An Exploratory Examination of UTAUT Factors Associated with Mobile Health Services Adoption Among Purposively Selected Healthcare Provider Decision-Makers in the United States

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Abstract

This study examined the factors associated with healthcare provider decision-makers' intentions to adopt Mobile Health Services in the United States. Although mobile health technologies can support access, communication, and patient engagement, adoption across healthcare organizations remains uneven. This situation reflects a limited understanding of the factors associated with decisions made by individuals responsible for evaluating and approving new technologies. The purpose of the study was to determine the extent to which constructs from the Unified Theory of Acceptance and Use of Technology are associated with the adoption of mobile health services. The researcher sought to provide context-specific insights into how these constructs manifest in organizational environments and how these relationships may inform theoretical understanding of technology adoption in healthcare settings. A non-experimental quantitative correlational design was used. Participants were healthcare provider decision-makers working in information technology roles across the United States. A purposive sampling approach was applied to recruit individuals who met predefined criteria. Data were collected through a self-administered online questionnaire, and descriptive statistics, correlation analysis, and hierarchical multiple regression were used to examine associations among variables. The results indicated that Self-concept showed the strongest association with behavioral intention, followed by social influence, effort expectancy, and performance expectancy. Facilitating conditions and behavioral intention were both associated with mobile health services adoption. Future researchers may use random sampling to expand generalizability and may incorporate longitudinal or qualitative approaches to deepen understanding of decision-making processes.

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Chapter 1: Introduction

The rapid evolution of healthcare technology has ushered in a new era of medical practice characterized by integrating Mobile Health Services (MHS) (Istepanian, 2022). As healthcare providers increasingly seek innovative solutions to enhance patient care and operational efficiency, adopting MHS presents a pivotal opportunity for transformation within the United States (US) healthcare system (Williams & Radnor, 2022). This phenomenon reflects the broader movement towards digitized healthcare, which aims to improve accessibility, streamline communication, and facilitate real-time health monitoring (Istepanian, 2022). Consequently, understanding the factors that are associated with healthcare provider decision-makers' intentions to adopt these technologies is essential for the successful implementation of MHS (Rodić et al., 2024).

The larger context of this study encompasses a healthcare landscape continuously challenged by escalating costs, increasing patient demands, and the urgent need for improved health outcomes (Niaz & Nwagwu, 2023). Integrating MHS technologies is a potential remedy to these challenges, enabling healthcare providers to deliver services more effectively and efficiently (Istepanian, 2022). However, despite the promising nature of MHS, adoption rates among United States healthcare provider decision-makers remain inconsistent, highlighting a gap in understanding the factors associated with influencing these intentions (Niaz & Nwagwu, 2023). This inconsistency raises questions regarding the interplay between technological innovation and decision-makers' acceptance in healthcare settings (Niaz & Nwagwu, 2023). As such, the findings of this study may enhance the scholarly conversation regarding healthcare provider decision-makers' adoption intention of MHS and contribute to future research in various contexts.

The relevance of this research is underscored by the growing body of literature that examines MHS technologies within various health contexts (Istepanian, 2022; Niaz & Nwagwu, 2023). Previous studies have highlighted the potential of MHS to enhance patient engagement, reduce hospital readmissions, and promote preventive care (Istepanian, 2022; Niaz & Nwagwu, 2023; Rodić et al., 2024). However, the focus has often been on patient perspectives, leaving a significant void in understanding decision-makers in healthcare adoption intentions (Niaz & Nwagwu, 2023). The empirical examination of this topic is warranted to bridge this gap in literature (Niaz & Nwagwu, 2023). As healthcare systems increasingly invest in advanced technologies, understanding the facilitators and barriers to adopting MHS becomes paramount for academic inquiry (Istepanian, 2022).

A review of existing literature reveals a plethora of theoretical frameworks employed to analyze technology adoption, emphasizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as a preeminent model (Abbad, 2021; Alqahtani & Erfani, 2021; Venkatesh et al., 2003). UTAUT posits that key constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Self-Concept (SC) significantly influence users' Behavioral Intention (BI), Facilitating Conditions (FC), and Behavioral Intention (BI) significantly influence users' adoption of technology (Venkatesh et al., 2003 and Azam et al., 2023). Previous research utilizing UTAUT has successfully elucidated the factors associated with technology acceptance across various domains, including education, e-commerce, and healthcare (Abbad, 2021; Alqahtani & Erfani, 2021; Venkatesh et al., 2003). The robustness and adaptability of UTAUT make it particularly relevant for this study, as it allows for an examination of the multifaceted influences on healthcare providers' decision-makers'

intentions to adopt MHS within the unique context of the U.S. healthcare system model (Abbad, 2021; Alqahtani & Erfani, 2021; Venkatesh et al., 2003).

Moreover, the application of UTAUT in this research holds empirical significance, as it provides a structured approach to dissecting the complex interplay of individual, organizational, and technological factors (Alqahtani & Erfani, 2021). By aligning the study with this established theoretical framework, the research will contribute to the broader academic discourse on technology adoption in healthcare, offering insights grounded in empirical evidence. The relevance of UTAUT extends to its potential for informing future research directions, enabling scholars to identify key leverage points for understanding adoption among healthcare providers.

As the healthcare sector continues to grapple with issues related to technology acceptance, the successful adoption of MHS is contingent upon understanding the diverse factors that shape healthcare provider decision-makers intentions, which can ultimately influence the quality of care delivered to patients (Alqahtani & Erfani, 2021). By illuminating these factors, the findings of this research will provide insights that can guide scholarly discussions in the field of MHS technologies. This focus on theoretical contribution aligns with the need for an evidence-based understanding of the complexities of healthcare technology adoption (Alqahtani & Erfani, 2021).

In synthesizing the existing body of knowledge and positioning this research within the broader context of MHS adoption, the findings of this study will underscore the significance of understanding the purposively selected healthcare provider decision-makers' perspectives. As healthcare remains a dynamic and evolving field, the insights from this research will contribute to academic discourse and enhance the theoretical frameworks used to analyze technology

adoption. By addressing the intricacies of healthcare provider decision-makers' adoption intentions, the findings of this study will contribute to the literature.

Statement of the Problem

The problem addressed in this study was the insufficient understanding of the factors associated with the adoption of MHS among healthcare provider decision-makers in the US, resulting in inconsistent adoption despite its potential benefits. (Istepanian, 2022; Niaz & Nwagwu, 2023). A growing body of literature highlights the advantages of MHS, such as improved patient engagement and reduced hospital readmissions (Rodić et al., 2024). However, the factors associated with the decision-making processes regarding their adoption remain poorly understood (Rodić et al., 2024).

What remains unknown is the specific interplay among factors associated with healthcare provider decision-makers' intentions to adopt MHS, a perspective that has often been overshadowed by patient-focused studies (Niaz & Nwagwu, 2023). If this problem is not addressed, the healthcare sector may continue to experience inefficiencies in healthcare delivery, escalating costs, suboptimal health outcomes, and stagnation in the advancement of healthcare technologies, exacerbating the existing challenges of escalating patient demands (Niaz & Nwagwu, 2023). Furthermore, the limited empirical examination of the factors associated with healthcare provider decision-makers intentions to adopt MHS may hinder the overall progress toward a digitized healthcare system, leaving providers without important insights necessary for informed decision-making (Alqahtani & Erfani, 2021). Addressing this problem is important for advancing academic discourse on technology adoption in healthcare settings (Alqahtani & Erfani, 2021). By determining the factors that are associated with adoption through the lens of

established frameworks such as UTAUT, the findings of this study will contribute to theoretical knowledge, contributing to future scholarly research in MHS.

Purpose of the Study

The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States. Rather than seeking generalizable findings, the researcher aimed to explore patterns of association within a targeted group of individuals with direct experience and responsibility in technology-related decision-making. By focusing on this knowledgeable subset, the study sought to provide context-specific insights into how UTAUT constructs manifest in organizational environments and how these relationships may inform theoretical understanding of technology adoption in healthcare settings. The findings were intended to contribute to the scholarly discourse by offering exploratory, theory-informing evidence that may guide future research employing probability-based sampling or alternative methodological approaches. By examining variables such as PE, EE, SI, SC, FC, and BI, the findings of this research will contribute to the theoretical framework and future investigations. The overarching goal was to provide knowledge that fosters a deeper understanding of the dynamics in MHS adoption from healthcare decision-makers' perspective, ultimately benefiting researchers seeking to enhance healthcare delivery through technological innovation. This research was a logical response to the identified gap in literature and the determinants of MHS adoption among healthcare provider decision-makers (Niaz & Nwagwu, 2023).

To achieve this, participants in this study consisted of decision-makers in healthcare providers' Information Technology departments who were selected purposively across every

region of the US. Data will be collected through self-administered questionnaires distributed via social media platforms. This process ensured that informed consent was obtained while prioritizing the confidentiality of participants. Based on G*Power3 analysis, a minimum sample size of 98 participants is required for this study (Chaokromthong & Sintao, 2021). Correlational analysis was used to assess relationships among variables.

Introduction to Theoretical Framework

The guiding framework for this research was UTAUT. This comprehensive model elucidates the factors associated with purposively selected healthcare provider decision-makers' adoption intentions of MHS in the United States. This theoretical framework was developed by Venkatesh et al. (2003) and posits that technology acceptance is predominantly shaped by five key constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self Concept (SC), and Facilitating Conditions (FC) (Azam et al., 2023; Venkatesh et al., 2003). PE, EE, SI, and SC are important in informing users' behavioral intentions (BI) regarding adopting new technologies, particularly in the healthcare sector (Azam et al., 2023; Alqahtani & Erfani, 2021). Facilitating Conditions (FC) and Behavioral Intention (BI) are associated with technology adoption (AD) (Azam et al., 2023; Alqahtani & Erfani, 2021). The integration of these constructs provides a structured framework for analyzing the complex dynamics governing decision-making in the context of MHS.

PE signifies the degree to which healthcare providers perceive that using MHS will improve their service delivery and patient outcomes, while EE reflects the perceived ease of use of these technologies (Abbad, 2021). SI denotes the impact of peers, superiors, and organizational culture on decision-makers' adoption choices, highlighting the role of interpersonal dynamics in technology acceptance (Abbad, 2021). SC pertains to healthcare

decision-makers' internal self-perception and psychological understanding regarding the significance and appeal of MHS. FC pertains to the infrastructure and resources available to support the effective use of MHS, including training and technical support (Abbad, 202). BI refers to healthcare decision-makers' subjective probability regarding the adoption of a particular behavior. From a theoretical standpoint, behavioral intention influences MHS adoption and utilization. Together, these constructs interact to shape the adoption of MHS by healthcare decision-makers, forming the basis for this research.

The UTAUT framework guided the research decisions by informing the formulation of the problem statement, which addresses an insufficient understanding of the factors that are associated with the adoption of MHS among healthcare provider decision-makers despite their recognized benefits (Istepanian, 2022; Niaz & Nwagwu, 2023). The purpose statement was crafted to investigate how the interplay of UTAUT constructs, specifically PE, EE, SI, SC, FC, and BI, are associated with the intentions of healthcare decision-makers regarding MHS adoption. Research questions were developed from the framework to explore the association among these constructs and their collective impact on MHS adoption. By anchoring the study within the UTAUT model, the researcher investigated these associations, contributing to the existing body of knowledge on healthcare technology adoption.

Additionally, the UTAUT framework informed the methodology by guiding the selection of relevant variables such as PE, EE, SI, SC, FC, BI, and AD, as well as the design of data collection instruments designed by Azam et al. (2023). Self-administered questionnaires captured participants' perceptions of each UTAUT construct, ensuring an assessment of factors associated with MHS adoption. The choice of a correlational quantitative approach aligns with UTAUT's emphasis on measuring the relationships between these defined constructs, facilitating statistical

analysis of the collected data to explore patterns of association within a targeted group of individuals with direct experience and responsibility in technology-related decision-making (Alqahtani & Erfani, 2021). This methodology was essential for deriving meaningful conclusions that can inform future research.

Introduction to Research Methodology and Design

The researcher employed a non-experimental quantitative correlational analysis design to investigate the factors associated with healthcare provider decision-makers' intentions to adopt MHS. Correlational analysis is a methodological approach that has been used in many seminal articles to facilitate the examination of the relationships between multiple independent variables PE, EE, SI, SC, and FC, and the dependent variable of Behavioral Intention (BI) and MHS adoption (AD) (Azam et al., 2023; Lim & Kim, 2022; Sun et al., 2013; Venkatesh et al., 2003; Yang et al., 2024). Data was collected using self-administered questionnaires developed by Azam et al. (2023) and distributed to purposively selected healthcare decision-makers in Information Technology (IT) departments across the United States. This data collection method gathers quantifiable insights essential for statistical analysis and seeks to provide context-specific insights(Lim & Kim, 2022). By employing this methodology, the findings of this research may inform theoretical understanding of technology adoption in healthcare settings and contribute to the scholarly discourse by offering exploratory, theory-informing evidence.

The data collection procedure involved the dissemination of the questionnaires through Facebook to purposively selected healthcare decision-makers. The questionnaire was designed by Azam et al. (2023) to incorporate established measurement scales that align with the constructs of the UTAUT framework, thereby allowing for analysis of the variables. Participants were purposively selected to focus on decision-makers; this may introduce biases and reduce the

generalizability of the findings (Abbad, 2021). Informed consent was obtained from all participants, ensuring adherence to ethical standards while maintaining the confidentiality of their responses. This data collection approach aligns with the study's overarching goals by facilitating the investigation and determination of the factors associated with MHS adoption intentions.

A non-experimental correlational analysis is suited to address the research problem, highlighting the problem of insufficient understanding of the factors associated with the adoption of MHS among healthcare provider decision-makers in the US. The correlational methodology allows for investigating the interrelationships among the UTAUT constructs without inferring causation, thus providing an understanding of how these factors collectively shape decision-makers' intentions (Istepanian, 2022). By focusing on relationships among the variables, the findings of the research will identify factors associated with MHS adoption, illuminating the complexities inherent in the decision-making process regarding MHS among the purposively selected decision-makers. Furthermore, this methodological alignment ensures that the research questions are addressed, allowing for meaningful insights into the barriers and facilitators of technology adoption in healthcare settings.

Additionally, the quantitative design of this research enabled the application of statistical analysis techniques, which are essential for validating the relationships identified among the variables (Lim & Kim, 2022). The study aimed to explore patterns of association within a targeted group of individuals. Correlational analyses determined the strength and direction of the association between the UTAUT constructs and BI and AD using the Statistical Package for the Social Sciences (SPSS) (Lim & Kim, 2022). This approach strengthened the credibility of the findings and provided actionable insights to inform researchers seeking to improve the

integration of MHS (Lim & Kim, 2022). The result of this research contributed to the existing body of knowledge on healthcare technology by providing theory-informing evidence that may guide future research employing probability-based sampling or alternative methodological approaches.

Research Questions

The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States. The research questions detailed below have been developed to enable a thorough examination of the topic.

RQ1

To what extent, if any, is performance expectancy associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

RQ2

To what extent, if any, is effort expectancy associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

RQ3

To what extent, if any, is social influence associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

RQ4

To what extent, if any, is self-concept associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

RQ5

To what extent, if any, are facilitating conditions associated with healthcare provider decision-makers' intention to adopt MHS in the US?

RQ6

To what extent, if any, are behavioral intention associated with healthcare provider decision-makers' intention to adopt MHS in the US?

Hypotheses

The hypotheses listed below were established in response to the research questions presented in this study.

$H1_0$

There is no statistically identifiable association between performance expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H1_a$

There is a statistically identifiable association between performance expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H2_0$

There is no statistically identifiable association between effort expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H2_a$

There is a statistically identifiable association between effort expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H3_0$

There is no statistically identifiable association between social influence and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H3_a$

There is a statistically identifiable association between social influence and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H4_0$

There is no statistically identifiable association between self-concept and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H4_a$

There is a statistically identifiable association between self-concept and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H5_0$

There is no statistically identifiable association between facilitating conditions and healthcare provider decision-makers' adoption of MHS in the US.

