FACTORS IMPACTING THE ACTUAL USE OF DIGITAL HEALTH TECHNOLOGIES TO IMPROVE HEALTH OUTCOMES: INTEGRATION OF UTAUT AND THE HEALTH BELIEF MODEL

By

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A dissertation submitted to the faculty of
The University of North Carolina
in partial fulfilment of the requirements for the
degree of Doctor of Business Administration

Charlotte

2024

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ABSTRACT

NICOLE ELLIOTT GODLOCK, Factors Impacting the Actual Use of Digital Health Technologies to Improve Health Outcomes: Integration of UTAUT and the Health Belief Model (Under the direction of DR. REGINALD SILVER)

In the healthcare domain, the development of digital health technologies, including mobile applications, telehealth, wearables, and portals, have created new avenues to deliver patient care, track chronic illnesses, and distribute health information. Digital health technologies allow physicians and patients to interact outside of the traditional care settings; therefore, increasing access to care for disparate populations. Understanding the factors that impact a patient's decision to adopt digital health technologies is essential to maximizing the Actual Use of digital health technologies and addressing health disparities. This research integrates the Health Belief Model (HBM) and Unified Theory of Acceptance and Use of Technology (UTAUT) to examine technology use behaviors specifically in the context of healthcare. This study evaluates three independent variables – Intention to Use, Perceived Health Benefit, and Social Influence to determine their impact on Actual Use of technology. This study also investigates how Trust in Technology and eHealth Literacy moderate the relationship between Actual Use of technology and its antecedents. Data from a sample of adults in the United States (N= 293) provides insights into the relationships of the proposed research model.

Key Words: Digital Health Technology, Actual Use, Technology Adoption, eHealth Literacy, UTAUT, Health Consciousness, Trust, Perceived Health Benefit, Behavioral Intention, Health Belief Model, Social Influence

DEDICATION

I dedicate this dissertation to my beloved husband, my three amazing children, my dearest parents, and my cherished little brother. Your unwavering prayers, support, patience, and unconditional love have been instrumental to me achieving this milestone.

To my husband, without your support the completion of this doctoral program or dissertation would not be possible. You have made countless sacrifices and investments to support the fulfilment of my dreams. I could never thank you enough for your support and encouragement which has enabled me to achieve this milestone. To my mom and dad, thank you for the strong foundation you laid for me and the unwavering guidance, support, and love you have shown throughout my life. The diligence, perseverance, and integrity that you instilled in me have shaped my professional and academic endeavors and my character. To my little brother, thank you for your unwavering love and support. Your trailblazing spirit continues to inspire me. To my children, your presence and love inspires me to be the best version of myself. Your innocence and joy have given me strength during the challenging times of this journey. Everything I do is for all three of you and it is my sincerest hope that mama has made you all proud.

I dedicate this achievement to all of you as a testament to the sacrifices we have all made together. Thank you from the bottom of my heart and I love you all beyond words.

ACKNOWLEDGEMENTS

First and foremost, I give all glory and honor to God for allowing me to achieve this significant milestone. I am so thankful.

I extend my heartfelt appreciation to my dissertation Chair, Dr. Reginald Silver, and my amazing committee members, Dr. Chandrasekar Subramaniam, Dr. Chandrika Johnson, and Dr. Laura Stanley for their invaluable investment in me. Their time, guidance, and support have been instrumental in my success. I am genuinely grateful for the thought-provoking questions and constructive feedback that have shaped and refined my research.

I am indebted to my cherished family and key supporters: my husband, Emmanuel Godlock Jr.; my children, Miyanna Godlock, Emmanuel (Trey) Godlock III, and Nicholas Godlock; my parents, Joseph Elliott Jr. and Cheryl Elliott; and my brother, Joey Elliott. I could not have achieved this milestone without them. I am also thankful for my in-laws, friends, and extended family members who have consistently shown love and support throughout this journey.

Special thanks to Dr. Tyler Coker for his invaluable support and friendship. What started as a study session to prepare for a statistics exam has turned into a lifelong friendship. I am thankful for the countless hours he spent studying with me and pushing me towards the finish line for the past several years.

Lastly, I am thankful for my DBA Cohort, “Cohort V.” This journey has been filled with both challenges and joys, and I have treasured every moment that we have gone through this together. I am thankful for the collaboration and support of the entire Cohort throughout this academic journey.

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LIST OF ABBREVIATIONS

EHR	Electronic Health Record
CIS	Clinical Information System
EMR	Electronic Medical Record
DV	Dependent Variable
UTAUT	Unified Theory of Acceptance and Use of Technology
IS	Information Systems
IT	Information Technology
IV	Independent Variable
PLS	Partial Least Squares
SEM	Structural Equation Modeling
US	United States
HBM	Health Belief Model
TR	Trust in Technology
PHB	Perceived Health Benefit
SI	Social Influence
DL	Digital Literacy
EHL	eHealth Literacy
HC	Health Consciousness
AU	Actual Use
BI	Behavioral Intention

CHAPTER 1: INTRODUCTION

Digital health technologies continue to evolve in the healthcare industry as organizations aim to reach patients beyond the scope of the traditional care model and expand access to greater populations of patients outside of the clinical setting. As defined by Mesko et al. (2017), digital health is "the cultural transformation of how disruptive technologies that provide digital and objective data accessible to both caregivers and patients leads to an equal level doctor-patient relationship with shared decision-making and the democratization of care" (Mesko et al., 2017, p.1). The term 'digital health technology' encompasses several technological advances that contribute to the evolution of medicine, including patient portals, telehealth, telemedicine, mobile health apps, and wearables. Key benefits of digital health technology include patients' ability to access their health data consistently, physicians' ability to provide care via technology, and patients' ability to track and monitor their health status without being in an actual physician's office. Researchers and practitioners alike are interested in understanding how to expand the adoption and use of digital health technology to lead to better health outcomes (Crawford & Serhal, 2020; Hu et al., 2002; Kuek & Hakkennes, 2020; Meskó et al., 2017). The global healthcare delivery model has rapidly become more technologically driven by clinicians and organizations in recent years. However, the success of digitization lies in patients leveraging the technology (Leader et al., 2021).

To address the questions around technology adoption, several models and theories have been established to explain how technology is adopted across various industries, including healthcare, banking, and retail. Technology adoption refers explicitly to the use and acceptance of a technology (Davis et al., 1989; Venkatesh et al., 2003). Two of the most widely studied technology adoption theories in the healthcare industry are the Technology Acceptance Model

(TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Guo et al., 2013; Hoque & Sorwar, 2017; Nunes et al., 2019; Venkatesh et al., 2003). According to prior research, the widely supported UTAUT model explains 70% of the variance in intention to use technology and, therefore, was selected as the technology adoption model to base this study (Venkatesh et al., 2003). Although widely supported, UTAUT was not explicitly designed to explain technology adoption behavior in the healthcare industry. Therefore, it is important to examine different variables that influence health behaviors and technology behaviors to understand the adoption of digital health technologies further.

This study aims to integrate the information systems UTAUT model with the healthcare-focused Health Belief Model to explain technology adoption in a healthcare context. In addition, this study examines the potential outcome of using digital health technology. To achieve the optimal benefits of digital health technology and expand product usage, organizations and clinicians need to consider patients' perceptions of digital health technology, trust in technology, social influences, and their ability to use technology.

1.1 Research Gap

Much information systems literature focuses on technology adoption, as this is a widely studied area of research (Liao et al., 2009; Rahi et al., 2020; Venkatesh, 2006). Two existing antecedents of technology adoption – intention to use and Social Influence are derived directly from the UTAUT model and are included in this study (Venkatesh et al., 2003). In prior studies, the established direct relationship is between Social Influence and intention to use, with Social Influence being the independent variable and intention to use as the dependent variable (Venkatesh et al., 2003). Consequently, intention to use also directly relates to Actual Use of technology (Davis, 1989; Venkatesh et al., 2003). However, there is little evidence of a direct relationship between Social Influence and Actual Use. Therefore, this study expands the existing framework to draw a direct connection between Social Influence and Actual Use without the mediating effect of intention to use. Perceived Health Benefit, derived directly from the Health Belief Model, has been studied in healthcare research to understand why individuals engage in specific behaviors (Champion, 1984; Champion & Skinner, 2008). Perceived Benefit is typically evaluated as part of the Health Belief Model in clinical studies to understand health-related actions, such as dietary and nutrition patterns, health screening behaviors, medication adherence, and vaccination decisions (Al-Metwali et al., 2021; Kamran et al., 2014; Vassallo et al., 2009; Zare et al., 2016). However, examining the perceived benefit in the context of technology is necessary to understand why individuals would use a technology.

Thus far, many studies regarding technology adoption in healthcare primarily focus on the antecedents of technology usage. The factors influencing digital health technology adoption have gained much attention from scholars. User perception, social factors, facilitating conditions, and user attributes are widely studied areas that previous scholars have evaluated to understand digital health technology adoption. Contrarily, the study of outcomes and consequences is limited (Alam et al., 2021). A figure summarizing the previous research on digital health technology adoption is included in Appendix I. This study investigates both antecedents and outcomes of digital health technology use, as examining the outcomes is essential to determining and confirming the actual benefits of the technology. Therefore, it is necessary to understand what drives a user to adopt technology and what outcomes result from the Actual Use.

In addition to user perception, Social Influence, and Behavioral Intention, there are ethical aspects, such as trust, that can impact the use of technology. Trust in Technology is supported in prior research as impacting individuals' choice to adopt or accept a technology (Akter et al., 2013; Ashraf et al., 2014; Kesharwani & Bisht, 2012). Research suggests a correlation between trust and technology usage, indicating that as Trust in Technology increases, then usage intentions increase (Choudhury & Shamszare, 2023; Gefen et al., 2003; Hooda et al., 2022; Van Velsen et al., 2015). In a healthcare context, this observation suggests that if patients or consumers do not trust technology to provide accurate health advice or safeguard their health information, they are less inclined to use the technology. Similarly, if patients trust technology, they are more apt to leverage it for their personal and professional needs and trust the information shared through the technology. Therefore, examining Trust in Technology and understanding its influence on the use of technology can help organizations proactively mitigate this concern with patients to expand the use of digital health technologies within communities. Current information systems literature examining Trust in Technology as a moderating factor between technology adoption antecedents and the Actual Use of technology is underdeveloped, as the extant research is primarily focused on trust as an actual antecedent to Behavioral Intention to adopt a technology (Alaiad & Zhou, 2014; Belanger & Carter, 2008; Dhagarra et al., 2020; Gefen et al., 2003; Tung et al., 2008). This study aims to determine if Trust in Technology moderates the relationship between the technology use antecedents and the Actual Use of technology.

Furthermore, user attributes such as eHealth Literacy can influence one's use of technology. eHealth Literacy is the combination of multiple skills needed to effectively use digital technologies to access and manage healthcare information (Norman & Skinner, 2006b). The term eHealth Literacy originated from the evolution of health literacy and digital literacy and the gap between the ability to effectively navigate and understand health technologies and the use of health technologies (Norman, 2011). As healthcare organizations move towards digital care models, eHealth Literacy becomes increasingly essential to bridge the gaps in care. eHealth Literacy can enable individuals to use and understand digital health resources effectively. However, if eHealth Literacy is not proactively addressed, it can widen the gaps in care across different sociodemographic groups (Yao et al., 2022). Therefore, examining eHealth Literacy and its impact on technology adoption is essential to addressing the digital divide in healthcare.

1.2 Addressing Gaps in Literature and Research Questions

To fill gaps in the literature, the UTAUT theory and the HBM are evaluated to understand technology adoption and healthcare behaviors. The critical constructs of both models are integrated in an empirical study to help explain what drives patients to adopt technologies, specifically in the healthcare industry. Furthermore, Trust in Technology and eHealth Literacy and their influences on the relationships between Perceived Health Benefit, Behavioral Intention, Social Influence, and Actual Use of digital health technology are explored. By evaluating a patient's literacy skills towards using digital technologies and exploring the moderating role of Trust in Technology, this paper further expands the extant literature on technology adoption in healthcare. In addition, this empirical study also expands the current technology adoption literature by including an outcome variable to understand how healthcare technology impacts the patient after it has been adopted.

Our primary research questions are as follows:

1) What are the factors that explain digital health technology adoption?
2) Does digital health technology usage increase an individual's health consciousness?
3) Does the level of Trust in Technology moderate the relationship between technology use antecedents and the Actual Use of digital health technology?

4) Does eHealth Literacy moderate the relationship between technology use antecedents and the Actual Use of digital health technology?
5) Does digital health technology usage vary based on sociodemographic groups?

A comprehensive analysis of the existing technology adoption literature is completed to understand the key components that drive technology adoption across industries. An additional evaluation of research on the healthcare industry fosters a comprehensive understanding of healthcare technologies and behaviors. This study proposes an integrated model that contains UTAUT and HBM variables, such as Behavioral Intention to use, Social Influence, and Perceived Health Benefit, to explain the Actual Use of digital health technology. The proposed research model includes the moderating effects of eHealth Literacy and Trust in Technology. Lastly, this dissertation builds on the existing technology adoption literature framework to propose Health Consciousness as an outcome of the Actual Use of digital health technologies. This empirical study will evaluate the antecedents and outcomes of using digital health technology to help software companies and healthcare organizations further evolve how care and healthcare is distributed to communities.

1.3 Organization of Discussion

The remainder of this document will discuss the theoretical framework and present the theory development and research model. This study contains eleven hypotheses based on the research questions: five with a direct effect relationship and six with moderating relationships. Following the presentation of hypotheses are the methods of analysis and research design, followed by a discussion of the results. In conclusion, the findings and their theoretical and managerial implications are presented.

CHAPTER 2: LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

A comprehensive and in-depth literature review facilitates the understanding of the prior research on technology adoption within the healthcare industry and the theoretical foundations underpinning prior studies. The Health Belief Model and UTAUT were evaluated to understand their importance in the prior research and to support the theoretical underpinning of this study. The literature review aided in identifying current gaps in technology adoption research, specifically surrounding individuals' use of digital health technologies. This literature review consists of three main sections. The first section defines the variables in the conceptual model and explains the history of each term. The second section details this study's theoretical framework, which integrates the Unified Theory of Technology Adoption and Use theory (UTAUT) and the Health Belief Model (HBM) in the context of this research. Lastly, the final section concludes this chapter by presenting the research model and hypotheses that explain the usage of digital health technology and its overall influence on health consciousness, ultimately contributing to improving health outcomes.

2.1 Definitions

Behavioral Intention to Use

Behavioral intention to use is a variable in various technology adoption models, including the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), UTAUT, and UTAUT2 (Ajzen, 1991; Davis, 1989; Davis et al., 1989; Venkatesh et al., 2003; Venkatesh et al., 2012). Behavioral intention (BI) is the extent to which a person plans to perform or not perform a specific action (Davis et al., 1989). An extensive review of the technology adoption literature demonstrates the relationship between the intention to use technology and the actual usage of technology (Davis et al., 1989; Venkatesh et al., 2003; Venkatesh et al., 2008; Venkatesh et al., 2012).

Perceived Health Benefit

The Heath Belief Model introduced the construct of Perceived Benefit to explain a person's belief in the potential benefits of a health-related action to reduce the threat of severe diseases (Wang et al., 2021). Perceived Health Benefit suggests that unless a specific health-related action is deemed beneficial and effective, an individual is unlikely to pursue such health-related actions (Wang et al., 2021). The construct Perceived Benefit has been applied to various industries, including finance and healthcare. In this dissertation, Perceived Benefit is used interchangeably with Perceived Health Benefit as it applies to actions specifically related to an individual's health.

Social Influence

The UTAUT model introduced the construct of Social Influence to explain why individuals adopt technology (Venkatesh et al., 2003). Social influence is one of four independent variables in the original UTAUT model (Venkatesh et al., 2003). Social influence is "the degree to which an individual considers the significance of the beliefs of others when adopting a new information system" (Venkatesh et al., 2003, p. 450). Social relationships such as family, friends, and colleagues can influence and change an individual's perception of technology adoption. In healthcare, an individual's social influences include physicians and nurses. Extensive prior research suggests Social Influence has an impact on technology adoption behaviors across various technologies and industries (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Cavdar et al., 2020; Dash & Sahoo, 2021; Dino & Guzman, 2015; Gao et al., 2015; Hoque & Sorwar, 2017; Nunes et al., 2019; Seethamraju et al., 2018; Venkatesh et al., 2003). In the context of both the original UTAUT model and the extended UTAUT2 model, Social Influence directly impacts an individual's Behavioral Intention to adopt a technology (Venkatesh et al, 2003; Venkatesh et al., 2012). As previously defined, Behavioral Intention to adopt technology is not the same as the actual usage of technology (Davis, 1989). Individuals are more likely to adopt a technology based on their social groups or the influence of their network if they will be rewarded for the desired behavior or punished for non-compliance with the desired behavior (Seethamraju et al., 2018).

In the healthcare context precisely, Social Influence has been linked to the Behavioral Intention to adopt various healthcare technologies, including mHealth, telehealth, and wearables (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Cavdar et al., 2020; Dash & Sahoo, 2021; Dino & Guzman, 2015; Gao et al., 2015; Hoque & Sorwar, 2017; Nunes et al., 2019; Seethamraju et al., 2018; Venkatesh et al., 2003). Scholars suggest that a patient's adoption of technology can be influenced by social networks (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Cavdar et al., 2020; Dash & Sahoo, 2021; Dino & Guzman, 2015; Gao et al., 2015; Hoque & Sorwar, 2017; Nunes et al., 2019; Seethamraju et al., 2018). On the contrary, there have been mixed results when examining the professionals' and clinicians' adoption. Some studies show that Social Influence does not play an essential role in clinicians' Behavioral Intention to adopt technologies because they are confident in their own decisions and do not seek third-party validation from their social network (Sun et al., 2013). While most studies evaluating the role of Social Influence on the Behavioral Intention of patients to adopt technology demonstrate a significant relationship, one study by Cimperman et al. (2016) evaluated older users' adoption of telehealth services and found that Social Influence was not associated with the Behavioral Intention to adopt telehealth services in their study (Cimperman et al., 2016).

Cimperman et al. (2016) suggest that the lack of support for the relationship between Social Influence and Behavioral Intention is due to the elderly not conforming to societal influences (Cimperman et al., 2016). Another possible contributing factor could be the type of technology evaluated in Cimperman et al.'s (2016) study since many studies evaluating the elderly show a significant relationship between Social Influence and Behavioral Intention.

Trust in Technology

Webster's Dictionary defines *trust* as "assured reliance on the character, ability, strength, or truth of someone or something" (Merriam-Webster, n.d.). Furthermore, it defines the term as "one in which confidence is placed" (Merriam-Webster, n.d.). Trust can be applied to many scenarios; however, in academia, it has concisely and formally been defined as the belief that someone or something will deliver an expected value (Pavlou, 2003). In the information systems (IS) context, trust reflects a person's willingness to be vulnerable to technology while using the technology (Cho et al., 2007). Historically, much IS research focused on trust in humans or organizations. More recently, trust in IS research has expanded to include trust in an actual technological artifact (Lankton et al., 2015; McKnight et al., 2011). The construct specific to the model presented in this dissertation is "Trust in Technology," which is ultimately trust in a technological artifact – in this case, digital health technologies. There are both human and system-corresponding definitions of trust when considering Trust in Technology (Lankton et al., 2015; McKnight et al., 2011). The human characteristics of trust focus on integrity, benevolence, ability, and competence (Lankton et al., 2015; McKnight et al., 2011). In contrast, the system characteristics of trust focus on reliability, functionality, and helpfulness (Lankton et al., 2015; McKnight et al., 2011). For this dissertation, the system's corresponding definitions are applicable. Prior studies on Trust in Technology have focused on different technologies' reliability, functionality, and helpfulness, ranging from spreadsheets to knowledge management systems (Lankton et al., 2015; Lippert & Swiercz, 2005; McKnight et al., 2011).

e-Health Literacy

Digital literacy is essential to understanding the adoption and use of technologies across various industries for personal and professional use (Elhajjar & Ouaida, 2019; Mohammadyari & Singh, 2015; Nikou et al., 2022). Paul Gilster (1997) defines *digital literacy* as "the ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers" (Gilster, 1997, p.1). Digital literacy encompasses an individual's ability to comprehend and access information digitally (Eshet, 2012; Gilster, 1997).

Scholars agree that digital literacy is a modern-day life skill to process information in today's technologically driven society (Bawden, 2001; Mohammadyari & Singh, 2015). Several scholars have suggested that digital literacy has a relationship with antecedents of technology adoption (Bayrakdaroğlu & Bayrakdaroğlu, 2017; Nikou & Aavakare, 2021; Nikou et al., 2022; Yu et al., 2017). Specifically, these scholars suggest that if a user has high digital literacy, they will ultimately have a positive relationship with adopting technology (Bayrakdaroğlu & Bayrakdaroğlu, 2017; Nikou & Aavakare, 2021; Nikou et al., 2022; Yu et al., 2017). The term digital literacy can be applied to various industries and technologies. For example, university students and staff with high digital literacy are more likely to adopt e-learning technologies in higher education (Nikou & Aavakare, 2021). Also, other researchers have found that digital literacy influences technology adoption when examining workplace technologies (Nikou et al., 2022). On the contrary, literature has suggested that digital literacy has a direct relationship between two antecedents to the continuance of use in the e-learning environment – specifically, performance expectancy and effort expectancy (Mohammadyari & Singh, 2015). In the banking industry, researchers have also found that digital literacy contributes to an individual's perception that technology is useful or easy to use (Elhajjar & Ouaida, 2019), ultimately impacting technology adoption. Furthermore, in education, research suggests that digital literacy contributes to an individual's perception of a technology, which also impacts the adoption of technology (Mac Callum & Jeffrey, 2014).

In healthcare, digital literacy is combined with health literacy to explain digital health literacy and eHealth Literacy. Health literacy involves having the knowledge and competency to take health-related actions to improve personal and community health (Nutbeam, 2008). In extant research, digital health literacy is commonly used interchangeably with eHealth Literacy (Karnoe & Kayer, 2015; van der Vaart & Drossaert, 2017). The terms "digital health literacy" and eHealth Literacy have evolved from health literacy and digital literacy to align with the increasing digitization of healthcare (Norman & Skinner, 2006a; Norman & Skinner, 2006b; Karnoe & Kayer, 2015; van der Vaart & Drossaert, 2017). *eHealth Literacy* is the term encompassing digital literacy in the healthcare industry that will be used in this dissertation. Scholars have defined *eHealth Literacy* as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (Norman & Skinner, 2006b, p.2). The first eHealth Literacy article was published in 2006 (Norman & Skinner, 2006a; Norman & Skinner, 2006b; Wang et al., 2021). Between 2006 and 2011, there were not many eHealth Literacy studies; however, since 2011, the number of eHealth Literacy studies has consistently risen as the healthcare industry has become increasingly digitized (Wang et al., 2021).

Actual Use of Technology

Actual use of technology is considered a dependent variable in various empirical IS studies. It is typically preceded by the Behavioral Intention to adopt a technology as indicated in the Technology Acceptance Model (TAM), UTAUT model, and UTAUT2 model (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Davis, 1989; Hoque, 2016; Li et al., 2016; Hoque & Sorwar, 2017; Kissi et al., 2020; Venkatesh et al., 2003; Venkatesh et al., 2008; Venkatesh et al., 2012). The term Actual Use began gaining popularity in 1989 when Davis included it in the Technology Acceptance Model (TAM) (Davis, 1989). In Davis's study, he stated that Behavioral Intention influenced the Actual Use of technology, along with other antecedents or predecessors of Behavioral Intention (Davis, 1989). In other studies, scholars later expanded on Actual Use and defined it as the adoption and frequency of time an individual uses a technology. Urbach and Müller (2012) refer to the Actual Use of technology as the degree to which an information system is adopted (Urbach & Müller, 2012). Petter and McLean define Actual Use as the actual or self-reported consumption of an information system (Petter & McLean, 2009). The variable Actual Use of technology has been more widely applied to technologies that are not mandatory. In this dissertation, the Actual Use of technology is the adoption and consumption of technology as previously defined by Petter and McLean (Petter & McLean, 2009).

