Personality Trait Moderators & Performance Expectancy (PE)

Five moderating variables (MV) of openness, conscientiousness, extraversion, agreeableness, and neuroticism were examined as moderators of the relationship between the independent variable (IV) of performance expectancy (PE) and the dependent variable (DV) of intention to use (IU). Moderated multiple regression (MMR) was used to analyze the data and to test the null and alternative hypothesis based on the first research question, RQ1. Pre and post tests were conducted to ensure all assumptions of regression analysis between PE and IU were met: Visual inspection of a scatterplot confirmed that PE and IU had a linear relationship, as shown in Appendix J.

Autocorrelation between the PE and IU was not present based on the Durbin-Watson statistic, which indicated a value approximately equal to two ($d = 1.984$). A check for heteroscedasticity using the Breusch-Pagan test confirmed homoscedasticity ($B\text{-}P = .626$, $p = .429$). Multicollinearity was not present as both levels of tolerance ($T = .757$) and variance inflation factor ($VIF = 1.322$) were sufficient. Post analysis showed that PEs' residuals of the regression line were approximately normally distributed.

PE - Openness. The results of the regression analysis when loading openness and PE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 6.139$, $p < .001$, and predicted 15.8 % of the variance for IU ($R^2 = .158$). When loading into model 2 as a combined variable, the interaction term between PE and openness accounted for $\Delta R^2 = .006$, $F(1, 98) = .661$, $p = .418$. Based on these results openness showed as having no statistical significance ($p < .05$) in moderating the relationship between PE and IU.

PE - Conscientiousness. The results of the regression analysis when loading conscientiousness and PE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 6.669$, $p < .001$, and predicted 17.0 % of the variance for IU ($R^2 = .170$). When loading into model 2 as a combined variable, the interaction term between PE and conscientious accounted for $\Delta R^2 = .003$, $F(1, 98) = .366$, $p = .546$. Based on these results conscientiousness showed as having no statistical significance ($p < .05$) in moderating the relationship between PE and IU.

PE - Extraversion. The results of the regression analysis when loading extraversion and PE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 8.328$, $p < .001$, and predicted 20.3 % of the variance for IU ($R^2 = .203$). When loading into the model as a combined variable, the interaction term between PE and extraversion accounted for $\Delta R^2 = .036$, $F(1, 98) = 4.401$, $p = .038$, and was statistically significant ($p < .05$) in moderating the relationship between PE and IU. The results also showed a negative regression slope ($b = -.306$), implying an inverse relationship between extraversion and the relationship between PE and IU.

PE - Agreeableness. The results of the regression analysis when loading agreeableness and PE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 6.663$, $p < .001$, and predicted 16.9 % of the variance for IU ($R^2 = .169$). When loading into model 2 as a combined variable, the interaction term of PE and agreeableness accounted for $\Delta R^2 = .024$, $F(1, 98) = 2.775$, $p = .099$. Based on these results agreeableness showed as having no statistical significance ($p < .05$) in moderating the relationship between PE and IU.

PE - Neuroticism. The results of the regression analysis when loading neuroticism and PE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 5.829$, $p < .001$, and predicted 15.1 % of the variance for IU ($R^2 = .151$). When loading into model 2 as a combined variable, the interaction term of PE and neuroticism accounted for $\Delta R^2 = .003$, $F(1, 98) = .337$, $p = .563$. Based on these results neuroticism showed as having no statistical significance ($p < .05$) in moderating the relationship between PE and IU.

Personality Trait Moderators & Effort Expectancy (EE)

Five personality trait MVs of openness, conscientiousness, extraversion, agreeableness, and neuroticism were examined as moderators of the relationship between the IV of effort expectancy (EE) and the DV of intention to use (IU). MMR was used to analyze the data and to test the null and alternative hypotheses based on the second research question, RQ2. Pre and post tests were conducted to ensure all assumptions of regression analysis between EE and IU were met: Visual inspection of a scatterplot confirmed that EE and IU had a linear relationship, as shown in Appendix J. Autocorrelation between the EE and IU was not present based on the Durbin-Watson statistic, which indicated a value approximately equal to two (*d* = 2.004). A check for heteroscedasticity using the Breusch-Pagan test confirmed homoscedasticity (*B-P* = 1.245, $p = .264$). Multicollinearity was not present as both levels of tolerance ($T = .882$) and variance inflation factor (*VIF* = 1.134) were sufficient. Post analysis showed that PEs' residuals of the regression line were approximately normally distributed.

EE - Openness. The results of the regression analysis when loading openness and EE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 9.882$, $p < .001$, and predicted 23.2 % of the variance for IU ($R^2 = .232$). When loading into model 2 as a combined variable, the interaction term between EE and openness accounted for $\Delta R^2 = .001$, $F(1, 98) = .084$, $p = .773$. Based on these results openness showed as having no statistical significance ($p < .05$) in moderating the relationship between EE and IU.

EE - Conscientiousness. The results of the regression analysis when loading conscientiousness and EE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 10.675$, $p < .001$, and predicted 24.6 % of the variance for IU ($R^2 = .246$). When loading into model 2 as a combined variable, the interaction term between EE and conscientious accounted for $\Delta R^2 = .011$, $F(1, 98) = 1.381$, $p = .243$. Based on these results conscientiousness showed as having no statistical significance ($p < .05$) in moderating the relationship between EE and IU.

EE - Extraversion. The results of the regression analysis when loading extraversion and EE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 14.684$, $p < .001$, and predicted 31.0 % of the variance for IU ($R^2 = .310$). When loading into model 2 as a combined variable, the interaction term between EE and extraversion accounted for ΔR^2 = .076, $F(1, 98)$ = 10.851, p < .001, and was statistically significant (p < .05) in moderating the relationship between EE and IU. The results also showed a negative regression slope (b = -.481), implying an inverse relationship between extraversion and the relationship between EE and IU.

EE - Agreeableness. The results of the regression analysis when loading agreeableness and EE individually, showed that model 1 was significant in predicting IU: $F(3, 98)$ = 9.590, p < .001, and predicted 22.7 % of the variance for IU (R^2 = .227). When loading into model 2 as a combined variable, the interaction term of EE and agreeableness accounted for ΔR^2 < .001, $F(1, 98)$ = .051, p = .822. Based on these results agreeableness showed as having no statistical significance (p < .05) in moderating the relationship between EE and IU.

EE - Neuroticism. The results of the regression analysis when loading neuroticism and EE individually, showed that model 1 was significant in predicting IU: $F(3, 98)$ = 9.658, p < .001, and predicted 22.8 % of the variance for IU (R^2 = .228). When loading into model 2 as a combined variable, the interaction term of EE and neuroticism accounted for ΔR^2 < .001, $F(1, 98)$ = .004, p = .953. Based on these results neuroticism showed as having no statistical significance (p < .05) in moderating the relationship between EE and IU.

Personality Trait Moderators & Social Influence (SI)

Five MVs of openness, conscientiousness, extraversion, agreeableness, and neuroticism were examined as moderators of the relationship between the IV of social influence (SI) and the DV of intention to use (IU). MMR was used to analyze the data and to test the null and alternative hypotheses based on the third research question, RQ3.

Pre and post tests were conducted to ensure all assumptions of regression analysis between SI and IU were met: Visual inspection of a scatterplot confirmed that SI and IU had a linear relationship, as shown in Appendix J. Autocorrelation between the SI and IU was not present based on the Durbin-Watson statistic, which indicated a value approximately equal to two (d = 1.876). A check for heteroscedasticity using the Breusch-Pagan test confirmed homoscedasticity ($B\text{-}P$ = 1.446, p = .229). Multicollinearity was not present as both levels of tolerance (T = .840) and variance inflation factor (VIF = 1.190) were sufficient. Post analysis showed that SIs' residuals of the regression line were approximately normally distributed.

SI - Openness. The results of the regression analysis when loading openness and SI individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 8.603$, $p < .001$, and predicted 20.8 % of the variance for IU ($R^2 = .208$). When loading into model 2 as a combined variable the interaction term between SI and openness accounted for $\Delta R^2 = .005$, $F(1, 98) = .617$, $p = .434$. Based on these results openness showed as having no statistical significance ($p < .05$) in moderating the relationship between SI and IU.

SI - Conscientiousness. The results of the regression analysis when loading conscientiousness and SI individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 10.065$, $p < .001$, and predicted 23.6 % of the variance for IU ($R^2 = .236$). When loading into model 2 as a combined variable, the interaction term between SI and conscientious accounted for $\Delta R^2 = .013$, $F(1, 98) = 1.649$, $p = .202$. Based on these results conscientiousness showed as having no statistical significance ($p < .05$) in moderating the relationship between SI and IU.

SI - Extraversion. The results of the regression analysis when loading extraversion and SI individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 10.231$, $p < .001$, and predicted 23.9 % of the variance for IU ($R^2 = .239$). When loading into model 2 as a combined variable, the interaction term between SI and extraversion accounted for $\Delta R^2 = .022$, $F(1, 98) = 2.889$, $p = .092$. Based on these results extraversion showed as having no statistical significance ($p < .05$) in moderating the relationship between SI and IU.

SI - Agreeableness. The results of the regression analysis when loading agreeableness and EE individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 8.372$, $p < .001$, and predicted 20.4 % of the variance for IU ($R^2 = .204$). When loading into model 2 as a combined variable, the interaction term of SI and agreeableness accounted for $\Delta R^2 < .001$, $F(1, 98) = .039$, $p = .844$. Based on these results agreeableness showed as having no statistical significance ($p < .05$) in moderating the relationship between SI and IU.