$H5_a$

There is a statistically identifiable association between facilitating conditions and healthcare provider decision-makers' adoption of MHS in the US.

$H6_0$

There is no statistically identifiable association between behavioral intention and healthcare provider decision-makers' adoption of MHS in the US.

$H6_a$

There is a statistically identifiable association between behavioral intention and healthcare provider decision-makers' adoption of MHS in the US.

Significance of the Study

The significance of this study lies in its potential to enhance the understanding of the factors associated with healthcare provider decision-makers' adoption intentions of MHS, thereby addressing a gap in the existing literature. By employing the UTAUT as the guiding framework, this research delves into the dynamics that shape the intention of healthcare provider decision-makers to adopt MHS. The findings were intended to contribute to the scholarly discourse by offering exploratory, theory-informing evidence that may guide future research employing probability-based sampling or alternative methodological approaches.

Addressing the identified problem of this study and achieving its purpose benefited the broader academic community. While much of the current literature emphasizes patient perspectives, this study shifted the focus to the decision-makers viewpoints, broadening the scope of inquiry within the field of MHS. By elucidating the factors associated with healthcare provider decision-makers' intentions to adopt MHS, the findings of this study fostered a better understanding of the facilitators and barriers to technology integration within the purposively selected sample.

Definition of Key Terms

Digital Healthcare Solutions

These refer to mobile applications and services that allow users to manage their health information and access healthcare resources through smartphones and tablets (Yang et al., 2024).

Digital Infrastructure

This term encompasses the technological systems and services that facilitate the delivery of digital solutions, ensuring efficient access to health information and resources (Akiogbe et al., 2024).

Healthcare Delivery

This concept describes the various methods and practices of providing health services to individuals and communities to ensure effective patient care (Lee et al., 2023).

Health Literacy

It signifies an individual's capability to obtain, process, and comprehend essential health information and services for making informed health-related decisions (Lee et al., 2023).

Innovative Health Solutions

This term pertains to new and creative approaches or technologies developed to enhance health outcomes and improve the efficiency of healthcare delivery (Akiogbe et al., 2024).

Telehealth

The provision of healthcare services through telecommunications technology, allowing patients to receive care remotely via video calls, phone consultations, or online messaging (Istepanian, 2022).

Summary

This research investigated and identified the factors associated with purposively selected healthcare provider decision-makers' intentions to adopt MHS in the US, emphasizing the need to understand this phenomenon as healthcare technology evolves. Despite the potential benefits of MHS, the adoption rates among healthcare providers remain inconsistent, necessitating a thorough exploration of the determinants influencing decision-making processes. The findings of

the study bridged the gap in the literature by focusing on the decision-makers' perspectives, which have been overshadowed by patient-centric research. By employing the UTAUT framework, the research elucidated the interplay of factors such as PE, EE, SI, SC, FC, and BI.

The significance of this research lies in its potential to enrich the understanding of technology adoption within healthcare settings, ultimately contributing to the academic discourse on MHS. The researcher aimed to explore patterns of association within a targeted group of individuals with direct experience and responsibility in technology-related decision-making. The methodology involves a non-experimental quantitative correlational design, utilizing self-administered questionnaires to collect data from purposively selected healthcare decision-makers across the US. This approach aligns with the established UTAUT framework, allowing for an analysis of the association between the identified constructs and their collective impact on adoption intentions. The research questions and corresponding hypotheses were designed to assess the association of each UTAUT variable. By addressing these aspects, the findings of this study provided insights that can contribute to literature and guide future research.

Chapter 2: Literature Review

The problem addressed in this study was the insufficient understanding of the factors associated with the adoption of MHS among healthcare provider decision-makers in the US, resulting in inconsistent adoption despite its potential benefits. (Istepanian, 2022; Niaz & Nwagwu, 2023). This limited clarity hampers the healthcare decision-makers' ability to effectively integrate MHS technologies, thereby limiting improvements in patient engagement and operational efficiency (Rodić et al., 2024). The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States. The findings of this research enhanced academic discourse on the complexities of MHS adoption and provided insight for future researchers.

This literature review encompassed four subtopics. The first topic addressed is the historical evolution and transformation of MHS. The second topic addressed different motivators and obstacles associated with adopting MHS, providing essential insights into the factors associated with decision-making processes within healthcare settings. The third topic focused on the evolving landscape of MHS. The final topic addressed the research, prospects, and technology adoption issue of MHS. This review illuminated the critical need for empirical research on the predictors of MHS adoption intention of healthcare decision-makers, establishing the foundational context and driving forces behind this investigation (Istepanian, 2022). Overall, the review substantiated the validity of the problem, purpose, and significance of the study.

A comprehensive literature review was undertaken for this research, focusing on the factors that predict the adoption of MHS among healthcare provider decision-makers in the

United States (US). The primary sources consisted of peer-reviewed publications that exhibited substantial scientific rigor and research significance (Paul & Criado, 2020; Snyder, 2019). The review utilized a range of online databases to identify relevant peer-reviewed literature, including ProQuest Dissertations & Theses at National University and Global, PubMed, IEEE Xplore, ScienceDirect, SpringerLink, JSTOR, CINAHL, Scopus, Google Scholar, Taylor & Francis Online, ACM Digital Library (Fink, 2019).

The search strategy incorporated a variety of keywords related to the topic, such as technology adoption in healthcare, the UTAUT, UTAUT2, mobile health services, healthcare technology acceptance, and the factors influencing MHS adoption, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Threat Appraisal (TA). Additionally, textbooks authored by experts in healthcare technology and reports issued by reputable health organizations were explored (e.g., Institute of Medicine). Preference was given to publications within the last five years. However, older foundational works that contributed critical insights into technology adoption theories and the UTAUT framework were also included in the review.

One hundred publications were identified through this search. The distribution of sources from the online databases is as follows: ten were from ProQuest Dissertations & Theses at Northcentral University and Global, eighteen were from PubMed, twelve were from IEEE Xplore, ten were from ScienceDirect, twelve were from SpringerLink, and five were from JSTOR. Additionally, eight publications were from Google Scholar, eight were from CINAHL, seven were from Scopus, five were from Taylor & Francis Online, and five were from ACM Digital Library. The categorization based on search keywords yielded twelve publications on technology adoption in healthcare, twenty on UTAUT, five on UTAUT2, eighteen on MHS,

nineteen addressing facilitators and barriers to MHS adoption, and sixteen on integrating MHS and its challenges, and ten on the future of health technology.

Theoretical Framework

The theoretical framework for this research is the Unified Theory of Acceptance and Use of Technology (UTAUT). A theoretical framework is a foundational research component, providing the context and structure for understanding and analyzing the phenomena under investigation (Varpio et al., 2020). It encompasses a set of concepts and theories that inform the research design, methodology, and interpretation of findings, effectively guiding the researcher's inquiry (Reed et al., 2021). By situating a study within existing literature, the theoretical framework highlights the significance of the research and connects it to broader academic discussions and debates (Dmytriyev et al., 2021). Theoretical frameworks aid in identifying key variables and their interrelations, which are essential for formulating hypotheses and conducting rigorous analysis (Yi & Duval-Couetil, 2022). Ultimately, a well-defined theoretical framework enhances the credibility, facilitating a deeper understanding and relevance of the research (Varpio et al., 2020).

Unified Theory of Acceptance and Use of Technology (UTAUT)

The theoretical framework for this research is the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been extensively utilized in the examination of technology adoption behaviors across various domains (Alqahtani & Erfani, 2021; Sun et al., 2013; Venkatesh et al., 2003). This well-established framework posits that an individual's behavioral intention to adopt technology is influenced by the following constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Self-Concept (SC) while Facilitating Conditions (FC) and Behavioral Intention (BI) influences MHS adoption (AD), (Azam et al.,

2023; Niaz & Nwagwu, 2023; Sun et al., 2013). The integration of these constructs provides a robust theoretical foundation for investigating the factors that predict healthcare provider decision-makers' adoption of Mobile Health Services (MHS) in the United States.

The selection of the UTAUT model for this study is well-justified, as it has demonstrated its efficacy in explaining technology adoption behaviors in various healthcare settings (Istepanian, 2022). Moreover, the UTAUT framework has been extended and refined over the years with the emergence of UTAUT2, which further enhances the model's explanatory power by incorporating additional factors, such as hedonic motivation, price value, and habit (Venkatesh et al., 2012). The comprehensive nature of the UTAUT and subsequent iterations make it a suitable theoretical lens for this investigation, as it allows for a nuanced understanding of the multifaceted factors that influence healthcare provider decision-makers' intentions to adopt MHS (Niaz & Nwagwu, 2023). The application of the UTAUT framework in the context of MHS adoption is particularly relevant, as it enables the examination of the complex interplay between technological, organizational, and individual factors that shape the decision-making processes of healthcare provider decision-makers (Istepanian, 2022). By delving into the specific constructs of the UTAUT, the findings of this study may elucidate the key determinants that drive or impede the adoption of MHS, thereby contributing to the existing body of knowledge and informing future research in healthcare technology integration.

Performance Expectancy (PE). As delineated in the UTAUT, PE is a critical determinant influencing the adoption of MHS among healthcare provider decision-makers (Venkatesh et al., 2003). It is defined as the degree to which an individual perceives that utilizing a specific technology will enhance their job performance (Venkatesh et al., 2003). Numerous studies have underscored the significance of PE in the context of healthcare technology adoption,

suggesting that when healthcare decision-makers believe that MHS will lead to improved patient outcomes, operational efficiency, and overall workflow, their intention to adopt such services increases significantly (Duarte & Pinho, 2019; Shakibaei et al., 2024). This notion is particularly pertinent in a sector where integrating innovative technologies is essential for meeting rising patient demands and addressing operational challenges (Williams & Radnor, 2022). Furthermore, empirical evidence indicates that PE influences initial adoption intentions and plays a pivotal role in the sustained use of MHS as healthcare provider decision-makers continue to engage with technologies that they perceive as beneficial (Rodić et al., 2024). Therefore, understanding the nuances of PE is paramount for developing strategies that facilitate the effective integration of MHS within healthcare systems.

In examining the factors contributing to PE, it becomes evident that healthcare provider decision-makers' familiarity with technology and prior experiences with similar systems significantly shape their expectations regarding MHS (Van Biesen et al., 2022). Research has shown that positive prior experiences with health technologies can enhance performance expectancy, fostering a greater likelihood of adoption (Alqahtani & Erfani, 2021). Conversely, negative encounters or a lack of exposure can diminish perceived utility and hinder adoption intentions (Alqahtani & Erfani, 2021).

Effort Expectancy (EE). It is the degree of ease associated with using a technology (Venkatesh et al., 2003). In the context of MHS, EE becomes particularly significant as healthcare provider decision-makers assess the operational feasibility of integrating such technologies into their existing workflows (Paul & Criado, 2020). Research indicates that the perceived ease of use directly influences adoption intentions, as decision-makers are more inclined to embrace innovations requiring minimal implementation effort (Alqahtani & Erfani,

2021; Paul & Criado, 2020; Sun et al., 2013). Furthermore, aligning MHS with established routines and processes is essential for reducing resistance to change, thereby facilitating smoother transitions to technological adoption (Paul & Criado, 2020). Studies have shown that when healthcare provider decision-makers anticipate a low effort requirement, their engagement with MHS increases, enhancing patient care delivery (Alqahtani & Erfani, 2021; Paul & Criado, 2020; Sun et al., 2013).

Moreover, the implications of EE extend beyond mere user acceptance; they also encompass broader organizational impacts within healthcare systems (Van Biesen et al., 2022). When decision-makers perceive MHS as easy to use, it fosters a culture of innovation, encouraging further exploration and adoption of emerging technologies (Niaz & Nwagwu, 2023). Conversely, high EE can be a barrier, deterring healthcare providers from adopting MHS due to anticipated complexities and disruptions to established practices (Niaz & Nwagwu, 2023).

Social Influence (SI). Social influence encompasses the notion that individuals recognize the expectations of significant people in their lives, such as family and friends, which leads them to believe that they should utilize a particular technology (Venkatesh et al., 2003; Sun et al., 2013). In the context of MHS adoption, this construct plays a crucial role in shaping the intentions and behaviors of healthcare provider decision-makers (Alqahtani & Erfani, 2021). The perception that peers, superiors, or respected colleagues endorse using MHS can significantly enhance the likelihood of adoption, as individuals often seek to align their actions with the expectations of their social circles (Alqahtani & Erfani, 2021). This alignment reflects a desire for social conformity and fosters a sense of legitimacy and support for integrating MHS within healthcare practices (Duarte & Pinho, 2019). As such, SI emerges as a vital factor that can either facilitate or impede the acceptance of innovative health technologies, depending on the

prevailing attitudes and behaviors within a given healthcare environment (Duarte & Pinho, 2019). Understanding this dynamic is essential for identifying strategies that can effectively promote the adoption of MHS among healthcare provider decision-makers (Duarte & Pinho, 2019).

Moreover, the implications of SI extend beyond mere encouragement; they encompass the collaborative processes and knowledge sharing that occur within healthcare settings (Istepanian, 2022). As healthcare decision-makers engage in conversations regarding MHS, their intentions are often shaped by their peers' collective experiences and attitudes, contributing to a culture of innovation and openness (Niaz & Nwagwu, 2023). In this context, informal support mechanisms, such as mentorship programs and peer-led training sessions, can significantly enhance the understanding and acceptance of MHS (Istepanian, 2022).

Self-Concept (SC). Self-concept refers to individuals' perception and evaluation of their capabilities, competencies, and identity in relation to adopting and utilizing new technologies (Azam et al., 2023; Gao et al., 2015). It encompasses self-assessment of technological proficiency, professional identity, and perceived role in implementing healthcare innovations (Dwivedi et al., 2016). In healthcare technology adoption, SC is fundamental as it shapes how healthcare professionals view their ability to integrate Mobile Health Services (MHS) into their clinical practice (Azam et al., 2023). The literature indicates that an individual's self-concept can significantly influence their willingness to embrace innovative solutions, as confidence in technological capabilities and professional alignment may enhance adoption (Azam et al., 2023; Nadri et al., 2018). Furthermore, a comprehensive understanding of SC can illuminate healthcare professionals' motivations and barriers to adopting MHS (Azam et al., 2023). This self-

evaluation informs the adoption process and highlights the importance of developing strategies that enhance professional self-efficacy and technological confidence.

The relationship between SC and the adoption of MHS is complex and often influenced by factors such as professional experience, technological literacy, and organizational support (Azam et al., 2023). Research indicates that healthcare providers with positive self-concept are more likely to adopt MHS, as their self-perceptions align with the competencies required for technology use (Azam et al., 2023; Cao et al., 2022). Empirical evidence suggests that SC significantly influences behavioral intention to adopt mHealth, demonstrating its crucial role in technology acceptance (Azam et al., 2023). Additionally, healthcare professionals who view MHS as compatible with their professional identity and self-image demonstrate higher adoption rates and sustained usage behavior (Dwivedi et al., 2016; Gao et al., 2015).