Health Consciousness

Health consciousness is one's self-awareness or focus on overall health. Prior studies have measured one's psychological state of self-awareness as it pertains to their overall health in the context of food choices, health behaviors, and health information technology adoption, and suggest that individuals who are health conscious are willing to monitor their health and place an emphasis on healthy behaviors (Gould, 1988; Kaskutas & Greenfield, 1997). In the IS domain, Health Consciousness has been previously included as an antecedent in technology adoption studies specific to healthcare technologies. The prior research suggests that one's level of Health Consciousness positively impacts their decision to adopt healthcare technologies. Contrary to the extant literature, this dissertation refers to Health Consciousness as an outcome or dependent variable of technology adoption rather than an antecedent or contributing factor to technology adoption.

2.2 Theoretical Framework

UTAUT Theory

This dissertation incorporates constructs from the UTAUT theory to explain the adoption of digital health technology. The UTAUT theory originated from Venkatesh in 2003 and has been used to explain technology adoption and acceptance across various industries and technologies (Venkatesh et al., 2003). The UTAUT theory is derived from eight previously used models to explain technology adoption. The eight models that contributed to the establishment of the UTAUT theory include the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behavior, a model that combines the technology acceptance model and the theory of planned behavior, the model of PC utilization, the innovation diffusion theory, and the social cognitive theory (Venkatesh et al., 2003). The models contributing to UTAUT originate in various disciplines, including sociology, psychology, and information systems (Davis et al., 1989; Venkatesh & Davis, 2000). The UTAUT model explains 70% of the variance of intention to use technology, in comparison to the models that comprise the UTAUT model, which explain 40% of the variance of the intention to use technology (Davis et al., 1989; Venkatesh et al., 2003; Venkatesh & Davis, 2000). As presented in Figure 1, there are four constructs that UTAUT uses to explain the behavioral intent to adopt technology: performance expectancy, effort expectancy, Social Influence, and facilitating conditions (Venkatesh et al., 2003). In addition, an individual's Behavioral Intention to adopt a technology influences the Actual Use of the technology according to the UTAUT theory (Venkatesh et al., 2003). Although UTAUT has successfully explained the adoption of many technologies in various industries, scholars have proposed that increasing the quantity of external variables can enhance this model's ability to predict the acceptance of IT (Cimperman et al., 2016; Kabra et al., 2017; Maillet et al., 2015).

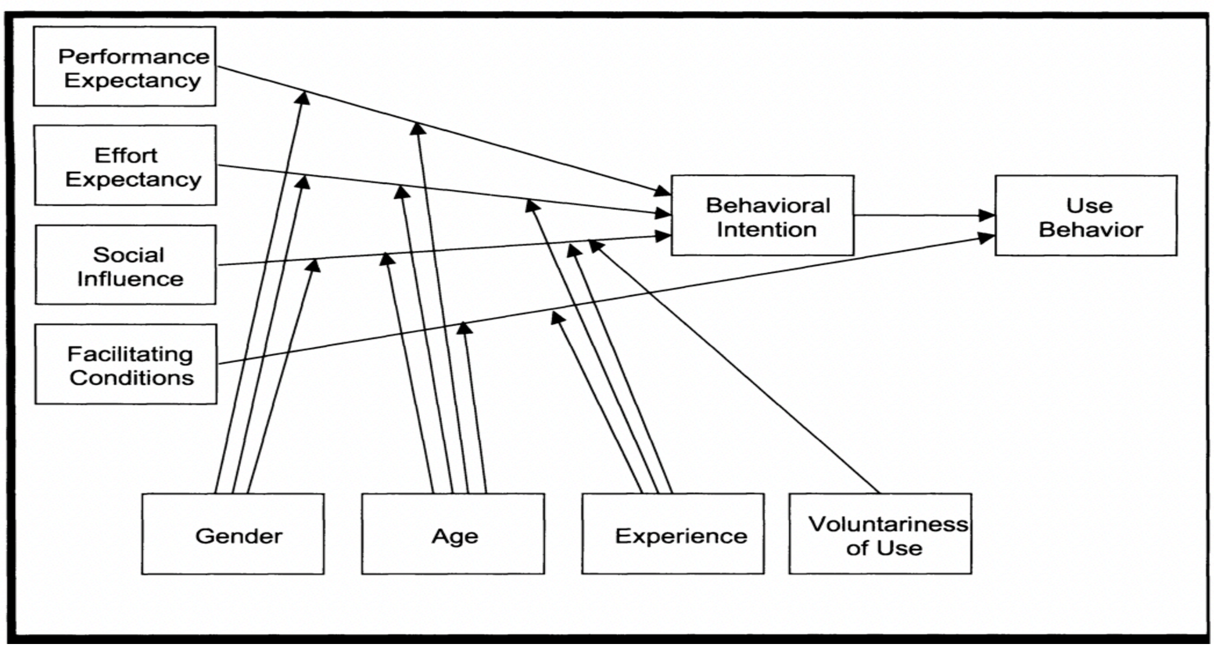


Figure 1: UTAUT Model (Venkatesh et al., 2003)

In 2012, Venkatesh et al. created an extension of the UTAUT model called UTAUT2 (Venkatesh et al., 2012). As seen in Figure 2, UTAUT2 adds three additional constructs to the original UTAUT model: hedonic motivation, habit, and price value. Hedonic motivation is defined by Venkatesh et al. (2012) as "the fun or pleasure derived from using a technology" (Venkatesh et al., 2012, p. 161). Habit is "the extent to which people tend to perform behaviors automatically because of learning (Venkatesh et al., 2012, p. 161). *Price value* is defined by Venkatesh et al. (2012) as an individual's perception of the tradeoff between the benefits of using a technology and the monetary cost of the technology (Venkatesh et al., 2012). As an alternative to UTAUT, which was established to explain technology adoption in an organizational setting, UTAUT2 was developed to explain technology adoption and acceptance specifically in the context of consumer use (Venkatesh et al., 2012). UTAUT2 has successfully explained consumer IT adoption across a wide range of technologies, including wearables and fitness apps (Dhiman et al., 2020; Yuan et al., 2015); mobile banking and payments (Alalwan et al., 2017; Arenas Gaitan et al., 2015; Merhi et al., 2019); and e-commerce (Escobar-Rodriguez & Carvajal-Trujillo, 2013; Lee et al., 2019; Shaw & Sergueeva, 2019). Therefore, similar to UTAUT, UTAUT2 has been applied to various contexts and maintains a reputation as a robust technology adoption model.

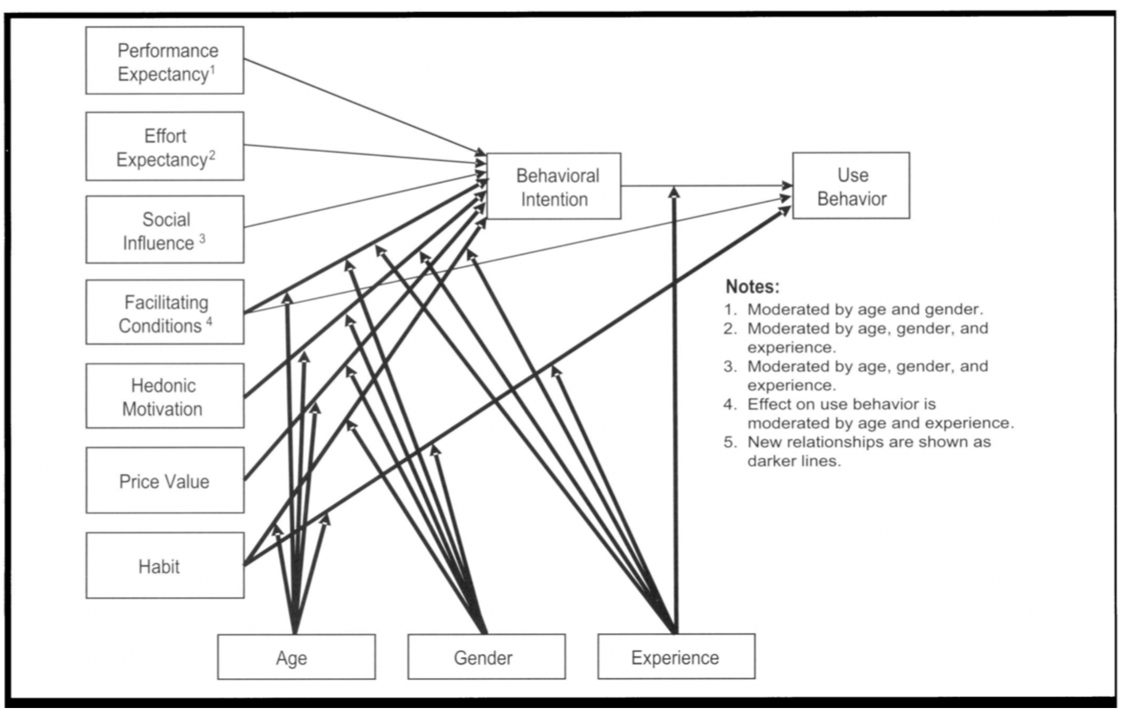


Figure 2: UTAUT2 (Venkatesh et al., 2012)

For this study, UTAUT was selected instead of UTAUT2 for the theoretical underpinning. As mentioned previously, UTAUT2 was created for a consumer context. A widely debatable topic is whether to consider a patient a consumer. Some scholars interchange the terms 'patient' and 'consumer' and consider patients consumers of health services (Tavares & Oliveira, 2016). In contrast, other scholars clearly distinguish between patients and consumers and do not consider a patient a consumer (Gusmano et al., 2019). For the context of this study, it is agreed that patients are not consumers. Healthcare is not like other traditional marketplaces. In healthcare, patients are vulnerable and dependent on physicians for care, which removes the independence of choice that consumers have in other industries. Patients also do not have the same level of information as medical providers, which can also impact their decision-making freedom and ability, unlike other industries. From a technology standpoint, patients do not have an autonomous selection over the types of technology offered by their physician practices or hospitals. For instance, if a patient goes to the hospital, they do not have any decision over which patient portal or electronic health record vendor a hospital uses. If a patient has a telemedicine visit with their doctor, they do not have any selection over what telemedicine platform is used. In healthcare technologies, organizations have more decision-making authority and input into the technology used compared to individual users. Therefore, although some individual factors influence technology adoption, organizational components also have a significant influence. According to Magsamen-Conrad et al. (2019), health IT adoption resembles mandatory organizational adoption contexts, especially for older adults (Magsamen-Conrad et al., 2019). Therefore, the UTAUT2 constructs focused on consumerism - hedonic motivation, price value, and habit- are not fully applicable in healthcare. For these reasons, UTAUT is a more suitable theoretical framework than UTAUT2 for this study.

Health Belief Model

The Health Belief Model (HBM) evolved in the 1950s when psychologists attempted to understand why citizens were not taking preventative and precautionary measures to avoid certain diseases and illnesses (Rosenstock, 1974). The Health Belief Model is considered one of the most commonly referenced behavioral theories, along with the Theory of Reasoned Action, Social Cognitive Theory, and Trans Theoretical Model (Painter et al., 2008; Sulat et al., 2018; Zimmerman & Vernberg, 1994). The Health Belief Model is composed of the desire to avoid illness and the belief that a specific health action will prevent disease or illness (Rosenstock, 1974; Janz & Becker, 1984). Individuals who believe an adverse health outcome is unlikely to affect them are less likely to engage in preventative actions or behaviors. Similarly, if an individual believes an adverse health outcome has a high severity associated with it, they are more motivated to avoid that outcome (Rosenstock, 1974; Janz & Becker, 1984).

The Health Belief Model consists of four fundamental constructs: perceived susceptibility, perceived severity, perceived benefits, and perceived barriers, as displayed in Figure 3 (Rosenstock, 1974). *Perceived susceptibility* is an individual's belief in their chances of acquiring a condition or disease (Champion, 1984; Champion & Skinner, 2008; Rosenstock, 1974). *Perceived severity* is an individual's belief in the seriousness of an illness or disease (Champion, 1984; Champion & Skinner, 2008; Rosenstock, 1974). *Perceived benefit* is an individual's belief in a defined action's ability to reduce the chances of acquiring a condition or disease (Champion, 1984; Champion & Skinner, 2008; Rosenstock, 1974). *Perceived barrier* is defined as an individual's belief in the cost or obstacles to executing an action to reduce the chances of acquiring a condition or disease (Champion, 1984; Champion & Skinner, 2008; Rosenstock, 1974). This dissertation focuses specifically on the perceived benefits dimension of the health belief model to further understand why individuals choose to use digital health technology. The Health Belief Model can complement the technology-focused UTAUT model to integrate technology and health-related behaviors to further explain the adoption of technologies in a healthcare context. This dissertation will integrate the HBM and UTAUT components to expand the technology adoption research specific to the healthcare industry. Based on the comprehensive literature review, research that integrates the Health Belief Model and UTAUT model using digital health technologies from an individual patient's perspective is scarce.

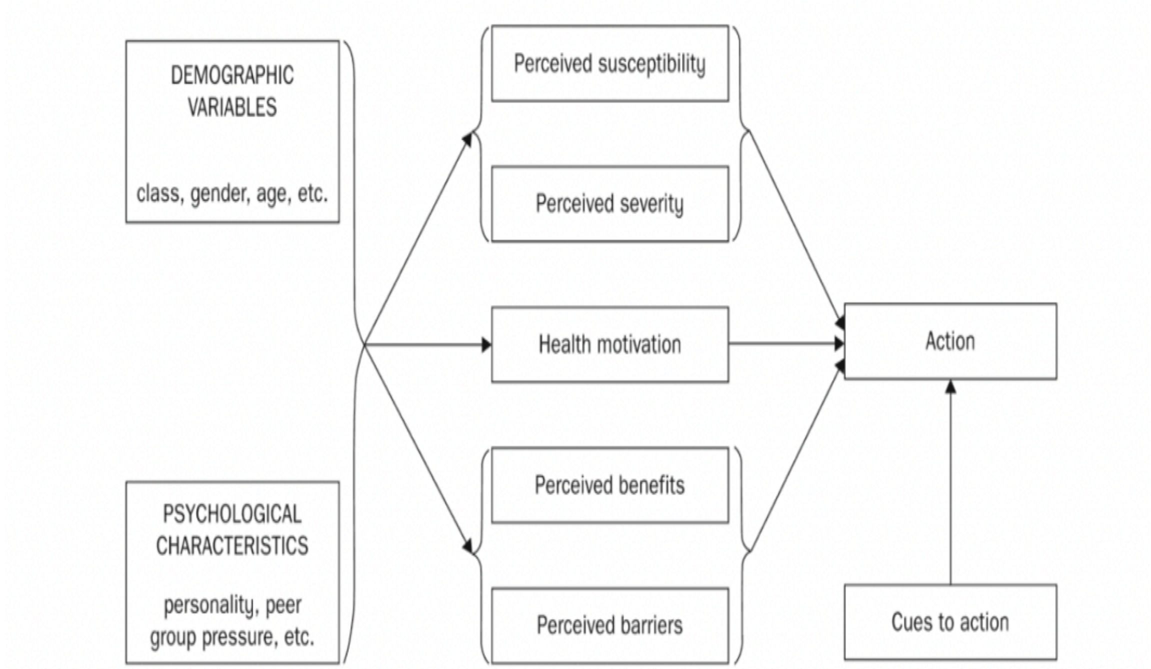


Figure 3: Health Belief Model (Abraham & Sheeran, 2015; Champion, 1984; Rosenstock, 1974)

2.3 Hypothesis and Research Model

Based on the presented theoretical framework and the defined constructs, the proposed research model for this study (Figure 4) is presented. This research model focuses on three key constructs – Behavioral Intention to use, Perceived Health Benefit, and Social Influence, and their relationship with the Actual Use of digital health technology. As depicted in the research model, this study will investigate the moderating effects of eHealth Literacy and Trust in Technology on the relationship between the aforementioned key constructs and the Actual Use of digital health technology. Furthermore, the relationship between Actual Use of digital health technology and Health Consciousness will be tested as presented in the proposed research model.

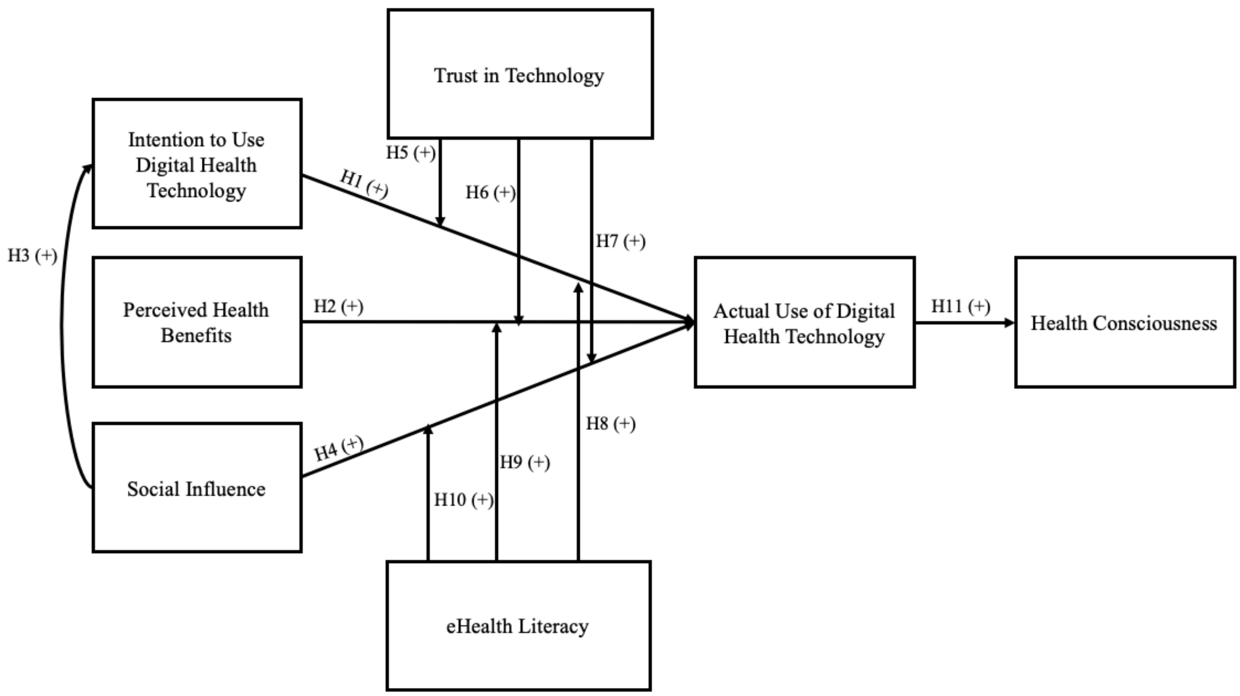


Figure 4: Proposed Research Model

Behavioral Intention to Use Digital Health Technology and Actual Use of Digital Health Technology

In alignment with the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003), this study investigates the relationship between Behavioral Intention to use technology, often referred to as intention to use, and the Actual Use of technology in the context of digital health technologies. The relationship between the Behavioral

Intention to use technology and Actual Use has been widely addressed and supported in empirical studies (Alam et al., 2020a; Alam et al., 2020b; Davis, 1989; Hoque, 2016; Hoque & Sorwar, 2017; Venkatesh et al., 2003; Venkatesh et al., 2012). As defined previously, the Behavioral Intention to use is an individual's perception of their willingness to use a technology service. Given its established role as an antecedent of technology usage, intention to use is a fundamental construct in the proposed research model supporting the UTAUT theoretical framework (Venkatesh et al., 2003). Scholars have previously suggested that Behavioral Intention is the most crucial determinant of Actual Use behavior (Abubakar & Ahmad, 2013; Jackson et al., 1997). Thus, I hypothesize:

H_1: The intention to use digital health technology is positively associated with the Actual Use of digital health technology.

Perceived Health Benefit and Actual Use of Digital Health Technology

If an individual believes that there is a health benefit to performing a specific action, they are more likely to perform the action (Champion, 1984; Janz & Becker, 1984; Rosenstock, 1974). According to the Health Belief Model, Perceived Health Benefit are derived from a person's opinion on the usefulness or benefit of performing a behavior in lowering the risk of illness or disease (Janz & Becker, 1984; Rosenstock, 1974). Prior studies have affirmed the relationship between perceived benefit and performing a health behavior as part of the Health Belief Model (van der Waal et al., 2022). When evaluating technology adoption, prior research suggests that perceived benefit is the most important HBM construct to explain technology adoption behavior (Walrave et al., 2020). Furthermore, some studies have attempted to combine the Health Belief Model with technology adoption models, as intended in this study. A study by Ahadzadeh et al. (2015) integrated the Health Belief Model and the Technology Acceptance

Model to evaluate the relationship between perceived risk and using wearables (Ahadzadeh et al., 2015). A recent study looked at the Perceived Health Benefit of using COVID-19 contract tracing applications in the context of the UTAUT theory (van der Waal et al., 2022). In the study conducted by van der Waal et al. (2022), the two strongest constructs of the HBM that impacted adoption of the COVID-19 contract tracing applications were perceived benefit and perceived barrier (van der Waal et al., 2022). Because literature supports the integration of the Health Belief Model and technology adoption models, and perceived benefit is supported in the literature as influencing health-related actions, I propose the following hypothesis:

H_2: The Perceived Health Benefit of digital health technology is positively associated with the Actual Use of digital health technology.

Social Influence and Behavioral Intention to Use Digital Health Technology

Herbert Kelman, a social psychologist, suggested that Social Influence can be classified into three groups: compliance, identification, and internalization (Ifinedo, 2016; Kelman, 1958; Kelman, 1974). Each of these classifications of Social Influence suggests that an individual changes their actions or behaviors to conform with an influencer (Ifinedo, 2016; Kelman, 1958; Kelman, 1974). Compliance is altering one's feelings or behaviors due to fear of punishment or desire to gain rewards (Ifinedo, 2016; Kelman, 1958). Identification occurs when individuals alter their behaviors or views to gain a desired relationship with a person or group of influence (Ifinedo, 2016; Kelman, 1958). Internalization occurs when individuals adopt a behavior of a person or group of influence because the behavior is inherently rewarding and aligns with one's values (Ifinedo, 2016; Kelman, 1958). In the context of technology adoption, *Social Influence* is defined by Venkatesh as the extent to which individuals perceive that people who are important to them believe they should use a technology (Venkatesh et al., 2003). According to UTAUT, Social Influence is directly correlated to the intention to use technology (Venkatesh et al., 2003). Specifically in healthcare, several studies have supported the notion that Social Influence impacts the Behavioral Intention to use a technology. Cajita et al. (2017) noted that Social Influence significantly impacts the intention to adopt mHealth when evaluating the adoption intentions of older adults with heart failure (Cajita et al., 2017). Cajita et al. (2017) suggest that physicians and nurses are trusted and respected resources for patients about their health, and the trusted relationship between patient and provider can impact the intention to use healthcare technologies (Cajita et al., 2017). Sun et al. (2013) also support the relationship between Social Influence and Behavioral Intention, and they analyzed this relationship by studying elderly consumers of mHealth services in China (Sun et al., 2013). The decision of a patient to adopt healthcare technologies based on their provider's respected and influential relationship is an example of identification in Herbert Kelman's classifications of influence. As mentioned, identification occurs when an individual adopts a behavior to follow an influential figure or person they respect (Ifinedo, 2016; Kelman, 1958). Both family members and physicians can be influential to patients. However, a physician's expertise in their field can further contribute to influencing a patient's technology adoption behavior (Cimperman et al., 2016). While physicians have professional autonomy in their field and the authority to make decisions, a study by Pynoo et al. (2012) found that Social Influence contributed to physicians' adoption of clinical information systems (CIS) (Pynoo et al., 2012). When physicians feel that their workplace and social environment strongly promote the use of a technology, they are more likely to accept and use it (Pynoo et al., 2012). In alignment with the UTAUT model as originated by Venkatesh et al. (2003), and to maintain consistency with the theoretical framework of this study, I propose the following hypothesis:

H_3: Social influence is positively associated with the intention to use digital health technology.