SI - Neuroticism. The results of the regression analysis when loading neuroticism and SI individually, showed that model 1 was significant in predicting IU: $F(3, 98) = 9.661$, $p < .001$, and predicted 22.8 % of the variance for IU ($R^2 = .228$). When loading into model 2 as a combined variable, the interaction term of SI and neuroticism accounted for $\Delta R^2 < .023$, $F(1, 98) = 2.886$, $p = .093$. Based on these results neuroticism showed as having no statistical significance ($p < .05$) in moderating the relationship between SI and IU.

Results of Hypotheses Testing

Hypothesis H1 (PE)

Based on the results from the five MMR analysis related to PE, only one personality trait showed to have moderated a significant relationship between PE and IU. As stated in *H1*, if a personality trait significantly moderates the relationship between PE and IU ($p < .05$), then the null hypothesis should be rejected. Extraversion was the single personality trait that showed to significantly moderate the relationship between PE and IU ($p = .038$). As a result, there was a rejection of the null hypothesis ($H1_0$), and thus the failure to reject the alternative hypothesis ($H1_1$).The implications from the results of hypothesis *H1* are further summarized under its corresponding research question (RQ1) in Chapter 5. Table 16 presents the MMR analysis results for testing personality trait moderation between PE and IU.

Table 16

MMR Analysis:
Moderation Between Performance Expectancy (PE) and Intention to Use (IU).

Moderator	*b*	*Std. Error*	*Beta*	*R^2 Change*	*t*	*F Change*	*Sig. F Change (p-value)*
Openness	-.183	.225	-.792	.006	-.813	.661	.418
Conscientiousness	-.116	.192	-.522	.003	-.605	.366	.546
Agreeableness	-.390	.234	-1.752	.024	-1.666	2.775	.099
Extraversion	-.306	.146	-1.358	.036	-2.098	4.401	.038*
Neuroticism	.095	.163	.327	.003	.581	.337	.563

Note. Load 1 for IU (*Y*), PE (*X*), Extraversion (*M*): $F(3, 98) = 8.328$, $p < .001$, $R^2 = .203$.
* $p < .05$

Hypothesis H2 (EE)

Based on the results from the five MMR analysis related to EE, only one personality trait showed to have moderated a significant relationship between EE and IU. As stated in *H2,* if a personality trait significantly moderates the relationship between EE and IU ($p < .05$), then the null hypothesis should be rejected. Extraversion was the single personality trait that showed to significantly moderate the relationship between EE and IU ($p < .001$). As a result, the null hypothesis ($H2_0$) was rejected, and thus the failure to reject the alternative hypothesis ($H2_1$). The implications from the results of hypothesis *H2* are further summarized under its corresponding research question (RQ2) in Chapter 5. Table 17 presents the MMR analysis results for testing personality trait moderation between EE and IU.

Table 17

MMR Analysis: Moderation Between Effort Expectancy (EE) and Intention to Use (IU).

Moderator	*b*	*Std. Error*	*Beta*	*R^2 Change*	*t*	*F Change*	*Sig. F Change (p-value)*
Openness	-.056	.195	-.234	.001	-.290	.084	.773
Conscientiousness	.230	.196	.976	.011	1.175	1.381	.243
Agreeableness	-.043	.191	-.186	.000	-.225	.051	.822
Extraversion	-.481	.146	-2.209	.076	-3.294	10.851	.001**
Neuroticism	-.011	.179	-.037	.000	-.059	.004	.953

Note. Load 1 for IU (*Y*), EE (*X*), Extraversion (*M*): $F(3, 98) = 14.684$, $p < .001$, $R^2 = .310$.
* $p < .05$ ** $p < .001$

Hypothesis H3 (SI)

Based on the results from the five MMR analysis related to SI, no personality traits showed to have moderated a significant relationship between SI and IU. As stated in *H3,* if a personality trait significantly moderates the relationship between SI and IU ($p < .05$), then the null hypothesis should be rejected. As a result, there was a failure to reject the null hypothesis ($H3_0$), and thus the rejection of the alternative hypothesis ($H3_1$). The implications from the results of hypothesis *H3* are further summarized under its corresponding research question (RQ3) in Chapter 5. Table 18 presents the MMR analysis results for testing personality trait moderation between SI and IU.

Table 18
MMR Analysis: Moderation Between Social Influence (SI) and Intention to Use (IU).

Moderator	*b*	*Std. Error*	*Beta*	*R^2 Change*	*t*	*F Change*	*Sig. F Change (p-value)*
Openness	.201	.256	.727	.005	.785	.617	.434
Conscientiousness	.256	.200	.999	.013	1.284	1.649	.202
Agreeableness	.044	.223	.180	.000	.197	.039	.844
Extraversion	-.292	.172	-1.144	.022	-1.700	2.889	.092
Neuroticism	-.312	.184	-.958	.023	1.699	2.886	.093

Summary of Results

This chapter reaffirmed the research methodology along with the characteristics of the physical and virtual environments used for the distribution of the survey and the collection of the sample data. This included a description of the 378-bed tertiary research hospital located in southeast Michigan where the research occurred, in addition to the sample population that consisted of full or part-time employed nurses that participated in the research.

This chapter also provided a summary of the pre-analysis screening process used to visually inspect and statistically examine the datasets, resulting in the removal of two outliers. Cronbach's Alpha was used to measure the reliability for the IVs PE, EE, SI, and FC, all five personality trait MVs, and the DV IU. The results confirmed high reliability for all variables. Multiple methods were used to test the sample data for normality, including the Kolmorov-Smirnov and Shapiro-Wilk tests, and also levels of skewness and kurtosis. An accumulative evaluation showed that the data was approximately normally distributed. This chapter also described the essential characteristics of the collected data, in the form of demographic and descriptive statistical summaries. The results showed various age groups of participating nurses, predominate gender type and also unsuspected counts from the dichotomous technology experience question.

Also provided in this chapter, was a thorough narrative with visual representations of the statistical analysis and processes used in the MLR and MMR models' predictions of moderation, and intention to use WIMDs for patient care. This included a full description of the testing phase for the null and alternative hypotheses, and of which were rejected or failed to be rejected based on the measured statistical significance of the MV's indirect effects between the IV and DV relationships.

Chapter 5

Conclusions, Implications, Recommendations, and Summary

This chapter presents the conclusions drawn from the multiple linear regression (MLR) and moderated multiple regression (MMR) analyses and whether the main goal driving this research was achieved. The test results for each set of null and alternative hypotheses, and answers to each of the three main questions that guided this research were reviewed and answered. Implications of this research, and of related studies, along with recommendations for future research are also discussed. This chapter concludes with a compiled summary of this research in its entirety, and its overall contribution to the body of knowledge.

Conclusions

The main goal of this research was to empirically investigate the influence of identifiable personality traits on a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) for patient care. At the beginning of this research and to fulfill the main research goal, three questions defining the structure for each quantitative condition were established with the purpose of guiding this research. A set of null and alternative hypotheses linked to the research questions were also created, then tested, and finally rejected or failed to be rejected. This was completed through regression analysis, and in building the predictive model used to test for statistical significance of the variable relationships used in this research.

This predictive model statistically measured the five personality traits as moderating variables (MV), between each set of combined independent variable (IV) and dependent variable (DV) relationships as defined in the hypotheses. In total there were 15 hypothesis conditions. To test, a moderated multiple regression (MMR) model using a two-step process was used; first by loading the aggregated mean values followed by the interaction term values. Using this procedure each research hypothesis was either rejected or failed to be rejected if the interaction term's regression coefficient was above or below the defined threshold value ($p < .05$). If the condition held true ($p < .05$) then the null hypothesis would be rejected, and the alternative hypothesis failed to be rejected. This translates to mean that the IV significantly predicts the DV when the MV is present. The output from the regression analysis provided the statistical characteristics for each of the interactions and for the conditional effects between IV and DV. This output, and the hypotheses tests results provided the necessary information to answer each research question.

Research Question One (RQ1)

RQ1: Will performance expectancy (PE) influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs), and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

In accordance with the results from the five MMR analyses related to PE, only the personality trait of extraversion showed to have moderated a significant relationship between PE and IU ($p = .038$). The remaining MVs of openness ($p = .418$), conscientiousness ($p = .546$), agreeableness ($p = .099$), and neuroticism ($p = .563$) did not show statistical significance in moderating the relationship between PE and IU. Under this condition, the null hypothesis ($H1_0$) was rejected, and the alternative hypothesis ($H1_1$) failed to be rejected.

In examining additional statistical characteristics, the MMR model's output showed that when loading extraversion and PE into the model, the interaction term between them accounted for an adjusted change in variance of 3.6% ($\Delta R^2 = .036$). However, the results also showed that the regression slope of the interaction variable held a negative value ($b = -.306$). This implied that an increase in extraversion will negatively affect the level of strength and weaken the relationship between PE and IU.

This interaction was further investigated by analyzing the conditional effects of extraversion at three levels of PE; at the mean value ('Average'), one standard deviation above the mean ('High'), and one standard deviation below the mean ('Low'). The results show that there was a statistically significant relationship between PE and IU, when extraversion was at the mean value ($p < .001$), when at one standard deviation below the mean ($p < .001$), but not at one standard deviation above the mean ($p = .081$). Figure 12 shows a visual representation of these results. In addition, the Johnson-Neyman technique reported that extraversion significantly moderated the relationship between PE and IU for all values at and below 3.918 (82.35% below and significant) (Hayes, 2018).