Facilitating Conditions (FC). Facilitating conditions refer to the resources, infrastructure, and support systems that enable individuals to utilize a given technology effectively (Istepanian, 2022). This concept is integral to understanding the dynamics of technology adoption, particularly in the healthcare sector, where integrating novel systems such as MHS is often contingent upon the availability of necessary FC (Sun et al., 2013). Facilitating conditions encompass tangible and intangible elements significantly influencing healthcare decision-makers' intentions to adopt MHS (Istepanian, 2022). These elements may include access to requisite hardware and software, technical support, training opportunities, and organizational policies that encourage the use of new technologies (Sun et al., 2013; Istepanian, 2022). In MHS adoption, robust FC can mitigate perceived barriers and enhance the overall user experience, fostering a more favorable environment for technology acceptance (Istepanian, 2022). As a result, grasping the importance of FC is vital for healthcare organizations that intend

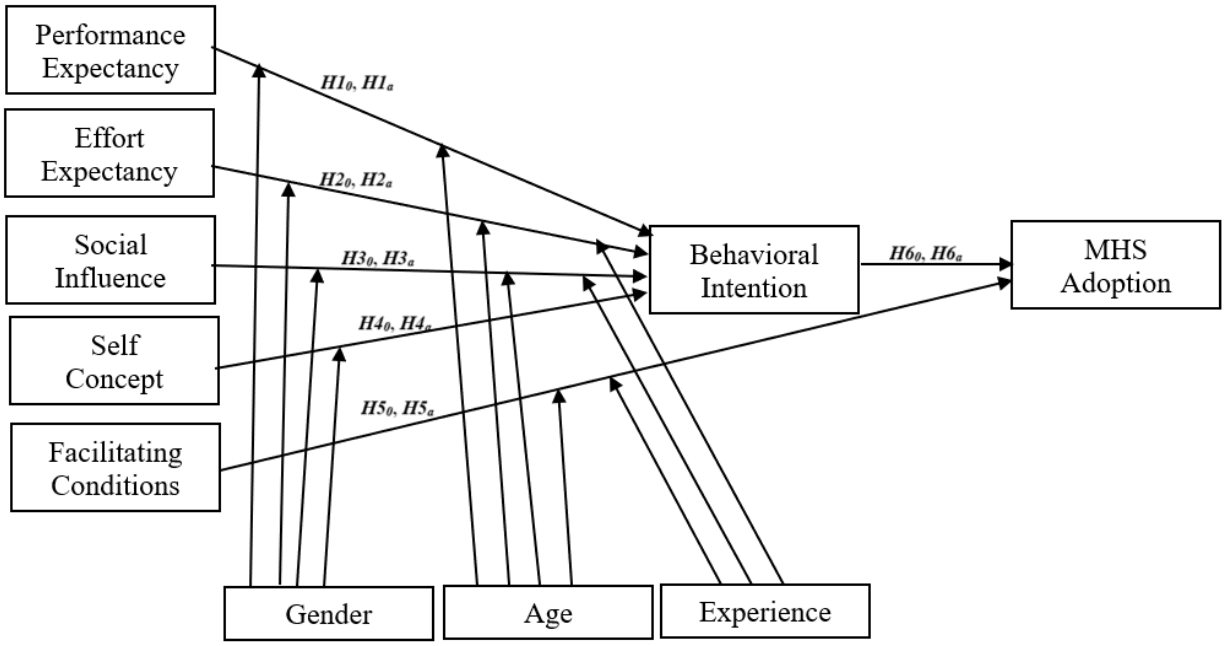
to enhance their operational efficiency and boost patient engagement by integrating MHS (Duarte & Pinho, 2019).

The perception of FC significantly impacts healthcare provider decision-makers' adoption of MHS (Al-Rawashdeh et al., 2022). Research by Niaz and Nwagwu (2023) illustrates that when healthcare decision-makers perceive strong FC, they are more likely to adopt MHS, as these conditions alleviate concerns regarding implementation challenges and operational disruptions. Additionally, facilitating conditions can enhance decision-makers' confidence in their ability to navigate new technologies, fostering a culture of innovation within healthcare organizations (Al-Rawashdeh et al., 2022). Conversely, lacking adequate FC can lead to resistance and apprehension regarding technology adoption, as highlighted by Rodić et al. (2024).

Figure 1 illustrates a comprehensive graphical model of the UTAUT framework, delineating the interrelationships between various constructs that influence behavioral intention toward MHS adoption. Central to this model are key components such as Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions, each serving as pivotal determinants of MHS adoption among healthcare provider decision-makers. Furthermore, the model incorporates moderating variables, including Gender, Age, and Experience, which may significantly alter the strength and direction of the relationships between the primary constructs and behavioral intention.

Figure 1

Graphical Model of UTAUT Framework



Note. The UTAUT Framework adopted from Azam et al. (2023) illustrates that PE, EE, SI, SC, and FC influence MHS adoption and BI with effects moderated by gender, age, and experience.

Relationships Among the Constructs

In examining the adoption intention of MHS within the UTAUT framework, it is imperative to delineate the intricate relationships among the core constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), and Facilitating Conditions (FC). Each of these constructs predicts healthcare provider decision-makers' adoption intentions of MHS and interacts in multifaceted ways that shape the overall technology adoption landscape (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). PE, the degree to which technology is perceived to enhance job performance, is often regarded as the most critical determinant of behavioral intention (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). When healthcare providers believe that MHS can significantly improve patient outcomes

and operational efficiency, their likelihood of adopting such technologies increases substantially (Iyanna et al., 2022). Conversely, a low perception of PE can engender skepticism and reluctance toward embracing MHS, highlighting the necessity of fostering positive perceptions regarding the benefits of these technologies (Venkatesh, 2022). Thus, the relationship between PE and adoption intention is foundational, underpinning the relevance of further exploration into how the other constructs influence it (Iyanna et al., 2022).

Assumptions underlying the UTAUT framework suggest that Effort Expectancy (EE) is vital in mediating the relationship between PE and adoption intention (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). Specifically, it is posited that when healthcare provider decision-makers view MHS as easy to use, their confidence in utilizing the technology is bolstered, enhancing the perceived benefits associated with its adoption (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). This assumption underscores the importance of usability and accessibility in the design and implementation of MHS, as decision-makers are more inclined to adopt these (Iyanna et al., 2022). Furthermore, the interaction between EE and PE posits that a favorable perception of ease of use can amplify the perceived performance benefits of MHS, creating a synergistic effect that promotes adoption (Iyanna et al., 2022).

Social Influence (SI) is another significant construct that influences the adoption of MHS, operating on the premise that individuals are inclined to align their behaviors with the expectations of peers and superiors (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). This assumption posits that the endorsement of MHS by respected colleagues or organizational leaders can significantly enhance decision-makers' intentions to adopt these technologies (Yang et al., 2024). As such, the interplay between SI and the other constructs is essential for understanding how social dynamics within healthcare environments can shape technology

acceptance. When healthcare providers perceive that their peers are adopting MHS, they may be more likely to follow suit, driven by a desire for social conformity and validation (Yang et al., 2024). Consequently, SI motivates adoption and amplifies the effects of PE and EE, as collective endorsement reinforces the perceived benefits and ease of use associated with MHS (Yang et al., 2024).

Self-Concept (SC) is another significant construct that influences the adoption of MHS, operating on the premise that individuals' self-perceptions and professional identity significantly shape their technology acceptance behaviors (Azam et al., 2023; Dwivedi et al., 2016; Gao et al., 2015). This assumption posits that healthcare professionals' self-evaluation of their technological competencies and the alignment of MHS with their professional self-image can significantly enhance their intentions to adopt these technologies (Azam et al., 2023). As such, the interplay between SC and other constructs is essential for understanding how personal identity and self-efficacy within healthcare environments can shape technology acceptance. When healthcare providers possess a positive self-concept regarding their technological capabilities and view MHS as congruent with their professional identity, they are more likely to embrace these innovations (Azam et al., 2023). Consequently, SC motivates adoption and amplifies the effects of Performance Expectancy and Effort Expectancy, as positive self-perception reinforces confidence in utilizing and deriving benefits from MHS (Azam et al., 2023).

Facilitating Conditions (FC) are critical in shaping the adoption intentions of healthcare provider decision-makers, as they encompass the resources and support systems necessary for effectively utilizing MHS (Istepanian, 2022). The assumption is that robust FC, including access to training, technical support, and adequate infrastructure, can significantly alleviate barriers to technology adoption (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). This construct

interacts with the other UTAUT variables by enhancing the perceived feasibility of integrating MHS into healthcare settings. When decision-makers perceive that they have access to sufficient resources, their confidence in adopting new technologies increases, which can, in turn, strengthen the influence of PE and EE on their intentions (Istepanian, 2022). Therefore, a comprehensive understanding of FC is essential for healthcare organizations seeking to foster an environment conducive to MHS adoption.

The relationships among these constructs can be viewed as interdependent and cyclical, where the outcomes of initial adoption decisions influence future perceptions and behaviors (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). Successful experiences with MHS can enhance PE and EE over time, reinforcing healthcare provider decision-makers' confidence in the technology and its benefits (Sun et al., 2013). Conversely, negative experiences can create a feedback loop of resistance, where initial hesitance leads to diminished perceptions of PE and increased SC (Azam et al., 2023; Sun et al., 2013). This cyclical nature of technology adoption emphasizes the need for ongoing support and assessment, as initial perceptions can evolve and significantly impact sustained engagement with MHS (Sun et al., 2013).

Origin and Development of Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) as a culmination of previous theoretical frameworks in the field of technology acceptance. This model emerged from a systematic review of eight prominent models, including the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Technology Acceptance Model (TAM) (Davis, 1989), Motivational Model (MM) (Davis et al., 1992), Theory of Planned Behavior (TPB) (Ajzen, 1991), Combined TAM and TPB (C-TAM-TPB) (Taylor & Todd, 1995), Model of PC Utilization (MPCU) (Thompson et al., 1991), Innovation Diffusion

Theory (IDT) (Rogers, 1995), and Social Cognitive Theory (SCT) (Bandura, 1986). By synthesizing these models and theories, UTAUT provides a more comprehensive understanding of the variables influencing technology acceptance and usage. The development of UTAUT was significant in that it addressed the fragmented nature of existing models, providing a cohesive theoretical foundation that could be applied across various contexts (Venkatesh et al., 2003).

The foundation of UTAUT rests heavily on the insights gained from the Technology Acceptance Model (TAM) (Davis, 1989), which suggests that perceived ease of use and perceived usefulness are essential factors influencing technology acceptance (Venkatesh et al., 2003). While TAM has been highly influential, it has also been critiqued for its limited scope, particularly its failure to consider external factors such as social influences and contextual conditions (Al-Nuaimi & Al-Emran, 2021). In response to these limitations, UTAUT incorporates social influence as a key construct, recognizing that individuals are often affected by the opinions and behaviors of their peers and social networks when deciding whether to adopt new technologies (Sun et al., 2013; Venkatesh et al., 2003). This addition reflects a growing awareness of the social dimensions of technology acceptance, acknowledging that broader social contexts often shape user behavior (Alqahtani & Erfani, 2021).

Performance Expectancy (PE) is a construct within the UTAUT framework that encapsulates the degree to which an individual perceives that utilizing a particular technology will enhance their job performance (Venkatesh et al., 2003). This construct is primarily derived from the Technology Acceptance Model (TAM), which posits that perceived usefulness significantly influences users' intentions to accept and use technology (Cheng, 2019; Davis, 1989). Additionally, the Theory of Reasoned Action (TRA) contributes to this construct by highlighting the role of positive attitudes toward technology in shaping behavioral intentions

(Cheng, 2019; Fishbein & Ajzen, 1975). The Innovation Diffusion Theory (IDT) further emphasizes the importance of performance-related benefits, suggesting that the perceived advantages of a technology can drive its adoption within a social context (Al-Rahmi et al., 2021; Rogers, 1995). Collectively, these theories underscore the critical nature of PE in facilitating technology acceptance, as users are more inclined to embrace innovations that they believe will yield tangible improvements in their professional effectiveness (Al-Rahmi et al., 2021).

Effort Expectancy (EE), another key construct of UTAUT, refers to the perceived ease of use associated with technology and is integral to influencing user adoption (Venkatesh, 2022). This construct is grounded in the perceived ease of use dimension from the Technology Acceptance Model (TAM), which asserts that lower perceived effort correlates with a higher likelihood of technology acceptance (Davis, 1989; Nadlifatin et al., 2020). In addition, the Theory of Planned Behavior (TPB) (Ajzen, 1991) contributes to this construct by incorporating the notion of perceived behavioral control, positing that ease of use can significantly affect an individual's intention to engage with a technology (Ajzen, 1991; Wang et al., 2022). The interplay of these models elucidates that when users perceive a technology as user-friendly and intuitive, their willingness to adopt it increases (Venkatesh, 2022). Thus, EE emerges as a pivotal factor in the overarching narrative of technology acceptance, as it directly impacts users' comfort and confidence in utilizing new tools (Venkatesh, 2022).

Social Influence (SI) is a construct that captures the degree to which individuals perceive that significant others believe they should use a specific technology, thereby highlighting the social context of technology adoption (Venkatesh, 2022). This construct draws heavily from the Theory of Planned Behavior (TPB), which incorporates subjective norms as a determinant of behavioral intentions, illustrating how social pressures can shape an individual's decision to

adopt technology (Ajzen, 1991; Deng et al., 2021). Furthermore, Social Cognitive Theory (SCT) underscores the importance of observational learning and social validation in adoption (Bandura, 1986; Khudzari et al., 2019). It suggests that users will likely emulate the behaviors and attitudes they observe within their social networks (Khudzari et al., 2019). The synthesis of these theories reveals that social influence is a powerful motivator in technology acceptance, as individuals often look to their peers for cues on the desirability and appropriateness of new technological innovations (Venkatesh, 2022). Consequently, this construct reinforces that technology adoption is not merely an individual decision but a phenomenon deeply embedded within social dynamics and interactions (Venkatesh, 2022).

Self-Concept (SC) refers to an individual's psychological perception and evaluation of their capabilities and identity regarding technology adoption, making it a significant construct in understanding healthcare decision-makers' acceptance of MHS (Azam et al., 2023). This construct is informed by Social Cognitive Theory (SCT), which emphasizes the importance of self-perception and internal evaluation in shaping behavior and technology acceptance (Bandura, 1991). The concept has been further enriched by researchers who recognized the integrated effect of psychological phenomena on individuals' willingness to adopt technology, particularly highlighting how personalities and internal self-perceptions regarding the significance of any product have an added appeal in conceptualizing consumer preferences (Bandura, 1991; Nadri et al., 2018). The interaction of these theoretical perspectives illustrates that SC acts as a crucial determinant of technology adoption, as healthcare professionals are more likely to embrace mHealth when they possess positive self-perceptions about their technological capabilities and view the technology as aligned with their professional identity (Azam et al., 2023). This construct underscores the importance of understanding and enhancing healthcare decision-

makers; self-concept to facilitate their engagement with new technologies, thereby improving the likelihood of successful MHS adoption (Azam et al., 2023; Dwivedi et al., 2016; Gao et al., 2015).

Facilitating Conditions (FC) refers to the perceived resources and support available to users for effectively utilizing technology, making it a critical construct in the UTAUT framework (Venkatesh, 2022). This construct is informed by the Model of PC Utilization (MPCU), which emphasizes the significance of organizational support, technical assistance, and resource availability in determining technology usage outcomes (Anthony, 2022). Innovation Diffusion Theory (IDT) also contributes to this construct by highlighting the role of infrastructure and support systems in the successful diffusion of technological innovations within social systems (Venkatesh, 2022). The interaction of these frameworks illustrates that FC is an enabler or barrier to technology adoption, as users are more likely to embrace technology when they perceive adequate support mechanisms (Venkatesh, 2022). This construct underscores the necessity of ensuring that users have access to the requisite resources and support to facilitate their engagement with new technologies, thereby enhancing the likelihood of successful adoption (Sun et al., 2013; Venkatesh, 2022).