Social Influence and Actual Use of Technology

While UTAUT suggests a relationship between Social Influence and intention to use, it also suggests a direct relationship between intention to use and the Actual Use of a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). Therefore, intention to use mediates the relationship between Social Influence and Actual Use (Venkatesh, 2003; Venkatesh, 2012). Few studies have examined the direct relationship between Social Influence and the Actual Use of technology without the mediating relationship of Behavioral Intention. One study exploring the direct relationship between Social Influence and Actual Use determined a direct relationship between the two constructs in the context of adopting 3g mobile telecommunications (Wu et al., 2007). In the healthcare industry, Maillet et al. (2015) conducted a study that examined the impact of Social Influence on nurses using an electronic health record (EHR) (Maillet et al., 2015). By conducting a cross-sectional study to evaluate the technology adoption behaviors of nurses at four hospitals, they determined a significant relationship between Social Influence and the Actual Use of EHRs (Maillet et al., 2015). There is a noticeable gap in research that evaluates the direct relationship between Social Influence and Actual Use, specifically focusing on digital health technology. While there is an abundance of literature that supports the relationship between Social Influence and Behavioral Intention to use (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Alam et al., 2022; Cavdar et al., 2020; Dash & Sahoo, 2021; Dino & Guzman, 2015; Gao et al., 2015; Hoque & Sorwar, 2017; Nunes et al., 2019; Seethamraju et al., 2017; Shiferaw et al., 2021; Venkatesh et al., 2003), and also, the relationship between Behavioral Intention and Actual Use (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Dash & Sahoo, 2021; Davis, 1989; Dou et al., 2017; Hoque & Sorwar, 2017; Kissi et al., 2019; Li et al., 2016; Venkatesh et al., 2003); this study attempts to enhance the limited research on the direct relationship between Social Influence and Actual Use. Therefore, I present the following hypothesis:

H_4: Social influence is positively associated with the Actual Use of digital health technology.

The Moderating Role of Trust in Technology

This paper examines Trust in Technology to determine the strength of the relationship between intention to use and Actual Use, Social Influence and Actual Use, and Perceived Health Benefit and Actual Use. Based on the existing technology adoption research, trust has been previously studied as a moderating factor in whether or not individuals choose to adopt or accept a technology across various industries (Akter et al., 2013; Ashraf et al., 2014; Kesharwani & Bisht, 2012). I propose that trust can also moderate the relationship between the Actual Use of digital health technologies and the antecedents proposed in the research model – Behavioral Intention, Social Influence, and Perceived Health Benefit.

Trust is a broadly defined term examined in the context of people and technology. As explained by Gefen (2000), trust in people is defined as one's confidence and expectation that another person will do what they claim (Gefen, 2000). Trust in Technology refers to a person's willingness to be vulnerable to technology while using the technology (Cho et al., 2007). This study specifically focuses on Trust in Technology. Trust in Technology is essential to consider across all industries, especially in highly regulated industries such as healthcare. In healthcare, Trust in Technology can be evaluated from the perspective of clinicians and patients alike. Clinicians depend on the reliability and functionality of a technology and must trust a technology to perform correctly for clinical decision-making (Grissinger, 2019). On the contrary, patients are more concerned with privacy and data protection and must trust technology to safeguard their protected health information, including diagnoses, medication history, and procedures. Prior research explains that privacy and security concerns are two main barriers to Trust in Technology (Abbas et al., 2018). Mitigating those concerns and thoroughly examining the barriers and impact of Trust in Technology can help scholars further understand technology adoption and usage at an individual patient level.

Several researchers have suggested that an individual's Trust in Technology has a significant direct relationship with Behavioral Intention to adopt technology (Alaiad & Zhou, 2014; Choudhury & Shamszare, 2023; Deng et al., 2018; Oldeweme et al., 2021; Shahbaz et al., 2019). Trust has been integrated into the TAM and UTAUT models in many empirical studies across various technologies – including food delivery apps, healthcare technologies, and mobile learning applications. Specifically in healthcare-related studies, trust in specific technological artifacts continues to be a strong predictor in the Behavioral Intention of individuals to adopt and use technologies (Alaiad & Zhou, 2014; Choudhury & Shamszare, 2023; Deng et al., 2018; Oldeweme et al., 2021; Shahbaz et al., 2019). A study by Choudhury and Shamszare (2023) evaluated adults in the United States to demonstrate that trust impacts their Behavioral Intention to use ChatGPT to address healthcare questions and concerns (Choudhury & Shamszare, 2023). In addition, within healthcare organizations, research has shown that trust positively impacts employees' Behavioral Intention to adopt big data analytics platforms (Shahbaz et al., 2019). Similarly, an empirical study by Alaiad & Zhou (2014) demonstrates the impact of trust on patients' Behavioral Intention to adopt home healthcare robots (Alaiad & Zhou, 2014). In recent years, the relationship between trust and intention to use has been examined in relation to patients adopting COVID-19 tracing applications, mHealth, and innovative healthcare services. In 2018, an empirical study was conducted on patients in China, which suggested that trust was a determinant of the Behavioral Intention to adopt mHealth (Deng et al., 2018). In 2021, Oldeweme et al. (2021) demonstrated a positive correlation between trust and intention to use in the context of COVID-19 tracing applications (Oldeweme et al., 2021). More recently, in 2022, trust was strongly supported as an influencing factor in the Behavioral Intention of patients to use smart healthcare services, further demonstrating the importance of trust as a variable in technology adoption studies (Liu & Tao, 2022). As demonstrated in prior healthcare studies, when individuals Trust in Technology, it positively impacts their decisions and intentions toward using a technology (Arfi et al., 2021; Nisha et al., 2019). However, when technology is not trusted, it can be under-utilized (Jermutus et al., 2022).

Research on the relationship between Trust in Technology and Actual Use of technology is limited compared to the extensive research on the relationship between Trust in Technology and Behavioral Intention to use or adopt technology. However, understanding the relationship between Trust in Technology and the Actual Use of technology has gained attention in recent years, resulting in few studies demonstrating a relationship between trust and the Actual Use of technology. A significant positive relationship between trust and Actual Use of technology was supported by Sarmah et al. (2021) when studying the technology adoption behavior of millennials using e-wallets (Sarmah et al., 2021). Trust was also shown to have a significant direct relationship with Actual Use when investigating adults' adoption of ChatGPT to address healthcare inquiries (Choudhury & Shamszare, 2023). Furthermore, a recent study to explain mobile banking in India demonstrated that trust moderated the relationship between Behavioral Intention and Actual Use of mobile banking technology. Because of the extensive extant literature supporting a relationship between trust and Behavioral Intention, as well as the recent literature supporting a relationship between Trust in Technology and Actual Use of technology, I propose the following hypothesis:

H_5: Trust in technology moderates the relationship between intention to use digital health technology and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between intention to use digital health technology and Actual Use of digital health technology is strengthened.

The Health Belief Model explains health behaviors based on an individual's perceived susceptibility, severity, benefits, and barriers to a specific action (Champion, 1984; Champion & Skinner, 2008; Rosenstock, 1974). Specifically, this study examines individuals' perceptions of the health benefits of using digital health technologies. Few studies have examined trust in parallel with the Health Belief Model in the healthcare field. Wong et al. (2021) intertwined trust and the Health Belief Model to explain vaccination acceptance – specifically with the COVID-19 vaccine (Wong et al., 2021). In the context of a study by Wong et al. (2021), trust was evaluated based on trust in the healthcare system, not Trust in Technology. Another study by Yuen et al. (2021) integrated trust and the Health Belief Model to explain the adoption of autonomous vehicles (Yuen et al., 2021). Because literature combining HBM and trust in the context of healthcare technology adoption is limited, this study attempts to address the gap in the extant literature. However, because the few studies that integrate HBM and trust have supported a relationship between HBM constructs and trust, I propose the following hypothesis:

H_6: Trust in technology moderates the relationship between Perceived Health Benefit and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between Perceived Health Benefit and Actual Use of digital health technology is strengthened.

Prior research suggests that one's social network of family, friends, and influencers often plays a vital role in the decision to use technology (Rajak & Shaw, 2021). An individual's social network and a referral from a trusted individual can increase the likelihood that one will trust a technology (Alaiad & Zhou, 2014). According to the UTAUT model, Social Influence is a determinant of one's Behavioral Intention to adopt technology (Venkatesh et al., 2003). Similarly, Behavioral Intention impacts one's Actual Use of technology according to the widely supported UTAUT model (Venkatesh et al., 2003). According to Rajak and Shaw (2021), the impact of Social Influence on technology adoption is stronger when the individuals are in a mandatory setting. The assessment of Rajak and Shaw (2021) is consistent with research conducted on hospital organizations where scholars have determined the significance of Social Influence in the adoption of EMR systems (Holtz & Krein, 2011; Hoque & Sorwar, 2017; Wills et al., 2008). In parallel, Social Influence also influences individual consumers in the healthcare context. Hoque and Sorwar's (2017) study on mHealth adoption supports the idea that Social Influence impacts one's decision to use mHealth (Hoque & Sowar, 2017). Cajita et al. (2017) achieved similar results as Hoque and Sorwar when evaluating elderly adult's decision to use mHealth (Cajita et al., 2017). According to Cajita et al. (2017), primary healthcare providers have a significant influence on their patient's decision to use healthcare technologies (Cajita et al., 2017). Trust, as previously mentioned, can be examined from the perspective of an individual or a technology. Healthcare patients are often vulnerable and, therefore, have a degree of trust in their providers (Cajita et al., 2017). However, just because a patient may trust their provider and can be influenced by them does not mean they trust technology. One may be highly influenced by one's social network to adopt a technology, but if one does not trust technology, the adoption decision may change. Conversely, one may be influenced by their social network to use technology, and their high Trust in Technology may make them more likely to engage. The direct relationship between Trust in Technology and Social Influence has not been widely studied in healthcare. However, there is ample extant literature that demonstrates both trust and Social Influence independently contribute to technology adoption (Alaiad & Zhou, 2014; Choudhury & Shamszare, 2023; Deng et al., 2018; Oldeweme et al., 2021; Shahbaz et al., 2019; Venkatesh et al., 2003; Venkatesh et al., 2012). As previously mentioned, the literature defines the relationship between Social Influence and Behavioral Intention to adopt, as well as Behavioral Intention and Actual Use (Venkatesh et al., 2003; Venkatesh et al., 2012). Moreover, considering the existing research showing the strong influence that trust also has on technology adoption (Alaiad & Zhou, 2014; Choudhury & Shamszare, 2023; Deng et al., 2018; Oldeweme et al., 2021; Shahbaz et al., 2019); I therefore present the following hypothesis:

H_7: Trust in technology moderates the relationship between Social Influence and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between Social Influence and Actual Use of digital health technology is strengthened.

The Moderating Role of eHealth Literacy

Traditional literacy encompasses the ability to read, write, and understand information; however, in the current age, this term has expanded to include other types of literacy to explain various types of information that can be processed in various formats (Bawden, 2008). Digital literacy is reading and understanding information in the digital era (Bawden, 2008; Mohammadyari & Singh, 2015). Nonetheless, as Gilster (1997) explains, digital literacy extends beyond reading content in a digital format; it is the understanding of how to apply the information to one's life and leverage the analytical skills to make informed decisions based on the information retrieved (Gilster, 1997; Bawden, 2001; Bawden, 2008). For digital technologies to be effective, digital literacy is a prerequisite (Elhajjar & Ouaida, 2019), as one's ability and skill level with technology will influence their decision to adopt or continuously use it (Elhajjar & Ouaida, 2019). For example, during the COVID-19 pandemic, many healthcare organizations adopted a virtual business model and required patients to leverage portals and telehealth appointments to receive care. However, although a healthcare organization may require certain visits to be done virtually, if a person has low digital literacy it will influence their decision to use the technology. Scholars have recently studied digital literacy's impact on technology adoption in various contexts (Ng, 2012; Cetindamar et al., 2021). In the workplace context, Cetindamar et al. (2021) studied the direct relationship between digital literacy and the adoption of cloud technology. According to Cetindamar et al. (2021), individuals with low digital literacy find adopting technology more challenging and the technology itself less valuable. In contrast, individuals with high literacy are more likely to adopt and use technology (Cetindamar et al 2021). Ng (2012) studied the relationship between digital nativeness, digital literacy, and technology adoption. In his study, he determined that individuals born after 1980, who are "digital natives," are more familiar with technology and a digital lifestyle and, therefore, more apt to adopt technologies, even when the technology is unfamiliar (Ng, 2012).

Specifically in the context of healthcare, eHealth Literacy has been consistently gaining popularity amongst scholars and practitioners as the healthcare industry moves towards more digital methods of delivering healthcare information and care (van der Vaart & Drossaert, 2017; Wang et al., 2021). Prior research shows that eHealth Literacy levels differ based on different sociodemographic groups (Kontos et al., 2014; Magsamen-Conrad et al., 2019). This variance has the potential to contribute to health disparities in different populations because eHealth

Literacy is necessary for health technologies to be effectively utilized. A study by Kontos et al. (2014) suggests that socioeconomic status, age, and gender impact engagement with eHealth technologies. In this study, Kontos et al. (2014) found that older adult males from a lower socioeconomic status were less likely to utilize digital health technology to communicate with physicians or track their health information (Kontos et al., 2014).

The comprehensive review of the literature produced limited studies that evaluate the moderating effect of eHealth Literacy on the relationship between the technology usage antecedents and actual usage of technology. This research gap is one that this study attempts to address. One prior study evaluated eHealth Literacy as a moderator (Chang et al., 2021). The study by Chang et al. (2021) evaluated patients at a Taiwanese hospital and determined that eHealth Literacy positively moderated the relationship between a UTAUT and UTAUT2 variable – performance expectancy and the Behavioral Intention to use medical apps (Chang et al., 2021). Because of the limited research leveraging eHealth Literacy as a moderator in digital health technology studies, the conceptual model for this study introduces eHealth Literacy as a moderator to determine its impact on the relationships between the Actual Use of digital health technologies and its antecedents.

The extant research evaluating the relationship between eHealth Literacy and intention to use has recently gained traction in IS and healthcare research. When the relationship between eHealth Literacy and intention to use healthcare technologies has been evaluated in prior studies, there have been mixed results (Aydin & Kumru, 2022; Cajita et al., 2017). As stated by Norman and Skinner (2006), "consumer-directed eHealth resources, from online interventions to informational websites, require the ability to read text, use information technology, and appraise the content of these tools to make health decisions" (Norman & Skinner, 2006b, p.1). Aydin and

Kumru (2022) conducted a study evaluating the Gen-Z population and determined that eHealth Literacy impacted Behavioral Intention to use personal eHealth records (Aydin & Kumru, 2022). On the contrary, the impact of eHealth Literacy on the Behavioral Intention to use mHealth was evaluated in a population of older adult patients with heart failure (Cajita et al., 2017). In this study by Cajita et al. (2017), an appended version of the Technology Adoption Model was established to include eHealth Literacy, and it was determined that eHealth Literacy did not have an impact on the intention to use mHealth (Cajita et al., 2017). Literature is abundant on the direct relationship between Behavioral Intention and Actual Use of technology, as supported by the UTAUT, UTAUT 2, and TAM models (Alam et al., 2020a; Alam et al., 2020b; Alam et al., 2021; Davis, 1989; Hoque, 2016; Hoque & Sorwar, 2017; Kissi et al., 2020; Li et al., 2016; Venkatesh et al., 2003; Venkatesh et al., 2008; Venkatesh et al., 2012). Literature supporting a direct relationship between eHealth Literacy and the Actual Use of technology is very scarce, which provides an opportunity for this study to address the gap in the literature. Therefore, with the extant literature on the direct relationship between Behavioral Intention and Actual Use and the recent emphasis on the relationship between eHealth Literacy and Behavioral Intention, I propose the following hypothesis:

H_8: eHealth Literacy moderates the relationship between intention to use digital health technology and Actual Use of digital health technology, such that when eHealth Literacy is high, the relationship between intention to use digital health technology and Actual Use of digital health technology is strengthened.

Consistent with the Health Belief Model, individuals are more likely to perform health-related actions when they perceive a benefit associated with the actions (Janz & Becker, 1984; Rosenstock, 1974). As previously stated, the traditional term "literacy" – the ability to read, write, and understand information; has expanded to explain an individual's ability to understand and apply information in various areas, including health, finances, and technology. Prior research demonstrates an association between preventative health behaviors and literacy levels. White et al. (2008) evaluated the relationship between health literacy and preventative health measures (White et al., 2008). Their study indicated that individuals with lower health literacy levels are less likely to engage in preventative health measures (White et al., 2008). A study by Bennett et al. (2009) concluded that health literacy contributes to disparities and that individuals with a lower health literacy were less likely to engage in preventative health behaviors (Bennett et al., 2009). Specific to eHealth Literacy, Li et al. (2021) determined a correlation between eHealth Literacy and preventative health behaviors when examining college students in China during the COVID-19 pandemic (Li et al., 2021). Regardless of the subcategory of literacy being examined, literacy levels, even in a broader sense, may impact one's ability to understand the benefits of performing specific activities. When adopting digital health solutions, individuals with a lower literacy level may not fully perceive the benefits of leveraging digital health technologies. Quinn et al. argue that eHealth Literacy contributes to the quality of information individuals find online (Quinn et al., 2017). Those with higher eHealth Literacy are more likely to identify quality healthcare information from which they can benefit (Quinn et al., 2017; Leung & Chen, 2019). If individuals do not perceive the benefits of effectively using health technologies, they are less likely to use them. In contrast, individuals with a greater level of eHealth Literacy are more likely to have a greater intention to use eHealth apps (Chang et al., 2021). Therefore, I present the following hypothesis:

H_9: eHealth Literacy moderates the relationship between Perceived Health Benefit and Actual Use of digital health technology, such that when eHealth Literacy is high, the relationship between Perceived Health Benefit and Actual Use of digital health technology is strengthened.

Both eHealth Literacy and Social Influence have previously been supported as factors influencing technology acceptance and use in healthcare. While Venkatesh et al. (2003) include Social Influence as a construct in the UTAUT model as a contributor to Behavioral Intention, few scholars have evaluated a direct connection between Social Influence and the Actual Use of technology (Maillet et al., 2015; Wu et al., 2007; Venkatesh et al., 2003; Venkatesh et al., 2012). According to Norman & Skinner (2006b), eHealth Literacy is "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (Norman & Skinner, 2006b, p.2). Although prior research establishing a direct relationship between eHealth Literacy and Actual Use is limited, the extant research suggests that lower levels of eHealth Literacy negatively impact technology use (Knitza et al., 2020). Knitza et al. (2020) evaluated the relationship between eHealth Literacy and mHealth usage of rheumatoid arthritis patients and determined that low eHealth Literacy levels were consistent with low mHealth usage (Knitza et al., 2020). Additionally, there is a gap in the literature for studies examining the moderating impact of eHealth Literacy on the relationship between Social Influence and technology use. Yu et al. (2021) studied the moderating effect of digital literacy on the relationship between Behavioral Intention and two UTAUT technology adoption antecedents – performance expectancy and effort expectancy (Yu et al., 2021). Their study found that digital literacy negatively moderated the relationship between performance expectancy and Behavioral Intention (Yu et al., 2021). However, their study did not support digital literacy as a moderating factor in the relationship between Effort Expectancy and Behavioral Intention (Yu et al., 2021). In the context of the UTAUT model, both Social Influence, a UTAUT construct, and eHealth Literacy have been identified as influential variables in an individual's decision to adopt or use technology (Knitza et al., 2020; Maillet et al., 2015; Venkatesh et al., 2003; Venkatesh et al., 2012). To address the gap in the existing literature, this study leverages the relationship between Social Influence and Actual Use and the relationship between eHealth Literacy and Actual Use to propose the following hypothesis:

H_{10}: eHealth Literacy moderates the relationship between Social Influence and Actual Use of digital health technology, such that when eHealth Literacy is high, the relationship between Social Influence and Actual Use of digital health technology is strengthened.

Actual Use of Technology and Health Consciousness

Health consciousness has previously been considered an antecedent contributing to technology adoption in healthcare (Damberg, 2022). Damberg's study demonstrated that Health Consciousness impacted the Behavioral Intention to use fitness apps among adults in the United Kingdom (Damberg, 2022). In addition, Health Consciousness was supported as a positive and significant indicator of individuals' decision to use smartphone health apps in South Korea (Cho et al., 2014). The extant research focuses on the impact of Health Consciousness on the use of healthcare technologies and presents the relationship with Health Consciousness as the independent variable and Actual Use as the dependent variable. However, there was no existing literature within the scope of this literature review that evaluated the impact of digital health technology usage on one's level of Health Consciousness, with digital health technology usage being the independent variable and Health Consciousness being the outcome or dependent variable.

As previously mentioned, digital health technologies help improve the efficiency, effectiveness, and access to healthcare and medical resources. Through digital health technologies, individuals can monitor their health proactively, seek and gain access to healthcare information, and communicate with healthcare providers (Awad et al., 2021). Digital health technologies can also improve access to care and reduce health disparities for populations impacted by social determinants of health (Kemp et al., 2021; Smith & Magnani, 2019). If individuals accept and effectively use technologies, they can achieve the intended benefits of digital health solutions (Dino et al., 2015). I predict that effectively using digital health technologies will benefit individuals and allow them to better understand their health status and have self-awareness regarding their health. Therefore, I propose the following hypothesis:

H_{11}: Actual use of digital health technology is positively associated with an individual's Health Consciousness.

Table 1 summarizes the hypotheses presented in this study. Chapter 3 will present the methodology that was utilized to test the proposed research model and explain the data collection and analysis procedures.

Table 1: Summary of Hypotheses

#	Hypothesis
H_1	The intention to use digital health technology is positively associated with the Actual Use of digital health technology.
H_2	The Perceived Health Benefit of digital health technology is positively associated with the Actual Use of digital health technology.
H_3	Social influence is positively associated with the intention to use digital health technology.
H_4	Social influence is positively associated with the Actual Use of digital health technology.
H_5	Trust in technology moderates the relationship between intention to use digital health technology and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between intention to use digital health technology and Actual Use is strengthened.
H_6	Trust in technology moderates the relationship between Perceived Health Benefit and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between Perceived Health Benefit and Actual Use is strengthened.
H_7	Trust in technology moderates the relationship between Social Influence and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between Social Influence and Actual Use is strengthened.
H_8	eHealth Literacy moderates the relationship between intention to use digital health technology and Actual Use of digital health technology, such that when eHealth Literacy is high the relationship between intention to use digital health technology and Actual Use is strengthened.
H_9	eHealth Literacy moderates the relationship between Perceived Health Benefit and Actual Use of digital health technology, such that when eHealth Literacy is high the relationship between Perceived Health Benefit and Actual Use is strengthened.
H_{10}	eHealth Literacy moderates the relationship between Social Influence and Actual Use of digital health technology, such that when eHealth Literacy is high the relationship between Social Influence and Actual Use is strengthened.
H_{11}	Actual use of digital health technology is positively associated with an individual's Health Consciousness.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Overview

This chapter provides a detailed description of the methodology used to test the proposed hypotheses outlined previously in Chapter II. This quantitative study leveraged survey data measured with scales previously validated and widely used in the IS and healthcare literature. The following sections provide additional details regarding participants, data collection procedures, measures, and data analysis.

3.2 Participants and Sample

This study targeted United States respondents, as healthcare practices and policies are different in various countries, and this study focuses on digital healthcare adoption in the United States. Respondents consisted of various demographics and backgrounds so that the results would be representative of the actual population, including all genders, races, cultures, socioeconomic statuses, and levels of education. Because the unit of analysis was at the individual level, all individual survey respondents answered questions based on their own experience.

Inclusions and Exclusions Criteria

Because the survey was administered online, participants had to have experience with technology. Additionally, patients had to be at least 21 years old and have attended a doctor's visit in the past 18 months. The minimum age range was established to exclude minors whose healthcare and associated communications and access to digital health technology are typically managed by their parent or guardians. The exclusion criteria for doctor visits in the past 18 months was established to remove individuals who do not monitor their health or interact with physicians regularly because they are also less likely to utilize digital health technologies. This criterion was included in the IRB application and the survey instructions. Before administering the survey, this study received formal IRB approval for protocol number IRB-24-0302 by the University of North Carolina Charlotte Office of Research Compliance on January 17, 2024.