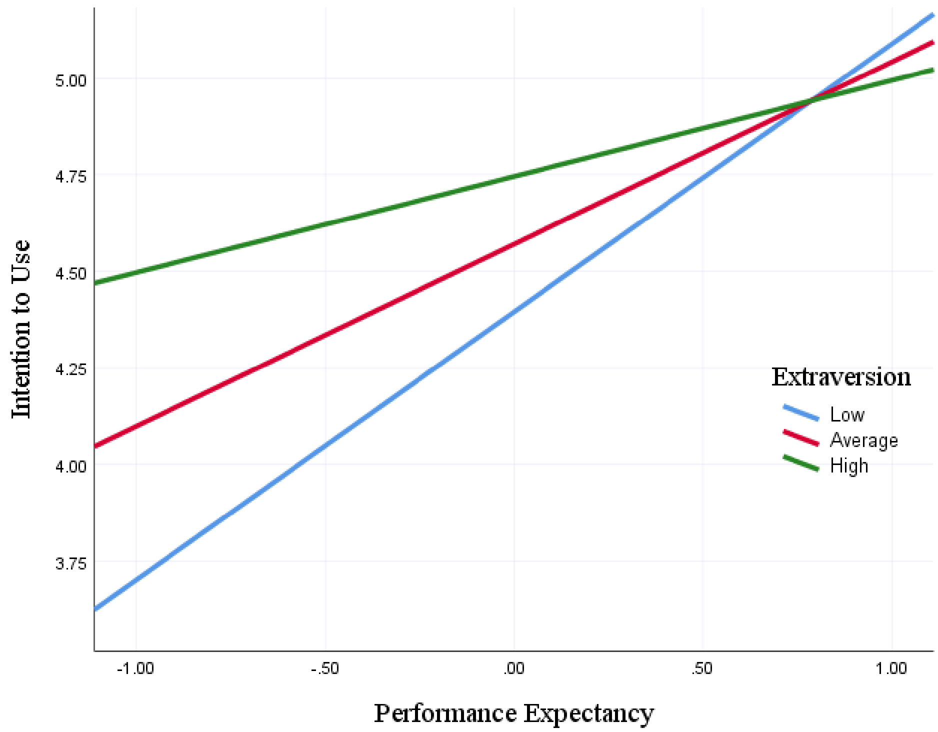


Figure 12: Conditional Effects of Extraversion on PE-IU

RQ1 Answers

Based on the MMR analysis the personality trait of extraversion significantly moderated the relationship between PE and IU. Therefore, the following five statements are held true:

- Performance expectancy (PE) will influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by extraversion.
- PE will not influence a nurse's IU WIMDs when moderated by openness.
- PE will not influence a nurse's IU WIMDs when moderated by conscientiousness.
- PE will not influence a nurse's IU WIMDs when moderated by agreeableness.
- PE will not influence a nurse's IU WIMDs when moderated by neuroticism.

Research Question Two (RQ2)

RQ2: Will effort expectancy (EE) influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs), and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

According to the results from the five MMR analyses related to EE, only the personality trait of extraversion showed to have moderated a significant relationship between EE and IU ($p < .05$). The remaining MVs of openness ($p = .773$), conscientiousness ($p = .243$), agreeableness ($p = .822$), and neuroticism ($p = .953$) did not show statistical significance in moderating the relationship between EE and IU. Under this condition, the null hypothesis ($H2_0$) was rejected, and the alternative hypothesis ($H2_1$) failed to be rejected.

In examining additional statistical characteristics, the MMR model's output showed that when loading extraversion and EE into the model, the interaction term between EE and extraversion accounted for an adjusted change in variance of 7.6% (ΔR2 = .076). However, the results also showed that the regression slope of the interaction variable held a negative value ($b = -.481$). This implied that an increase in extraversion will negatively affect the level of strength and weaken the relationship between EE and IU.

This interaction was further investigated by analyzing the conditional effects of extraversion at three levels of EE; at the mean value ('Average'), one standard deviation above the mean ('High'), and one standard deviation below the mean ('Low'). The results show that there was a statistically significant relationship between EE and IU, when extraversion was at the mean value ($p < .001$), when at one standard deviation below the mean ($p < .001$), but not at one standard deviation above the mean ($p = .276$). Figure 13 shows a visual representation of these results. In addition, the Johnson-Neyman technique reported that extraversion significantly moderated the relationship between EE and IU for all values at and below 3.799 (72.55% below and significant).

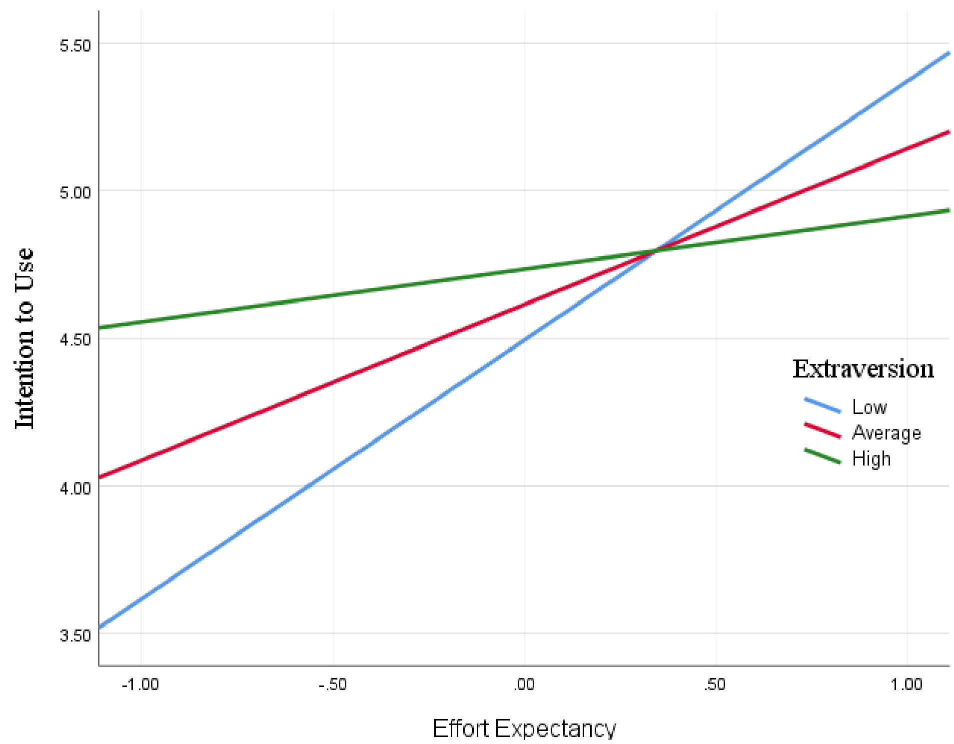


Figure 13: Conditional Effects of Extraversion on EE-IU

RQ2 Answers

Based on the MMR analysis the personality trait of extraversion significantly moderated the relationship between EE and IU. Therefore, the following five statements are held true:

- Effort Expectancy (EE) will influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by extraversion.
- EE will not influence a nurse's IU WIMDs when moderated by openness.

- EE will not influence a nurse's IU WIMDs when moderated by conscientiousness.
- EE will not influence a nurse's IU WIMDs when moderated by agreeableness.
- EE will not influence a nurse's IU WIMDs when moderated by neuroticism.

Research Question Three (RQ3)

RQ3: Will social influence (SI) influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs), and be moderated by openness, conscientiousness, extraversion, agreeableness, and neuroticism?

As shown from the results of the five MMR analyses related to SI, there were no personality traits that showed to have moderated a significant relationship between SI and IU. The regression coefficient for each of the five did not meet the threshold of statistical significance. Specifically, the MVs of openness (p = .434), conscientiousness (p = .202), extraversion (p = .092), agreeableness (p = .844), and neuroticism (p = .093) did not show statistical significance in moderating the relationship between SI and IU. Under this condition, the null hypothesis ($H3_0$) failed to be rejected, and the alternative hypothesis ($H3_1$) rejected.

RQ3 Answers

Based on the MMR analysis there were no personality traits that significantly moderated the relationship between SI and IU. Therefore, the following statements are held true:

- Social influence (SI) will not influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) when moderated by extraversion.
- SI will not influence a nurse's IU WIMDs when moderated by openness.

- SI will not influence a nurse’s IU WIMDs when moderated by conscientiousness.
- SI will not influence a nurse’s IU WIMDs when moderated by agreeableness.
- SI will not influence a nurse’s IU WIMDs when moderated by neuroticism.

Implications

The results of this research have several implications for the existing body of knowledge in the health information and technology fields of study. A conceptual framework was developed by combining constructs from Venkatesh, Morris, Davis, and Davis’s (2003) unified theory of acceptance and use of technology (UTAUT) model, and the Five Factor personality trait model (FFM), based on McCrae and John’s (1992), and Goldberg’s (1992, 1999) five dimension personality trait research. This framework was transformed into an operational model and used to predict a nurses’ intention to use wireless implantable medical devices (WIMDs). UTAUT constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), and intention to use (IU) were transformed into measurable independent (IV) and dependent variables (DV). The FFM personality traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism were transformed into moderating variables (MV). This model was used to test the statistical significance of variable relationships, and specifically if the FFM personality traits moderate the relationships between the three UTAUT IVs of PE, EE, and SI, and the single DV of IU.

The three main contributions that this research makes to the field of study and to the overall body of knowledge include 1) empirical validation of a theoretical model that predicts over 30% of the variance in nurses' intention to use WIMDs for patient care; 2) it identifies both behavioral intentions in the form of performance expectancy and effort expectancy, and individual human factors in the form of the extraversion personality trait, as either direct or indirect predictors of nurses' intention to use advanced medical technology in the form of WIMDs; 3) it provides a thorough investigation and expands on previous research and the current body of knowledge.