The advancement from UTAUT to UTAUT2 marked a significant evolution in the theoretical framework for understanding technology acceptance, enhancing its applicability and breadth (Venkatesh et al., 2012). Introduced by Venkatesh et al. (2012), UTAUT2 expands upon the original model by incorporating three additional constructs: hedonic motivation, price value, and habit. Hedonic motivation addresses the enjoyment or pleasure of using technology, recognizing that users are often influenced by their emotional responses and the intrinsic satisfaction associated with technology use (Venkatesh et al., 2012). This enhancement is

particularly relevant in contexts such as social media and entertainment platforms, where functional benefits and enjoyment drive user engagement these technologies provide (Venkatesh et al., 2012). By recognizing the role of hedonic motivation, UTAUT2 offers a more comprehensive perspective that accounts for both utilitarian and hedonic factors influencing technology acceptance. Furthermore, UTAUT2 includes the construct of price value, which reflects the trade-off users perceive between the benefits gained from using technology and the costs incurred (Venkatesh et al., 2012). This addition is particularly pertinent when users consider subscription fees, maintenance costs, or the opportunity costs associated with technology adoption (Venkatesh et al., 2012). The inclusion of price value acknowledges that economic considerations can significantly influence acceptance decisions, particularly in consumer-oriented technology markets (Venkatesh et al., 2012). Additionally, the construct of habit recognizes that past experiences with technology can shape future usage behaviors, emphasizing the importance of established routines in technology acceptance (Venkatesh et al., 2012). By integrating these constructs, UTAUT2 enhances the original model's explanatory power, providing a more nuanced understanding of the diverse factors influencing technology adoption in modern contexts (Venkatesh et al., 2012). This evolution reflects the need for a dynamic framework that can adapt to the complexities of contemporary technology use, further solidifying UTAUT's relevance in the ever-changing digital innovation landscape.

The current literature on the UTAUT framework illustrates its extensive applicability across various domains, highlighting the factors influencing technology acceptance (Akinnuwesi et al., 2022; Bommer et al., 2022; 2020; Kosiol et al.; 2024). The foundational study by Venkatesh et al. (2003) established the core constructs of the UTAUT model, which have been validated in numerous contexts, including education, healthcare, and public services. Subsequent

works, such as those by Bala et al. (2021) and Dwivedi et al. (2019), have explored the evolution of the model and identified research gaps, particularly concerning demographic factors and the digital divide. These insights underscore the importance of understanding the socio-economic contexts in which technology is adopted, paving the way for more inclusive technology implementation strategies.

In the education sector, Kosiol et al. (2024) concluded that constructs such as social influence and facilitating conditions significantly affect students' acceptance of e-learning technologies. These findings highlight the need for educational institutions to consider user perceptions and experiences when implementing new technologies. Similarly, Scherer et al. (2019) emphasize that performance and effort expectancy are critical for the acceptance of e-health technologies, revealing the high stakes involved in user adoption within this sector. Such research contributes to a nuanced understanding of how user-specific factors impact technology acceptance, reinforcing the relevance of the UTAUT framework in diverse settings.

The exploration of emerging technologies is another prominent theme in the literature, with studies investigating the acceptance of mobile payment systems (Gu et al., 2021) and smart home technologies (Kang et al., 2022). These investigations reveal that security concerns, ease of use, and lifestyle compatibility are essential determinants of user acceptance in rapidly evolving technological landscapes. Adapting the UTAUT framework to these new contexts validates its robustness (Gu et al., 2021; Kang et al., 2022). Furthermore, applying the model to cloud computing adoption in the public sector, as explored by Kayali & Alaaraj (2020), illustrates the framework's versatility in addressing different organizational contexts.

Cross-cultural studies have also gained traction, emphasizing the influence of cultural factors on technology acceptance within the UTAUT framework (Ye et al., 2025). Research

indicates that cultural dimensions significantly impact users' perceptions and behaviors, necessitating tailored approaches to technology implementation across diverse demographics (Ye et al., 2025). This focus on cultural variance, as highlighted in various articles, enriches the theoretical discourse surrounding the UTAUT framework and its applicability on a global scale (Al-Rawashdeh et al., 2022; Istepanian, 2022; Ng, 2021; Venkatesh et al., 2012; Ye et al., 2025). Overall, the literature underscores the evolving nature of technology acceptance research, advocating for a comprehensive understanding of user behavior that considers technological attributes and contextual and cultural influences.

Existing Research that used UTAUT in a Similar Way

The collective body of research demonstrates significant methodological rigor in examining technology acceptance across diverse contexts, with the UTAUT model serving as a foundational theoretical framework (Azam et al., 2023; Demsash et al., 2024; Napitupulu et al., 2021; and Zamberlan & Watanabe 2020). The integration of novel constructs, including self-concept (Azam et al., 2023), decision-makers opinion (Napitupulu et al., 2021), and paraconsistent logic (Zamberlan & Watanabe, 2020), represents substantial theoretical advancement in understanding technology adoption. Sample sizes vary considerably across studies, from Napitupulu et al. (2021) 118 respondents to Demsash et al. (2024) 769 participants, affecting statistical power and generalizability of findings. The studies collectively demonstrate strong internal validity through comprehensive validation procedures, though external validity varies due to sampling limitations and contextual specificity. The predominant use of structural equation modeling and Partial Least Square Structures Equation Modeling (PLS-SEM) provides sophisticated statistical analysis while maintaining methodological consistency across

investigations. While providing valuable insights, the cross-sectional nature of these studies limits causal inferences about the relationships between variables.

Performance Expectancy (PE) and Effort Expectancy (EE) are consistent predictors of technology acceptance, though their relative importance varies significantly across contexts and user populations. Demsash et al. (2024) identified substantial path coefficients for Effort Expectancy (EE) (β=0.61) and Social Influence (SI) (β=0.510), while Napitupulu et al. (2021) revealed unexpected patterns in SI during the COVID-19 pandemic. The role of Facilitating Conditions (FC) demonstrates considerable variation, with infrastructure and resource constraints particularly salient in developing country contexts, as highlighted by Azam et al. (2023). Demographic moderators show inconsistent effects across studies, with Zamberlan & Watanabe (2020) challenging established assumptions about gender influence on technology adoption among decision-makers. Cultural and contextual factors receive varying levels of attention across studies, though Demsash et al. (2024) provide valuable insights specific to resource-limited healthcare settings. The collective findings suggest that technology acceptance factors are highly context-dependent, necessitating careful consideration of local conditions in implementation strategies.

The theoretical implications of these studies advance the literature while revealing important gaps requiring further investigation. The successful integration of additional constructs into the UTAUT model demonstrates the framework's adaptability to specific contexts, though theoretical relationships between novel constructs need firmer conceptual grounding. The findings regarding the variable influence of social factors and facilitating conditions across different settings highlight the need for more nuanced theoretical models. Napitupulu et al. (2021) findings during the COVID-19 pandemic particularly illustrate how exceptional

circumstances can alter established theoretical relationships. The Studies contribute substantially to understanding technology acceptance in specialized contexts while identifying significant areas for theoretical development. The studies demonstrate the importance of considering universal and context-specific factors in technology acceptance models.

Methodological approaches across the studies demonstrate sophistication and limitations in their execution and analysis. The reliance on self-reported data introduces potential biases across all investigations, though researchers employ various strategies to mitigate these limitations. Zamberlan & Watanabe's (2020) innovative combination of traditional statistical approaches with paraconsistent logic represents a significant methodological advancement. The transparent reporting of limitations and statistical procedures enhances reproducibility while highlighting areas for methodological improvement. The predominant use of quantitative methods suggests a need for more mixed-method approaches to capture nuanced contextual factors. The studies demonstrate strong measurement validity through comprehensive validation procedures, though longitudinal validation could strengthen causal inferences.

The practical implications derived from these studies offer valuable insights for technology implementation across various contexts. The consistent significance of effort expectancy highlights the crucial importance of user-friendly interfaces and adequate technical support across all settings. The variable influence of social factors suggests the need for context-specific implementation strategies considering local cultural and organizational dynamics. Infrastructure and resource constraints emerge as critical considerations in developing country contexts, requiring careful attention to facilitating conditions. The impact of professional authority, particularly evident in healthcare settings through decision-makers opinions (Napitupulu et al., 2021), suggests the importance of stakeholder engagement in technology

adoption. The collective findings provide actionable guidance for decision-makers while acknowledging the complexity of technology implementation in diverse settings.

The studies collectively reveal several critical areas requiring further investigation and methodological advancement. The moderate explanatory power of some models suggests the potential existence of additional influential factors not captured in current frameworks. The limited exploration of cultural and contextual factors across studies indicates a need for a more comprehensive examination of these variables. The predominant focus on cross-sectional data highlights the need for longitudinal studies to examine how acceptance factors evolve. The successful integration of context-specific constructs suggests the potential for similar adaptations in other specialized settings. The variation in findings across different contexts emphasizes the need for more comparative studies to understand how technology acceptance patterns differ across settings and populations.

Areas of Convergence and Divergence. The studies demonstrate significant convergence regarding the fundamental role of performance and effort expectancy in technology acceptance across diverse contexts. Demsash et al. (2024) and Azam et al. (2023) identify strong positive relationships between these constructs and behavioral intention in healthcare settings, with path coefficients consistently exceeding 0.5. Zamberlan & Watanabe (2020) corroborate these findings in educational contexts, achieving a 77.33% explanation of technology acceptance among decision-makers. However, notable divergence emerges in the relative importance of these factors, with Napitupulu et al. (2021) finding effort expectancy more influential than performance expectancy during the COVID-19 pandemic, contrary to traditional UTAUT findings. This divergence might be attributed to the unique circumstances of pandemic-driven

adoption, where ease of use became paramount due to rapid implementation requirements and limited training opportunities.

Social influence presents an exciting area of divergence across the studies, with varying degrees of impact on technology acceptance. Demsash et al. (2024) report significant social influence effects (β=0.510) in healthcare settings, while Napitupulu et al. (2021) find no significant impact during the pandemic period. Zamberlan & Watanabe (2020) challenge traditional assumptions about demographic moderators, particularly regarding gender effects. These contradictions might be explained by contextual factors such as voluntary versus mandatory use settings, professional autonomy levels, and cultural differences across study locations. The variation in findings suggests that social influence operates through complex mechanisms highly sensitive to contextual conditions and implementation approaches.

Methodological approaches reveal both convergence and divergence in research design and analytical strategies. All studies employ quantitative methods with structural equation modeling variants, demonstrating agreement on appropriate analytical tools for technology acceptance research. However, sample sizes vary substantially, from 118 to 769 participants, potentially explaining some divergent findings. The studies converge on the importance of construct validity and reliability measures, consistently reporting comprehensive validation procedures. Notable divergence appears in the treatment of cultural and contextual factors, with some studies (Azam et al., 2023; Demsash et al., 2024) providing more detailed consideration of resource-limited settings while others focus more on technical aspects. This methodological variation might reflect differences in research objectives and contextual priorities rather than fundamental disagreements about approach.

Integrating novel constructs into the UTAUT model represents both convergence in theoretical extension efforts and divergence in specific approaches. All studies successfully incorporate additional constructs to enhance model explanatory power, demonstrating agreement on the need for context-specific adaptations. However, they differ significantly in their choice of constructs, with Azam et al. (2023) focusing on self-concept, Napitupulu et al. (2021) incorporating decision-maker opinions, and Zamberlan & Watanabe (2020) introducing paraconsistent logic. These differences reflect the requirements of different implementation contexts rather than theoretical disagreements. The successful integration of diverse constructs suggests the UTAUT model's flexibility while highlighting the importance of context-specific modifications.

The studies demonstrate significant convergence regarding implementation challenges in resource-limited settings while revealing divergent approaches to addressing these challenges. Infrastructure constraints and technical support requirements emerge as consistent themes across studies, particularly in healthcare contexts. However, studies differ in their recommendations for addressing these challenges, with Azam et al. (2023) and Demsash et al. (2024) emphasizing technical solutions, while Napitupulu et al. (2021) and Zamberlan & Watanabe (2020) focus on organizational and social interventions. This divergence might reflect differences in resource availability, institutional capacity, and cultural contexts across study settings. The variation in proposed solutions suggests the need for flexible, context-sensitive implementation strategies rather than one-size-fits-all approaches.

Authority, Audience, and Bias. The studies demonstrate varying levels of authority through institutional affiliations and methodological rigor, though potential biases emerge in geographical and contextual representation. Azam et al. (2023) and Demsash et al. (2024)

establish strong academic credentials through their institutional affiliations, while Zamberlan & Watanabe (2020) bring educational technology expertise to their analysis. Napitupulu et al. (2021) contribute valuable pandemic-era insights, though their relatively small sample size (n=118) may limit generalizability. The studies rely heavily on established theoretical frameworks, with all authors utilizing the UTAUT model as their foundation. Demsash et al. (2024) demonstrate particularly strong methodological authority through their large sample size (n=769) and comprehensive structural equation modeling. The authors' transparent acknowledgment of limitations and potential biases strengthens their scholarly credibility, with Azam et al. (2023) providing an in-depth discussion of methodological constraints.

The research collectively exhibits audience considerations that potentially influence their scope and accessibility. Zamberlan & Watanabe (2020) target an academic audience through their sophisticated paraconsistent logic approach, while Napitupulu et al. (2021) maintain greater accessibility through more apparent practical implications. Demsash et al. (2024) balance methodological rigor and practical applicability in examining mobile-based clinical guidelines. Azam et al. (2023) focus primarily on theoretical contributions, potentially limiting practical utility for healthcare implementers. The technical language employed by all authors, particularly in statistical analyses, suggests a predominant academic orientation. Napitupulu et al. (2021) provide the most direct practitioner-oriented insights, likely influenced by their pandemic context focus.

Methodological biases emerge across the studies, particularly in sampling approaches and data collection methods. Azam et al. (2023) acknowledge potential selection bias in their purposive sampling approach, while Demsash et al. (2024) employ more robust stratified random sampling. Zamberlan & Watanabe (2020) demonstrate innovation in their methodological

approach but face potential institutional bias due to their single-organization focus. Napitupulu et al. (2021) acknowledge limitations in their convenience sampling during pandemic conditions. The cross-sectional nature of all studies introduces temporal bias, with Demsash et al. (2024) particularly noting this limitation in their healthcare context. The researchers' positions within academic institutions may influence their perspective on practical implementation challenges, though Napitupulu et al. (2021) provide valuable insights from crisis conditions.

The studies exhibit varying degrees of cultural and contextual bias in their theoretical frameworks and interpretations. Azam et al. (2023) provide detailed consideration of developing country contexts, while Zamberlan & Watanabe (2020) focus primarily on institutional dynamics within a Brazilian educational setting. Demsash et al. (2024) demonstrate strong sensitivity to resource-limited healthcare environments, though their theoretical framework remains grounded in the UTAUT framework. Napitupulu et al. (2021) offer unique cultural insights from an Indonesian perspective during the pandemic, though their findings may be situation-specific. The collective research would benefit from more diverse perspectives, with Azam et al. (2023) and Demsash et al. (2024) providing the most comprehensive treatment of cultural factors. The studies' funding sources and institutional affiliations could potentially influence research priorities, though all authors generally transparently report these relationships.

Alternative Frameworks and Justification for Choosing UTAUT

Mobile Health Services (MHS) adoption in the healthcare sector has garnered significant attention, primarily due to the transformative potential these technologies hold for enhancing patient care and operational efficiency (Azamet al., 2023). However, the complexities surrounding technology adoption necessitate a robust theoretical framework to elucidate the factors influencing healthcare provider decision-makers' intentions (Demsash et al., 2024). While

UTAUT has been extensively employed in prior studies, alternative frameworks such as UTAUT2, the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Diffusion of Innovations (DOI) offer valuable insights into technology adoption behaviors (Duarte & Pinho, 2019). The selection of UTAUT over these alternative models is justified by its comprehensive nature, as it consolidates various theoretical constructs into a unified framework that addresses individual and contextual factors influencing technology acceptance (Venkatesh et al., 2003).