Minimum Sample Size Calculation

G*Power® (Erdfelder et al., 1996; Faul et al., 2007) was used to calculate this study's minimum sample size, as shown in Figure 5. Based on the power analysis results, a minimum sample size of 153 was determined for this study. However, scholars recommend an acceptable sample size is ideally ten times larger than the number of variables to be analyzed (Hair et al., 2021). To ensure a sufficient sample size, the threshold for this study was set as a minimum of 300 surveys to be collected.

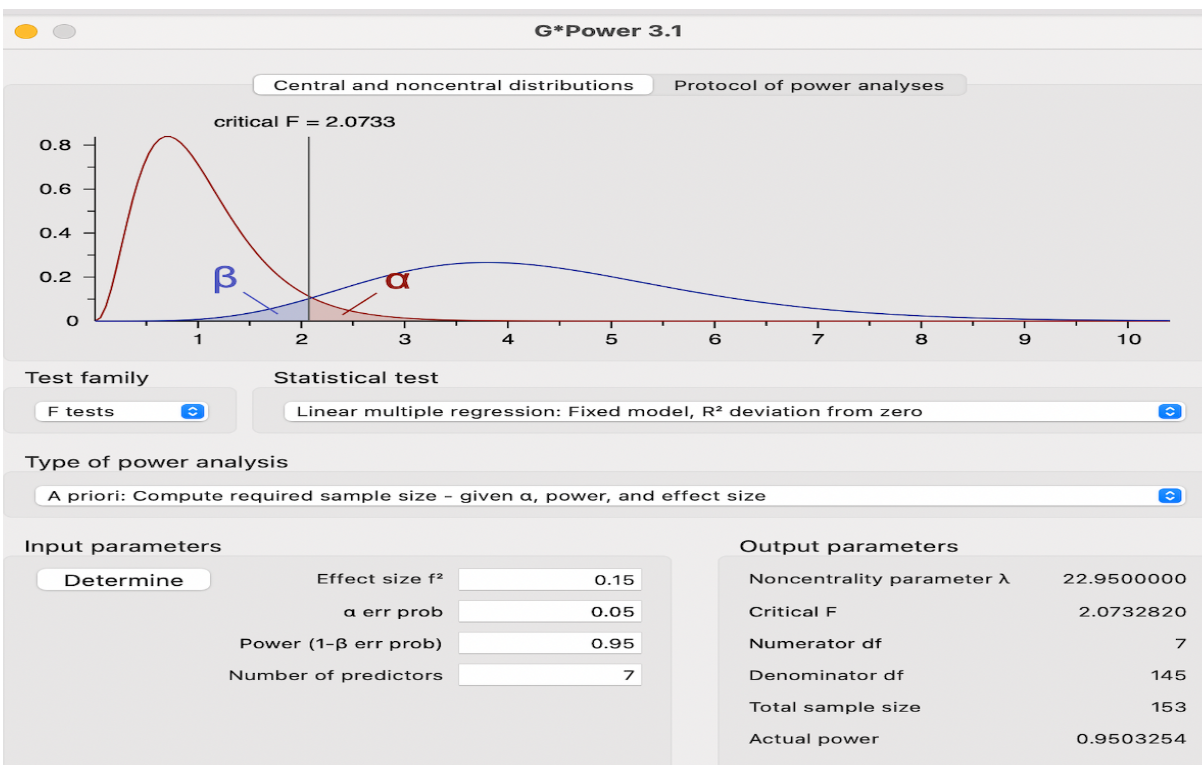


Figure 5: G*Power® Analysis

3.3 Data Collection

This study adopted the survey method and leveraged both Prolific and Qualtrics to build the survey and collect the data. The survey was constructed using Qualtrics, and the Qualtrics survey link was administered through Prolific. Prolific was selected because it is both user-friendly and accessible to participants across various geographies, providing researchers with a diverse sample. Each participant was provided with a consent form detailing the purpose of the study, which they were to acknowledge prior to completing the survey. All participants were informed that their responses were anonymous and no personally identifiable information was collected, and they proceeded to complete the survey at will. Prolific provided a monetary payment of $2 USD to each participant upon survey completion.

3.4 Measures

Behavioral Intention to Use Digital Health Technology

Behavioral intention (BI) to use was measured using the 3-item scale that was previously developed by Davis et al. (1989) and later used by Venkatesh et al. (2003) to develop the UTAUT model. The Behavioral Intention scale which Davis et al. (1989) established has been widely used in technology acceptance research. Answers were assessed using a 7-point Likert Scale: Strongly disagree (1), Disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), or Strongly agree (7).

Perceived Health Benefit

The original scale for Perceived Health Benefit was developed by Champion (1984) as five items measured through a 5-point Likert Scale as part of the measurements for Health Belief Model constructs. The scale was initially developed to measure the benefits of conducting self-breast exams (Champion, 1984). The scale has since been applied in various ways in healthcare studies and has recently been used to understand the motivation behind adopting a COVID-19 tracing app (Walrave et al., 2020). The scale measures the individual and social benefits an individual believes they have from engaging in a particular health behavior. To standardize the scales used in this study, the original 5-point Likert Scale was converted to a 7-point Likert Scale for this measure. The 7-point Likert Scale consisted of the following answers for the Perceived Health Benefit questionnaire items: Strongly disagree (1), Disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), or Strongly agree (7).

Social Influence

Social Influence (SI) was measured using the three items from the UTAUT scales that were previously developed and adopted by Venkatesh et al. (2003) and later modified in Venkatesh's extension of UTAUT (Venkatesh et al., 2012). The original scale (Venkatesh et al., 2003) was adopted by scales established by Ajzen (1991) and Thompson et al. (1991) to measure social norms (Ajzen, 1991) and subjective factors (Thompson et al., 1991) as it pertains to adoption and acceptance of technology. The original studies were focused on workplace technologies. Therefore, minor yet acceptable adjustments will be made to the questions to make them specific to healthcare technologies instead of workplace technologies. Similar to the studies by Venkatesh et al. (2003, 2012), Social Influence was assessed using a 7-point Likert Scale: Strongly disagree (1), disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), or strongly agree (7) (Venkatesh et al., 2003 and Venkatesh et al., 2012).

Trust in Technology

Trust in Technology (TR) was measured using six items adopted from previously established consumer trust and supplier trust scales (Doney & Cannon, 1997; Jarvenpaa et al., 2000; Gefen, 2000). Items contained minor adjustments to make specific to digital health technology. Answers were assessed using a 7-point Likert Scale: Strongly disagree (1), disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), or Strongly agree (7).

eHealth Literacy

eHealth literacy (EHL) was measured using the eHealth Literacy scale (eHEALS), established by Norman and Skinner (2006). The eHEALS was created to evaluate consumers' perception of their own skills for using technology in a healthcare context (Norman & Skinner, 2006). The original eHEALS contained eight items measured by a 5-point Likert scale. However, to standardize the scales used in this study, the items were measured by a 7-point Likert scale consisting of the following options: Strongly disagree (1), Disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), or Strongly agree (7).

Actual Use of Digital Health Technology

The Actual Use (AU) behavior of digital health technology was measured by leveraging a scale that was initially established by Venkatesh et al. (2012) to develop the UTAUT model (Venkatesh et al., 2012). While Venkatesh et al. (2012) used a 5-point Likert Scale to assess frequency, this study used a 7-point Likert Scale to maintain standardization of the scales used across the study (Venkatesh et al., 2012). Selection options to measure frequency include Never (1), Very Rarely (2), Rarely (3), Sometimes (4), Often (5), Very Often (6), Always (7). The frequency scale used was adopted from Iowa State University Extension (Brown, 2010).

Health Consciousness

Health Consciousness (HC) was measured using the 9-item scale established by Gould (Gould, 1990). The Health Consciousness scale was derived from the Self-Consciousness scale, also established by Gould (Gould, 1988). Answers were assessed using a 7-point Likert Scale: Strongly disagree (1), disagree (2), Somewhat disagree (3), Neither agree nor disagree (4), Somewhat agree (5), Agree (6), or Strongly agree (7).

A table containing all measures and items for this study, the original items, and their source of reference is included in Appendix II.

3.5 Control Variables

Gender

Gender has been widely studied in technology adoption and acceptance research (Seethamraju et al., 2018). In a study by Venkatesh and Morris (2000), gender differences in technology adoption were evaluated in the context of the Technology Acceptance Model (Venkatesh & Morris, 2000). Their findings suggested that women are more influenced by social factors when deciding to adopt technology, and men are more influenced by the usefulness of the technology (Venkatesh & Morris, 2000). Venkatesh et al. (2003) later incorporated gender into the UTAUT model to measure gender's impact on Behavioral Intention to adopt technology (Venkatesh et al., 2003). The research conducted by Venkatesh et al. (2003) suggests that gender is a moderator of the relationship between UTAUT constructs and Behavioral Intention to use technology (Venkatesh et al., 2003). In healthcare, several scholars have studied gender's impact on technology adoption (Alam et al., 2020; Hoque, 2016; Seethamraju et al., 2018; Zhang et al., 2014). In this dissertation, gender consisted of the participant's identified gender at the time of the study. Participants selected one option from a multiple-choice question to identify their gender as Male, Female, Non-Binary, or Gender Fluid. Gender data was dummy coded into numerical values for analysis in SmartPLS®.

Race

Race is a valuable variable when evaluating technology adoption because different racial groups have different access to and perspectives regarding technology. In healthcare, understanding how different races perceive and adopt technology can be critical to addressing health disparities and expanding healthcare access through technology to all racial groups equally. In this study, race was collected as part of the questionnaire and fell into seven groups: White, Black, American Indian, Latino, Asian, Hawaiian, and Other. Race data was dummy-coded into numerical values for analysis in SmartPLS®.

Level of Education

Because this study includes gender as a control variable, and prior studies suggest that education level is an important co-variate of gender level of education is being included as an additional control variable (Lefkowitz, 1994; Venkatesh et al., 2000). Level of education was captured in the questionnaire by participants selecting one value from the following list: Did Not Complete High School, High School Graduate / Diploma, Associate Degree, Bachelor Degree, Master's Degree, Doctorate Degree. The level of education data was dummy-coded into numerical values for analysis in SmartPLS®.

Age

As suggested by Venkatesh et al. (2012), age significantly impacts technology acceptance and adoption, specifically in relation to UTAUT constructs (Venkatesh et al., 2012). In addition to UTAUT, age has also been studied in the context of the Technology Acceptance Model, and similarly, there was a suggested relationship between age and technology adoption (Chung et al., 2010; Morris & Venkatesh, 2000; Porter & Donthu, 2006). Participants of this study were required to provide their age in the number of years that they were at the time of the study. Age was captured as a continuous variable for analysis in SmartPLS®.

3.6 Analytical Procedures

To maximize the accuracy of the data, analytical procedures were completed to clean and prepare the data for testing of the hypotheses. First, all collected data was exported to Excel to efficiently inspect and format the data. The formatting process included removing incomplete responses and erroneous responses. Attention checker questions that yielded invalid responses were also removed from the sample. Once the data was appropriately formatted, the clean dataset was converted to a CSV file for import into SmartPLS®. Next, SmartPLS® was used to confirm descriptive statistics and reliability. Descriptive Statistics provided a summary of the characteristics of the data, including the mean and standard deviation. This allowed for a simplistic interpretation of the data.

Research Model Testing

The data collected as part of this study was tested using partial least squares structural equation modeling (PLS-SEM) through SmartPLS® 4 to thoroughly analyze and test the relationships between the seven constructs in the conceptual model – Behavioral Intention to use digital health technology, Perceived Health Benefit, Social Influence, Trust in Technology, eHealth Literacy, Actual Use of digital health technology, and Health Consciousness. PLS-SEM has been used in many social science research studies and is a desirable analysis method when examining a model with multiple constructs and paths (Hair et al., 2019). Because of the numerous paths and multiple constructs of this model, PLS-SEM was a necessary method of analysis for this study. Once the data was imported into SmartPLS®, the measurement and structural model assessments were performed.

Measurement Model Assessment

As part of the measurement model assessment, an initial PLS algorithm was executed to evaluate the indicator loadings and determine the reliability of each indicator. Scholars have previously stated that a loading criterion of at least 0.6 is acceptable (Garson, 2016; Mustofa et al., 2022). However, according to Hair et al. (2019), the acceptable loading criteria for reliability is at least 0.7 (Hair et al., 2019). Upon assessing the indicator loadings, VIF was evaluated to assess multicollinearity. Furthermore, Cronbach's alpha was performed to confirm construct reliability. Cronbach's alpha (α) is determined on a scale of 0-1, and an acceptable Cronbach's alpha (α) is above 0.70, therefore suggesting the data is reliable (Cronbach, 1951; Tavakol & Dennick, 2011). As Hair et al. (2019) suggests, once indicator loadings and construct reliability were assessed, convergent and discriminant validity were determined (Hair et al., 2019). Convergent validity was used to confirm that the measures or items associated with each construct have commonality and alignment in measuring the same concept (Hair et al., 2019). This indicates that the measures for each construct are consistent in their assessment of the construct. Convergent validity was determined using the SmartPLS® 4 tool to compute the Average Variant Extracted (AVE) for the items of each construct (Hair et al., 2019). According to Hair et al. (2019), the AVE for each construct should be greater than 0.5 (Hair et al., 2019). Discriminant validity was used to confirm that each construct in the model is distinct from other constructs (Hair et al., 2019). The objective for discriminant validity was to obtain a Heterotrait-Monotrait Ratio score of less than 0.9 (Hair et al., 2019). Lastly, to complete the measurement model, indicator weights needed to be assessed to determine measurement model quality (Hair et al., 2019).

Structural Model Assessment

After completing the measurement model assessment, the structural model was assessed to explain the relationships between the constructs in the model and argue the hypotheses presented in this dissertation. Bootstrapping analysis of the model with 5,000 samples was executed in SmartPLS® to determine the explanatory power, directionality, and support of the hypothesized relationships. Figure 6 presents the constructs and their hypothesized relationships after initial import into SmartPLS®.

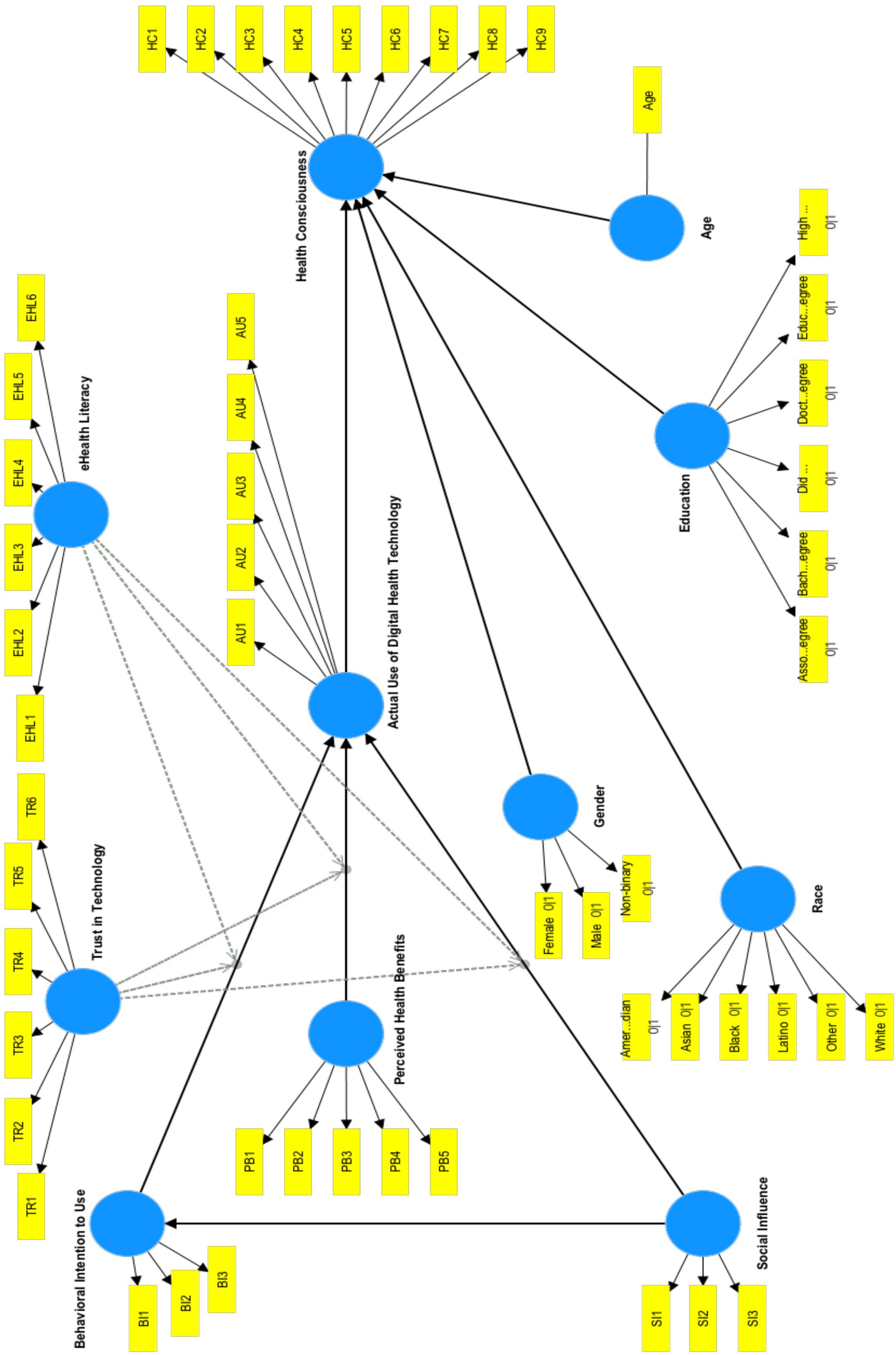


Figure 6: SmartPLS® Research Model

CHAPTER 4: RESULTS

4.1 Overview

This chapter presents the results derived from the survey data collection and evaluation of the research model. The survey was initially administered to 303 respondents via Prolific, an online research panel. The dataset was cleaned to remove survey responses from participants who did not agree to the consent form at the start of the survey and those who did not pass the attention checker questions. The data collection resulted in 293 completed survey responses. The response time to complete the survey was evaluated to ensure that data reflected reasonable response times. The average response time for completing the survey was 5.7 minutes.

4.2 Descriptive Statistics and Demographics

Upon initial import into SmartPLS®, the survey data was evaluated to determine descriptive statistics and gain an overview of the data, including the mean, standard deviation, and range. The descriptive statistics were beneficial in summarizing the main features and characteristics of the dataset. There were 293 observations included in the dataset. The data was evaluated to gain an overview of the respondent's demographic information, including their gender, age, education level, and race. All participants were residents of the United States, as this was part of the exclusion criteria. According to the results, the gender composition of the respondents was 43% male, with 127 males completing the survey; 54% percent female, with 156 females completing the survey; 3% nonbinary, with ten people identifying as non-binary completing the survey; and 0% gender-fluid, with 0 participants identifying as gender-fluid. The age range of the participants was 21-94 years old. The average respondent age was 39 years old at the time of the survey. Furthermore, the participant's race was examined as part of the study. Based on the survey responses, 208 participants identified as White (71%). The next largest racial group was Latino, with 28 participants (10%). 24 respondents identified as Black (8%). 23 respondents identified as Asian (8%). 1 respondent identified as American Indian. 9 respondents identified as "other" (3%). However, the participants did not specify what races they classified as "other." None of the participants in the study identified as Native Hawaiian / Pacific Islander. Lastly, the final demographic examined was education. 37% of survey respondents had a Bachelor's degree, the largest group within the education category. The next largest group was high school graduates/diploma at 24%. Fewer individuals did not complete high school or had an Associate degree (16%), Master's degree (20%), or Doctorate (3%). Figures 7, 8, and 9 below display the demographic results outlined above. Appendix V contains a full table of the output of descriptive statistics.

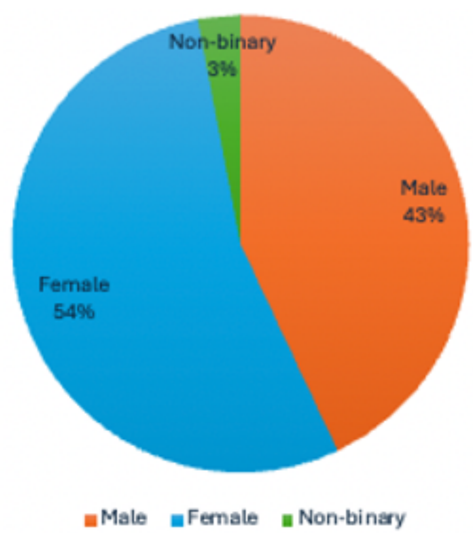


Figure 7: Sample Gender Distribution

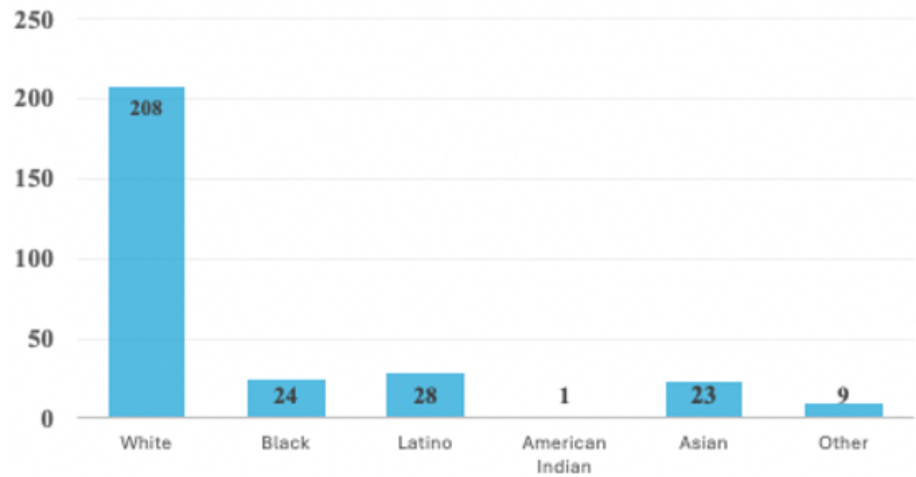


Figure 8: Sample Race Distribution

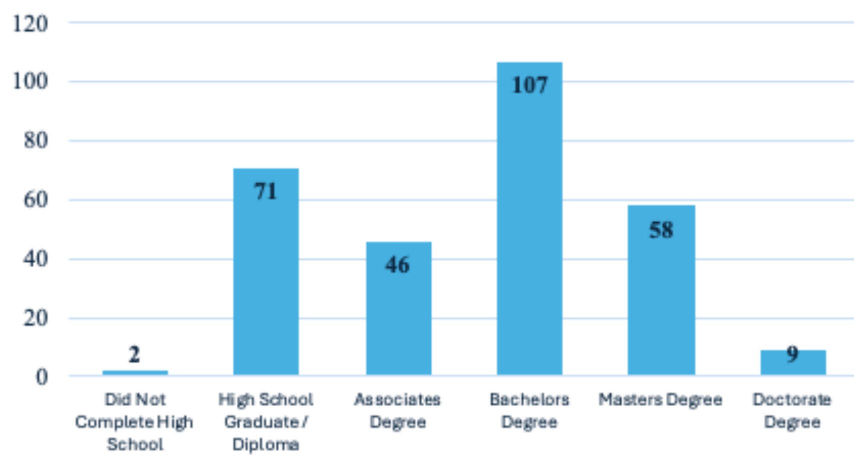


Figure 9: Sample Education Distribution

4.3 Measurement Model Assessment

When leveraging PLS-SEM to evaluate a proposed research model, there are two primary steps: measurement model assessment and structural model assessment. Each primary step has several subcomponents. Following the steps outlined by Hair et al. (2019), I conducted the measurement model assessment to confirm the model fit and the reliability and validity of the reflective constructs.