From a practical standpoint, the results from this research may offer some guidance on areas of training and awareness in terms of adopting technology into a nurse's daily workflow. The results also provided a snap shot on just how much technology is already pervasive in nurses' jobs. As the descriptive data from technology work experience (TWE) item showed that 80% of the 102 valid participants reported as having hands on experience using a WIMD. This would be expected in a niche setting of a cardio-based treatment facility or department, but not from a majority of general RN positions at a hospital. The results may also imply to hospital supervisors and administration the importance of a nurse's individual perspective, and that other factors may influence a nurse's ability to adopt technology; or the inability to respond in the same manner and to the same methods as others. New implementation strategies and training initiatives pertaining to advanced technology in a nurse's workflow may be considered, or at minimum evaluated.

Limitations

Several limitations were identified. One limitation was due to investigating only a single technology in the form of WIMDs. Because various devices and systems are now pervasive in hospitals, data results relating to WIMDs might not always be generalizable with other healthcare technology environments. A second limitation was due to the sample, consisting of only nurses from a hospital in one geographical region in southeastern Michigan. This, in addition to be being only voluntarily, likely led to a smaller than expected number of participating nurses. Additional contributions in other geographical areas and being open to larger populations would improve on the overall generalizability of the research.

A third limitation was that over 80 percent of the respondents were women, and thus less than 20 percent men. Although the national level is even higher at approximately 90 percent women, a higher representation of men, or more even one, may produce differing results (Bureau of Labor and Statistics, 2018). A fourth limitation is demonstrated by the high percentage of respondents who reported to have used technology in their jobs, in the context of this research's TWE construct. Specifically, over 75 percent stated yes, that they have experience in using devices such as and related to WIMDs. Having an equal or greater number of respondents who have not had experience using this type of technology may yield different results.

Another limitation is demonstrated in that the 67 percent of the nurses were between 31 and 50 years old. Whereas just over 16 were between the age of 18 and 30, and just under 17 percent for nurses older than 50. Based on these percentages, differing results may occur if there was a larger percentage of either younger than 30, or older than 50 nurses were the majority respondents. A final limitation is due to the large size of the questionnaire. There is a greater risk of inaccuracies, and also a possible decrease in participation with a large number of questions.

Recommendations

The conceptual framework and quantitative nature of this research has provided avenues for future investigation. As individual human factors become more apparent in research involving the adoption of technology, having validated models and constructs to apply in different settings allows researchers to more easily build upon this and similar studies. Research in other domains involving personality traits and technology acceptance may provide ample avenues of valid research as well.

The results have identified several areas of research closely linked to the characteristics presented within this research's framework; including relevant healthcare professionals (nurses), the individual factors that impact the successful adoption of technology (personality traits), and the emerging technologies increasingly utilized for patient care (WIMDs). Future research such as with TWE, and how it might have a larger role in a nurses, or other healthcare professional's intention to use WIMDs, or other technology-driven devices used for patient care, should be taken into consideration.

Similar research using this framework that looks to compare and validate the impact that demographic characteristics have on adopting new technologies should also be considered. For example, comparing the results of a younger nursing population to that of the older, likely less technically trained nurse population. Additional research can be conducted that investigates the differences between nurses that work full-time or part-time, or whom work in a hospital versus clinic, versus independent contract work. Also, investigations between nurses that work in different hospital departments can provide valid contribution to research. For example, will a nurse who works in the emergency room (ER) department show significantly different tendencies in adopting a technology-driven device for patient care than a nurse who works in the operating room (OR), the radiology department, or the laboratory? Plugging in new facets of the data may improve the overall generalizability of this research, while simultaneously setting up unique and valid opportunities for future and relevant studies.

Based on the results of this study, future recommendations specific to this research framework may start with a continuation of, and an extended study on the extraversion personality trait. Specifically, further evaluation of extraversion's influence on an individual's intention to use emerging technologies. Conducting research both within and outside of the healthcare domain, with different participants, and different technologies may help to determine if the significance extraversion showed was specific to the sample, the environment, or to the technology itself.

A final recommendation is, because the number of respondents did not result in a relatively high response rate, the same or similar research may be conducted again, though on a larger scale with additional population to draw from. For example including more than one local hospital group. In doing so the initial research can be validated to a higher level by comparing the results of each iteration of the research.

Summary

The main goal of this research was to determine if identifiable personality traits influence a nurse's intention to use (IU) wireless implantable medical devices (WIMDs) for patient care. At the beginning of this investigation a conceptual framework was developed, and from it, three questions and three hypotheses that has guided this research. In order to fulfill this goal and to gather the necessary data to properly conduct a quantitative study, a survey methodology was employed.

A three-part 72-item online questionnaire was developed based on pre-existing scale items that have been extensively tested for validity and reliability through valid research and literature. The instruments were adopted from the FFM and UTAUT models that form the theoretical underpinnings of this research. The questionnaire was hosted through a dedicated online survey platform and distributed exclusively online using email through the hospital's domain.

To gather the necessary data the questionnaire was used to query a sample frame of nurses employed at a tertiary teaching hospital located in southeast Michigan. The sample population consisted of full or part-time registered, or equivalently qualified nurses employed by the hospital. In total there were 102 completed questionnaires that were successfully submitted and used in these results. Participating in this research was not a requirement by the hospital, thus all submitted questionnaires were done so by nurses voluntarily.

Prior to statistical analysis the collected dataset went through both a pre-analysis screening process as well as being tested for the necessary assumptions to ensure that the final inputted data was valid. A correlation matrix was also created to compare the correlation coefficients between variables. This was conducted as a preliminary step to the regression analysis, and also as way to visually scan for violations of the data. These processes resulted in confirming that the sample data was approximately normally distributed, that data outliers were no longer present, and that the constructs were tested as reliable and valid. Required assumptions of regression were also tested and met, and as such, there were no findings of heteroscedasticity, multicollinearity, autocorrelation, or other violations. After the cleaning and validation processes were completed, 102 datasets remained and were moved forward into the analysis phase.

Multiple linear regression (MLR) was used to test goodness of fit, and to develop the model used to measure the statistical contribution of the IVs of PE, EE, and SI in predicting IU. In administering MLR, aggregated mean values were assigned to each variable. These values were then loaded into the MLR model, with PE, EE, and SI together as IVs and IU as the single DV. The MLR output showed that the overall model was statistically significant, confirming that it was a good fit in predicting IU: $R^2 = .385$, $F(3,98) = 20.407$, $p < .001$. IBM SPSS version 25.0 was used to conduct the MLR analysis.

The second part of the analysis phase was in using moderated multiple regression (MMR). MMR was used to statistically analyze each of the five MV’s indirect effects between the three IVs and the single DV. As with MLR, aggregated measures were assigned to the variables prior to loading, including the mean values, and the interaction term values, of which were transformed by calculating the product of each individual MV – IV combinations as defined within the research hypotheses. In setting up MMR, a two-step variable loading process was administered. The first step consisted of loading a combination of three variables into the first regression model, including a single MV, IV, and the DV. The second step consisted of loading two variables into the second regression model, consisting of only two variables, the single DV and the interaction term.

To analyze each of these combinations through the MMR model, 15 separate regression tests were carried out as a way to measure the strength and direction between PE and IU, EE and IU, and SI and IU, and to determine if the three relationships were statistically significant while being moderated by one or more of the personality trait MVs of openness, conscientiousness, extraversion, agreeableness, and neuroticism. The statistical results were compiled, summarized, and finally used to test each set of the null and alternative hypothesis corresponding to each of the three IV and DV relationships defined in this study's three foundational research questions. IBM SPSS version 25.0 was used to conduct the MMR analysis. Hayes (2018) PROCESS macros was also used as a secondary testing method, with all results being replicated.

The operational goal of this research was to determine if any of the five identifiable personality traits of openness, conscientiousness, extraversion, agreeableness, and neuroticism, significantly moderated one or more of the relationships between PE and IU, EE and IU, or SI and IU. This was determined by the value of the regression coefficient being less than .05 ($p < .05$). The results from the regression model showed that only extraversion significantly moderated the relationship between PE and IU, and also EE and IU, therefore rejecting the null hypothesis under both H*1* and H*2.* There was no significant moderation between SI and IU, therefore the null hypothesis failed to be rejected for H*3.* The final conclusions drawn from the findings of this research show that through the use of the five factor model (FFM) and the unified theory of acceptance and use of technology (UTAUT), the identifiable personality trait of extraversion showed to have negatively influenced the relationship between the independent variable (IV) of performance expectancy (PE) and the dependent variable (DV) of intention to use (IU), and also between the IV effort expectancy (EE) and IU.

In review, this research attempted to build on Barnett et al.'s, (2015), McElroy, et al.'s (2007), Devaraj et al.'s (2008), and Svendsen et al.'s (2013) previous studies that investigated the connection between personality traits and technology acceptance. This research did so by empirically investigating the influence of identifiable personality traits on nurses' intention to use emerging technology in the form of wireless implantable medical devices (WIMDs) for patient care. The results of this study also contributed to the overall body of knowledge (BOK) involving individual human factors and adoption of emerging technologies within the healthcare domain.

Upon request, the resulting data may be shared with the hospital's chief nursing officer (CNO), the chief academic officer (CAO), and also distributed to supporting nursing supervisory staff as requested by the CNO. Wider disbursement of the results to general RN staff is not planned at this time. This anonymous data may also fulfill secondary goals by helping healthcare institutions, vendors, and practitioners alike.

Appendix A

Questionnaire - Section I: Demographics

(Your responses will be kept in absolute confidence. All survey submissions are anonymous).