UTAUT2. UTAUT2 was developed by Venkatesh et al. (2012). UTAUT framework was deliberately selected for this study over its successor, UTAUT2, owing to its foundational robustness and well-established applicability in technology adoption research, particularly within healthcare contexts (Abbad, 2021). The UTAUT framework encapsulates critical constructs such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Threat Appraisal, which have been empirically validated across diverse technological domains, thereby offering a comprehensive lens through which to examine the intricacies of Mobile Health Services (MHS) adoption among healthcare decision-makers (Alqahtani & Erfani, 2021; Paul & Criado, 2020; Sun et al., 2013). While UTAUT2 introduces additional dimensions, namely Hedonic Motivation, Price Value, and Habit, the primary focus of this investigation on decision-makers adoption intentions necessitates a streamlined approach that prioritizes the core determinants of intention and behavior over extraneous factors that may dilute the focus of the study (Demsash et al., 2024). Furthermore, the UTAUT framework's emphasis on social dynamics and contextual influences provides a nuanced understanding of how healthcare provider decision-makers navigate the complexities of adopting innovative technologies, making it particularly relevant for exploring the intricate interdependencies between individual

perceptions and organizational contexts (Abbad, 2021). The prevailing literature further reinforces the decision to employ UTAUT over UTAUT2, which consistently emphasizes the significance of the original constructs in elucidating technology acceptance behaviors, thereby ensuring that the study's findings are anchored in a theoretically sound foundation that resonates with existing scholarly discourse (Alqahtani & Erfani, 2021; Paul & Criado, 2020; Sun et al., 2013). Ultimately, utilizing the UTAUT framework facilitates a rigorous examination of the predictors influencing healthcare decision-makers' adoption intention of MHS and aligns with the overarching aim of contributing to the scholarly body of knowledge.

The Technology Acceptance Model (TAM). TAM, developed by Davis (1989), posits that perceived ease of use and perceived usefulness are primary determinants influencing technology adoption. Although TAM provides a foundational understanding of user acceptance, it has been critiqued for its limited scope, particularly regarding incorporating social influences and external variables (Venkatesh et al., 2003). In contrast, UTAUT encompasses a broader range of constructs, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Threat Appraisal (TA) (Sun et al., 2013). This multidimensional approach enables a more nuanced exploration of how various factors shape healthcare provider decision-makers' intentions to adopt MHS (Zamberlan & Watanabe, 2020). It is particularly relevant in complex healthcare environments where multiple variables converge (Zamberlan & Watanabe, 2020).

Theory of Reasoned Action (TRA). TRA, developed by Fishbein & Ajzen (1975), emphasizes the role of individual attitudes and subjective norms in predicting behavioral intentions. While TRA provides valuable insights into the psychological underpinnings of decision-making processes, it lacks consideration of the specific contextual elements that may

influence technology adoption in healthcare settings (Venkatesh et al., 2003). UTAUT addresses this gap by integrating constructs that account for individual perceptions and organizational support systems, thereby creating a more holistic framework for understanding the adoption of MHS (Venkatesh et al., 2003). This comprehensive nature of UTAUT enables researchers to delve deeper into the complexities of healthcare technology adoption, thereby enriching the academic discourse surrounding this critical area of study (Venkatesh, 2022).

Diffusion of Innovations (DOI) Theory. DOI, developed by Rogers (1995), explores how new technologies are disseminated and adopted within social systems. Although DOI offers valuable insights into innovation diffusion processes, it may not adequately address the specific factors that influence individual decision-makers' intentions to adopt MHS (Venkatesh, 2022). By contrast, UTAUT focuses on individual-level constructs while simultaneously acknowledging the influence of social context, making it a more suitable framework for examining healthcare provider decision-makers' adoption intentions (Venkatesh, 2022). This alignment with the specific nuances of the healthcare sector reinforces the justification for selecting UTAUT as the guiding theoretical framework for this research.

Task-Technology Fit (TTF). TTF framework developed by Goodhue & Thompson (1995) presents another perspective by examining the alignment between the characteristics of a technology and the tasks it is intended to support. TTF posits that a favorable fit between technology and user requirements enhances the likelihood of successful adoption and utilization (Goodhue & Thompson, 1995). This framework is particularly pertinent in healthcare settings, where the specific functionalities of MHS must align with the operational needs of healthcare providers to foster acceptance (Sun et al., 2013). While TTF provides valuable insights into the task-specific dimensions of technology adoption, it lacks the broader social and environmental

context that UTAUT encompasses, reinforcing the justification for UTAUT as the selected framework for this study (Venkatesh, 2022).

Social Cognitive Theory (SCT). SCT, introduced by Bandura (1986), emphasizes the role of observational learning, imitation, and social reinforcement in influencing behavior. In the context of technology adoption, SCT highlights how the behaviors of peers and colleagues can shape individual decisions to adopt new technologies (Alqahtani & Erfani, 2021). This framework is instrumental in understanding the social dynamics within healthcare organizations, particularly in fostering a culture of innovation and support for new technologies (Alqahtani & Erfani, 2021). However, SCT may not adequately address the specific constructs related to technology acceptance, such as Performance Expectancy and Effort Expectancy, which are central to the UTAUT framework (Venkatesh, 2022). Therefore, while SCT provides valuable insights into the social influences on adoption, UTAUT remains the preferred framework due to its comprehensive construct integration (Venkatesh, 2022).

Extended Technology Acceptance Model (TAM2). TAM, developed by (Venkatesh & Davis, 2000), also offers a relevant perspective by incorporating social influence and cognitive instrumental processes into the original TAM framework. TAM2 posits that social influence and perceived ease of use significantly impact users' intentions to adopt technology, particularly in collaborative environments (Venkatesh & Davis, 2000). However, the model focuses primarily on individual perceptions and may not account for the broader contextual factors that UTAUT effectively incorporates (Venkatesh, 2022). By selecting UTAUT, this research will leverage a framework that integrates individual and contextual influences on technology adoption, providing a more holistic understanding of the factors influencing the intention of healthcare provider decision-makers to adopt MHS.

Health Information Technology Acceptance Model (HITAM). HITAM, developed by Kim & Park (2012), explicitly addresses the adoption of health information technologies. HITAM considers factors such as trust, perceived risks, and social influence, reflecting healthcare providers' unique challenges in adopting new technologies (Kim & Park, 2012). While HITAM provides valuable insights into the healthcare context, its narrower focus on health information technologies may limit its applicability to the broader spectrum of MHS. UTAUT's comprehensive approach enables a more thorough examination of the multifaceted factors influencing MHS adoption across various healthcare settings (Sun et al., 2013).

Furthermore, UTAUT's empirical validation across diverse contexts enhances its credibility as a framework for understanding technology adoption (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). Numerous studies have demonstrated the model's robustness in predicting user acceptance in healthcare, education, and various organizational settings. The framework's adaptability to different contexts further supports its selection, allowing for a thorough investigation of the factors influencing healthcare provider decision-makers' intentions to adopt MHS (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024).

The Relationship Between the UTAUT Framework and the Study

The UTAUT framework is intricately aligned with this study, which investigates the factors influencing the adoption intentions of MHS among healthcare provider decision-makers in the United States. By incorporating constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), and Facilitating Conditions (FC), the UTAUT framework provides a comprehensive lens through which the multifaceted dynamics of technology acceptance can be examined (Azam et al., 2023; Sun et al., 2013; Venkatesh, 2022). This framework is particularly relevant as it explores how these constructs interact to shape

decision-makers' behavioral intentions and MHS adoption in a complex healthcare environment increasingly reliant on technology for improved patient care and operational efficiency (Azam et al., 2023). The empirical foundation of UTAUT, grounded in extensive research across various domains, reinforces its applicability to this study, as it has successfully elucidated the factors influencing technology adoption behaviors in settings including healthcare (Al-Rawashdeh et al., 2022; Istepanian, 2022; Ng, 2021; Venkatesh et al., 2012). Thus, the UTAUT framework elucidates the predictors of technology adoption and contextualizes the challenges healthcare provider decision-makers face in adopting MHS.

Moreover, the UTAUT framework facilitates a systematic analysis of the contextual variables influencing healthcare decision-makers' behavioral intention and adoption of MHS, enriching the study's theoretical underpinnings. The UTAUT framework emphasizes the importance of social dynamics and organizational support in technology acceptance, which are vital for the successful integration of MHS (Azam et al., 2023). The framework's emphasis on Performance Expectancy aligns with the study's focus on how perceived benefits influence decision-makers' intentions, as it underscores the critical role that anticipated improvements in patient outcomes and operational efficiency play in driving technology adoption (Azam et al., 2023). Additionally, the construct of Effort Expectancy is particularly pertinent in this context, as it addresses the perceived ease of using MHS, which can significantly impact healthcare providers' decision-makers' willingness to embrace these innovations (Azam et al., 2023). By incorporating these constructs, the findings of the study may generate empirical insights that contribute to the theoretical discourse on technology adoption in healthcare. Thus, the UTAUT framework is a robust foundation for examining the complexities of MHS adoption, providing a

structured approach to understanding the interplay of various factors that shape healthcare decision-makers' behavioral intention and adoption (Azam et al., 2023).

Relationship Between UTAUT and the Problem, Purpose, and the Research Question

The UTAUT framework served as a critical framework in shaping the problem statement for this research by providing a structured lens through which to examine the multifaceted factors influencing healthcare provider decision-makers' adoption of MHS. By delineating the core constructs of PE, EE, SI, SC and FC, UTAUT elucidates the complex interplay of variables that impact technology acceptance in healthcare settings. These constructs will allow a comprehensive understanding of the barriers and facilitators affecting technology adoption, thus directly informing the problem statement focusing on the insufficient understanding of factors that predict MHS adoption among healthcare decision-makers. Furthermore, the emphasis of UTAUT on the significance of contextual factors enabled the formulation of the problem statement that highlights the necessity for empirical research tailored to the specific environment of healthcare providers in the United States. Ultimately, the framework's systematic approach facilitated a robust articulation of the problem statement, aligning it with broader academic discussions on technology adoption in healthcare.

The UTAUT framework was instrumental in shaping the purpose statement of this research by providing a robust theoretical framework to investigate the determinants of healthcare provider decision-makers' adoption of MHS. By leveraging the constructs of PE, EE, SI, SC and FC, the purpose statement was formulated to specifically examine how these variables interact to influence decision-making processes within the healthcare sector. This alignment with UTAUT ensures a comprehensive exploration of the factors affecting MHS adoption and enhances the study's relevance within existing theoretical discourse. By situating

the research within the UTAUT framework, the purpose statement highlights the significance of addressing the complexities inherent in technology adoption, ultimately aiming to contribute valuable insights to the literature and future research.

The UTAUT framework guided the formulation of the research questions by providing a structured framework that delineates the key constructs influencing MHS adoption among healthcare provider decision-makers. By identifying and operationalizing the constructs of PE, EE, SI, FC, and BI, the research questions were crafted to determine the specific relationships and interactions among these variables. Each research question was designed to probe the nuances of how these constructs contribute to decision-makers' adoption of MHS, thereby enhancing the clarity and focus of the investigation. This alignment with UTAUT ensures that the research questions are theoretically grounded and relevant to current issues in healthcare technology integration. Ultimately, the development of the research questions, informed by UTAUT, positions the study to yield critical insights that may inform current academic discourse and future research.

Historical Evolution and Transformation of MHS

The inception of Mobile Health Services (MHS) can be traced back to the rudimentary medical outreach programs of the 1940s, where healthcare providers utilized vehicles to reach underserved populations in remote areas (Matricardi et al., 2020). Initially conceptualized by the World Health Organization (WHO) in 1948, these early mobile health initiatives primarily focused on basic medical care and vaccination programs (Doshmangir et al., 2020). The fundamental principle of bringing healthcare directly to patients, particularly in resource-constrained settings, laid the groundwork for what would eventually evolve into modern MHS (Wood et al., 2019). During this period, mobile health units predominantly operated as

extensions of traditional healthcare facilities, providing essential medical services to rural and isolated communities (Wood et al., 2019). The post-World War II era witnessed a significant expansion of these services, particularly in developing nations (Wood et al., 2019). The primary objective was to address the stark disparities in healthcare accessibility between urban and rural populations (Wood et al., 2019).

A significant and crucial turning point for MHS in the 1960s was highlighted by the early adoption of telecommunications technology despite its developmental stage (Leung & Chen, 2019). The introduction of radio-based medical consultations represented a revolutionary step forward in remote healthcare delivery (Leung & Chen, 2019). This decade witnessed the establishment of more structured mobile health programs, with organizations like Médecins Sans Frontières incorporating mobile units into their humanitarian operations (Leung & Chen, 2019). The concept of telemedicine began to emerge, though limited by the technological capabilities of the era (Bakalar, 2022). The period also saw the development of standardized protocols for mobile health operations, enhancing the efficiency and effectiveness of service delivery (Bakalar, 2022). These advancements laid the crucial foundation for the future digital transformation of MHS.

Significant technological innovations revolutionized the scope and capabilities of MHS in the 1970s and 1980s. The advent of portable medical equipment and diagnostic tools enabled mobile health units to provide more comprehensive care outside traditional healthcare settings (Hernández-Neuta et al., 2019). This era witnessed the integration of computerized systems in mobile health units, albeit in their primitive form (Hernández-Neuta et al., 2019). During this period, the World Health Organization formally recognized MHS as vital to primary healthcare delivery systems (Wood et al., 2019). Developing more sophisticated communication systems

enhanced the coordination between mobile units and base hospitals (Wood et al., 2019). Specialized mobile health services emerged in this decade, including dental care, maternal health, and mental health support (Wood et al., 2019).

Significant advancements in the 1990s fundamentally altered the MHS operational paradigm (Aagja et al., 2023). The term "mHealth" was coined during this period, reflecting the growing integration of mobile telecommunications and multimedia technologies in healthcare delivery (McCoolet al., 2022). The proliferation of cellular networks enabled real-time communication between healthcare providers and patients, revolutionizing remote consultations (McCoolet al., 2022). Advanced diagnostic equipment became increasingly portable, expanding the range of services available through mobile health units (McCoolet al., 2022). The introduction of electronic health records (EHRs) significantly improved patient data management and continuity of care (Tapuria et al., 2021). There was also emergence of the first mobile health applications in this decade, though their functionality was limited compared to modern standards (Sim, 2019).

The early 2000s marked a transformative period with the widespread adoption of smartphones and mobile internet connectivity. The WHO officially defined Mobile Health Services as "medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices" in 2003 (Alanzi et al., 2024). There was an exponential increase in mobile health applications and platforms targeting healthcare providers and patients during this period (Alanzi et al., 2024). Integrating the Global Positioning System (GPS) technology enabled better coordination and deployment of mobile health units in emergencies (Alanzi et al., 2024). The concept of "connected health" emerged, emphasizing the importance of continuous patient

monitoring and data collection (Abdolkhani et al., 2019). The development of cloud computing infrastructure further enhanced the capabilities of MHS by enabling secure data storage and sharing (Idoga et al., 2019).

Between 2010 and 2015, there was unprecedented growth in MHS capabilities, driven by technological advancements and increasing healthcare demands (Agarwal et al., 2020). The proliferation of wearable devices and biosensors revolutionized patient monitoring and data collection capabilities (Agarwal et al., 2020). Mobile health applications became increasingly sophisticated, incorporating artificial intelligence and machine learning algorithms for diagnostic support (Agarwal et al., 2020). Integrating telehealth services with mobile health platforms created comprehensive digital healthcare ecosystems. There were significant improvements in data security and privacy protocols, addressing crucial concerns in mobile healthcare delivery in this era (Agarwal et al., 2020). The emergence of 4G networks enhanced the reliability and speed of mobile health communications (Nasralla et al., 2023).

The years 2015-2020 marked a period of consolidation and standardization in MHS development (Hoque et al., 2020). International organizations established comprehensive guidelines for mobile health implementation and evaluation (Hoque et al., 2020). The integration of blockchain technology began to address data integrity and interoperability issues in MHS (Clim et al., 2019). Advanced analytics capabilities enabled more sophisticated health monitoring and predictive diagnostics (Clim et al., 2019). The development of 5G networks revolutionized real-time medical consultations and remote procedures (Ahad et al., 2020). There was also an increased focus on user experience and accessibility in mobile health applications during this period (Ahad et al., 2020).