Outer Loadings, Variance Inflation Factor, Reliability and Validity

An initial analysis of the model in SmartPLS® was conducted, and the outer loadings of the overall sample were assessed to determine the reliability of each indicator. Some scholars believe a loading criterion of at least 0.6 is acceptable (Garson, 2016; Mustofa et al., 2022). However, according to Hair et al. (2019), the acceptable loading criteria for reliability is at least 0.7 (Hair et al., 2019). This study follows the guidance of Hair et al. (2019) and considers 0.7 as the minimal loading criteria to determine reliability. The outer loadings for Behavioral Intention, eHealth Literacy, Health Consciousness, Perceived Health Benefit, Social Influence, and Trust in Technology are all acceptable with loadings greater than 0.7, as indicated in Figure 10. Three items for Actual Use of digital health technology have outer loadings less than 0.7 – AU1, AU2, and AU4. AU1 has an outer loading of 0.597, AU2 has an outer loading of 0.501, and AU4 has an outer loading of 0.676. In addition, the control variables of education, gender, and race all have outer loadings less than the minimum acceptable criteria. According to Hair et al. (2021), items with outer loadings less than the minimum criteria can be removed as they do not adequately represent the construct (Hair et al., 2021). As a result, the items for the Actual Use construct that did not meet the outer loading threshold – AU1, AU2, and AU4 were removed after the initial PLS algorithm and bootstrapping. However, the control variables remained included in the study even though they did not meet the outer loading threshold because they provide additional views of the data and potentially can suggest relationships that were not previously evaluated in the initial model. Figure 10 presents the SmartPLS® model with each construct's initial factor loadings. Upon removing the items for Actual Use that do not meet the minimum outer loading threshold, the only remaining items under the threshold are the control variables – gender, race, age, and level of education. Table 2 presents all outer loadings after removing AU1, AU2, and AU4.

Figure 10: SmartPLS® Model Initial PLS Algorithm and Factor Loadings

Table 2: Factor Loadings

	Outer loadings
Actual Use of Digital Health Technology	
AU3 <- Actual Use of Digital Health Technology	0.851
AU5 <- Actual Use of Digital Health Technology	0.818
Behavioral Intention to Use	
BI1 <- Behavioral Intention to Use	0.986
BI2 <- Behavioral Intention to Use	0.987
BI3 <- Behavioral Intention to Use	0.972
Health Consciousness	
HC1 <- Health Consciousness	0.834
HC2 <- Health Consciousness	0.836
HC3 <- Health Consciousness	0.845
HC4 <- Health Consciousness	0.837
HC5 <- Health Consciousness	0.858
HC6 <- Health Consciousness	0.849
HC7 <- Health Consciousness	0.797
HC8 <- Health Consciousness	0.728
HC9 <- Health Consciousness	0.822
Perceived Health Benefit	
PB1 <- Perceived Health Benefit	0.81
PB2 <- Perceived Health Benefit	0.794
PB3 <- Perceived Health Benefit	0.852
PB4 <- Perceived Health Benefit	0.807
PB5 <- Perceived Health Benefit	0.819
Social Influence	
SI1 <- Social Influence	0.941
SI2 <- Social Influence	0.974
SI3 <- Social Influence	0.957
Trust in Technology	
TR1 <- Trust in Technology	0.857
TR2 <- Trust in Technology	0.731
TR3 <- Trust in Technology	0.897
TR4 <- Trust in Technology	0.838
TR5 <- Trust in Technology	0.855
TR6 <- Trust in Technology	0.877

	Outer loadings
Age	
Age <- Age	1
eHealth Literacy	
EHL1 <- eHealth Literacy	0.903
EHL2 <- eHealth Literacy	0.894
EHL3 <- eHealth Literacy	0.888
EHL4 <- eHealth Literacy	0.902
EHL5 <- eHealth Literacy	0.847
EHL6 <- eHealth Literacy	0.816
Education	
Education_Associate Degree <- Education	-0.013
Education_Bachelor Degree <- Education	0.289
Education_Did not complete high school <- Education	0.271
Education_Doctorate Degree <- Education	0.192
Education_High school graduate / Diploma <- Education	-0.914
Education_Master's Degree <- Education	0.506
Gender	
Gender_Female <- Gender	0.768
Gender_Male <- Gender	-0.947
Gender_Non-binary <- Gender	0.474
Race	
Race_American Indian or Alaska Native <- Race	0.092
Race_Asian <- Race	0.323
Race_Black or African American <- Race	0.561
Race_Latino <- Race	0.565
Race_Other <- Race	0.196
Race_White <- Race	-0.983
Trust in Technology x Perceived Health Benefit -> Trust in Technology x Perceived Health Benefit	1
Trust in Technology x Behavioral Intention to Use -> Trust in Technology x Behavioral Intention to Use	1
eHealth Literacy x Social Influence -> eHealth Literacy x Social Influence	1
eHealth Literacy x Behavioral Intention to Use -> eHealth Literacy x Behavioral Intention to Use	1
Trust in Technology x Social Influence -> Trust in Technology x Social Influence	1
eHealth Literacy x Perceived Health Benefit -> eHealth Literacy x Perceived Health Benefit	1

The Variance Inflation Factor (VIF) was evaluated upon confirming the indicator loadings to assess multicollinearity among the items and variables. Multicollinearity is when predictor variables or items are highly correlated with each other. According to Hair et al. (2009), the threshold for VIF values is less than 10 (Hair et al., 2009; Kock & Lynn, 2012). High correlation can lead to inaccurate calculations. Therefore, Hair et al. (2021, 2022) recommend excluding one of the variables within a pair of highly correlated variables (Hair et al., 2021; Hair et al., 2022). Based on the initial VIF results, BI1 has a VIF of 20.317 and BI2 has a VIF of 21.580. All remaining predictor variables have items with VIF values less than 10, as indicated in Appendix V table. Because BI1 and BI2 items are part of the Behavioral Intention measure and the item pair contains VIF values greater than 10, Hair's recommendation was followed, and one of the items – BI2, was removed. After removing the BI2 item, the PLS algorithm was recalculated to continue the measurement and structural model assessments.

After the indicator loadings and the VIF were assessed and items below or above the threshold were removed, Cronbach's alpha was evaluated to assess the construct reliability. Hair et al. (2019) state that a Cronbach's alpha value greater than 0.7 is acceptable. As indicated in Table 3, Behavioral Intention to use, Health Consciousness, Perceived Health Benefit, Social Influence, Trust in Technology, and eHealth Literacy have acceptable Cronbach's alpha values above 0.7. Behavioral intention to use has a Cronbach's alpha of 0.964; Health Consciousness has a Cronbach's alpha of 0.941; Perceived Health Benefit has a Cronbach's alpha of 0.876; Social Influence has a Cronbach's alpha of 0.955; Trust in Technology has a Cronbach's alpha of 0.918; and eHealth Literacy has a Cronbach's alpha of 0.939. However, similar to the behavior demonstrated in the outer loadings, Actual Use of digital health technology has a Cronbach's alpha value below the minimum threshold. Actual Use has a Cronbach's alpha of 0.565.

In addition, composite reliability was calculated to assess the construct reliability further. A composite reliability above 0.7 is acceptable (Hair et al., 2019). As indicated in Table 3, the data reflects an acceptable composite reliability of >0.7 for all the constructs, indicating composite reliability is satisfied for each variable. Although Actual Use had a Cronbach's alpha less than the threshold, the composite reliability for this variable is acceptable; therefore, indicating acceptable reliability for the construct.

In alignment with the process outlined by Hair et al. (2019), the convergent validity was evaluated (Hair et al., 2019). Convergent validity is determined by the Average Variant Extracted (AVE). The AVE for each construct should be greater than 0.50 (Hair et al., 2019). As displayed in Table 3, all constructs have values greater than 0.50, indicating that the indicators have acceptable convergent validity. Behavioral Intention and Social Influence constructs have AVE values greater than 0.90, precisely 0.965 for Behavioral Intention and 0.917 for Social Influence. The variables Trust in Technology and eHealth Literacy have AVE values greater than 0.70. Specifically, Trust in Technology has an AVE of 0.713 and eHealth Literacy has an AVE of 0.766. Lastly, Health Consciousness has an AVE of 0.679, Actual Use has an AVE of 0.697, and Perceived Health Benefit has an AVE of 0.667.

Table 3: Construct Reliability and Validity

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
AU	0.565	0.821	0.697
BI	0.964	0.982	0.965
HC	0.941	0.95	0.679
PHB	0.876	0.909	0.667
SI	0.955	0.971	0.917
TR	0.918	0.937	0.713
eHL	0.939	0.952	0.766

Discriminant validity assesses whether each construct uniquely measures the same phenomenon as other items. Several tests can be conducted to determine discriminant validity. According to Henseler et al., (2015), Fornell-Larcker criterion is not reliable when the indicator loadings on a construct differ slightly (Hair et al., 2019; Henseler et al., 2015). As indicated in Figure 10 and Table 2, the indicator loadings for each construct do not have a wide range; therefore Fornell-Larcker criterion will not reliably identify discriminant validity concerns (Hair et al., 2019; Hair et al., 2021; Henseler et al., 2015; Radomir & Moiscul, 2019). Prior studies have proposed the Heterotrait-Monotrait Ratio Matrix (HTMT) as one of the stronger methods to evaluate discriminant validity (Hair et al., 2019; Henseler et al., 2015). As displayed in Table 4, the HTMT ratios for the constructs of this study indicate strong discriminant validity by demonstrating readings less than .90.

Table 4: Heterotrait - Monotrait Ratio

eHL x BI													
eHL x SI													0.443
eHL x PHB												0.426	0.249
TR x SI											0.25	0.32	0.16
TR x BI										0.62	0.21	0.13	0.3
TR x PHB									0.75	0.698	0.315	0.16	0.173
eHL								0.025	0.089	0.028	0.126	0.257	0.213
TR							0.372	0.247	0.334	0.03	0.034	0.062	0.125
SI						0.468	0.277	0.035	0.148	0.074	0.022	0.015	0.09
PHB					0.56	0.707	0.308	0.225	0.264	0.085	0.078	0.057	0.073
HC				0.577	0.4	0.476	0.357	0.114	0.153	0.072	0.029	0.076	0.053
BI			0.388	0.443	0.432	0.421	0.245	0.256	0.429	0.183	0.021	0.089	0.165
AU		0.508	0.514	0.523	0.428	0.489	0.307	0.037	0.172	0.089	0.048	0.069	0.024
	AU	**BI**	**HC**	**PHB**	**SI**	**TR**	**eHL**	**TR x PHB**	**TR x BI**	**TR x SI**	**eHL x PHB**	**eHL x SI**	**eHL x BI**

Correlation Analysis

Upon completion of the initial review of the descriptive statistics, bivariate correlations amongst the variables were evaluated. A table containing all the bivariate correlations is in Appendix VII. According to the data, Actual Use significantly correlated with most of the control variables – age, gender, and race. In addition, Actual Use also correlated with most of the independent and moderator variables, Behavioral Intention, Health Consciousness, Perceived Health Benefits, Social Influence, Trust in Technology, and eHealth Literacy. Behavioral Intention also significantly correlated with Health Consciousness, Perceived Health Benefits, Social Influence, Trust in Technology, and eHealth Literacy. The strongest correlations presented in the data include a moderate significant correlation between Health Consciousness and Perceived Health Benefits, a moderate significant correlation between Perceived Health Benefits and Trust in Technology, and a moderate significant correlation between Social Influence and Perceived Health Benefits.

4.4 Structural Model Assessment

After completing the measurement model assessment, the structural model assessment was conducted to evaluate the strength of the relationships in the model. The structural model assessment explains the relationships between the constructs in the model.

R-Squared

In this study, R^2 was evaluated in addition to statistical significance. R^2 is calculated on a 0-1 scale and explains a model's explanatory power (Hair et al., 2021; Shmueli & Koppius, 2011). As indicated in Table 5, the results of this study contain an adjusted R^2 of 0.211 for Actual Use of digital health technology, 0.169 for Behavioral Intention to use, and 0.182 for Health Consciousness. These results indicate that the model has good explanatory power, as it explains 21% of the variance in the Actual Use of digital health technology, 17% of the variance in Behavioral Intention to use digital health technology, and 18% of the variance in Health Consciousness.

Table 5: R^2 and Adjusted R^2

	R-square	R-square adjusted
Actual Use of Digital Health Technology	0.241	0.211
Behavioral Intention to Use	0.172	0.169
Health Consciousness	0.196	0.182

Effect Size

The f^2 effect size was evaluated to determine if the absence of the exogenous constructs impacted the endogenous constructs. Exogenous variables are also referred to as predictors, and they are not influenced by other variables in the model. Endogenous constructs are the dependent variables that are influenced by other variables in the model. According to Hair et al. (2019), The effect size (f^2) is a metric used to evaluate the relative impact of a predictive construct on an endogenous construct. According to Hair et al. (2019), an f^2 effect size of 0.02 is a small effect, 0.15 is a medium effect, and 0.35 is a large effect (Cohen, 1988; Hair et al., 2019). Actual use has a medium to large effect on Health Consciousness. Social influence also has a medium to large effect on Behavioral Intention to use. On the contrary, Behavioral Intention has a small to medium effect on Actual Use.

Table 6: Effect Size (f^2)

	f-square
AU -> HC	0.162
BI -> AU	0.051
PHB -> AU	0.016
SI -> AU	0.003
SI -> BI	0.207
TR x PHB -> AU	0.002
TR x BI -> AU	0.002
TR x SI -> AU	0.004
eHL x PHB -> AU	0
eHL x SI -> AU	0.001
eHL x BI -> AU	0.006
AU -> HC	0.162
BI -> AU	0.051

Bootstrapping / Statistical Significance

In addition to evaluating the adjusted R^2 value, bootstrapping analysis was employed to determine the path coefficients to determine the significance and directionality of the relationships in the model. The acceptable value for statistical significance is $p < 0.05$ (Hair et al., 2019). As indicated in Table 7, the relationship between Behavioral Intention and Actual Use of digital health is significant, with $p < 0.001$. In addition, the relationship between the Actual Use of digital health technology and Health Consciousness is significant, with $p < 0.001$. Furthermore, the relationship between Perceived Health Benefit and Actual Use of digital health technology is significant, with $p = 0.023$. The relationship between Social Influence and Behavioral Intention is significant, with $p < 0.001$. In addition, one relationship that was not hypothesized is also significant. The relationship between race and Health Consciousness is significant, with $p < 0.001$.

Table 7: Path Coefficients

	Original sample	Sample mean	Standard deviation	T statistics	P values
Actual Use -> Health Consciousness	**0.372**	**0.376**	**0.046**	**8.06**	**< 0.001**
Age -> Health Consciousness	-0.064	-0.061	0.053	1.21	0.227
Behavioral Intention -> Actual Use of Digital Health Technology	**0.245**	**0.246**	**0.07**	**3.489**	**< 0.001**
Education -> Health Consciousness	0.21	0.172	0.362	0.58	0.562
Gender -> Health Consciousness	0.353	0.352	0.291	1.212	0.226
Perceived Health Benefit -> Actual Use	**0.157**	**0.153**	**0.069**	**2.28**	**0.023**
Race -> Health Consciousness	**0.796**	**0.839**	**0.199**	**3.997**	**< 0.001**
Social Influence -> Actual Use	0.058	0.056	0.067	0.871	0.384
Social Influence -> Behavioral Intention	**0.414**	**0.414**	**0.049**	**8.421**	**< 0.001**
Trust in Technology -> Actual Use	0.106	0.109	0.069	1.54	0.124
eHealth Literacy -> Actual Use	0.086	0.09	0.057	1.521	0.128
Trust in Technology x Perceived Health Benefit -> Actual Use	0.048	0.042	0.063	0.751	0.453
Trust in Technology x Behavioral Intention -> Actual Use	-0.044	-0.04	0.069	0.634	0.526
Trust in Technology x Social Influence -> Actual Use	0.075	0.079	0.071	1.067	0.286
eHealth Literacy x Perceived Health Benefit -> Actual Use	-0.015	-0.007	0.057	0.268	0.788
eHealth Literacy x Social Influence -> Actual Use	0.031	0.03	0.068	0.458	0.647
eHealth Literacy x Behavioral Intention to Use -> Actual Use	0.075	0.069	0.056	1.343	0.179

Hypothesis Testing

In this study, SmartPLS® was leveraged to evaluate eleven hypotheses. Table 8 presents the results of the hypotheses, indicating which hypotheses are supported and which are not. H1 evaluated whether the Behavioral Intention had a positive association with the Actual Use of digital health technology. PLS-SEM results suggest that Behavioral Intention to use digital health technology is positively associated with the Actual Use of digital health technology. This relationship was statistically significant, with $p < 0.001$. H2 evaluated if Perceived Health Benefit is positively associated with the Actual Use of digital health technology. PLS-SEM results suggest that Perceived Health Benefit is positively associated with the Actual Use of digital health technology, with a $p = 0.023$. H3 evaluated whether Social Influence is positively associated with the Behavioral Intention to use digital health technology. The results from PLS-SEM support this hypothesis, with $p < 0.001$. H11 evaluated the relationship between the Actual Use of digital health technology and Health Consciousness. Based on the results of this study, the Actual Use of digital health technology is positively associated with Health Consciousness, with $p < 0.001$. The other hypotheses in the model are not supported. Out of 11 hypothesized relationships, four are supported in this study as reported in Table 8. Figure 11 contains a diagram of the research model with statistically significant paths and nonsignificant paths. Significant paths are indicated by solid lines and nonsignificant paths are indicated by dotted lines.

Table 8: Summary of Hypothesized Results

#	Hypothesis	Result
H_1	**The intention to use digital health technology is positively associated with the Actual Use of digital health technology.**	Supported
H_2	**The Perceived Health Benefit of digital health technology is positively associated with the Actual Use of digital health technology.**	Supported
H_3	**Social influence is positively associated with the intention to use digital health technology.**	Supported
H_4	Social influence is positively associated with the Actual Use of digital health technology.	Not Supported
H_5	Trust in technology moderates the relationship between intention to use digital health technology and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between intention to use digital health technology and Actual Use is strengthened.	Not Supported
H_6	Trust in technology moderates the relationship between Perceived Health Benefit and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between Perceived Health Benefit and Actual Use is strengthened.	Not Supported
H_7	Trust in technology moderates the relationship between Social Influence and Actual Use of digital health technology, such that when Trust in Technology is high, the relationship between Social Influence and Actual Use is strengthened.	Not Supported
H_8	eHealth Literacy moderates the relationship between intention to use digital health technology and Actual Use of digital health technology, such that when eHealth Literacy is high the relationship between intention to use digital health technology and Actual Use is strengthened.	Not Supported
H_9	eHealth Literacy moderates the relationship between Perceived Health Benefit and Actual Use of digital health technology, such that when eHealth Literacy is high the relationship between Perceived Health Benefit and Actual Use is strengthened.	Not Supported
H_{10}	eHealth Literacy moderates the relationship between Social Influence and Actual Use of digital health technology, such that when eHealth Literacy is high the relationship between Social Influence and Actual Use is strengthened.	Not Supported
H_{11}	**Actual use of digital health technology is positively associated with an individual's Health Consciousness.**	Supported

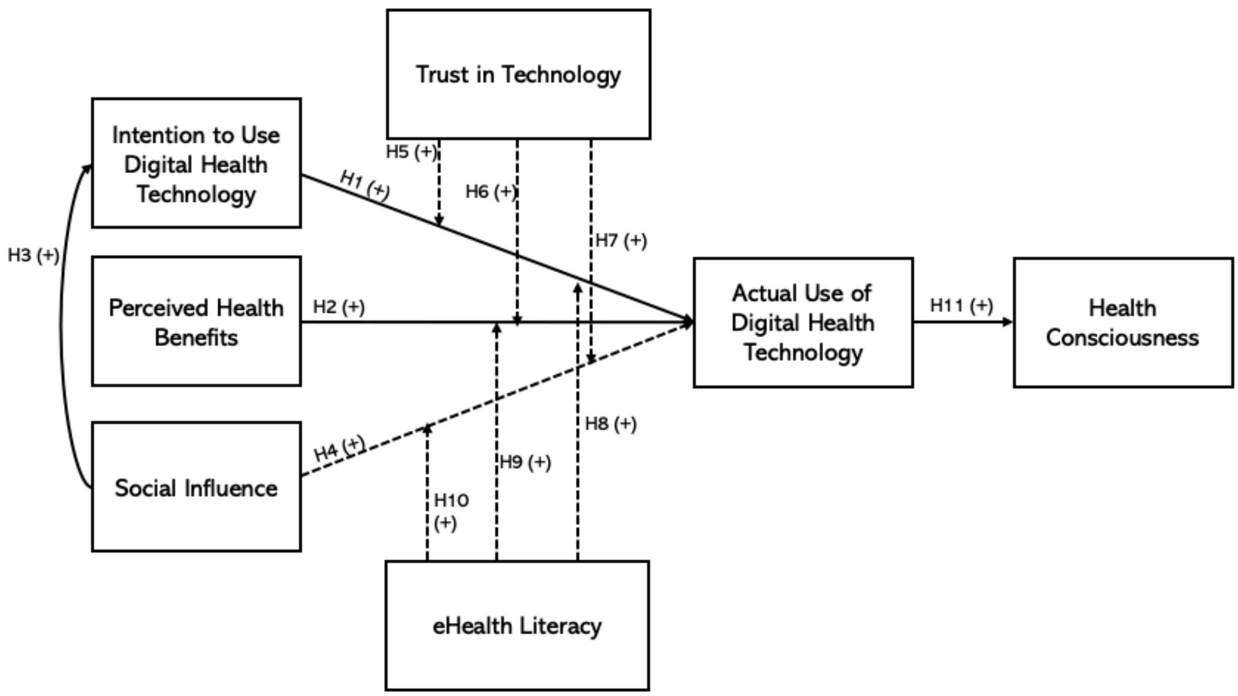


Figure 11: Model with Significant and Nonsignificant Paths

CHAPTER 5: DISCUSSION

This chapter presents an overview of the study and the insights gathered through the research in five sections. The first section restates the goals of this study. The second section presents the research findings. The third section discusses the contributions and implications. The fourth section discusses the limitations. Lastly, the fifth section presents future research ideas.

5.1 Overview

With the continued evolution of technology across healthcare, this study aimed to explore the factors that influence an individual to adopt digital health technology. Furthermore, this study aimed to determine if digital health technology improves health outcomes by making individuals more health conscious. In addition, age, gender, race, and level of education were evaluated as control variables to determine the effects of these variables on the hypotheses. While the UTAUT model has been widely studied and supported across various industries, it was not designed explicitly for healthcare. This study aimed to integrate technology adoption behaviors and healthcare behaviors to analyze if the two combined areas explain digital healthcare technology adoption by individuals.

5.2 Findings

H_1: Behavioral Intention and Actual Use

Venkatesh et al. (2003) proposed that there is a relationship between Behavioral Intention to adopt technology and the Actual Use of technology (Venkatesh et al., 2003). Several studies have supported this relationship across various technologies and industries (Alam et al., 2020a; Alam et al., 2020b; Davis, 1989; Hoque, 2016; Hoque & Sorwar, 2017; Venkatesh et al., 2003; Venkatesh et al., 2012). This study supports the current literature on UTAUT by demonstrating that a significant relationship between Behavioral Intention and Actual Use exists in digital health technology adoption. The bootstrapping analysis reports the relationship between Behavioral Intention and Actual Use as ($\beta = 0.245$, $t = 3.489$ and $p < 0.001$), indicating a significant relationship. The original UTAUT model has four fundamental constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions that explain Behavioral Intention to adopt technology, and then Behavioral Intention explains the Actual Use behavior (Venkatesh et al., 2003). This study did not focus on the antecedents to Behavioral Intention but instead focused on the relationship between Behavioral Intention and Actual Use.

H_2: Perceived Health Benefit and Actual Use

The Health Belief model suggests that people are more likely to act if they believe a health benefit is associated with it. Prior studies have supported the integration of the Health Belief Model and technology adoption models, as has been done in this study (Ahadzadeh et al., 2015; van der Waal et al., 2022; Walrave et al., 2020). While there is limited extant research evaluating the relationship between the Perceived Health Benefit construct and technology adoption specifically, one study examined and demonstrated a relationship between Perceived Health Benefit and Behavioral Intention when adopting COVID-19 contract tracing applications (van der Waal et al., 2022). However, no prior studies specifically test the relationship between Perceived Health Benefit and Actual Use of technology. The bootstrapping analysis reports the relationship between Perceived Health Benefit and Actual Use as ($\beta = 0.157$, $t = 2.280$ and $p = 0.023$), indicating a significant relationship. Therefore, this study extends the literature supporting the integration of HBM and UTAUT by demonstrating a relationship between

Perceived Health Benefit and the Actual Use of technology in the context of digital health technology adoption.