1. Please indicate your age group:

   A. 18-30 B. 31-40 C. 41-50 D. 51-60 E. 60 or older

2. Please indicate your gender (preferred, not required):

   A. Male B. Female C. ________

3. Have you had hands on experience using a Wireless Implantable Medical Device (WIMD) for patient care?

   (Please read the explanation of a WIMD below prior to answering)

   A. Yes B. No

PLEASE READ: *WIMD's are devices such as pacemakers, implantable cardioverter defibrillators (ICD), insulin pumps, and pain infusion pumps that are invasive AND incorporate wireless functionality. For example, interacting with one of these implantable medical devices using a wireless connection to control various functionalities, such as to 'turn-on' or 'turn-off'; to monitor or download medical data (e.g. health vitals); to measure or to administer medication.*

Questionnaire (Section II: Personality Traits)

SECTION 2: How Accurately Can You Describe Yourself?

Describe yourself as you generally are now, **not** as you wish to be in the future. Describe yourself as you honestly see yourself. On a scale from 1 to 5, indicate for each statement whether it is 1. Very Inaccurate, 2. Somewhat Inaccurate, 3. Neither Accurate Nor Inaccurate, 4. Somewhat Accurate, or 5. Very Accurate as a description of you. So that you can describe yourself in an honest manner, your responses will be kept in absolute confidence, and to reiterate, all survey submissions are anonymous.

		Very Inaccurate	Somewhat Inaccurate	Neither Accurate Nor Inaccurate	Somewhat Accurate	Very Accurate
E01.	I am the life of the party.	1	2	3	4	5
A02.	I feel little concern for others.	1	2	3	4	5
C03.	I am always prepared.	1	2	3	4	5
N04.	I get stressed out easily.	1	2	3	4	5
O05.	I have a rich vocabulary.	1	2	3	4	5
E06.	I don't talk a lot.	1	2	3	4	5
A07.	I am interested in people.	1	2	3	4	5
C08.	I leave my belongings around.	1	2	3	4	5
N09.	I am relaxed most of the time.	1	2	3	4	5
O10.	I have difficulty understanding abstract ideas.	1	2	3	4	5
E11.	I feel comfortable around people.	1	2	3	4	5
A12.	I insult people.	1	2	3	4	5
C13.	I pay attention to details.	1	2	3	4	5
N14.	I worry about things.	1	2	3	4	5

O15.	I have a vivid imagination.	1	2	3	4	5
E16.	I keep in the background.	1	2	3	4	5
A17.	I sympathize with others' feelings.	1	2	3	4	5
C18.	I make a mess of things.	1	2	3	4	5
N19.	I seldom feel blue.	1	2	3	4	5
O20.	I am not interested in abstract ideas.	1	2	3	4	5
E21.	I start conversations.	1	2	3	4	5
A22.	I am not interested in other people's problems.	1	2	3	4	5
C23.	I get chores done right away.	1	2	3	4	5
N24.	I am easily disturbed.	1	2	3	4	5
O25.	I have excellent ideas.	1	2	3	4	5
E26.	I have little to say.	1	2	3	4	5
A27.	I have a soft heart.	1	2	3	4	5
C28.	I often forget to put things back in their proper place.	1	2	3	4	5
N29.	I get upset easily.	1	2	3	4	5
O30.	I do not have a good imagination.	1	2	3	4	5
E31.	I talk to a lot of different people at parties.	1	2	3	4	5
A32.	I am not really interested in others.	1	2	3	4	5
C33.	I like order.	1	2	3	4	5
N34.	I change my mood a lot.	1	2	3	4	5

O35.	I am quick to understand things.	1	2	3	4	5
E36.	I don't like to draw attention to myself.	1	2	3	4	5
A37.	I take time out for others.	1	2	3	4	5
C38.	I avoid my duties.	1	2	3	4	5
N39.	I have frequent mood swings.	1	2	3	4	5
O40.	I use difficult words.	1	2	3	4	5
E41.	I don't mind being the center of attention.	1	2	3	4	5
A42.	I feel others' emotions.	1	2	3	4	5
C43.	I follow a schedule.	1	2	3	4	5
N44.	I get irritated easily.	1	2	3	4	5
O45.	I spend time reflecting on things.	1	2	3	4	5
E46.	I am quiet around strangers.	1	2	3	4	5
A47.	I make people feel at ease.	1	2	3	4	5
C48.	I am exacting in my work.	1	2	3	4	5
N49.	I often feel blue.	1	2	3	4	5
O50.	I am full of ideas.	1	2	3	4	5

Questionnaire (Section III: Technology Acceptance)

SECTION 3: Wireless Implantable Medical Devices (WIMDs):

For the following statements pertaining to Wireless Implantable Medical Devices (WIMD), please circle the number that indicates what best fits your level of agreement or disagreement on a scale from 1 to 7, where 1 = completely disagree, 2 = strongly disagree, 3 = somewhat disagree, 4 = neither agree nor disagree, 5 = somewhat agree, 6 = strongly agree, and 7 = completely agree. You may or may not have experience using WIMDs, feedback for both are of equal value. Your responses will be kept in absolute confidence. All survey submissions are anonymous.

(WIMD's are devices such as pacemakers, implantable cardioverter-defibrillators (ICD), insulin pumps, and pain infusion pumps that are invasive AND incorporate wireless functionality. For example, interacting with one of these implantable medical devices using a wireless connection to control various functionalities, such as to 'turn-on' or 'turn-off'; to monitor or download medical data (e.g. health vitals); to measure or to administer medication)

	Completely Disagree			Neither Agree or Disagree			Completely Agree
PE01. I would find the WIMD useful in my job.	1	2	3	4	5	6	7
PE02. Using the WIMD enables me to accomplish tasks more quickly.	1	2	3	4	5	6	7
PE03. Using the WIMD increases my productivity.	1	2	3	4	5	6	7
PE04. If I use the WIMD, I will increase my chances of getting a raise.	1	2	3	4	5	6	7
EE05. My interaction with the WIMD would be clear and understandable.	1	2	3	4	5	6	7
EE06. It would be easy for me to become skillful at using the WIMD.	1	2	3	4	5	6	7
EE07. I would find the WIMD easy to use.	1	2	3	4	5	6	7
EE08. Learning to operate the WIMD is easy for me.	1	2	3	4	5	6	7
SI09. People who influence my behavior think that I should use the WIMD.	1	2	3	4	5	6	7
SI10. People who are important to me think that I should use the WIMD.	1	2	3	4	5	6	7

SI11. The senior management of this hospital has been helpful in the use of the WIMD.	1	2	3	4	5	6	7
SI12. In general, the hospital has supported the use of the WIMD.	1	2	3	4	5	6	7
FC13. I have the resources necessary to use the WIMD.	1	2	3	4	5	6	7
FC14. I have knowledge necessary to use the WIMD.	1	2	3	4	5	6	7
FC15. The WIMD is not compatible with other devices I use.	1	2	3	4	5	6	7
FC16. A specific person (or group) is available for assistance with WIMD difficulties.	1	2	3	4	5	6	7
IU17. I intend to use the WIMD in the next 3 months if the decision was mine.	1	2	3	4	5	6	7
IU18. I predict I would use the WIMD in the next 3 months if the decision was mine.	1	2	3	4	5	6	7
IU19. I plan to use the WIMD in the next 3 months.	1	2	3	4	5	6	7

Appendix B

Participation Letter

Title of Study: The Influence of Identifiable Personality Traits on Nurses' Intention to Use Wireless Implantable Medical Devices

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Description of Study: Vincent Molosky is a doctoral student at Nova Southeastern University engaged in research for the purpose of satisfying a requirement for a Doctor of Philosophy degree. The intent of this study is to gain a better understanding of nurses' intention to use methods of patient care that utilize emerging technologies in the form of wireless and implantable medical devices (WIMDs). By collecting this data this study will empirically investigate the influence of personality traits on nurses' intention to use devices such as WIMDs.

Benefits of Research:

- This research may provide formal evidence leading to a better understanding of the role personality traits have on a nurse's intention to adopt emerging technologies for patient care.
- It may identify previously unknown factors that impact nurses when adopting emerging technologies into their workflow.
- It may help to establish more effective methods of implementation strategies in the form of learning and training for nurses.
- It may also identify real and perceived challenges facing nurses when required to administer emerging technologies as part of patient care.
- This research will enrich the current body of knowledge by contributing new data demonstrating the impact of identifiable personality traits on a nurse's intention to use emerging technologies in the form of wireless and implantable devices for patient care.

Participation: If you agree to participate, you will be asked to complete the attached questionnaire. This questionnaire will help the researcher identify possible relationships between identifiable personality traits and a nurse's intention to use WIMDs. This data will be used to identify factors that may help contribute to more successful adoption and sustainability of technology into a nurse's workflow, and help to administer quality patient care.

The questionnaire will take approximately ten minutes to complete.

Risks/Benefits to the Participant: There may be minimal risk involved in participating in this study. There are no direct benefits to for agreeing to be in this study. Please understand that although you may not benefit directly from participation in this study, you have the opportunity to enhance the body of knowledge, and the intent to improve patient care. If you have any concerns about the risks/benefits of participating in this study, you can contact the researcher and/or the university's human research oversight board (the Institutional Review Board or IRB) at the numbers listed above.

Cost and Payments to the Participant: There is no cost for participation in this study. Participation is completely voluntary and no payment will be provided.

Confidentiality: Information obtained in this study is strictly confidential unless disclosure is required by law. All data will be secured in a locked combination safe. No identifiers will be used in the reporting of information in publications or conference presentations. No survey questions will ask for personal identifiable information. Therefore, any and all data collected during this survey will be completely anonymous.