The COVID-19 pandemic (2020-2022) catalyzed unprecedented acceleration in MHS adoption and innovation (Omotayo et al., 2024). The global health crisis necessitated the rapid expansion of remote healthcare delivery capabilities, pushing MHS to the forefront of healthcare provision (Omotayo et al., 2024). Telehealth consultations became the norm rather than the exception, driving significant improvements in mobile health platforms and infrastructure (Omotayo et al., 2024). Integrating artificial intelligence and machine learning in mobile health applications reached new heights, enabling more accurate diagnostic support and predictive analytics (Enholmet al., 2022). The pandemic period witnessed the emergence of innovative solutions for remote patient monitoring and contact tracing (Omotayo et al., 2024). This era demonstrated the crucial role of MHS in maintaining healthcare accessibility during global crises (Omotayo et al., 2024).

The current landscape (2023-2025) of MHS represents a convergence of multiple technological innovations and healthcare delivery models (Aagja et al., 2023). Integrating augmented reality and virtual reality technologies is expanding the capabilities of remote medical training and consultations (Aagja et al., 2023). Advanced robotics and drone technology are being incorporated into mobile health delivery systems, particularly for reaching remote areas (Mbunge et al., 2022). The emergence of 6G technology promises further revolutionization of the speed and reliability of mobile health communications (Nasralla et al., 2023). Quantum computing applications are beginning to influence mobile health data analytics and security protocols. The focus on personalized medicine is driving the development of more sophisticated mobile health monitoring and treatment systems (Nasralla et al., 2023).

Looking toward the future (2025 and beyond), MHS continues to evolve with emerging technologies and changing healthcare needs. Integrating quantum computing and advanced AI

systems promises to revolutionize diagnostic capabilities and treatment planning in mobile health applications (Thacharodi et al., 2024). Developments in nanotechnology are expected to enhance remote monitoring and drug delivery systems (Thacharodi et al., 2024). The "Internet of Medical Things" (IoMT) concept is becoming increasingly central to MHS evolution (Naghib et al., 2025). The literature indicates that MHS will become increasingly automated and personalized, leveraging advanced data analytics and artificial intelligence (Naghib et al., 2025). These developments suggest a future where MHS will be even more crucial in global healthcare delivery.

Motivators and Obstacles Associated with the Adoption of MHS

Performance Expectancy (PE) motivates MHS (Azam et al., 2023). Studies by Istepanian (2022) and Niaz & Nwagwu (2023) strongly emphasize that healthcare decision-makers are significantly motivated when they perceive MHS will enhance operational efficiency and patient outcomes. However, Williams & Radnor (2022) presents a contrasting view, suggesting that PE's influence may be moderated by organizational size and resource availability. Rodić et al. (2024) bridge this divergence by proposing that the impact of PE varies across different healthcare contexts and implementation stages. The methodological rigor of these studies varies considerably, with Istepanian's (2022) study demonstrating robust empirical evidence through large-scale surveys, while Williams & Radnor's (2022) conclusions stem from more limited case studies. These methodological differences may partially explain the varying conclusions regarding PE's role in MHS adoption.

Effort Expectancy (EE) emerges as both a potential motivator and obstacle in the literature, with researchers presenting nuanced perspectives on its impact. Paul & Criado (2020) and Sun et al. (2013) argue that perceived ease of use significantly influences adoption

intentions, particularly among healthcare provider decision-makers with limited technological expertise. Conversely, Alqahtani & Erfani (2021) suggest that EE's importance diminishes as users gain experience with similar technologies. Van Biesen et al. (2022) attempt to reconcile these viewpoints by proposing a dynamic model where EE's influence evolves throughout the adoption process. The methodological approaches in these studies demonstrate varying levels of sophistication, with Paul & Criado (2020) utilizing advanced statistical analyses while Alqahtani and Erfani (2021) relied more heavily on qualitative insights. These differences in research design may have contributed to the apparent contradictions in findings regarding EE's role.

Social Influence (SI) presents a complex picture of its role in MHS adoption, with researchers identifying both positive and negative aspects. Duarte & Pinho (2019) emphasize SI's crucial role in shaping adoption intentions through peer influence and professional networks. However, Heavey et al. (2020) caution that excessive social pressure may lead to superficial adoption without meaningful integration. Kosiol et al. (2024) propose that SI's effectiveness depends on organizational culture and leadership support. The varying theoretical frameworks these researchers employ, from social network analysis to organizational behavior theories, contribute to the richness and complexity of understanding SI's impact. The studies demonstrate different methodological strengths, with Duarte & Pinho (2019) research showing strong internal validity while Heavey et al. (2020) research offers superior external validity.

Self-Concept (SC) plays a complex and multifaceted role in adopting MHS. Researchers have highlighted the positive and negative aspects of how an individual's self-perception and identity can influence their intention to use MHS. On the positive side, studies have shown that a strong self-concept, where individuals view MHS as aligned with their values and image, can significantly increase their intention to adopt these technologies. For example, Nadri et al. (2018)

found that healthcare decision-makers with a higher self-concept regarding the importance and relevance of MHS were more likely to intend to adopt them. This suggests that fostering a positive self-concept around the utility and compatibility of MHS with one's professional identity can be a key driver of adoption.

However, the literature also cautions that an overly rigid or inflexible self-concept can hinder MHS adoption (Azam et al., 2023; Nadri et al., 2018). Dwivedi et al. (2016) found that healthcare providers with a strong attachment to traditional practices and a resistance to change were less likely to embrace MHS, even if they recognized its potential benefits. This highlights the need to address both the practical and psychological aspects of self-concept in the context of MHS adoption. The varying theoretical frameworks researchers employ, such as social cognitive theory and technology acceptance models, contribute to the richness of understanding the role of self-concept. Studies by Azam et al. (2023) and Nadri et al. (2018) used quantitative methods to demonstrate the statistical significance of self-concept, while Dwivedi et al. (2016) utilized a more qualitative approach to explore the nuanced, contextual factors shaping self-concept and its influence on MHS adoption.

Facilitating Conditions (FC) motivates MHS adoption (Venkatesh et al., 2003). Research on FC reveals significant variations in how healthcare contexts influence MHS adoption among healthcare decision-makers. Istepanian (2022) and Al-Rawashdeh et al. (2022) emphasize the critical role of organizational infrastructure and technical support in successful adoption. However, Niaz & Nwagwu (2023) highlight that resource constraints in some healthcare settings may limit FC's effectiveness. Rodić et al. (2024) propose that the relationship between FC and adoption success is non-linear, suggesting diminishing returns beyond certain resource thresholds. The methodological approaches vary considerably, with some studies employing

rigorous quantitative analyses while others rely on case studies, potentially explaining some of the divergent findings.

The literature examining Threat Appraisal (TA) demonstrates consensus and disagreement regarding its influence on MHS adoption. Sharma & Gupta (2023) and Ng (2021) agree that security and privacy concerns significantly impact the adoption intention of healthcare decision-makers. However, Al-Rawashdeh et al. (2022) suggest that organizational size and technological maturity may moderate TA's influence. Venkatesh et al. (2012) propose a more nuanced view, arguing that TA's impact varies across different healthcare contexts and user groups. The methodological approaches in these studies range from sophisticated quantitative analyses to in-depth qualitative investigations, contributing to the rich but sometimes contradictory understanding of TA's role. These variations in research methods may partly explain the divergent findings regarding TA's importance in MHS adoption.

An analysis of the interrelationships among these factors reveals complex dynamics that influence MHS adoption among healthcare decision-makers. Sun et al. (2013) and Venkatesh (2022) demonstrate strong correlations between PE and EE, suggesting their synergistic effect on adoption intentions. However, Yang et al. (2024) present evidence of potential conflicts between these constructs in resource-constrained environments. The methodological rigor varies across studies, with some employing advanced statistical techniques while others rely on more descriptive approaches. These differences in research design may contribute to the varying conclusions regarding the relationships between constructs.

The temporal evolution of these constructs' influence on MHS adoption is a significant theme in the literature. Iyanna et al. (2022) and Yang et al. (2024) demonstrate that the relative importance of different constructs changes throughout the adoption process. However, some

researchers question the generalizability of these findings across different healthcare contexts (Nordhoff et al., 2020; Sun et al., 2013). The methodological approaches range from longitudinal studies to cross-sectional analyses, with each offering unique insights but also carrying specific limitations. These variations in research design contribute to the ongoing debate about how these construct influences evolve.

The literature also reveals significant geographical and cultural variations in how these constructs influence MHS adoption among healthcare decision-makers (Choudrie et al., 2020). Studies conducted in different regions demonstrate varying patterns of construct importance, suggesting the need for context-specific approaches to MHS implementation. However, researchers disagree about the extent to which these findings can be generalized across different healthcare systems (Akinnuwesi et al., 2022; Bommer et al., 2022; 2020; Kosiol et al., 2024). The methodological approaches vary considerably, from large-scale international surveys to focused regional studies, contributing to the complex understanding of cultural influences on MHS adoption.

As the literature reflects, integrating emerging technologies with existing healthcare systems presents opportunities and challenges. Researchers demonstrate varying optimism regarding the potential for successful integration, with some emphasizing technological capabilities while others highlighting organizational barriers (Akinnuwesi et al., 2022; Bommer et al., 2022; 2020; Kosiol et al., 2024). The methodological approaches range from technical analyses to organizational case studies, providing diverse perspectives on integration challenges. These variations in research focus and methodology contribute to the ongoing debate about optimal approaches to MHS implementation.

Authority, Audience, and Bias

The scholarly discourse surrounding Mobile Health Services (MHS) adoption, as examined by Azam et al. (2023), Istepanian (2022), and Niaz & Nwagwu (2023), exhibits diverse methodological approaches and varying levels of empirical rigor, warranting careful consideration of source authority and potential biases. Notable distinctions emerge in the methodological robustness, with studies like Istepanian (2022) demonstrating superior empirical validity through large-scale surveys, while others, such as Williams & Radnor (2022) and Paul & Criado (2020), rely on more limited case studies, potentially affecting the generalizability of their conclusions. As identified by Duarte & Pinho (2019) and Heavey et al. (2020), the target audience for these studies predominantly comprises healthcare decision-makers and academic researchers. However, the accessibility and applicability of findings vary significantly across different organizational contexts and healthcare settings. A critical examination reveals potential geographical and contextual biases, as evidenced by Sharma & Gupta (2023) and Ng (2021), showing the predominance of studies from developed healthcare systems, which may limit the applicability of findings to resource-constrained environments. The authors' institutional affiliations and research backgrounds, particularly noted in works by Al-Rawashdeh et al. (2022) and Rodić et al. (2024), suggest a balanced representation of academic and practitioner perspectives. However, some studies may exhibit inherent biases from funding sources or organizational relationships. Furthermore, the temporal distribution of the cited works by Venkatesh et al. (2003, 2012) through recent studies by Kosiol et al. (2024) indicates a contemporary understanding of MHS adoption factors, although the rapid evolution of healthcare technology might necessitate ongoing validation of earlier findings.

The Evolving Landscape of MHS

The literature examining emerging capabilities within MHS reveals complex perspectives on implementation and effectiveness. Thacharodi et al. (2024) emphasize the transformative potential of advanced MHS features in improving healthcare accessibility, particularly in remote areas. However, Williams & Radnor (2022) present evidence suggesting significant disparities in MHS adoption across different healthcare settings, attributing these variations to resource availability and organizational readiness. Putteeraj et al. (2022) bridge these perspectives by proposing a multi-tiered implementation framework that accounts for varying organizational capabilities and resource constraints. Demsash et al. (2024) further contribute to this discourse by highlighting the critical role of healthcare provider training in successful MHS integration. The methodological approaches in these studies demonstrate significant variation, with Thacharodi et al. (2024) employing rigorous quantitative analyses while Williams & Radnor rely more heavily on qualitative case studies. These methodological differences may explain the varying conclusions regarding complex perspectives on the evolving MHS landscape, impact, and implementation challenges.

Wearable MHS Technologies

The integration of wearable technologies with MHS platforms is a significant development area in the literature. Research by Vijayan et al. (2021) highlights the potential of wearable devices to enhance continuous patient monitoring and data collection capabilities. Conversely, Napitupulu et al. (2021) raise concerns about data accuracy and reliability issues associated with consumer-grade wearable devices in clinical settings. Abbad (2021) presents a more nuanced perspective, suggesting that the effectiveness of wearable integration varies significantly across different medical conditions and patient populations. Zamberlan & Watanabe

(2020) contribute valuable insights regarding the technical challenges of integrating diverse wearable devices with existing MHS platforms. The methodological rigor varies considerably among these studies, with some employing sophisticated technical analyses while others focus on practical implementation challenges. These variations in the research approach contribute to the ongoing debate about the role of wearables in MHS evolution.

Blockchain Integration in MHS

The literature analyzing blockchain integration in MHS reveals diverse perspectives on its potential impact and practical implementation challenges. Studies by Rasel et al. (2023) and Dahiya et al. (2024) emphasize blockchain's potential to enhance data security and interoperability within healthcare systems. However, Ghadi et al. (2024) present evidence suggesting significant technical and organizational barriers to widespread blockchain adoption in healthcare settings. Mackey et al. (2019) propose a balanced perspective, acknowledging blockchain's potential benefits while highlighting the need for careful consideration of implementation challenges. Wenhua et al. (2023) contribute valuable insights regarding blockchain integration's scalability and performance implications in MHS. The methodological approaches range from technical feasibility studies to organizational impact assessments, with varying levels of rigor and scope. These differences in research focus and methodology help explain the divergent conclusions regarding blockchain's role in MHS evolution.

Artificial Intelligence (AI) and Machine Learning (ML) in MHS

Integrating artificial intelligence (AI) and machine learning (ML) in MHS is a contentious topic in the literature, revealing complex perspectives on implementation challenges and potential benefits. Khanna et al. (2020) and Reddy et al. (2021) argue that AI/ML integration represents a transformative advancement in healthcare delivery capabilities, particularly in

diagnostic support and predictive analytics. Their research significantly improves clinical decision-making processes and patient outcome predictions through AI-enhanced MHS platforms. Conversely, Albahri et al. (2023) raise concerns about the practical challenges of implementing these technologies in real-world healthcare settings, highlighting issues related to data quality, algorithm bias, and integration with existing workflows. Ostherr (2022) presents a more nuanced perspective through a longitudinal analysis, suggesting that AI/ML benefits vary significantly across healthcare contexts and specialties.

Ostherr (2022) contributes valuable insights regarding the technical requirements for successful AI/ML integration, emphasizing the importance of robust data infrastructure and standardized protocols. The research identifies critical success factors for AI implementation, including data quality management and algorithmic validation processes. Zając et al. (2023) further enrich this discourse through their comparative analysis of AI adoption patterns across healthcare institutions, revealing how organizational readiness and technical capabilities influence implementation outcomes. Demsash et al. (2024) provide additional perspectives through their investigation of AI-enhanced clinical workflows, demonstrating both the potential benefits and practical challenges of implementation.

Security Protocols in MHS

The evolution of security protocols in MHS demonstrates both areas of consensus and significant disagreement among researchers. Zhang et al. (2023) and Venkatesh (2022) emphasize the critical importance of developing adaptive security frameworks that can respond to emerging threats while maintaining system usability. Their research presents evidence of successful security implementations that balance protection with accessibility. However, Rodić et al. (2024) highlight significant challenges in maintaining robust security measures without

compromising system performance and user experience. Istepanian (2022) contributes valuable insights through their analysis of emerging security threats and mitigation strategies, emphasizing the need to adapt security protocols continuously.

Data Analytics Capabilities within MHS

The literature examining data analytics capabilities within MHS reveals evolving perspectives on processing requirements and analytical methodologies. Niaz & Nwagwu (2023) present evidence of advanced analytics improving clinical decision-making processes through real-time data processing and predictive modeling. Their research demonstrates significant advancements in processing capabilities and analytical sophistication. However, Al-Rawashdeh et al. (2022) highlight challenges in implementing advanced analytics in resource-constrained settings, emphasizing the need for scalable solutions. Napitupulu et al. (2021) provide additional perspectives through their investigation of analytics implementation strategies, revealing how different organizational contexts necessitate varied approaches to data analysis.