H_3: Social Influence and Behavioral Intention

Prior research suggests a relationship between Social Influence and Behavioral Intention to use (Cajita et al., 2017; Pynoo et al., 2012; Sun et al., 2013; Venkatesh et al., 2003; Venkatesh et al., 2012). In healthcare-related studies, Social Influence is linked to the Behavioral Intention to adopt various technologies, including mHealth and electronic medical records (Cajita et al., 2017; Pynoo et al., 2012; Sun et al., 2013). The bootstrapping analysis demonstrates that the relationship between Social Influence and Behavioral Intention is significant ($\beta = 0.414$, $t = 8.421$, and $p < 0.001$). The significant relationship reported in this study aligns with the results previously reported by Venkatesh et al. (2003) and supported by many other scholars (Cajita et al., 2017; Pynoo et al., 2012; Sun et al., 2013; Venkatesh et al., 2003). Therefore, this study further suggests that patients' technology adoption can be influenced by their social network – physicians, families, friends, and caregivers.

H_4: Social Influence and Actual Use

Extant literature supports the relationship between Social Influence and Behavioral Intention to use technology (Venkatesh et al., 2003). Furthermore, extant literature suggests that Behavioral Intention mediates the relationship between Social Influence and Actual Use (Venkatesh et al., 2003). Few studies focus on the direct relationship between Social Influence and Actual Use. However, there are a few instances where scholars have demonstrated a strong relationship between the two constructs – specifically when analyzing the adoption of 3g mobile communications and the use of electronic health records (Maillet et al., 2015; Wu et al., 2007). This study evaluated the direct relationship between Social Influence and Actual Use in the context of digital health technology usage. However, the bootstrapping analysis demonstrates that the relationship between Social Influence and Actual Use is not supported ($\beta = 0.058$, $t = 0.871$, $p = 0.384$).

H_5: Trust in Technology moderates the relationship between Behavioral Intention to use and Actual Use

Trust has been supported as a factor influencing the intention to use technology in prior studies (Alaiad & Zhou, 2014; Choudhury & Shamszare, 2023; Deng et al., 2018; Oldeweme et al., 2021; Shahbaz et al., 2019). In healthcare-specific studies, trust in specific technological artifacts continues to influence their decision or intention to use a technology (Arfi et al., 2021; Nisha et al., 2019). While prior studies suggest that Trust has a direct relationship with Behavioral Intention, the bootstrapping analysis of this study demonstrates that Trust in Technology is not supported as a moderator between Behavioral Intention to use and Actual Use ($\beta = -0.044$, $t = 0.634$, and $p = 0.526$). One possible explanation for this finding could be the demographics of the study participants, which may have influenced their responses. Age and education can influence individuals' perceptions and behaviors, consequently influencing their responses to survey questions. The average participant age in this study was 39 years old, with most participants holding a Bachelor's degree. Many participants in this study are the Millennial generation, who typically embrace technology. Furthermore, as Ng (2012) described, individuals born after 1980 are "digital natives"; therefore, it is possible that trust in technology may not have a significant influence on their technology behaviors (Ng, 2012).

H_6: Trust in technology moderates the relationship between Perceived Health Benefit and Actual Use

Trust has previously been studied and supported in parallel with HBM to explain COVID-19 vaccination acceptance, but not in the context of technology adoption in the healthcare industry (Wong et al., 2021). However, based on the bootstrapping analysis, Trust in Technology is not supported as a moderator between the HBM construct of Perceived Health Benefit and Actual Use when evaluating digital health technology usage. The bootstrapping analysis reports ($\beta = 0.048$ $t = 0.751$, and $p = 0.453$). One possible explanation for this stems from the survey method. The surveyed individuals had to access technology to take the survey electronically. Therefore, these individuals are comfortable with technology and likely have fewer trust issues in technology since they are accessing surveys through tablets, phones, and computers. Another possible contributing factor is the average age of the participants. Most of the participants have used technology before, have accessed health information via technology, and are of an age range where they have witnessed technology and healthcare integration; therefore, the trust factor may not be as influential as it is for someone who historically did not see an intersection between healthcare and technology.

H_7: Trust in Technology moderates the relationship between Social Influence and Actual Use

The bootstrapping analysis of this study demonstrates that Trust in Technology is not supported as a moderator between Social Influence and Actual Use, with ($\beta = 0.075$ $t = 1.067$ and $p = 0.286$). The non-supported relationship of Trust in Technology as a moderator between Social Influence and Actual Use is consistent with this study's non-supported relationship between Social Influence and Actual Use. Limited prior research supports the relationship between Social Influence and the Actual Use of technology (Maillet et al., 2015; Wu et al., 2007). However, this study did not support the relationship between Social Influence and Actual Use. Perhaps if this study evaluated Trust in Technology as a moderator of the relationship between Social Influence and behavioral influence, the result would have been supported, considering the relationship between Social Influence and Behavioral Intention is a much more widely supported relationship in existing UTAUT studies (Cajita et al., 2017; Pynoo et al., 2012; Sun et al., 2013; Venkatesh et al., 2003).

H_8: eHealth Literacy moderates the relationship between intention to use and Actual Use

Prior research that has examined the relationship between eHealth Literacy and Behavioral Intention to adopt technology in the healthcare industry has had mixed results (Aydin & Kumru, 2022; Cajita et al., 2017). This study evaluated eHealth Literacy as a moderating variable to determine if it moderates the relationship between Behavioral Intention and Actual Use. The bootstrapping analysis of this study demonstrates that eHealth Literacy is not supported as a moderator between Behavioral Intention and Actual Use, with ($\beta = 0.075$, $t = 1.343$ and $p = 0.179$). Prior research shows that eHealth Literacy levels differ based on different sociodemographic groups (Kontos et al., 2014; Magsamen-Conrad et al., 2019). While different sociodemographic variables were included as controls in this study, perhaps the controls selected contributed to the non-supported hypothesized moderating relationship.

H_9: eHealth Literacy moderates the relationship between Perceived Health Benefit and Actual Use

Prior research suggests that individuals with higher literacy levels are more likely to find health information online that they deem beneficial (Quinn et al., 2017). In addition, research also shows that individuals with lower health literacy are less likely to engage in preventative health behaviors (Bennett et al., 2009).   The rationale behind this hypothesized relationship was that if an individual has eHealth Literacy to find beneficial information through technology and can perceive the health benefits of that information, it will strengthen the relationship between Perceived Health Benefit and Actual Use. However, based on the bootstrapping analysis, this study did not support eHealth Literacy as a moderator between Perceived Health Benefit and

Actual Use of technology (β = -0.015 t = 0.268 and p = 0.788). Based on the population surveyed, there was a significant relationship between Perceived Health Benefit and Actual Use. However, eHealth Literacy did not strengthen the relationship between Perceived Health Benefit and Actual Use.

H_{10}: eHealth Literacy moderates the relationship between Social Influence and Actual Use

eHealth Literacy and digital literacy are closely related concepts, with eHealth Literacy being specific to the healthcare domain to align with the digital transformation of healthcare (Karnoe & Kayer, 2015; Norman & Skinner, 2006a; Norman & Skinner, 2006b; van der Vaart & Drossaert, 2017). eHealth Literacy has not been widely studied as a moderator between UTAUT variables. However, this study analyzed the relationship to address a gap in extant research. However, eHealth Literacy was not supported as a moderator between Social Influence and Actual Use. The bootstrapping analysis of this study demonstrates that eHealth Literacy is not supported as a moderator between Social Influence and Actual Use (β = 0.031 t = 0.458 and p = 0.647). Furthermore, the relationship between Social Influence and Actual Use has not been widely studied and supported, and in this study, the direct relationship between the two variables was not supported. While a recent study suggested that digital literacy negatively moderated the relationship between two UTAUT variables, the items included in the measure for this study had an optimistic tone, prompting the testing of a positive relationship to maintain the scale (Yu et al., 2021). A future research idea is to retest the relationship using a different scale, evaluate the negative relationship, and determine whether the results are supported under those conditions.

H_{11}: Actual use and Health Consciousness

Most existing technology adoption literature evaluates the antecedents to Actual Use instead of the outcomes. This study attempted to expand the literature and consider the outcome of adopting and using digital health technology, specifically focusing on an individual's level of Health Consciousness. Health Consciousness has previously been supported as an antecedent of technology adoption (Cho, 2014; Damberg, 2002). As a novel finding of this study, a positive relationship between Actual Use of digital health technology and Health Consciousness is supported. The bootstrapping analysis reports the relationship between Actual Use and Health Consciousness as ($\beta = 0.372$ $t = 8.060$ and $p < 0.001$), indicating a significant relationship. From a logical perspective, this was expected as the more aware people access digital health technology, the more health information they have readily available to them. More health information readily available prompts people to be more health conscious. The support of this hypothesis is the foundation for future research in this area to determine if the results are consistent when evaluating different health technologies or populations in different geographical areas.

Additional Findings

An additional finding that was not initially hypothesized was discovered through the bootstrapping analysis. The bootstrapping analysis indicates there is a positive relationship between race and Health Consciousness ($\beta = 0.520$ $t = 4.074$ and $p < 0.001$). Research suggests that Health Consciousness is directly related to health behaviors and health outcomes (Gould, 1990). Within the healthcare practice, organizations acknowledge and aim to address racial disparities and barriers in care for historically marginalized groups. Therefore, this finding highlights the importance of healthcare organizations developing outreach opportunities and addressing access barriers targeting diverse populations to improve health awareness. Future research can also determine the differences in attitudes regarding health and prioritization of health-related behaviors in individuals of different racial backgrounds.

5.3 Contributions and Implications

This study evaluated the relationship between several UTAUT variables as previously conceptualized by Venkatesh et al. (2003). While the UTAUT model traditionally evaluates the antecedents of technology use, it does not explore the outcomes of technology adoption. A novel finding and primary theoretical contribution of this study is its support of the relationship between the Actual Use of technology and Health Consciousness, a relationship previously unexplored in the UTAUT research. Additionally, this study supports the relationship between Behavioral Intention to adopt technology and the Actual Use, as well as the relationship between Social Influence and Behavioral Intention, within the context of digital health technology adoption.

While UTAUT has been applied to various technology studies across many industries and technology types, it has yet to be studied in combination with the Health Belief Model in the context of digital health technology adoption. This study integrated HBM and UTAUT to apply health behaviors explained through HBM to technology adoption. A theoretical contribution of this study is its support for integrating these two independent theories. This study supports a relationship between Perceived Health Benefit and the Actual Use of technology in the context of digital health technologies. This finding emphasizes the importance of considering additional factors outside of traditional technology adoption behaviors when evaluating technology adoption in the healthcare context. Given the unique nature of the healthcare industry, what is applicable in other industries may not specifically apply to healthcare, highlighting the need to understand technology adoption in healthcare settings. This study supports the idea that future research should integrate the Health Belief Model and UTAUT to explain further how health behaviors influence technology adoption in the healthcare industry.

Digital health technologies continue to revolutionize how medical services are delivered and received. This study supports the positive relationship between the Actual Use of digital health technology and Health Consciousness, which has significant implications for practitioners. Practitioners can use this as a catalyst to help improve patient outcomes by empowering their patients to leverage digital health technologies to increase their overall awareness of their health status. A patient's increased awareness of their overall health can enable proactive health interventions and a preventative rather than reactive approach to health management. In addition, the practical implication helps bridge the health equity gap by improving Health Consciousness across different racial groups through digital health technology.

5.4 Limitations

This study has five primary limitations. First, system data to measure the use of digital health technologies was not readily available. Second, unintentional bias was potentially introduced through the data collection method. Third, the data collected is cross-sectional. Fourth, the results may not be generalized to other countries and regions. Fifth, the control variables were constant

Limitation 1

This study lacks the system data to confirm and measure the actual usage of digital health technologies. Instead of system data, this study measured actual use based on the respondent's perceptions through a survey data collection method. This is a limitation because individuals may perceive their actual usage frequency differently than what reflects reality. In addition, the scale for frequency can be interpreted differently by different respondents, so without actual system data to confirm usage, this measure is left up to the respondent's interpretation of the question. It is very challenging to gain access to system data in healthcare due to various reasons, including the sensitivity of the data and the various privacy laws, the unstructured data elements in healthcare technology systems, and the industry silos that prevent widespread sharing and access to data. However, if time constraints were not an issue and the process of obtaining system data could be completed, the system data would lend additional credibility to the insights provided. Furthermore, it would prove beneficial in determining the demographics of the individuals using the data so that specific groups could be targeted to increase utilization.

Limitation 2

This study employed a survey methodology, which depends on individuals spending adequate time to complete the survey questions thoroughly and honestly. It also depends on participants' comprehension of the survey questions without the option for clarification from the researcher. While the online survey was intended to recruit a diverse population, the accessibility of the survey was limited to respondents with access to a computer, tablet, or mobile device. Furthermore, the survey is limited to people who complete online surveys, eliminating individuals who do not fit that criterion. The individuals who opt to participate in online surveys may not be an accurate representation of the broader population who uses digital health technologies. Given ample data collection time, an alternative approach would have been to administer the surveys to individuals directly instead of using an online portal to potentially capture a more representative sample.

Limitation 3

This study utilized cross-sectional data collection, as data was collected at a single point in time. This approach limits the ability to track and analyze behavior over a period of time to establish a cause-and-effect relationship. A longitudinal study design is preferred to understand how individuals adopt and use technology over time and the associated outcomes.

Due to time constraints, a longitudinal study was not an option for this study; however, this would be a beneficial study to pursue in the future.

Limitation 4

The target population for this study was United States residents. This option was selected due to the variation in healthcare laws and availability of services across different geographic locations. To target a population that has a consistent healthcare experience, the survey was restricted to United States residents. While this approach has benefits, it also introduces the limitation of generalizability of the data. There have been prior studies that evaluated digital health technology adoption in other areas – for instance, mHealth usage in Bangladesh or telehealth usage in the Philippines (Alam et al., 2020b; Dino & Guzman, 2014). Perhaps the restriction of geography limits the generalizability of the findings beyond the sampled population, therefore explaining why some of our results are not consistent with the results seen in prior studies.

Limitation 5

The control variables used in this study aligned with variables that were part of previous healthcare and technology studies. However, in this study, they were used in a limited manner, primarily to gain insights into the demographic distribution of the data. The controls were not extensively tested in this study. However, this would be a beneficial direction for future research that can enrich the results of the current study. Exploring the demographic variables used as controls in this study could provide a greater understanding of how these demographics impact digital health technology adoption. Furthermore, it can contribute to future health equity and technology research, providing valuable insights for practitioners and scholars alike.

5.5 Future Research

The current study prompts several future research ideas. One dimension to consider is to explore the control variables as moderators and evaluate their impact on the relationships between the primary constructs supported in this study – Behavioral Intention and Actual Use, Social Influence and Behavioral Intention, Perceived Health Benefit and Actual Use, and Actual Use and Health Consciousness. This could provide insight into how individuals of different races, genders, ages, and education levels view technology adoption in the healthcare industry and contribute to analyzing technology's impact on health equity.

Another avenue for future research is to conduct a longitudinal study and analyze digital health technology usage over time. It would be valuable to understand if the HBM and UTAUT constructs identified in this study produce the same results in a longitudinal study.

A third avenue for future research would be to use different UTAUT variables excluded in this study and evaluate if the perceived benefit of the health belief model influences different UTAUT variables. Prior research has supported a relationship between HBM and technology adoption models, so a future study should consider different variables to evaluate further and support the relationship between UTAUT and HBM (Ahadzadeh et al., 2015; van der Waal et al., 2022; Walrave et al., 2020).

Another dimension to consider is the trust variable. Trust in technology was the variable included in this study. However, trust is a multi-dimensional variable with various definitions. As examined in this study, Trust in Technology is just one component of trust. Previous studies support the relationship between trust and UTAUT; therefore, using a different dimension of trust in a future study may further help explain the impact that trust has on digital health technology usage. Furthermore, while none of the hypotheses in this study that included Trust in

Technology as a moderating variable were supported, another future research option is to examine the direct relationship between Trust in Technology and the Actual Use of digital health technologies.

An additional future research option is to further examine the relationship between race and Health Consciousness. While this relationship was not hypothesized in this study, the data suggests a relationship between these two variables. An additional evaluation of these variables examining different populations or technologies could help practitioners and scholars further research health equity and understand disparities and gaps in health outcomes of different racial groups.

Additionally, this study focused on the UTAUT model, but there is a newer UTAUT2 model that includes additional variables explaining why individuals adopt a technology. Conducting the study using the perceived benefit variable of HBM and integrating it with UTAUT2 model variables would further extend the research by integrating these two models. Lastly, an interesting future study will look at the variation in the results across different geographic regions. Different cultures and geographies address healthcare and technology differently, so it would be beneficial to see the variation in the antecedents and the outcomes of using technology and see if people still believe in different cultures and geographies that digital health technology usage makes them more health conscious. Much of the current research evaluates the antecedents of technology adoption, not the outcomes. Therefore, any research that further extends the outcomes literature and supports the results demonstrated in this study will extend the literature and improve the practical implications for practitioners.

Lastly, I would like to address the limitations of my current study sample by using a different data collection method in a future study. This study leveraged an online survey method to collect data. In a future study, I would like to employ a self-administered survey to gather data directly from respondents. This would enable me to gather a more diverse population, including individuals that do not complete online surveys and individuals with disabilities who may require accommodations.

5.6 Conclusion

This dissertation examined characteristics that impact the use of digital health technology by integrating the UTAUT variables of Behavioral Intention, Social Influence, and the HBM variable of Perceived Health Benefit. This dissertation also examined the outcome of using digital health technology by evaluating Health Consciousness. Through a thorough review of the literature, the prior research related to the Health Belief Model and the Unified Theory of Acceptance and Use of Technology was examined and considered as part of this study. Furthermore, the extant relationship surrounding Health Consciousness in technology adoption was evaluated. Lastly, the literature surrounding the hypothesized moderators of eHealth Literacy and Trust in technology was reviewed to understand the potential impacts of this study. Several hypotheses were supported, including Behavioral Intention and Actual Use, Perceived Health Benefit and Actual Use, Social Influence and Behavioral Intention, and Actual Use and Health Consciousness. Furthermore, an un-hypothesized relationship was discovered in the data, and that is the relationship between Race and Health Consciousness. Through the supported hypotheses, this study extends the current technology adoption research into healthcare. While UTAUT was not initially created to evaluate healthcare technologies, this study demonstrates that UTAUT applies to digital health technologies through the supported relationship between Behavioral Intention to adopt and the Actual Use of digital health technologies. Similarly, this study demonstrates that Social Influence significantly influences technology adoption behavior for patients who use digital health technologies. Furthermore, by integrating Perceived Health Benefit with UTAUT constructs to assess technology adoption, this study advances the understanding of how psychological factors, specifically perceptions of a technology's benefits, can influence a patient's decision to utilize healthcare technologies. A novel finding of this study is the relationship between Actual Use and Health Consciousness. Digital health technologies expand access to resources and data that patients use to monitor their health and communicate with healthcare providers. The findings of this study demonstrate the beneficial impact of using digital health technologies on an individual's health consciousness. Prior research suggests that health consciousness leads to proactive health management and improved health outcomes. Therefore, this study supports the notion that digital health technology usage can improve health outcomes by increasing individual's awareness of their health status. By leveraging the relationship between Actual Use of digital health technologies and Health Consciousness, healthcare organizations should continue to promote and implement digital health solutions to facilitate patient care delivery, improve patient awareness and engagement, and optimize health outcomes.

Unfortunately, the data did not support the hypothesized relationship between Social Influence and Actual Use. Furthermore, none of the hypothesized moderated relationships were supported in this study. While the relationship between Social Influence and Actual Use has not been widely studied in healthcare, it has been supported in a few studies evaluating nurses' usage of electronic medical records or electronic information management systems in an acute care environment. The studies that support this relationship in the healthcare environment have previously evaluated clinicians using mandated technologies. In contrast, this study evaluated patients using non-mandated digital health technologies, which perhaps influenced the difference in results. Furthermore, previous studies evaluating the relationship between Social Influence and Actual Use focused on participants in other countries – specifically Ghana, Taiwan, and Canada. In contrast, this study focused on participants in the United States. A potential future research option involves reevaluating the relationship between Social Influence and Actual Use in the context of digital health technology by using sample characteristics and control variables that align with prior research to determine if there is continued variation in findings. Furthermore, future research also presents options to extend the supported hypotheses to determine if the results are consistent across geographies, populations, and various technologies within healthcare.

REFERENCES

Abbas, R. M., Carroll, N., Richardson, I., & Beecham, S. (2018, January). Trust Factors in Healthcare Technology: A Healthcare Professional Perspective. In *HEALTHINF* (pp. 454-462).

Abraham, C., & Sheeran, P. (2015). The health belief model. *Predicting health behaviour: Research and practice with social cognition models*, *2*, 30-55.

Abubakar, F. M., & Ahmad, H. B. (2013). The moderating effect of technology awareness on the relationship between UTAUT constructs and behavioural intention to use technology: A conceptual paper. *Australian journal of business and management research*, *3*(2), 14-23.

Ahadzadeh, A. S., et al. (2015). “Integrating health belief model and technology acceptance model: an investigation of health-related internet use.” J Med Internet Res 17(2): e45.

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Akter, S., Ray, P., & D’Ambra, J. (2013). Continuance of mHealth services at the bottom of the pyramid: the roles of service quality and trust. Electronic Markets, 23(1), 29-47.

Alaiad, A., & Zhou, L. (2014). The determinants of home healthcare robots adoption: An empirical investigation. *International journal of medical informatics*, *83*(11), 825-840.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. *International Journal of Information Management*, *37*(3), 99-110.

Alam, M. Z., Alam, M. M. D., Uddin, M. A., & Mohd Noor, N. A. (2022). Do mobile health (mHealth) services ensure the quality of health life? An integrated approach from a developing country context. *Journal of Marketing Communications*, *28*(2), 152-182.

Alam, M. M. D., Alam, M. Z., Rahman, S. A., & Taghizadeh, S. K. (2021). Factors influencing mHealth adoption and its impact on mental well-being during COVID-19 pandemic: A SEM-ANN approach. *Journal of biomedical informatics*, *116*, 103722.

Alam, M. Z., Hoque, M. R., Hu, W., & Barua, Z. (2020a). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. International journal of information management, 50, 128-143.

Alam, M. Z., Hu, W., Kaium, M. A., Hoque, M. R., & Alam, M. M. D. (2020b). Understanding the determinants of mHealth apps adoption in Bangladesh: A SEM-Neural network approach. *Technology in Society*, *61*, 101255.

Al-Metwali, B. Z., Al-Jumaili, A. A., Al-Alag, Z. A., & Sorofman, B. (2021). Exploring the acceptance of COVID-19 vaccine among healthcare workers and general population using health belief model. *Journal of evaluation in clinical practice*, *27*(5), 1112-1122.

Arenas Gaitán, J., Peral, B., & Ramón Jerónimo, M. (2015). Elderly and internet banking: An application of UTAUT2. *Journal of Internet Banking and Commerce, 20 (1), 1-23.*

Arfi, W. B., Nasr, I. B., Khvatova, T., & Zaied, Y. B. (2021). Understanding acceptance of eHealthcare by IoT natives and IoT immigrants: An integrated model of UTAUT, perceived risk, and financial cost. *Technological Forecasting and Social Change*, *163*, 120437.

Ashraf, A. R., Thongpapanl, N., & Auh, S. (2014). The application of the technology acceptance model under different cultural contexts: The case of online shopping adoption. Journal of International Marketing, 22(3), 68-93.

Awad, A., Trenfield, S. J., Pollard, T. D., Ong, J. J., Elbadawi, M., McCoubrey, L. E., ... & Basit, A. W. (2021). Connected healthcare: Improving patient care using digital health technologies. *Advanced Drug Delivery Reviews*, *178*, 113958.

Aydin, G., & Kumru, S. (2022). Paving the way for increased e-health record use: elaborating intentions of Gen-Z. *Health Systems*, 1-18.

Bawden, D. (2001). Information and digital literacies: a review of concepts. *Journal of documentation*, *57*(2), 218-259.