Participant's Right to Withdraw from the Study: You have the right to refuse to participate in this study

I have read this letter and I fully understand the contents of this document and voluntarily consent to participate. All of my questions concerning this research have been answered. If I have any questions in the future about this study they will be answered by the investigator listed above or his/her staff.

I understand that the completion of this questionnaire implies my consent to participate in this study.

Appendix C

NOVA SOUTHEASTERN UNIVERSITY
Institutional Review Board

MEMORANDUM

To: **Vincent Molosky**

From: **Ling Wang, Ph.D.,**
Center Representative, Institutional Review Board

Date: **August 22, 2017**

Re: **IRB #: 2017-515; Title, "The Influence of Identifiable Personality Traits on Nurses' Intention to Use Wireless Implantable Medical Devices"**

I have reviewed the above-referenced research protocol at the center level. Based on the information provided, I have determined that this study is exempt from further IRB review under **45 CFR 46.101(b) (Exempt Category 2)**. You may proceed with your study as described to the IRB. As principal investigator, you must adhere to the following requirements:

1) CONSENT: If recruitment procedures include consent forms, they must be obtained in such a manner that they are clearly understood by the subjects and the process affords subjects the opportunity to ask questions, obtain detailed answers from those directly involved in the research, and have sufficient time to consider their participation after they have been provided this information. The subjects must be given a copy of the signed consent document, and a copy must be placed in a secure file separate from de-identified participant information. Record of informed consent must be retained for a minimum of three years from the conclusion of the study.

2) ADVERSE EVENTS/UNANTICIPATED PROBLEMS: The principal investigator is required to notify the IRB chair and me (954-262-5369 and Ling Wang, Ph.D., respectively) of any adverse reactions or unanticipated events that may develop as a result of this study. Reactions or events may include, but are not limited to, injury, depression as a result of participation in the study, life-threatening situation, death, or loss of confidentiality/anonymity of subject. Approval may be withdrawn if the problem is serious.

3) AMENDMENTS: Any changes in the study (e.g., procedures, number or types of subjects, consent forms, investigators, etc.) must be approved by the IRB prior to implementation. Please be advised that changes in a study may require further review depending on the nature of the change. Please contact me with any questions regarding amendments or changes to your study.

The NSU IRB is in compliance with the requirements for the protection of human subjects prescribed in Part 46 of Title 45 of the Code of Federal Regulations (45 CFR 46) revised June 18, 1991.

Cc: Maxine Cohen, Ph.D.
Ling Wang, Ph.D.

3301 College Avenue • Fort Lauderdale, Florida 33314-7796
(954) 262-0000 • 800-672-7223, ext. 5369 • Email: irb@nova.edu • Web site: www.nova.edu/irb

Appendix D

McLaren
HEALTH CARE

Research Integrity
Institutional Review Board
2701 Cambridge Ct., Suite 110
Auburn Hills, MI 48326
TEL: (248) 484-4950
FAX: (248) 276-9732
email: hrpp@mclaren.org

NOTICE OF MHC IRB REVIEW

DATE:	06/14/2018
TO:	Vincent Molosky, MBA, Nursing and Patient Care
	David Taylor, DPM, Nursing and Patient Care
FROM:	M. Ammar Hatahet, MD, MPH, FACP, MHC IRB
PROTOCOL TITLE:	The Influence of Identifiable Personality Traits on Nurses# Intention to Use Wireless Implantable Medical Devices
PROTOCOL NUMBER:	2018-00026

Dear Mr. Molosky:

The above referenced project meets the criteria outlined in 45 CFR 46.101 for EXEMPTION. You have been issued a waiver of the requirement to obtain a signed consent form, as per 45 CFR 46.117(c). The MHC IRB will be notified of this action at the regularly scheduled meeting on 07/06/2018.

THE FOLLOWING EXEMPT REVIEW CATEGORY APPLIES TO THIS PROJECT: 2

THIS APPROVAL INCLUDES THE FOLLOWING:

1. Survey cover letter, v1, dated 5.30.18;
2. Protocol document v2, dated 6.11.18;
3. Questionnaire, dated May 2018;
4. Data collection spreadsheet, undated.

All research must be conducted in accordance with all applicable Department of Health and Human Services regulations 45 CFR 46, Food and Drug Administration regulations 21CFR 50, 21CFR 56, 21 CFR 312, 21 CFR 812, 21 CFR 814 Subpart H (when applicable), and the Health Insurance Portability and Accountability Act (HIPAA).

ALL INVESTIGATORS MUST COMPLY WITH THE FOLLOWING:

1. Use only current IRB-approved tools (questionnaires, letters, advertisements, etc.) and informed consent forms (approved ICFs have IRB approval language in the footer).
2. Submit a Final Report to the IRB when the study is completed.
3. Submit a Modification and obtain pre-approval from MHC IRB for any changes in research.
4. Notify the MHC IRB office immediately if any problems / issues occur during the conduct of research that may increase the risk to subjects.
5. Report any complaints or issues of non-compliance to the HRPP office immediately.

IMPORTANT REMINDERS:

1. This approval may be recalled at any time if IRB Policies and Procedures are not followed.
2. The PI is responsible for ensuring that all personnel comply with institutional policies and have current McLaren-required training prior to and during participation in this project.
3. All research studies are expected to conform to Good Clinical Practice (GCP) guidelines, when applicable.
4. All studies are subject to audit by the Office of Research Compliance and/or Institutional Review Board to confirm adherence to institutional, state, and federal regulations.

The Office of the IRB does not send a hard copy of documents which have been electronically transmitted. These are the only copies of the regulatory documents you will receive.

Full Accreditation

Appendix E

McLaren HEALTH CARE

RESEARCH INTEGRITY
McLaren Health Care
2701 Cambridge Ct., Suite 110
Auburn Hills, MI 48326
Phone: (248) 484-4950
Fax: (248) 276-9752
e-mail hrpp@mclaren.org

PROJECT IMPACT STATEMENT

This form may be duplicated as needed

Researcher/Principal Investigator:

Identify any department (e.g. Medical Records, Pharmacy, Laboratory, Nursing, Finance, Radiology, Surgery, etc.) of your subsidiary hospital that will be affected by this research and obtain the Department Manager/Director's written approval.

You must provide this signed statement to the MHC IRB Office either by mail:
2701 Cambridge Ct., Suite 110
Auburn Hills, MI 48326
OR Fax: (248) 276-9732

MHC IRB Approval letter will not be issued until MHC IRB office receives a signed copy.

Department Manager/Director:

Be sure you have a clear understanding of the role(s) your department plays in this research project, and the reimbursement of expenses, if applicable.

You may request that the researcher provide you with documentation of the outcome of the MHC IRB's review before the project is initiated in your department.

Department Manager/Director

I have reviewed the project, entitled *The Influence of Identifiable Personality Traits on Nurses' Intention to Use Wireless Implantable Medical Devices*, with Vincent McCoskey (the researcher/PI) and I confirm the following **(please place a check mark in the boxes as confirmation that each item has been addressed):**

- [x] We discussed the impact this project will have on this department.
- [x] I have reviewed research procedures pertaining to this department with the PI or his/her designee
- [x] I understand the financial impact the research procedures may have on this department
- [x] I have been provided with a copy of this form for future reference.

JW 4/10/18

Approved by:

James Williams PhD RN

Signature of Department Manager/Director granting approval March 28, 2018 **Date**

James Williams, PhD, MSN, RN
Printed name of Department Manager/Director

Nursing
Department

McLaren – Flint – McLaren Healthcare
McLaren Subsidiary

Appendix F

MAY/03/2018/THU 02:57 PM CPG PC FAX No. 810 250 5050 P. 001

McLaren
HEALTH CARE

D/c 766-2041

RESEARCH INTEGRITY
MHC Institutional Review Board
3744 Cambridge Ct., Suite 110
Auburn Hills, MI 48326
Phone: (248) 484-4950 Fax: (248) 276-4732

- ☐ McLaren Oakland
- ☐ McLaren Cancer Institute
- ☐ McLaren Health Care Village at Clarkston
- ☐ McLaren Medical Group
- ☐ McLaren Visiting Nurse and Hospice
- ☐ McLaren Northern Michigan
- ☐ Other (please specify):

5. **The MHC IRB will rely on your careful consideration and review of the following 3 questions**

   a. Are the research procedures the least risky procedures that can be performed consistent with sound research design? ☑ **Yes** ☐ **No**

   b. Is the research likely to achieve its aims? ☑ **Yes** ☐ **No**

   c. Is the proposed research of sufficient scientific importance to justify the risks entailed? ☑ **Yes** ☐ **No**

Signature of the Reviewer *   5/2/18 **Date**

**The Reviewer's signature confirms the soundness of the research design and the ability of the research to achieve its aims. The Reviewer must be someone other than the PI.*

ATTENTION RESIDENTS: The Academic Advisor for your project must serve as the Reviewer.

Printed Name DAVID T. TANASKA   **Title:** DPM

Appendix G

PROTOCOL
Exempt Form
McLaren Health Care

Protocol # 2018-00026
PI: Vincent Molosky
Date Printed: 05/31/2018

Protocol Title:	The Influence of Identifiable Personality Traits on Nurses' Intention to Use Wireless Implantable Medical Devices
Protocol Type:	Exempt Form
Date Submitted:	Draft
Important Note:	This Print View may not reflect all comments and contingencies for approval. Please check the comments section of the online protocol. Questions that appear to not have been answered may not have been required for this submission. Please see the system application for more details.