Cloud Computing Integration in MHS

There are diverse perspectives on implementation strategies and security considerations in cloud computing integration into MHS. Darwish et al. (2019) and Tahir et al. (2020) present evidence of successful cloud implementations enhancing system scalability and accessibility. Their research demonstrates how cloud-based solutions can improve resource utilization and data accessibility across healthcare networks. However, Williams & Radnor (2022) highlight significant challenges in ensuring data privacy and compliance in cloud-based healthcare systems. Van Biesen et al. (2022) provide additional insights through their analysis of cloud implementation strategies, revealing how different organizational contexts influence adoption approaches.

Augmented Reality (AR) and Virtual Reality (VR) Technologies in MHS

Integrating augmented reality (AR) and virtual reality (VR) technologies in MHS represents an emerging frontier in healthcare delivery. Cao et al. (2019) and Goh et al. (2021) present evidence of successful AR implementation in surgical planning and medical training applications, demonstrating significant improvements in procedural accuracy and learning outcomes. However, McKnight et al. (2020) identify substantial challenges in implementing these technologies within existing healthcare workflows, particularly regarding hardware limitations and user adaptation. Arjomandi Rad et al. (2022) provide critical insights by evaluating VR applications in patient care, revealing promising outcomes and practical implementation barriers. Zhang et al. (2023) further enrich this discourse by examining the cost-benefit implications of AR/VR integration in different healthcare contexts.

Hardware Requirements and Performance Optimization

The evolution of mobile device capabilities for healthcare applications reveals complex considerations regarding hardware requirements and performance optimization (Yang et al., 2024). Iyanna et al. (2022) and Yang et al. (2024) demonstrate how advances in mobile processor capabilities have enabled more sophisticated clinical applications in MHS, particularly in diagnostic imaging and real-time monitoring. However, Williams & Radnor (2022) highlight ongoing challenges ensuring consistent performance across different device platforms and operating systems. Van Biesen et al. (2022) contribute valuable perspectives by analyzing hardware requirements for clinical applications, emphasizing the need for standardized performance benchmarks.

Integrating Edge Computing Capabilities in MHS

The development of edge computing capabilities in healthcare settings is a critical advancement in MHS evolution. Kong et al. (2022) and George et al. (2023) present evidence of edge computing enhancing real-time data processing capabilities, particularly in resource-intensive applications such as medical imaging analysis. However, Chang et al. (2021) identify significant challenges in implementing edge computing solutions within existing healthcare infrastructure. Napitupulu et al. (2021) provide insights into the practical considerations of edge computing deployment, emphasizing both technical and organizational factors. Rodić et al. (2024) further examine the impact of edge computing on healthcare delivery models, revealing both opportunities and implementation challenges.

Integration of 5G Technology in MHS

Integrating 5G technology in healthcare applications demonstrates transformative potential in enabling advanced MHS capabilities. Peralta-Ochoa et al. (2023) Suleiman & Adinoyi, (2023) present evidence of 5G networks enabling new possibilities in remote patient monitoring and MHS applications. Their research demonstrates significant improvements in data transmission reliability and latency reduction. However, Yaacoub & Alouini (2020) highlight challenges in ensuring consistent 5G coverage across different healthcare settings, mainly rural areas. Oughton et al. (2019) contribute valuable insights through their 5G implementation strategies analysis, emphasizing the need for comprehensive infrastructure planning.

Authority, Audience, and Bias

The scholarly discourse surrounding Mobile Health Services (MHS) demonstrates diverse methodological approaches and perspectives, with researchers exhibiting varying degrees of authority and potential in their investigations. Thacharodi et al. (2024), Williams & Radnor

(2022), and Putteeraj et al. (2022) present contrasting viewpoints on implementation challenges, with their methodological rigor varying from quantitative analyses to qualitative case studies, potentially influencing their conclusions and reflecting their institutional biases. The work of Vijayan et al. (2021), Napitupulu et al. (2021), and Abbad (2021) on wearable technologies reveals distinct audience considerations, with some research targeting technical practitioners while others focus on healthcare administrators, leading to different emphases in their findings. Khanna et al. (2020), Reddy et al. (2021), and Albahri et al. (2023) demonstrate varying levels of technical expertise in their analysis of AI/ML integration, with their authority particularly evident in their detailed examination of implementation challenges and potential benefits. Zhang et al. (2023), Venkatesh (2022), and Rodić et al. (2024) approach security protocols from different institutional perspectives, revealing how their organizational affiliations might influence their emphasis on either protection or accessibility. Finally, the research by Kong et al. (2022), George et al. (2023), and Peralta-Ochoa et al. (2023) on edge computing and 5G technology integration show a clear technical bias toward infrastructure development, potentially overlooking broader socio-economic implications in healthcare settings.

The Research, Prospects, and Technology Adoption Issue of MHS

The limitations of conventional healthcare delivery methods and emerging mobile technologies drove the research and advancement of MHS. The literature revealed the MHS technology adoption issue among healthcare decision-makers despite its notable benefit in overcoming the deficiencies of traditional healthcare delivery and emerging health technologies (Istepanian, 2022; Niaz & Nwagwu, 2023). More importantly, the lack of identification of factors that adversely impact MHS adoption prevents healthcare provider decision-makers from making effective mobile health technology decisions (Rodić et al., 2024). The existing healthcare

delivery systems failed to address rapidly evolving patient needs, resulting in reduced operational efficiency and compromised patient engagement (Van Biesen et al., 2022). Healthcare enhancement through mobile technologies attracted significant attention from researchers (Williams & Radnor, 2022). The rapid advancement of machine learning, cloud computing, and Internet of Things (IoT) has propelled healthcare technologies toward automation and intelligent decision-making (Heavey et al., 2020). This technological evolution has fundamentally transformed how healthcare services are delivered and managed across various settings (Paul & Criado, 2020).

Mobile Health Services (MHS) represents a critical strategic initiative for modernization and operational optimization in contemporary healthcare settings (Al-Rawashdeh et al., 2022). Mobile technologies have been driving innovation and revolution in healthcare, fundamentally changing service delivery paradigms (Duarte & Pinho, 2019). These technologies have increased usage in healthcare settings to enhance patient care delivery as a service optimization tool (Williams & Radnor, 2022). Healthcare technologies encompass two important aspects: service delivery and patient engagement, both playing fundamental roles in MHS applications (Shakibaei et al., 2024). Integrating MHS has demonstrated significant potential for improving healthcare outcomes and operational efficiency (Alqahtani & Erfani, 2021). Research indicates that MHS applications can significantly enhance patient engagement and treatment adherence (Sharma & Gupta, 2023). Furthermore, these technologies facilitate real-time monitoring and intervention capabilities previously unavailable in traditional healthcare settings (Sun et al., 2013).

Mobile Health Services (MHS) technology represents a broader application of digital health that can build healthcare delivery systems by learning and adapting over time based on

experience (Yang et al., 2024). These systems have demonstrated remarkable prospects in enhancing patient engagement and improving healthcare outcomes across various clinical settings (Venkatesh, 2022). The categorization of MHS technologies encompasses telemedicine, remote monitoring, patient portals, and mobile applications, each serving distinct yet interconnected purposes (Rodić et al., 2024). Implementation of these technologies has shown significant potential for transforming healthcare delivery models and patient care paradigms (Williams & Radnor, 2022). Research indicates that MHS-based service delivery and patient engagement represent novel features of next-generation healthcare systems (Iyanna et al., 2022). The integration of these technologies has facilitated improved access to healthcare services and enhanced patient-provider communication (Heavey et al., 2020). Moreover, these advancements have enabled healthcare providers to deliver more personalized and efficient care services (Kosiol et al., 2024).

Mobile Health Services (MHS) technology integration represents an interdisciplinary convergence of medical science, computer science, statistics, and digital health innovations (Van Biesen et al., 2022). Implementing MHS has fundamentally transformed interactions between health systems and human needs, creating new care delivery paradigms (Paul & Criado, 2020). MHS applications have demonstrated remarkable capabilities in processing patient data and understanding its implications, trends, and outcomes (Duarte & Pinho, 2019). These technologies have unique advantages in patient engagement, healthcare delivery, outcome monitoring, and service optimization (Sharma & Gupta, 2023). Research conducted by Van Biesen et al. (2022) extensively reviewed the usage of MHS techniques in enhancing patient care delivery across various healthcare settings. The integration of these technologies has facilitated more efficient and effective healthcare service delivery models (Al-Rawashdeh et al., 2022). Furthermore, these

advancements have enabled healthcare providers to implement more sophisticated and comprehensive patient care strategies (Williams & Radnor, 2022).

Researchers have determined that next-generation healthcare delivery systems must provide mobile accessibility alongside various healthcare functionalities (Istepanian, 2022; Niaz & Nwagwu, 2023). Integrating multiple delivery methods, including telemedicine, remote monitoring, and patient engagement systems, has become increasingly critical in modern healthcare settings (Williams & Radnor, 2022). Contemporary healthcare technologies encompass tools such as electronic health records, patient portals, and mobile applications, each serving specific yet interconnected purposes (Heavey et al., 2020). Despite the notable prospects in healthcare enhancement, factors predicting the adoption intention of MHS by healthcare decision-makers have not attracted proportionate research or development attention from academia (Rodić et al., 2024). Various technology models, including TAM, UTAUT, and UTAUT2, have been employed to investigate factors impacting MHS adoption (Sun et al., 2013; Yang et al., 2024; Venkatesh, 2022). These investigations have revealed complex interactions between technological capabilities and factors that predict acceptance by decision-makers (Paul & Criado, 2020). Additionally, research has highlighted the critical role of organizational and environmental factors in successful MHS implementation (Kosiol et al., 2024).

The development lifecycle of MHS encompasses comprehensive phases, including requirement gathering, analysis, design, implementation, testing, deployment, and maintenance (Al-Rawashdeh et al., 2022). This process demands rigorous assessment and selection of technologies, alongside careful design of system functions, architectures, modules, user interfaces, data communication, and integration of sub-systems (Paul & Criado, 2020). Healthcare decision-makers must meticulously plan and evaluate feasibility from multiple

perspectives, including technology, cost, schedule, and patient satisfaction (Kosiol et al., 2024). The implementation process requires careful consideration of various stakeholder needs and expectations (Sharma & Gupta, 2023). Technical infrastructure requirements must be balanced against practical implementation constraints and organizational capabilities (Van Biesen et al., 2022). System integration challenges often necessitate innovative solutions and adaptive implementation strategies (Williams & Radnor, 2022). Furthermore, ongoing maintenance and updates require sustained commitment and resource allocation (Heavey et al., 2020).

The ethical concerns surrounding MHS, particularly regarding privacy, security, and data protection, represent critical factors in the decision-making process of mobile health technology development (Sharma & Gupta, 2023). Healthcare leaders must carefully consider the preferences and perspectives of various potential MHS technology users throughout the implementation process (Williams & Radnor, 2022). Integrating these technologies necessitates a comprehensive understanding of user needs, expectations, and potential barriers to adoption (Van Biesen et al., 2022). Security protocols and data protection measures must be rigorously developed and implemented to ensure patient confidentiality and regulatory compliance (Al-Rawashdeh et al., 2022). Healthcare organizations must establish robust frameworks for managing and protecting sensitive patient information (Heavy et al., 2020). Implementing these protective measures requires significant resource allocation and ongoing monitoring (Paul & Criado, 2020). Additionally, healthcare providers must maintain transparent communication with stakeholders regarding data usage and protection protocols (Kosiol et al., 2024).

The literature has not sufficiently identified the comprehensive factors impacting MHS adoption among healthcare decision-makers (Rodić et al., 2024). The lack of detailed understanding of adoption factors has created significant challenges in designing effective

implementation strategies (Shakibaei et al., 2024). Healthcare organizations struggle to assess and select appropriate system functionalities, modules, user interfaces, and interoperability mechanisms (Williams & Radnor, 2022). The absence of comprehensive adoption models has hindered the development of effective training and support programs (Istepanian, 2022). Implementation challenges are further complicated by varying levels of technological literacy among healthcare provider decision-makers (Niaz & Nwagwu, 2023). These obstacles have significantly impacted the successful integration of mobile health technologies in various healthcare settings (Paul & Criado, 2020).

The insufficient understanding of adoption factors has resulted in inconsistent implementation despite the potential benefits of MHS in enhancing healthcare delivery and patient outcomes (Istepanian, 2022; Niaz & Nwagwu, 2023). Healthcare leaders face significant challenges in developing and executing effective MHS integration strategies (Williams & Radnor, 2022). The complexity of healthcare environments requires careful consideration of multiple stakeholder perspectives and needs (Van Biesen et al., 2022). Implementation success often depends on effectively addressing technical and human factors in the adoption process (Sharma & Gupta, 2023). Organizations must carefully balance innovation with practical implementation constraints (Heavy et al., 2020). Developing comprehensive adoption strategies requires significant resource allocation and organizational commitment (Al-Rawashdeh et al., 2022). Furthermore, successful implementation demands ongoing assessment and adjustment of adoption approaches (Paul & Criado, 2020).

Healthcare leaders and stakeholders continue to encounter difficulties in making effective MHS integration and development decisions to satisfy the needs of providers and patients (Paul & Criado, 2020). Healthcare environments' complexity necessitates carefully considering

multiple factors in technology adoption decisions (Williams & Radnor, 2022). Healthcare organizations must develop comprehensive strategies for addressing technical and organizational challenges (Van Biesen et al., 2022). Healthcare provider decision-makers must focus on immediate and long-term adoption goals (Heavy et al., 2020). Developing effective implementation strategies demands significant organizational resources and commitment (Al-Rawashdeh et al., 2022). Finally, successful adoption requires ongoing assessment and refinement of implementation approaches (Kosiol et al., 2024).

Summary

The literature review examined the factors associated with healthcare provider decision-makers' adoption of Mobile Health Services (MHS) through the Unified Theory of Acceptance and Use of Technology (UTAUT) theoretical lens. The historical evolution of MHS revealed a trajectory from basic mobile medical units in the 1940s to sophisticated digital health platforms incorporating artificial intelligence, blockchain, and edge computing capabilities in the contemporary healthcare landscape. The review demonstrated significant convergence regarding the fundamental role of UTAUT constructs, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), and Facilitating Conditions (FC) in predicting Behavioral Intentions (BI) and Adoption of MHS (AD) among healthcare provider decision-makers. The evolving landscape of MHS highlighted substantial advancements in technical capabilities, though implementation challenges persist across various healthcare settings. Notable divergence emerged in the literature regarding the relative importance of FC and SI across different organizational contexts and geographical locations. At the same time, the temporal evolution of these constructs' influence on MHS adoption represented a significant area of scholarly discussion. The integration of emerging technologies with existing healthcare systems

presented both opportunities and challenges, with researchers demonstrating varying degrees of optimism regarding successful implementation strategies.

Several gaps in the literature substantiated the need for this study's methodological approach to investigating MHS adoption among healthcare provider decision-makers in the United States. This study is an exploratory, theory-informing investigation rather than a predictive or generalizable analysis. The limited empirical investigation into the dynamic interplay between organizational readiness and MHS adoption success highlighted the need for more quantitative analysis of implementation sustainability. The complex relationship between technical infrastructure requirements and healthcare provider decision-makers' MHS adoption remained inadequately explored, particularly concerning emerging technologies such as artificial intelligence and blockchain integration. These identified gaps justified the proposed quantitative correlational design to examine the association between UTAUT constructs and MHS adoption. The methodological approach will address these gaps through statistical analysis, as detailed in the subsequent chapter on research methodology and design.

Chapter 3: Research Method

The problem addressed in this study was the insufficient understanding of the factors associated with the adoption of MHS among healthcare provider decision-makers in the US, resulting in inconsistent adoption despite its potential benefits. (Istepanian, 2022; Niaz & Nwagwu, 2023). The literature reveals that healthcare leaders face challenges in developing and executing effective MHS integration strategies (Williams & Radnor, 2022). Various theoretical frameworks, including the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and UTAUT2, have been adopted to investigate factors impacting MHS adoption (Sun et al., 2013; Venkatesh, 2022; Yang et al., 2024). However, there is a notable absence of sufficient literature specifically examining which factors are associated with the adoption of MHS by healthcare provider decision-makers (Rodić et al., 2024). Healthcare decision-makers struggle with limited insight into the factors associated with MHS adoption (Rodić et al., 2024). Consequently, healthcare provider decision-makers face challenges in assessing and selecting appropriate system functionalities, modules, user interfaces, and interoperability mechanisms within MHS implementations (Kosiol et al., 2024).