Bawden, D. (2008). Origins and concepts of digital literacy. *Digital literacies: Concepts, policies and practices*, *30*(2008), 17-32.

Bayrakdaroğlu, F., & Bayrakdaroğlu, A. (2017). A comparative analysis regarding the effects of financial literacy and digital literacy on internet entrepreneurship intention. Girişimcilik ve Kalkınma Dergisi.

Bennett, I. M., Chen, J., Soroui, J. S., & White, S. (2009). The contribution of health literacy to disparities in self-rated health status and preventive health behaviors in older adults. *The Annals of Family Medicine*, *7*(3), 204-211.

Bélanger, F., & Carter, L. (2008). Trust and risk in e-government adoption. *The journal of strategic information systems*, *17*(2), 165-176.

Brown, Sorrel. (2010, December). *Likert Scale Examples for Surveys*. Iowa State University Ext. https://www.extension.iastate.edu/documents/anr/likertscaleexamplesforsurveys.pdf

Cajita, M. I., Hodgson, N. A., Budhathoki, C., & Han, H. R. (2017). Intention to use mHealth in older adults with heart failure. *The Journal of cardiovascular nursing*, *32*(6), E1.

Cavdar Aksoy, N., et al. (2020). “Individuals’ intention to use sports wearables: the moderating role of technophobia.” International Journal of Sports Marketing and Sponsorship 21(2): 225-245.

Cetindamar, D., et al. (2021). “The role of employees in digital transformation: a preliminary study on how employees’ digital literacy impacts use of digital technologies.” IEEE Transactions on Engineering Management.

Champion, V. L. (1984). Instrument development for health belief model constructs. Advances in nursing science, 6(3), 73-85.

Champion, V. L. and C. S. Skinner (2008). “The health belief model.” Health behavior and health education: Theory, research, and practice 4: 45-65.

Chang, Y. T., Chao, C. M., Yu, C. W., & Lin, F. C. (2021). Extending the utility of UTAUT2 for hospital patients’ adoption of medical apps: moderating effects of e-health literacy. *Mobile Information Systems*, *2021*, 1-10.

Cho, D.-Y., Kwon, H. J., & Lee, H.-Y. (2007). Analysis of trust in internet and mobile commerce adoption. 2007 40th Annual Hawaii International Conference on System Sciences (HICSS’07).

Cho, J., Quinlan, M. M., Park, D., & Noh, G. Y. (2014). Determinants of adoption of smartphone health apps among college students. *American journal of health behavior*, *38*(6), 860-870.

Choudhury, A., & Shamszare, H. (2023). Investigating the Impact of User Trust on the Adoption and Use of ChatGPT: Survey Analysis. *Journal of Medical Internet Research*, *25*, e47184.

Chung, J. E., Park, N., Wang, H., Fulk, J., & McLaughlin, M. (2010). Age differences in perceptions of online community participation among non-users: An extension of the Technology Acceptance Model. Computers in Human Behavior, 26(6), 1674-1684.

Cimperman, M., et al. (2016). “Analyzing older users’ home telehealth services acceptance behavior—applying an Extended UTAUT model.” International journal of medical informatics 90: 22-31.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Mahwah, NJ: Lawrence Erlbaum.

Crawford, A., & Serhal, E. (2020). Digital health equity and COVID-19: the innovation curve cannot reinforce the social gradient of health. *Journal of medical Internet research*, *22*(6), e19361.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297-334.

Damberg, S. (2022). Predicting future use intention of fitness apps among fitness app users in the United Kingdom: the role of Health Consciousness. *International Journal of Sports Marketing and Sponsorship*, *23*(2), 369-384.

Dash, A. and A. K. Sahoo (2021). “Moderating effect of gender on adoption of digital health consultation: a patient perspective study.” International Journal of Pharmaceutical and Healthcare Marketing 15(4): 598-616.

Davis, F. D. (1989). “Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology.” MIS quarterly 13(3): 319-340.

Davis, F. D., et al. (1989). “User Acceptance of Computer Technology: A Comparison of Two Theoretical Models.” Management Science 35(8): 982-1003.

Deng, Z., Hong, Z., Ren, C., Zhang, W., & Xiang, F. (2018). What predicts patients' adoption intention toward mHealth services in China: empirical study. *JMIR mHealth and uHealth*, *6*(8), e9316.

Dhagarra, D., Goswami, M., & Kumar, G. (2020). Impact of trust and privacy concerns on technology acceptance in healthcare: an Indian perspective. *International journal of medical informatics*, *141*, 104164.

Dhiman, N., Arora, N., Dogra, N., & Gupta, A. (2020). Consumer adoption of smartphone fitness apps: an extended UTAUT2 perspective. *Journal of Indian Business Research*, *12*(3), 363-388.

Diño, M. J. S. and A. B. de Guzman (2015). "Using partial least squares (PLS) in predicting Behavioral Intention for telehealth use among Filipino elderly." Educational Gerontology 41(1): 53-68.

Doney, P. M., & Cannon, J. P. (1997). An examination of the nature of trust in buyer–seller relationships. Journal of marketing, 61(2), 35-51.

Dou, K., Yu, P., Deng, N., Liu, F., Guan, Y., Li, Z., ... & Duan, H. (2017). Patients' acceptance of smartphone health technology for chronic disease management: a theoretical model and empirical test. *JMIR mHealth and uHealth*, *5*(12), e177.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 21, 719-734.

Edo, O. C., et al. (2023). "Why do healthcare workers adopt digital health technologies – A cross-sectional study integrating the TAM and UTAUT model in a developing economy." International Journal of Information Management Data Insights 3(2): 100186.

Elhajjar, S., & Ouaida, F. (2019). An analysis of factors affecting mobile banking adoption. International Journal of Bank Marketing.

Erdfelder, E., Faul, F., & Buchner, A. (1996). GPOWER: A general power analysis program. *Behavior research methods, instruments, & computers*, *28*, 1-11

Escobar-Rodríguez, T., & Carvajal-Trujillo, E. (2013). Online drivers of consumer purchase of website airline tickets. *Journal of Air Transport Management*, *32*, 58-64.

Eshet, Y. (2012). Thinking in the digital era: A revised model for digital literacy. Issues in informing science and information technology, 9(2), 267-276.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior research methods*, *39*(2), 175-191.

Gao, Y., et al. (2015). “An empirical study of wearable technology acceptance in healthcare.” Industrial Management & Data Systems.

Garrity, T. F., et al. (1978). “Factors influencing self-assessment of health.” Social Science & Medicine. Part A: Medical Psychology & Medical Sociology 12: 77-81.

Garson, G. D. (2016). Partial least squares. Regression and structural equation models.

Gefen, D. (2000). E-commerce: the role of familiarity and trust. Omega, 28(6), 725-737.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS quarterly*, 51-90.

Gilster, P., & Glister, P. (1997). Digital literacy. Wiley Computer Pub. New York.

Gould, S. J. (1988). Consumer attitudes toward health and health care: A differential perspective. *Journal of Consumer Affairs*, *22*(1), 96-118.

Gould, S. J. (1990). Health consciousness and health behavior: the application of a new Health Consciousness scale. American Journal of Preventive Medicine, 6(4), 228-237.

Grissinger, M. (2019). Understanding human over-reliance on technology. *Pharmacy and Therapeutics*, *44*(6), 320.

Guo, X., Sun, Y., Wang, N., Peng, Z., & Yan, Z. (2013). The dark side of elderly acceptance of preventive mobile health services in China. *Electronic Markets*, *23*, 49-61.

Gusmano, M. K., Maschke, K. J., & Solomon, M. Z. (2019). Patient-centered care, yes; patients as consumers, no. *Health affairs*, *38*(3), 368-373.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European business review, 31(1), 2-24.

Hair Jr. J.F., et al. (2021). Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R, Classroom Companion: Business, https://doi.org/10.1007/978-3-030-80519-7_1

Hair, J. F., Hult, T., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Thousand Oaks, CA: Sage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science,43*(1), 115–135.

Holtz, B., & Krein, S. (2011). Understanding nurse perceptions of a newly implemented electronic medical record system. *Journal of Technology in Human Services*, *29*(4), 247-262.

Hooda, A., Gupta, P., Jeyaraj, A., Giannakis, M., & Dwivedi, Y. K. (2022). The effects of trust on Behavioral Intention and use behavior within e-government contexts. *International Journal of Information Management*, *67*, 102553.

Hoque, M. R. (2016). An empirical study of mHealth adoption in a developing country: the moderating effect of gender concern. BMC medical informatics and decision making, 16(1), 1-10.

Hoque, R. and G. Sorwar (2017). "Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model." International journal of medical informatics 101: 75-84.

Hu, P. J. H., Chau, P. Y., & Sheng, O. R. L. (2002). Adoption of telemedicine technology by health care organizations: An exploratory study. *Journal of organizational computing and electronic commerce*, *12*(3), 197-221.

Ifinedo, P. (2016). Applying uses and gratifications theory and Social Influence processes to understand students' pervasive adoption of social networking sites: Perspectives from the Americas. *International Journal of Information Management*, *36*(2), 192-206.

Jackson, C. M., Chow, S., & Leitch, R. A. (1997). Toward an understanding of the Behavioral Intention to use an information system. *Decision sciences*, *28*(2), 357-389.

Janz, N. K. and M. H. Becker (1984). "The Health Belief Model: A Decade Later." Health Education Quarterly 11(1): 1-47.

Jarvenpaa, S. L., Tractinsky, N., & Vitale, M. (2000). Consumer trust in an Internet store. Information technology and management, 1, 45-71.

Jermutus, E., Kneale, D., Thomas, J., & Michie, S. (2022). Influences on user trust in healthcare artificial intelligence: A systematic review. *Wellcome Open Research*, *7*.

Kabra, G., et al. (2017). "Understanding behavioural intention to use information technology: Insights from humanitarian practitioners." Telematics and Informatics 34(7): 1250-1261.

Kamran, A., Ahari, S. S., Biria, M., Malpour, A., & Heydari, H. (2014). Determinants of patient's adherence to hypertension medications: application of health belief model among rural patients. *Annals of medical and health sciences research*, *4*(6), 922-927.

Karnoe, A., & Kayser, L. (2015). How is eHealth Literacy measured and what do the measurements tell us? A systematic review. *Knowledge Management & E-Learning*, *7*(4), 576.

Kaskutas, L.A., & Greenfield, T. K. (1997). The role of Health Consciousness in predicting attention to health warning messages. American Journal of Health Promotion, 11(3), 186-193.

Kelman, H. C. (1958). Compliance, identification, and internalization three processes of attitude change. *Journal of conflict resolution*, *2*(1), 51-60.

Kemp, E., Trigg, J., Beatty, L., Christensen, C., Dhillon, H. M., Maeder, A., ... & Koczwara, B. (2021). Health literacy, digital health literacy and the implementation of digital health technologies in cancer care: the need for a strategic approach. *Health Promotion Journal of Australia*, *32*, 104-114.

Kesharwani, A., & Bisht, S. S. (2012). The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. International Journal of Bank Marketing.

Kissi, J., Dai, B., Dogbe, C. S., Banahene, J., & Ernest, O. (2020). Predictive factors of physicians' satisfaction with telemedicine services acceptance. *Health informatics journal*, *26*(3), 1866-1880.

Kontos, E., Blake, K. D., Chou, W. Y. S., & Prestin, A. (2014). Predictors of eHealth usage: insights on the digital divide from the Health Information National Trends Survey 2012. *Journal of medical Internet research*, *16*(7), e172.

Kuek, A., & Hakkennes, S. (2020). Healthcare staff digital literacy levels and their attitudes towards information systems. *Health informatics journal*, *26*(1), 592-612.

Lankton, N., et al. (2015). "Technology, Humanness, and Trust: Rethinking Trust in Technology." Journal of the Association for Information Systems 16(10): 880-918.

Layes, A., et al. (2012). "Whiners and deniers – What does self-rated health measure?" Social Science & Medicine 75(1): 1-9.

Leader, A. E., Capparella, L. M., Waldman, L. B., Cammy, R. B., Petok, A. R., Dean, R., ... & Dicker, A. P. (2021). Digital literacy at an urban cancer center: implications for technology use and vulnerable patients. *JCO Clinical Cancer Informatics*, *5*, 872-880.

Lee, S. W., Sung, H. J., & Jeon, H. M. (2019). Determinants of continuous intention on food delivery apps: extending UTAUT2 with information quality. *Sustainability*, *11*(11), 3141.

Leung, L., & Chen, C. (2019). E-health/m-health adoption and lifestyle improvements: Exploring the roles of technology readiness, the expectation-confirmation model, and health-related information activities. *Telecommunications Policy*, *43*(6), 563-575.

Lefkowitz, J. (1994). Sex-related differences in job attitudes and dispositional variables: Now you see them,…. Academy of Management Journal, 37(2), 323-349.

Li, H., Wu, J., Gao, Y., & Shi, Y. (2016). Examining individuals' adoption of healthcare wearable devices: An empirical study from privacy calculus perspective. *International journal of medical informatics*, *88*, 8-17.

Li, S., Cui, G., Kaminga, A. C., Cheng, S., & Xu, H. (2021). Associations between health literacy, ehealth literacy, and covid-19–related health behaviors among Chinese college students: Cross-sectional online study. *Journal of medical Internet research*, *23*(5), e25600.

Liao, C., Palvia, P., & Chen, J.-L. (2009). Information technology adoption behavior life cycle: Toward a Technology Continuance Theory (TCT). *International Journal of Information Management*, *29*(4), 309-320.

Lippert, S. K. and P. Michael Swiercz (2005). "Human resource information systems (HRIS) and technology trust." Journal of information science 31(5): 340-353.

Mac Callum, K., & Jeffrey, L. (2014). Factors impacting teachers' adoption of mobile learning. Journal of Information Technology Education, 13.

Maddox, G. L. (1962). "Some correlates of differences in self-assessment of health status among the elderly." Journal of Gerontology.

Magsamen-Conrad, K., Dillon, J. M., Verhoff, C. B., & Joa, C. Y. (2019). Toward a theory of HealthIT adoption across the lifespan: Findings from five years in the community. *Health Communication*.

Maillet, É., et al. (2015). "Modeling factors explaining the acceptance, Actual Use and satisfaction of nurses using an Electronic Patient Record in acute care settings: An extension of the UTAUT." International journal of medical informatics 84(1): 36-47.

Mcknight, D. H., et al. (2011). "Trust in a specific technology: An investigation of its components and measures." ACM Transactions on management information systems (TMIS) 2(2): 1-25.

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

Merriam-Webster. (n.d.). Trust. In *Merriam-Webster.com dictionary*. Retrieved November 8, 2023, from https://www.merriam-webster.com/dictionary/trust

Meskó, B., Drobni, Z., Bényei, É., Gergely, B., & Győrffy, Z. (2017). Digital health is a cultural transformation of traditional healthcare. *Mhealth*, *3*.

Mohammadyari, S., & Singh, H. (2015). Understanding the effect of e-learning on individual performance: The role of digital literacy. Computers & Education, 82, 11-25. https://doi.org/https://doi.org/10.1016/j.compedu.2014.10.025

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. Personnel psychology, 53(2), 375-403.

Mustofa, R. H., Pramudita, D. A., Atmono, D., Priyankara, R., Asmawan, M. C., Rahmattullah, M., ... & Pamungkas, L. N. S. (2022). Exploring educational students acceptance of using movies as economics learning media: PLS-SEM analysis. International Review of Economics Education, 39, 100236

Ng, W. (2012). "Can we teach digital natives digital literacy?" Computers & Education 59(3): 1065-1078.

Nikou, S., & Aavakare, M. (2021). An assessment of the interplay between literacy and digital technology in higher education. Education and Information Technologies, 26(4), 3893-3915.

Nikou, S., De Reuver, M., & Kanafi, M. M. (2022). Workplace literacy skills—how information and digital literacy affect adoption of digital technology. Journal of Documentation, 78(7), 371-391.

Nisha, N., Iqbal, M., & Rifat, A. (2019). The changing paradigm of health and mobile phones: An innovation in the health care system. *Journal of Global Information Management (JGIM)*, *27*(1), 19-46.

Norman, C. (2011). eHealth Literacy 2.0: problems and opportunities with an evolving concept. *Journal of medical Internet research*, *13*(4), e2035.

Norman, C. D., & Skinner, H. A. (2006a). eHEALS: the eHealth Literacy scale. Journal of medical Internet research, 8(4), e507.

Norman, C. D., & Skinner, H. A. (2006b). eHealth Literacy: essential skills for consumer health in a networked world. *Journal of medical Internet research*, *8*(2), e506.

Nunes, A., et al. (2019). “Acceptance of mobile health applications: examining key determinants and moderators.” Frontiers in psychology: 2791.

Oldeweme, A., Märtins, J., Westmattelmann, D., & Schewe, G. (2021). The role of transparency, trust, and Social Influence on uncertainty reduction in times of pandemics: empirical study on the adoption of COVID-19 tracing apps. *Journal of medical Internet research*, *23*(2), e25893.

Painter, J. E., Borba, C. P., Hynes, M., Mays, D., & Glanz, K. (2008). The use of theory in health behavior research from 2000 to 2005: a systematic review. *Annals of behavioral medicine*, *35*(3), 358-362.

Pavlou, P. A. (2003). “Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model.” International journal of electronic commerce 7(3): 101-134.

Petter, S. and E. R. McLean (2009). “A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level.” Information & Management 46(3): 159-166.

Porter, C. E., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics. Journal of business research, 59(9), 999-100

Pynoo, B., Devolder, P., Duyck, W., van Braak, J., Sijnave, B., & Duyck, P. (2012). Do hospital physicians’ attitudes change during PACS implementation? A cross-sectional acceptance study. *International journal of medical informatics*, *81*(2), 88-97.

Quinn, S., Bond, R., & Nugent, C. (2017). Quantifying health literacy and eHealth Literacy using existing instruments and browser-based software for tracking online health information seeking behavior. *Computers in Human Behavior*, *69*, 256-267.

Radomir, L., & Moisescu, O. I. (2019). Discriminant validity of the customer-based corporate reputation scale: Some causes for concern. *Journal of Product & Brand Management, 29(4),* 457–469.

Rahi, S., Khan, M. M., & Alghizzawi, M. (2020). Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of Internet banking user continuance intention. *International Journal of Quality & Reliability Management*.

Rajak, M., & Shaw, K. (2021). An extension of technology acceptance model for mHealth user adoption. *Technology in Society*, *67*, 101800.

Rosenstock, I. M. (1974). “Historical origins of the health belief model.” Health education monographs 2(4): 328-335.

Sarmah, R., Dhiman, N., & Kanojia, H. (2021). Understanding intentions and Actual Use of mobile wallets by millennial: an extended TAM model perspective. *Journal of Indian Business Research*, *13*(3), 361-381.

Shmueli, G., & Koppius, O. R. (2011). Predictive Analytics in Information Systems Research. *MIS Quarterly*, *35*(3), 553–572. https://doi.org/10.2307/23042796

Seethamraju, R., et al. (2018). “Intention to Use a Mobile-Based Information Technology Solution for Tuberculosis Treatment Monitoring – Applying a UTAUT Model.” Information Systems Frontiers 20(1): 163-181.

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Hu, Y. (2019). Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change. *Journal of Big Data*, *6*(1), 1-20.

Shaw, N., & Sergueeva, K. (2019). The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International journal of information management*, *45*, 44-55.

Shiferaw, K. B., Mengiste, S. A., Gullslett, M. K., Zeleke, A. A., Tilahun, B., Tebeje, T., ... & Mehari, E. A. (2021). Healthcare providers’ acceptance of telemedicine and preference of modalities during COVID-19 pandemics in a low-resource setting: An extended UTAUT model. *Plos one*, *16*(4), e0250220.

Smith, B., & Magnani, J. W. (2019). New technologies, new disparities: the intersection of electronic health and digital health literacy. *International journal of cardiology*, *292*, 280-282.

Sulat, J. S., Prabandari, Y. S., Sanusi, R., Hapsari, E. D., & Santoso, B. (2018). The validity of health belief model variables in predicting behavioral change: A scoping review. *Health Education*, *118*(6), 499-512.

Sun, Y., et al. (2013). "Understanding the acceptance of mobile health services: a comparison and integration of alternative models." Journal of electronic commerce research 14(2): 183.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International journal of medical education, 2, 53.

Tavares, J., & Oliveira, T. (2016). Electronic health record patient portal adoption by health care consumers: an acceptance model and survey. *Journal of medical Internet research*, *18*(3), e5069.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. MIS quarterly, 125-143.

Tung, F. C., Chang, S. C., & Chou, C. M. (2008). An extension of trust and TAM model with IDT in the adoption of the electronic logistics information system in HIS in the medical industry. *International journal of medical informatics*, *77*(5), 324-335.

Urbach, N. and B. Müller (2012). "The updated DeLone and McLean model of information systems success." Information Systems Theory: Explaining and Predicting Our Digital Society, Vol. 1: 1-18.

Van Der Vaart, R., & Drossaert, C. (2017). Development of the digital health literacy instrument: measuring a broad spectrum of health 1.0 and health 2.0 skills. *Journal of medical Internet research*, *19*(1), e27.

Van der Waal, N. E., et al. (2022). “Predictors of contact tracing app adoption: Integrating the UTAUT, HBM and contextual factors.” Technology in Society 71: 102101.

Van Velsen, L., Wildevuur, S., Flierman, I., Van Schooten, B., Tabak, M., & Hermens, H. (2015). Trust in telemedicine portals for rehabilitation care: an exploratory focus group study with patients and healthcare professionals. *BMC medical informatics and decision making*, *16*(1), 1-12.

Vassallo, M., Saba, A., Arvola, A., Dean, M., Messina, F., Winkelmann, M., ... & Shepherd, R. (2009). Willingness to use functional breads. Applying the Health Belief Model across four European countries. *Appetite*, *52*(2), 452-460.

Venkatesh, V. (2006). Where to go from here? Thoughts on future directions for research on individual-level technology adoption with a focus on decision making. *Decision Sciences*, *37*(4), 497-518.

Venkatesh, V. and F. D. Davis (2000). “A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies.” Management Science 46(2): 186-204.

Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, Social Influence, and their role in technology acceptance and usage behavior. *MIS quarterly,* 115-139.

Venkatesh, et al. (2003). “User Acceptance of Information Technology: Toward a Unified View.” MIS quarterly 27(3): 425-478.

Venkatesh, V., et al. (2008). “Predicting Different Conceptualizations of System Use: The Competing Roles of Behavioral Intention, Facilitating Conditions, and Behavioral Expectation.” MIS quarterly 32(3): 483-502.

Venkatesh, V., et al. (2012). “Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology.” MIS quarterly 36(1): 157-178.

Walrave, M., Waeterloos, C., & Ponnet, K. (2020). Adoption of a contact tracing app for containing COVID-19: A health belief model approach. JMIR public health and surveillance, 6(3), e20572.

Wang, M., et al. (2021). “To Wear or Not to Wear: Analysis of Individuals’ Tendency to Wear Masks during the COVID-19 Pandemic in China.” International journal of environmental research and public health 18(21): 11298.

White, S., Chen, J., & Atchison, R. (2008). Relationship of preventive health practices and health literacy: a national study. *American journal of health behavior*, *32*(3), 227-242.

Wills, M. J., et al. (2008). “Examining healthcare professionals’ acceptance of electronic medical records using UTAUT.”

Wong, M. C., Wong, E. L., Huang, J., Cheung, A. W., Law, K., Chong, M. K., ... & Chan, P. K. (2021). Acceptance of the COVID-19 vaccine based on the health belief model: A population-based survey in Hong Kong. *Vaccine*, *39*(7), 1148-1156.

Wu, Y.-L., et al. (2007). Using UTAUT to explore the behavior of 3G mobile communication users. 2007 IEEE international conference on industrial engineering and engineering management, IEEE.

Yao, R., Zhang, W., Evans, R., Cao, G., Rui, T., & Shen, L. (2022). Inequities in health care services caused by the adoption of digital health technologies: scoping review. *Journal of medical Internet research*, *24*(3), e34144.

Yu, T.-K., Lin, M.-L., & Liao, Y.-K. (2017). Understanding factors influencing information communication technology adoption behavior: The moderators of information literacy and digital skills. Computers in Human Behavior, 71, 196-208.