*** Assurance ***

Assurance

Obligations of the Principal Investigator include the following:

Modifications - Changes in any aspect of the study (for example, project design, procedures, consent forms, advertising materials, additional key personnel, or subject population) will be submitted to the IRB for approval before instituting the changes.

Consent Forms - All subjects will be given a copy of the signed consent form unless a waiver of consent has been approved. Investigators will be required to retain signed consent documents for seven (7) years after the close of the study.

Training - All research personnel will complete the required CITI training before engaging in any research-related activities, including recruitment and screening.

Unanticipated Problems - The principal investigator will promptly submit any reportable UPIRSO (unanticipated problem involving risk to subjects or others) that may occur in the course of this study.

This study will not begin until the investigator receives written final approval of exemption.

Vincent Molosky / May 31st, 2018

X The Principal Investigator has read and agrees to abide by the above obligations.

(Please provide a signed & dated (by the PI) copy of this Assurance page in the Attachments section.)

Page 1 of 1

Appendix H

Test for Normality *102 degrees of freedom (df)*

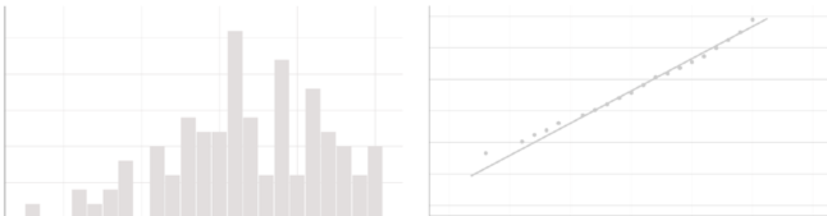
Construct	*Skew-ness Statistic*	*Skewness Standard Error (SE)*	*Skew-ness z-value*	*Kurtosis Statistic*	*Kurtosis Standard Error (SE)*	*Kurtosis z-value*	*Kolmogorov-Smirnov*[a] *Statistic*	*p-value*	*Shapiro-Wilk* *Statistic*	*p-value*
Intention to Use	.160	.239	.669	-.516	.474	-1.089	.089	.047	.981	.149
Performance Expectancy	-.237	.239	-.992	-.350	.474	-.738	.099	.039	.981	.161
Effort Expectancy	-.203	.239	-.849	-.654	.474	-1.380	.088	.047	.976	.055
Social Influence	-.281	.239	-1.176	-.218	.474	-.460	.138	.000	.975	.103
Facilitating Conditions	.120	.239	.502	-.339	.474	-.715	.113	.003	.974	.044
Openness	-.180	.239	-.753	-.101	.474	-.213	.071	.200	.991	.728
Conscien-ciousness	-.255	.239	-1.067	-.633	.474	-1.335	.086	.063	.974	.040
Extraversion	.087	.239	.364	-.361	.474	-.762	.090	.040	.984	.265
Agreeable-ness	-.375	.239	-1.569	-.277	.474	-.584	.085	.064	.975	.053
Neuroticism	.283	.239	1.184	-.204	.474	-.430	.069	.200	.985	.309

a Includes Lilliefors Significance Correction

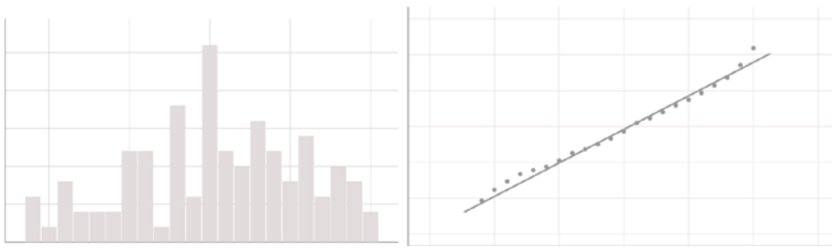
Appendix I

Histograms and Q-Q Plots

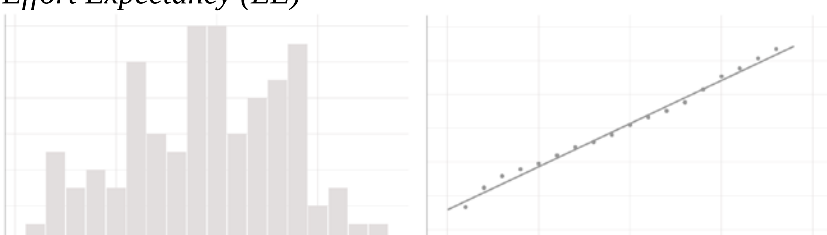
Agreeableness



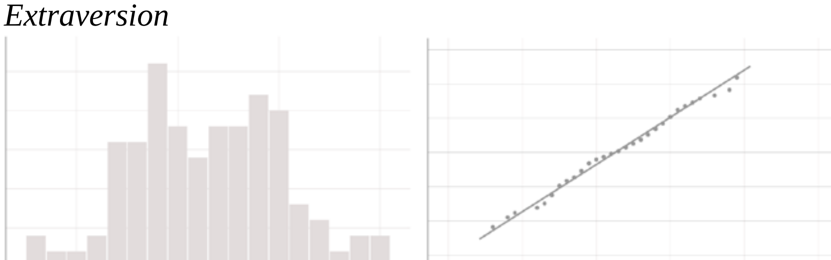
Conscientiousness



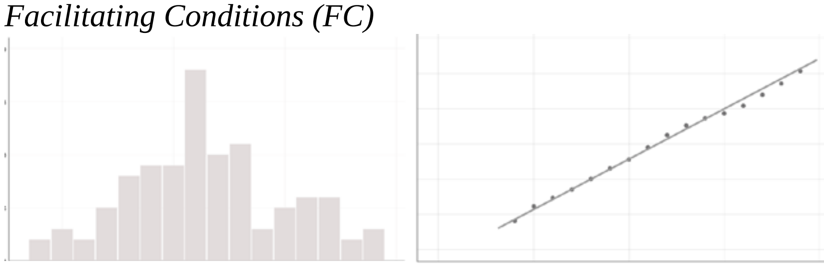
Effort Expectancy (EE)



Extraversion

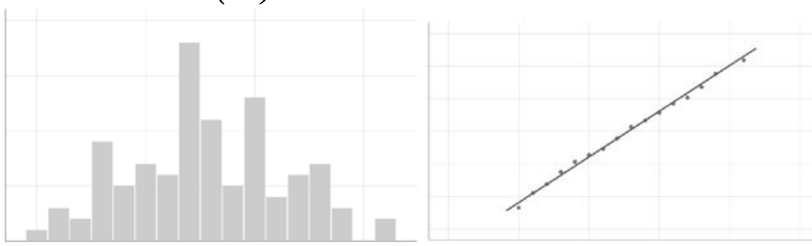


Facilitating Conditions (FC)

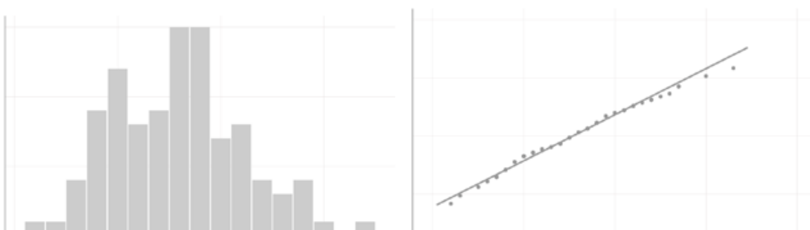


Appendix I (continued)

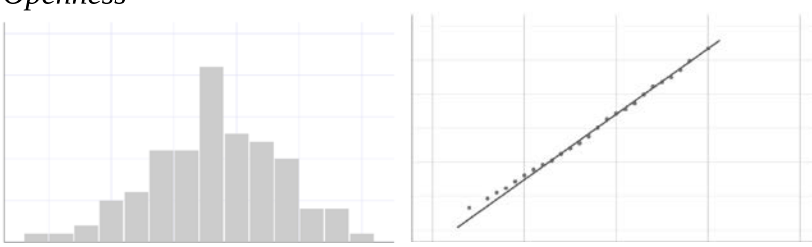
Intention to Use (IU)



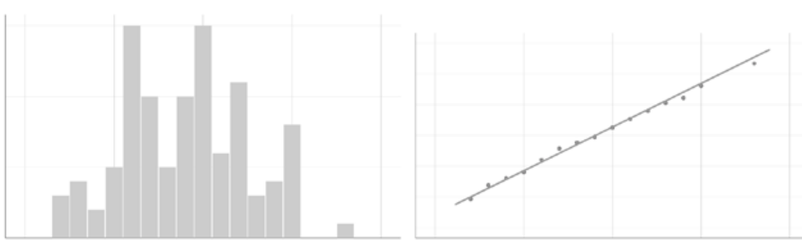
Neuroticism



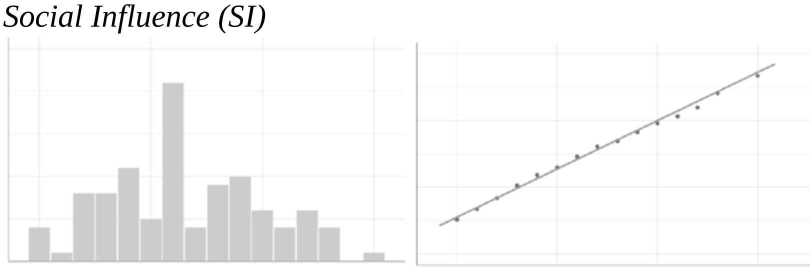
Openness



Performance Expectancy (PE)