Yu, C. W., Chao, C. M., Chang, C. F., Chen, R. J., Chen, P. C., & Liu, Y. X. (2021). Exploring Behavioral Intention to use a mobile health education website: An extension of the utaut 2 model. *Sage Open*, *11*(4), 21582440211055721.

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep using my health apps: Discover users' perception of health and fitness apps with the UTAUT2 model. *Telemedicine and e-Health*, *21*(9), 735-741.

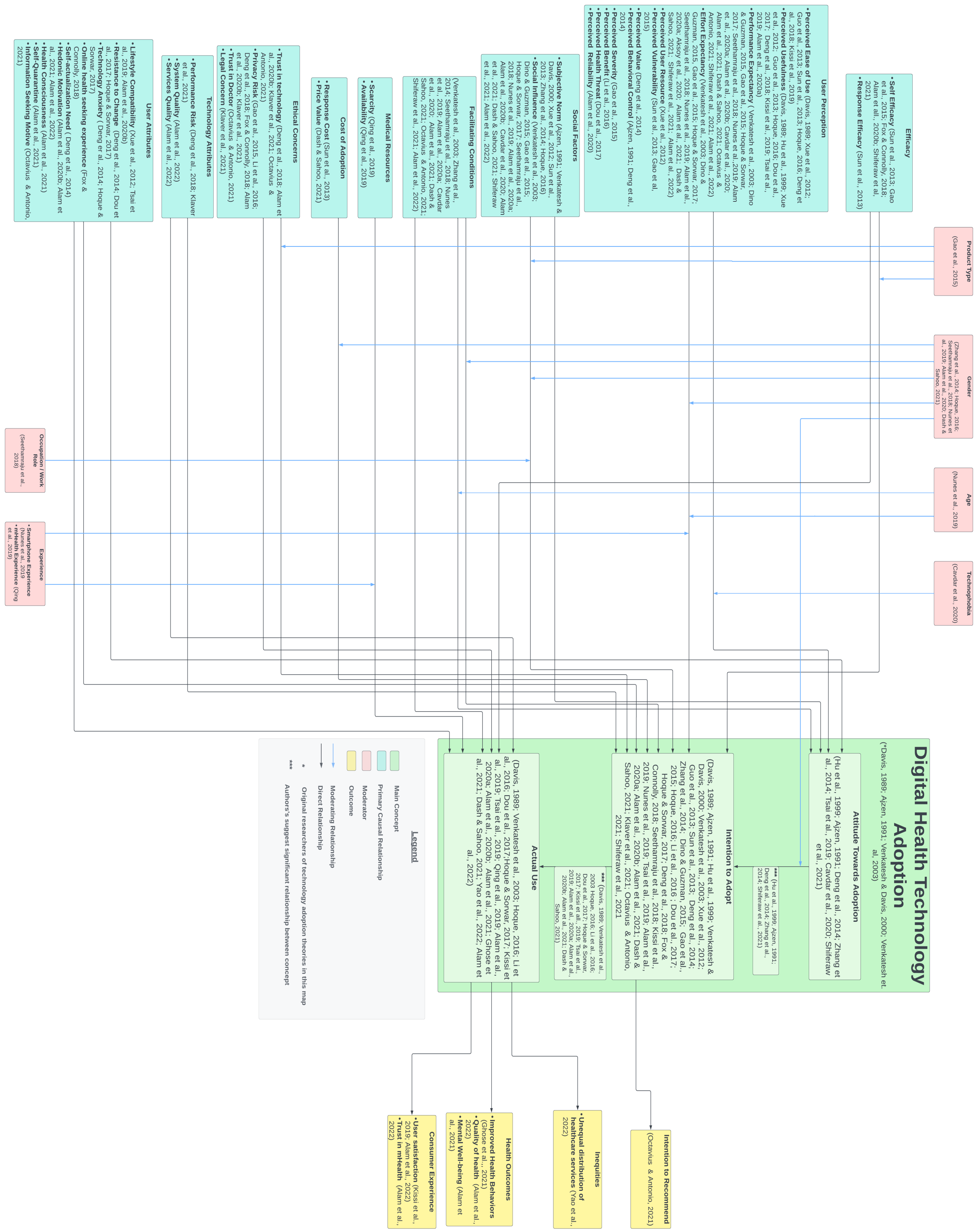
Yuen, K. F., Ma, F., Wang, X., & Lee, G. (2021). The role of trust in influencing consumers' adoption of automated vehicles: an application of the health belief model. *International journal of sustainable transportation*, *15*(11), 837-849.

Zare, M., Ghodsbin, F., Jahanbin, I., Ariafar, A., Keshavarzi, S., & Izadi, T. (2016). The effect of health belief model-based education on knowledge and prostate cancer screening behaviors: a randomized controlled trial. *International journal of community based nursing and midwifery*, *4*(1), 57.

Zhang, X., Guo, X., Lai, K. H., Guo, F., & Li, C. (2014). Understanding gender differences in m-health adoption: a modified theory of reasoned action model. Telemedicine and eHealth, 20(1), 39-46.

Zimmerman, R. S., & Vernberg, D. (1994). Models of preventive health behavior: Comparison, critique, and meta-analysis. *Advances in medical sociology*, *4*, 45-67.

APPENDIX I: CONCEPTUAL MAP – DIGITAL HEALTH TECHNOLOGY ADOPTION



APPENDIX II: MEASURES AND SCALE ITEMS

Measure	Items for this study	Items from Original Scale	Reference
Behavioral Intention	• BI1. I intend to use digital health technology in the next 6 months. • BI2. I predict I would use digital health technology in the next 6 months. • BI3. I plan to use digital health technology in the next 6 months.	• BI1. I intend to use the system in the next <n> months. • BI2. I predict I would use the system in the next <n> months. • BI3. I plan to use the system in the next <n> months.	Davis 1989, Venkatesh 2003
Perceived Health Benefit	• PB1. Using digital health technologies prevent future health problems for me. • PB2. I have a lot to gain by using digital health technology to manage my health conditions and track health goals. • PB3. Digital health technologies can help me detect health concerns. • PB4. If I use digital health technologies, I may detect an illness before it is discovered by regular health exams. • PB5. I would not be so anxious about diseases and illnesses if I use digital health technologies regularly.	• PB1. Doing self-breast exams prevents future problems for me. • PB2. I have a lot to gain by doing self-breast exams. • PB3. Self-breast exams can help me find lumps in my breast. • PB4. If I do monthly breast exams, I may find a lump before it is discovered by regular health exams. • PB5. I would not be so anxious about breast cancer if I did monthly exams.	Champion, 1984

APPENDIX II CONTINUED

Measure	Items for this study	Items from Original Scale	Reference
Social Influence	• SI1. People who influence my behavior think I should use digital health technologies. • SI2. People who are important to me think that I should use digital health technologies. • SI3. People whose opinions that I value prefer that I use digital health technologies.	• SI1. People who influence my behavior think that I should use mobile internet. • SI2. People who are important to me think I should use mobile internet. • SI3. People whose opinions that I value prefer that I use mobile internet.	Thompson, 1991; Ajzen, 1991; Venkatesh, 2003
Trust	• TR1. I trust digital health technologies. • TR2. I am quite certain what to expect from using digital health technologies. • TR3. I believe that digital health technologies are trustworthy. • TR4. I believe the medical information that digital health technologies provide is reliable. • TR5. I feel that I would trust digital health technology vendors' promises and commitment to satisfy my medical information needs. • TR6. I would trust the behavior of digital health technology vendors to meet my expectations.	• TR1. I trust Amazon.com. • TR2. I am quite certain what to expect from Amazon.com • TR3. I believe that Amazon.com is trustworthy. • TR4: We believe the information that this vendor provides us. • TR5. This store wants to be known as one who keeps promises and commitments. • TR6. This store's behavior meets my expectations.	Gefen, 2002; Doney & Cannon, 1997; Jarvenpaa et al., 2000

APPENDIX II CONTINUED

Measure	Items for this study	Items from Original Scale	Reference
eHealth Literacy	• EHL1. I know how to find helpful health resources on the internet. • EHL2. I know how to use the internet to answer my health questions. • EHL3. I know what health resources are available on the internet • EHL4. I know where to find helpful health resources on the internet. • EHL5. I know how to use the health information I find on the internet to help me. • EHL6. I have the skills I need to evaluate the health resources I find on the internet.	• EHL1. I know how to find helpful health resources on the internet. • EHL2. I know how to use the internet to answer my health questions. • EHL3. I know what health resources are available on the internet • EHL4. I know where to find helpful health resources on the internet. • EHL5. I know how to use the health information I find on the internet to help me. • EHL6. I have the skills I need to evaluate the health resources I find on the internet.	Norman & Skinner, 2006
Actual Use	• Please choose your usage frequency for each of the following: a) telehealth or telemedicine b) wearables c) mHealth apps d) medical information websites e) patient portal (frequency range from never to always)	• Please choose your usage frequency for each of the following: a) SMS b) MMS c) ringtone and logo download d) java games e) browse websites (frequency range from never to always)	Venkatesh, 2012

APPENDIX II CONTINUED

Measure	Items for this study	Items from Original Scale	Reference
Health Consciousness	• HC1. I reflect about my health a lot. • HC2. I'm very self-conscious about my health. • HC3. I'm generally attentive to my inner feeling about my health. • HC4. I'm constantly examining my health. • HC5. I'm alert to changes in my health. • HC6. I'm usually aware of my health. • HC7. I'm aware of the state of my health as I go through the day. • HC8. I notice how I feel physically as I go through the day. • HC9. I'm very involved with my health.	• HC1. I reflect about my health a lot. • HC2. I'm very self-conscious about my health. • HC3. I'm generally attentive to my inner feeling about my health. • HC4. I'm constantly examining my health. • HC5. I'm alert to changes in my health. • HC6. I'm usually aware of my health. • HC7. I'm aware of the state of my health as I go through the day. • HC8. I notice how I feel physically as I go through the day. • HC9. I'm very involved with my health.	Gould, 1990

APPENDIX III: CONSENT FORM

You are invited to participate in a research study. Participation in this research study is voluntary. The information provided is to give you key information to help you decide whether or not to participate.

The purpose of this study is to examine factors that influence the use of digital health technology and if the use of digital health technology motivates one to be more Health Consciousness. You are asked to complete a series of questions about various factors that may contribute to your decision to use or not use digital health technologies.

- All responses are completely anonymous.
- You must be age 21 or older to participate in this study.
- You must have attended a doctor's appointment for yourself within the last 18 months.
- You must reside in the United States as a US Citizen.
- It will take you approximately 15 to 20 minutes to complete the survey.
- We do not believe that you will experience any risk from participating in this study.
- No benefits are extended in exchange for your participation in this study, beyond a $5 incentive payment to participate from Qualtrics™.

Your privacy will be protected, and all survey responses are anonymous. Your responses will be treated as confidential, and this survey contains no identifiers that can point to your identity. We reserve the right to use the survey data for future research studies and we might share the non-identifiable survey data with other researchers for future research studies without additional consent from you.
Your participation in this study is completely voluntary. You may start participating and change your mind and stop participation at any time. Incentive payment is only provided upon successful completion of the survey.
If you have questions concerning the study, contact the principal investigator, Nicole Godlock, at nelliot6@uncc.edu or her faculty advisor, Dr. Reginald Silver at rsilver5@charlotte.edu

If you have further questions or concerns about your rights as a participant in this study, contact the Office of Research Compliance at (704) 687-1871 or uncc-irb@uncc.edu.

You may print a copy of this form. If you are 21 years of age or older, meet the participation criteria, have read, and understand the information provided, and freely consent to participate in the study, you may proceed to the survey.

To continue please select "I Agree".

APPENDIX IV: SURVEY

Digital Health Technology Usage

Consent Agreement   To continue, please select "I Agree"

- ○ I Agree (1)
- ○ I Disagree (2)

End of Block: Consent

Start of Block: Background Information

Age Please provide some background information about yourself. Please state your current age in years.

____

Gender Gender (Please select 1 of the following)

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary (3)
- ○ Gender fluid (4)

Race Race / ethnicity (Please select one of the following)

- ○ White (1)
- ○ Black or African American (2)
- ○ American Indian or Alaska Native (3)
- ○ Latino (4)
- ○ Asian (5)
- ○ Native Hawaiian or Pacific Islander (6)
- ○ Other (7)

Education What is your level of education? (Please select one of the following)

- ○ Did not complete high school (1)
- ○ High school graduate / Diploma (2)
- ○ Associate Degree (3)
- ○ Bachelor Degree (4)
- ○ Master's Degree (5)
- ○ Doctorate Degree (6)

End of Block: Background Information

Start of Block: Behavioral Intention

BehavioralIntention Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

Please select your level of agreement to each of the following statements (1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I plan to use digital health technology in the next 6 months. (1)	○	○	○	○	○	○	○
I intend to use digital health technology in the next 6 months. (2)	○	○	○	○	○	○	○
I predict I will use digital health technology in the next 6 months. (3)	○	○	○	○	○	○	○

End of Block: Behavioral Intention

Start of Block: Perceived Benefit

Perceived Benefit Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

Please select your level of agreement to each of the following statements (1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
Using digital health technologies will prevent future health problems for me. (1)	○	○	○	○	○	○	○
I have a lot to gain by using digital health technology to manage my health conditions and track health goals. (2)	○	○	○	○	○	○	○
Digital health technologies can help me detect health concerns. (3)	○	○	○	○	○	○	○
If I use digital health technologies, I may detect an illness before it is discovered by regular health exams. (4)	○	○	○	○	○	○	○

I would be less anxious about diseases and illnesses if I use digital health technologies regularly. (5)	○	○	○	○	○	○	○

End of Block: Perceived Benefit

Start of Block: Social Influence

Social Influence Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

Please select your level of agreement to each of the following statements (1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
People who influence my behavior think I should use digital health technologies. (1)	○	○	○	○	○	○	○
People who are important to me think I should use digital health technologies. (2)	○	○	○	○	○	○	○
People whose opinion I value think I should use digital health technologies. (3)	○	○	○	○	○	○	○
Select “Agree” to confirm you are accurately completing this survey. (4)	○	○	○	○	○	○	○

End of Block: Social Influence

Start of Block: Trust

Trust Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

Please select your level of agreement to each of the following statements (1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I trust digital health technologies. (1)	○	○	○	○	○	○	○
I am quite certain what to expect from using digital health technologies. (2)	○	○	○	○	○	○	○
I believe that digital health technologies are trustworthy. (3)	○	○	○	○	○	○	○

Trust2 Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

Please select your level of agreement to each of the following statements (1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I believe the medical information that digital health technologies provide is reliable. (1)	○	○	○	○	○	○	○
I feel that I would trust digital health technology vendors' promises and commitment to satisfy my medical information needs. (2)	○	○	○	○	○	○	○
I trust the behavior of digital health technology vendors to meet my expectations. (3)	○	○	○	○	○	○	○

End of Block: Trust

Start of Block: eHealth Literacy

eHealth Literacy Please select your level of agreement to each of the following statements about your skills and familiarity with using the internet.

(1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I know how to find helpful health resources on the internet. (1)	○	○	○	○	○	○	○
I know how to use the internet to answer my health questions. (2)	○	○	○	○	○	○	○
I know what health resources are available on the internet. (3)	○	○	○	○	○	○	○

eHealth Literacy2 Please select your level of agreement to each of the following statements about your skills and familiarity with using the internet.   (1 = Strongly disagree; 7 = Strongly agree)

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I know where to find helpful health resources on the internet. (1)	○	○	○	○	○	○	○
I know how to use the health information I find on the internet to help me. (2)	○	○	○	○	○	○	○
I have the skills I need to evaluate the health resources I find on the internet. (3)	○	○	○	○	○	○	○
Select “Disagree” to confirm you are paying attention while completing this survey. (4)	○	○	○	○	○	○	○

End of Block: eHealth Literacy

Start of Block: Actual Use

Actual Use Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

Please select your usage frequency for each of the following digital health technologies. (1 = Never; 7 = Always)

	Never (1) (1)	Very Rarely (2) (2)	Rarely (3) (3)	Sometimes (4) (4)	Often (5) (5)	Very Often (6) (6)	Always (7) (7)
Telehealth or Telemedicine (1)	○	○	○	○	○	○	○
Wearables (2)	○	○	○	○	○	○	○
mHealth Apps (3)	○	○	○	○	○	○	○
Medical Information Websites (4)	○	○	○	○	○	○	○
Patient Portals (5)	○	○	○	○	○	○	○

End of Block: Actual Use

Start of Block: Health Consciousness

Experience Digital health technologies include (Telehealth, Telemedicine, Wearables (Fitbit, Apple Watch, etc.), Patient Portals, mHealth apps).

	Please select one response to each of the following statements	
	Yes (1)	No (2)

I have previously used digital health technologies. (1)	○	○
I currently use digital health technologies. (2)	○	○

Consciousness Please select your level of agreement to each of the following statements about how you feel after using digital health technologies. (1 = Strongly disagree; 7 = Strongly agree)

After using digital health technologies:

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I reflect about my health a lot. (1)	○	○	○	○	○	○	○
I'm very self-conscious about my health. (2)	○	○	○	○	○	○	○
I'm generally attentive to my inner feelings about my health. (3)	○	○	○	○	○	○	○
I'm constantly examining my health. (4)	○	○	○	○	○	○	○
I'm alert to changes in my health. (5)	○	○	○	○	○	○	○

Consciousness2 Please select your level of agreement to each of the following statements about how you feel after using digital health technologies. (1 = Strongly disagree; 7 = Strongly agree)

After using digital health technologies:

	Strongly disagree (1) (1)	Disagree (2) (2)	Somewhat disagree (3) (3)	Neither agree nor disagree (4) (4)	Somewhat agree (5) (5)	Agree (6) (6)	Strongly agree (7) (7)
I'm usually aware of my health. (1)	○	○	○	○	○	○	○
I'm aware of the state of my health as I go through the day. (2)	○	○	○	○	○	○	○
I notice how I feel physically as I go through the day. (3)	○	○	○	○	○	○	○
I'm very involved with my health. (4)	○	○	○	○	○	○	○
Select "Agree" to confirm you have accurately completed this	○	○	○	○	○	○	○

survey.
(5)

End of Block: Health Consciousness

APPENDIX V: INITIAL DESCRIPTIVES

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	N=
AU1	3.522	4	1	7	1.56	-0.787	-0.041	293
AU2	3.867	4	1	7	2.331	-1.547	0.007	293
AU3	2.959	3	1	7	1.843	-0.892	0.507	293
AU4	4.468	4	1	7	1.361	-0.014	-0.311	293
AU5	4.539	5	1	7	1.529	-0.314	-0.276	293
Age	38.505	34	21	94	14.139	0.341	0.938	293
Amer. Indian	0.003	0	0	1	0.058	293	17.117	293
Asian	0.078	0	0	1	0.269	7.98	3.151	293
Black	0.082	0	0	1	0.274	7.444	3.065	293
Latino	0.096	0	0	1	0.294	5.687	2.766	293
Other	0.031	0	0	1	0.173	28.085	5.467	293
White	0.71	1	0	1	0.454	-1.143	-0.93	293
Associate Degree	0.157	0	0	1	0.364	1.603	1.895	293
Bachelor Degree	0.365	0	0	1	0.481	-1.695	0.563	293
Did not complete high school	0.007	0	0	1	0.082	143.972	12.041	293
Doctorate Degree	0.031	0	0	1	0.173	28.085	5.467	293
High school graduate Diploma	0.242	0	0	1	0.428	-0.542	1.209	293
Master's Degree	0.198	0	0	1	0.398	0.324	1.524	293
Female	0.532	1	0	1	0.499	-1.997	-0.131	293
Male	0.433	0	0	1	0.496	-1.94	0.27	293
Non-binary	0.034	0	0	1	0.182	24.777	5.158	293

APPENDIX V CONTINUED

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	N=
BI1	5.614	6	1	7	1.705	1.036	-1.371	293
BI2	5.601	6	1	7	1.723	1.032	-1.37	293
BI3	5.713	6	1	7	1.632	1.367	-1.446	293
EHL1	5.918	6	2	7	0.938	1.06	-0.857	293
EHL2	5.87	6	2	7	1.007	0.699	-0.826	293
EHL3	5.761	6	2	7	1.073	0.748	-0.929	293
EHL4	5.85	6	2	7	1.004	1.359	-0.996	293
EHL5	5.72	6	2	7	1.05	0.988	-0.914	293
EHL6	5.724	6	2	7	1.109	0.992	-0.974	293
HC1	4.911	5	2	7	1.365	-0.373	-0.511	293
HC2	4.887	5	1	7	1.479	-0.218	-0.6	293
HC3	5.191	5	1	7	1.236	0.52	-0.761	293
HC4	4.73	5	1	7	1.478	-0.343	-0.523	293
HC5	5.423	6	2	7	1.123	0.98	-0.89	293
HC6	5.481	6	2	7	1.004	1.16	-0.895	293
HC7	5.334	6	1	7	1.182	0.673	-0.835	293
HC8	5.567	6	2	7	1.157	0.859	-0.974	293
HC9	5.123	5	2	7	1.36	-0.264	-0.585	293
PB1	4.816	5	1	7	1.217	0.206	-0.499	293
PB2	5.259	5	1	7	1.256	0.991	-0.957	293
PB3	5.119	5	1	7	1.227	0.551	-0.731	293
PB4	4.573	5	1	7	1.407	-0.408	-0.336	293
PB5	4.331	4	1	7	1.599	-0.843	-0.033	293
SI1	3.706	4	1	7	1.513	-0.624	-0.093	293
SI2	3.792	4	1	7	1.57	-0.609	-0.093	293
SI3	3.959	4	1	7	1.545	-0.533	-0.205	293
TR1	5.195	5	1	7	1.025	1.6	-0.837	293
TR2	5.072	5	1	7	1.222	0.073	-0.6	293
TR3	5.13	5	1	7	1.088	0.652	-0.531	293

APPENDIX V CONTINUED

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	N=
TR4	5.113	5	1	7	0.99	0.749	-0.546	293
TR5	4.693	5	1	7	1.264	0.094	-0.536	293
TR6	4.816	5	1	7	1.212	0.474	-0.568	293

APPENDIX VI: INITIAL VARIANCE INFLATION FACTOR

	VIF
AU1	1.242
AU2	1.173
AU3	1.432
AU4	1.384
AU5	1.561
BI1	20.317
BI2	21.58
BI3	8.359
EHL1	4.622
EHL2	3.441
EHL3	3.168
EHL4	4.082
EHL5	2.995
EHL6	2.666
HC1	2.906
HC2	2.946
HC3	3.078
HC4	2.962
HC5	3.295
HC6	3.491
HC7	3.242
HC8	2.354
HC9	2.616
PB1	1.953
PB2	1.936
PB3	2.745
PB4	2.417
PB5	2.07
SI1	4.651
SI2	8.439
SI3	5.987

APPENDIX VI CONTINUED

	VIF
TR1	2.926
TR2	1.702
TR3	3.702
TR4	2.444
TR5	3.113
TR6	3.3

APPENDIX VII: BIVARIATE CORRELATIONS

	1	2	3	4	5	6	7	8	9	10	11
1. Actual Use of Digital Health Technology	1.000										
2. Age	**0.156****	1.000									
3. Behavioral Intention to Use	**0.375****	0.015	1.000								
4. Education	0.090	0.045	0.039	1.000							
5. Gender	**0.152****	-0.082	0.075	0.015	1.000						
6. Health Consciousness	**0.379****	-0.037	**0.373****	0.039	**0.134***	1.000					
7. Perceived Health Benefits	**0.378****	-0.039	**0.415****	-0.036	0.043	**0.527****	1.000				
8. Race	0.019	**-0.135***	-0.066	-0.103	0.014	**0.213****	0.112	1.000			
9. Social Influence	**0.315****	0.069	**0.414****	-0.020	0.042	**0.379****	**0.516****	0.045	1.000		
10. Trust in Technology	**0.354****	0.059	**0.395****	-0.027	0.003	**0.441****	**0.639****	0.065	**0.440****	1.000	
11. eHealth Literacy	**0.227****	0.105	**0.237****	0.019	0.069	**0.333****	**0.292****	0.015	**0.267****	**0.349****	1.000

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

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