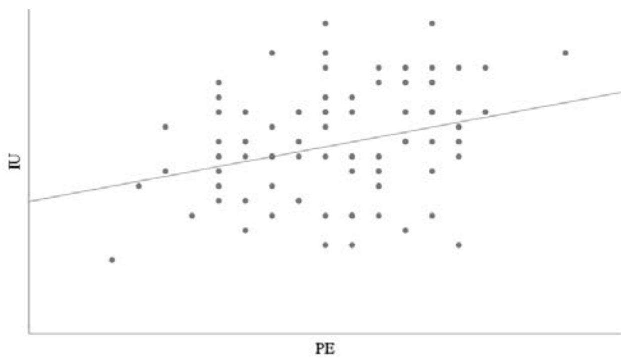
Social Influence (SI)



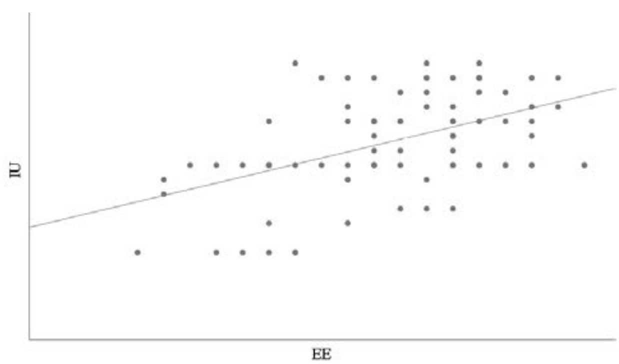
Appendix J

Scatterplots for IVs (X) and DV (Y)

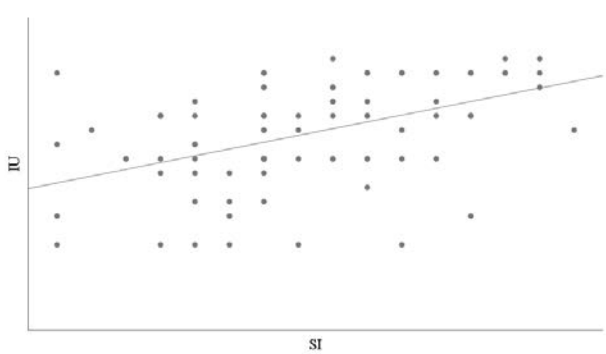
Scatterplot for PE & IU



Scatterplot for EE & IU



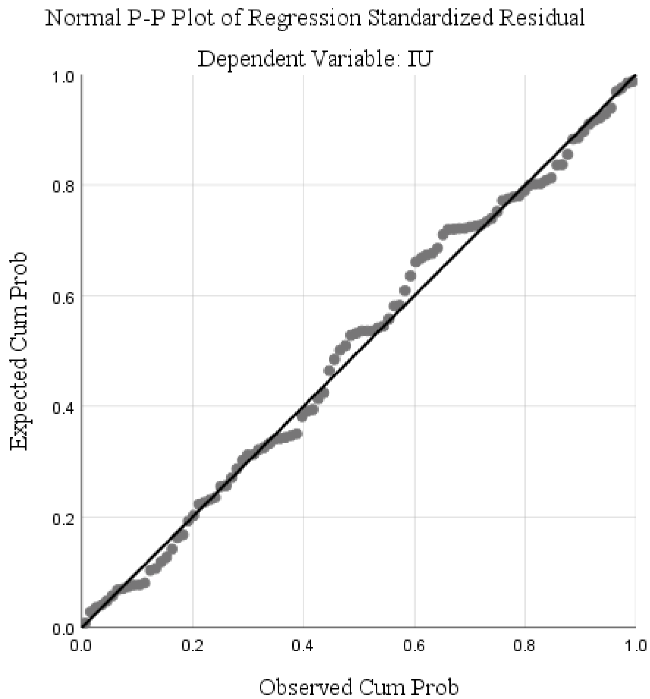
Scatterplot for SI & IU



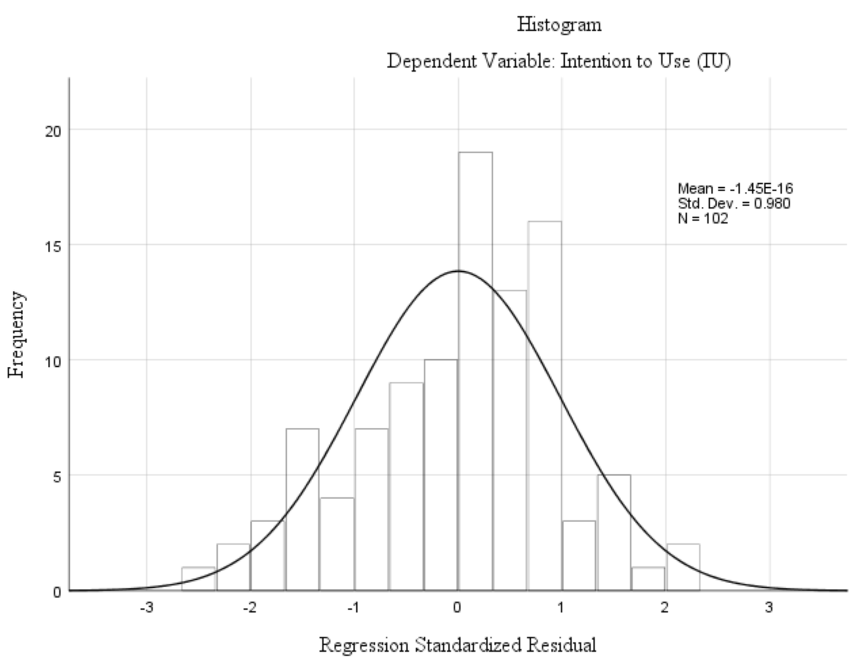
Appendix K

Regression Model Residuals

P-P plot



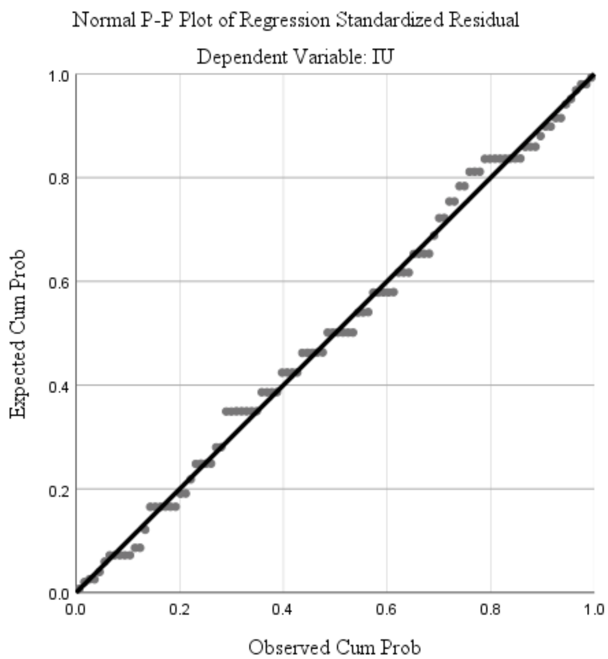
Histogram

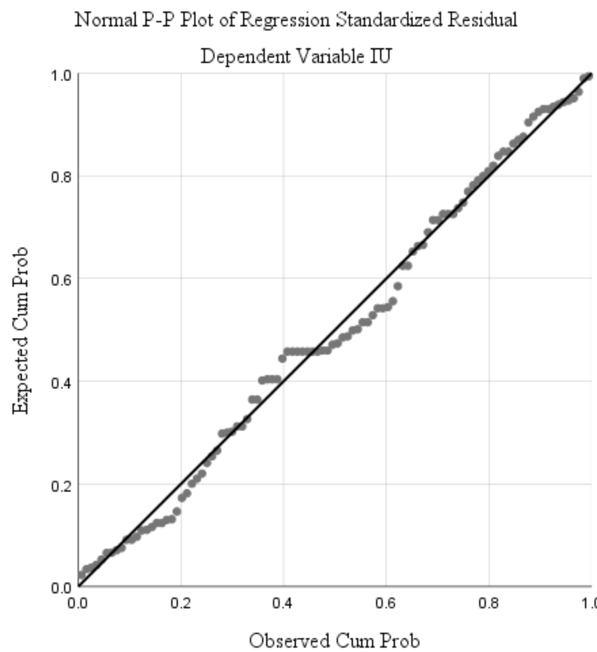


Appendix L

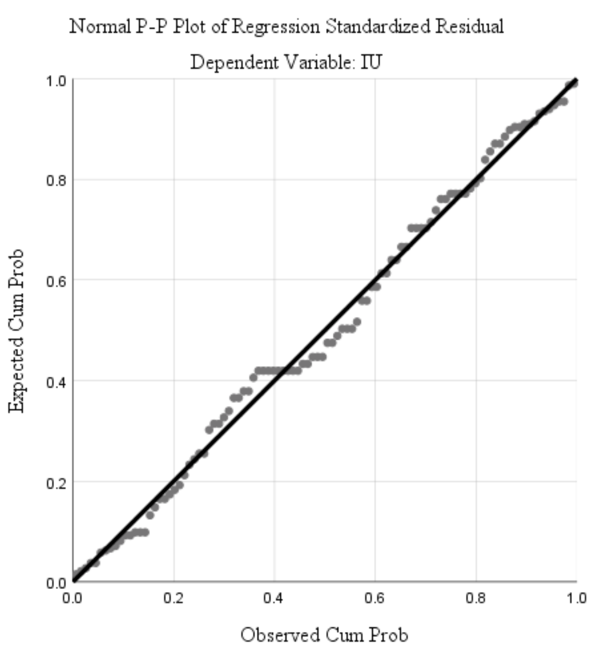
Regression Residuals – P-P plots

PE & EE





SI



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