The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States. A quantitative methodology and correlational design were adopted for this study. The quantitative methodology is appropriate for systematically examining the relationships between variables and testing hypotheses (Varpio et al., 2020). Correlational design is suitable for investigating the relationships between independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions) and the dependent

variable (Behavioral Intention and Adoption of MHS) without manipulating the variables (Reed et al., 2021). The quantitative methodology and correlational design have been extensively utilized to examine factors influencing technology adoption in healthcare settings (Azam et al., 2023; Demsash et al., 2024; Kosiol et al., 2024; Rodić et al., 2024; Yang et al., 2024).

The UTAUT framework was adopted to investigate the factors associated with healthcare provider decision-makers' adoption intentions of Mobile Health Services (MHS). The researched factors will include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), Facilitating Conditions (FC), and Behavioral Intention (BI) (Azam et al., 2023). The BI and MHS Adoption (AD) were measured as the dependent variable. Data was collected using self-administered questionnaires developed by Azam et al. (2023) and distributed to purposively selected healthcare decision-makers in Information Technology departments across the United States. Each measurement item employed a Likert-scale format to represent increasing degrees of agreement with the statements (Tanujaya et al., 2022). The target population consisted of healthcare provider decision-makers purposively sampled from the United States. G*Power3 analysis was used to determine the minimum sample size of 98 participants required for this study (Chaokromthong & Sintao, 2021). Data analysis procedures encompassed data cleaning, reliability testing through Cronbach's alpha, validity assessment, descriptive statistical analysis, data visualization, and statistical hypothesis testing. The researcher conducted assumption testing, including assessments of multicollinearity, normality, and outliers. Hierarchical multiple regression models and t-statistics were used to test the hypotheses (Reed et al., 2021). The researcher maintained methodological standards while acknowledging relevant assumptions, limitations, delimitations, and ethical considerations in the research process.

Research Methodology and Design

This researcher used a quantitative method to investigate the factors associated with healthcare provider decision-makers' adoption of Mobile Health Services (MHS) through the UTAUT framework. A quantitative method focuses on utilizing objective measurements, computational techniques, and numerical, mathematical, and statistical approaches to analyze data collected through self-administered questionnaires (Aithal & Aithal, 2020). The objective of this quantitative method is to determine the association between the independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions) and the dependent variable (Behavioral Intention and MHS Adoption). In this quantitative research, hypotheses were proposed, and sufficient sample data were collected from purposefully selected healthcare decision-makers in Information Technology departments across the United States, measured using Likert-scale formats, and analyzed through correlational analysis, hierarchical multiple regression models, and t-statistics. The quantitative approach is particularly applicable to quantify the factors influencing technology adoption in healthcare settings, as evidenced by recent studies (Azam et al., 2023; Demsash et al., 2024; Kosiol et al., 2024; Rodić et al., 2024; Yang et al., 2024). The methodology enables systematic examination of associations between variables and hypothesis testing, making it suitable for investigating technology adoption patterns in healthcare environments (Varpio et al., 2020).

Quantitative Methodology

Adopting a quantitative methodology to investigate factors associated with healthcare provider decision-makers' adoption intentions for Mobile Health Services (MHS) aligns with the study's problem of insufficient understanding of these factors. The nature of quantitative research enables examining association between specific UTAUT variables and MHS adoption through

statistical analysis and hypothesis testing (Hu et al., 2020). Quantitative methodology can measure and analyze numerical data, which makes it suitable for addressing the interplay of factors associated with MHS adoption decisions in healthcare settings (Hu et al., 2020). The quantitative approach facilitates standardized data collection through structured questionnaires, allowing for consistent measurement across the selected sample population of healthcare decision-makers (Hollin et al., 2020). The statistical strength inherent in quantitative research supports identifying an association between variables, directly addressing the knowledge gap in MHS adoption factors (Venkatesh, 2022). Furthermore, the quantitative methodology is objective, and its systematic measurement aligns with the healthcare industry's evidence-based decision-making paradigm (Brocklehurst et al., 2021).

The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States. Quantitative research provides the analytical framework required to examine the association of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), and Facilitating Conditions (FC) on Behavioral Intentions (BI) and MHS Adoption (AD) (Azam et al., 2023). The methodology enables developing and testing specific hypotheses regarding the relationships between these variables, contributing to the existing body of knowledge in healthcare technology adoption (Alaiad et al., 2019). This approach will position the study as a theory-informing contribution that provides context-specific insights into technology adoption in healthcare settings.

The structured nature of quantitative research allows for the collection and analysis of data from a purposively selected sample of healthcare provider decision-makers across the

United States (Venkatesh, 2022). The methodology's capacity for statistical analysis supports identifying patterns and associations that may inform future research (Venkatesh, 2022).

The research questions on the association between UTAUT variables and MHS adoption are inherently quantitative, requiring statistical analysis for meaningful answers. Quantitative methodology is used for measurement and statistical testing, which aligns with the need to determine the extent of the association between independent and dependent variables (Fey et al., 2023). The quantitative approach enables the operationalization of abstract concepts into measurable variables through validated instruments and scales (Venkatesh, 2022). The methodology supports the examination of multiple variables simultaneously, allowing for an understanding of their collective association with adoption intentions (Rodić et al., 2024). Additionally, quantitative methodology enables the assessment of direct and indirect associations between variables, providing a nuanced understanding of the adoption decision process (Rodić et al., 2024).

Quantitative methodology alignment with existing theoretical frameworks in technology adoption research strengthens its appropriateness for this study (Azam et al., 2023; Demsash et al., 2024; Kosiol et al., 2024; Rodić et al., 2024; Yang et al., 2024). The approach enables the testing and validation of established theoretical constructs within the specific context of healthcare provider decision-makers and MHS adoption. The methodology facilitates the comparison of findings with previous research. The quantitative approach supports examining moderating and mediating effects that may influence the relationships between variables (Yang et al., 2024). Quantitative methodologies and statistical analyses enable the investigation of complex relationships among multiple variables simultaneously (Yang et al., 2024). The approach also allows for identifying potential gaps in existing theoretical frameworks,

contributing to advancing technology adoption theory in healthcare contexts (Yang et al., 2024). The findings were intended to contribute to the scholarly discourse by offering exploratory, theory-informing evidence that may guide future research employing probability-based sampling or alternative methodological approaches.

Qualitative Methodology

The consideration of alternative methodological approaches, mainly qualitative and mixed methods, revealed several limitations that rendered them less suitable for investigating the factors associated with healthcare provider decision-makers' adoption of MHS. While qualitative methodologies could provide rich, descriptive insights into individual decision-makers' experiences and perceptions through interviews or focus groups, they would fail to quantify the relative importance and statistical significance of UTAUT variables in predicting adoption of MHS across a large population (Thompson et al., 2021). Furthermore, the time-intensive nature of qualitative data collection and analysis would restrict the sample size, potentially compromising the statistical power needed to draw meaningful conclusions about association relationships (Hays & McKibben, 2021). The interpretive nature of qualitative analysis might introduce researcher bias in identifying and categorizing adoption factors, potentially reducing the reliability and replicability of findings (Mackieson et al., 2019). Additionally, the absence of standardized measurement tools in qualitative approaches would make comparing findings with existing quantitative studies in healthcare technology adoption literature challenging (De Block & Vis, 2019).

Mixed Methodology

Mixed methods approaches, while offering the potential benefits of both quantitative and qualitative insights, presented significant practical and methodological challenges that made

them less appropriate for this study. The complexity of implementing both quantitative and qualitative components would substantially increase the resource requirements and timeline for completion, potentially compromising the study's feasibility within the prescribed doctoral research timeframe. Integrating qualitative and quantitative data analysis would introduce additional methodological complexity, potentially diluting the focus on establishing clear predictive relationships between UTAUT variables and MHS adoption (Dawadi et al., 2021). The potential discrepancies between qualitative and quantitative findings might create interpretive challenges, making it difficult to draw definitive conclusions about the factors influencing MHS adoption (Venkatesh, 2022). Mixed methods would require healthcare decision-makers to participate in surveys and interviews, potentially reducing participation rates due to time constraints and professional commitments (Dawadi et al., 2021). Furthermore, the additional complexity of mixed methods design might introduce confounding variables that could obscure the direct relationships between UTAUT variables and adoption intentions (Dawadi et al., 2021).

Correlational Design

The correlational design aligns closely with the study's problem of insufficient understanding of factors associated with Mobile Health Services (MHS) adoption among healthcare provider decision-makers in the United States. This design enables an examination of associations between the UTAUT variables without necessitating experimental manipulation, which is important given the complex nature of healthcare technology adoption processes (Magsamen-Conrad et al., 2020). The design's non-experimental nature accommodates the real-world context in which healthcare decision-makers operate, allowing for the natural observation of variable interactions without artificial constraints. The correlational approach facilitates the

investigation of multiple variables simultaneously, including Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions, which is essential for comprehensively addressing the identified gap in the literature (Nwagwu, 2023). Furthermore, the correlational design is used to quantify the strength of associations between variables and directly address the problem of inadequate understanding of the associated factors (Mohajan, 2020).

The purpose of the study, which focused on investigating and determining the association between UTAUT variables and MHS adoption among healthcare decision-makers, is supported by the correlational capabilities of the design. The design enables the researcher to examine the strength and direction of relationships between UTAUT variables and Behavioral Intention (BI) and MHS Adoption (AD), providing quantifiable insights that directly fulfill the purpose of this study. The correlational approach allowed the identification of association while controlling for potential confounding variables such as gender, age, and experience, enhancing the study's contribution to the literature and future research (Azam et al., 2023; Venkatesh, 2003). The design is used to analyze multiple variables simultaneously, aligning with the UTAUT framework's comprehensive nature (Venkatesh, 2022). The methodology facilitates examining both direct and indirect relationships between variables, providing a nuanced understanding of adoption factors (Mohajan, 2020). Additionally, the correlational design can be used to establish association models that align with the study's purpose of enriching the existing body of knowledge in healthcare technology adoption by offering exploratory, theory-informing evidence that may guide future research employing probability-based sampling or alternative methodological approaches (Mohajan, 2020).

In addressing the research questions, the correlational design provides a framework for examining the association between each UTAUT variable, BI, and AD. The design enabled the researcher to quantitatively assess the extent to which each independent variable is associated with the dependent variables, directly answering the research questions regarding association (Mohajan, 2020). The design allowed testing specific hypotheses about the association between each UTAUT component and MHS adoption, providing clear, empirical evidence in the context of the sample (Istepanian, 2022). The correlational approach facilitated the examination of potential moderating effects, adding depth to the understanding of variable relationships (Istepanian, 2022). The statistical procedures of the design enabled the researcher to determine the significance and magnitude of association, providing answers to the research questions (Istepanian, 2022).

Descriptive Design

The descriptive research design, while valuable for providing detailed observations and documentation of phenomena, would have been inadequate for addressing the primary objectives of this investigation into Mobile Health Services (MHS) adoption factors. The descriptive approach's primary limitation lies in its inability to establish associations between the UTAUT variables and MHS adoption, which is fundamental to the purpose of this study (Mõttus et al., 2020). While descriptive research could offer rich contextual information about healthcare provider decision-makers' current perceptions and experiences with MHS, it would fail to quantify the strength and significance of relationships between the variables. Moreover, descriptive research focuses on documenting existing conditions, but systematic variable analysis is not necessary to support testing specific hypotheses regarding predictive relationships (Doyle et al., 2020). The descriptive approach, which emphasizes detailed observation and

documentation, would not facilitate the statistical analyses required to examine multiple variables simultaneously (Doyle et al., 2020). Additionally, descriptive design is limited in controlling for confounding variables would compromise the requirement to isolate the specific effects of individual UTAUT components on MHS adoption (Doyle et al., 2020).

Experimental Design

The experimental design, despite its robustness in establishing causality, presents several significant limitations that make it unsuitable for investigating MHS adoption factors in healthcare settings (Siedlecki, 2020). The artificial manipulation of variables required in experimental designs would disrupt the natural decision-making processes of healthcare provider executives, potentially compromising the validity of the findings (Siedlecki, 2020). The random assignment of participants to control and treatment groups would be impractical and potentially unethical, given healthcare decision-makers' professional positions and responsibilities (Azam et al., 2023). Furthermore, the controlled environment necessary for experimental research would fail to capture the complex interplay of organizational, social, and technological factors that influence real-world technology adoption decisions (Venkatesh, 2022). The requirement for strict variable manipulation in experimental design would not align with the objective of the study of examining naturally occurring associations between UTAUT variables and adoption intentions (Venkatesh, 2022). The temporal and resource constraints associated with experimental manipulation would also limit the study's ability to examine multiple variables simultaneously.

Quasi-experimental Design

The quasi-experimental design, while offering some advantages over pure experimental approaches, would still present substantial limitations for this research into MHS adoption factors. The quasi-experimental approach's reliance on naturally occurring groups or pre-existing

conditions would not adequately address the need to examine association between UTAUT variables and adoption intentions (Gopalan et al., 2020). While this design might accommodate some real-world constraints, it would still introduce artificial controls that could distort the natural decision-making process for technology adoption in healthcare settings (Gopalan et al., 2020). The quasi-experimental design, with limited control over extraneous variables, would make it difficult to isolate the specific effects of individual UTAUT components on adoption intentions (Hu et al., 2020). The temporal sequence requirements of quasi-experimental research would also pose practical challenges for studying technology adoption decisions, which often involve complex, non-linear processes (Istepanian, 2022).

Population and Sample

The population for this quantitative correlational study encompasses purposively selected healthcare provider decision-makers across Information Technology departments in the United States, representing an important demographic responsible for technological implementations within healthcare organizations. These decision-makers hold positions of authority in determining the adoption and integration of Mobile Health Services (MHS) within their respective healthcare institutions, making them important stakeholders in advancing healthcare delivery systems (Sim, 2019). The target population explicitly includes individuals directly involved in technology adoption decisions, system functionality assessments, and implementation strategies within their healthcare organizations and are at least eighteen years old. The target population must have a minimum associate degree and at least three years of experience as decision-makers. According to the research methodology outlined, these decision-makers will be purposively sampled from various healthcare institutions across the United States (Iliyasu & Etikan, 2021). The population characteristics align with the objective of the study of

investigating the association of UTAUT variables with MHS adoption intentions, focusing on individuals with technical understanding and administrative authority. The population size was determined using G*Power3, which indicated a minimum sample size of 98 participants to achieve statistical significance.

Purposive selection was appropriate for this study because the research required participants with direct experience and responsibility in mobile health-related decision-making, ensuring that the data reflected informed, contextually grounded perspectives. This method enabled the study to explore how UTAUT constructs manifest among actual decision-makers, generating insights that would not have been accessible through a general population sample. However, a key limitation of purposive selection is that it restricts the ability to generalize findings beyond the specific group studied, as the sample does not represent the broader population of U.S. healthcare provider decision-makers. Despite this limitation, purposive sampling ensured that the conclusions drawn from this study were grounded in the lived experiences of knowledgeable professionals, supporting the exploratory and theory-informing aims of the research.

The selected population demonstrates several key characteristics that make it suitable for investigating MHS adoption factors. These include their professional expertise in healthcare technology implementation and decision-making authority within their organizations (Sim, 2019). These healthcare provider decision-makers are responsible for evaluating and selecting appropriate system functionalities, modules, user interfaces, and interoperability mechanisms within MHS implementations, making their perspectives particularly valuable for understanding adoption factors (Sim, 2019). The population's professional responsibilities encompass strategic technology planning, implementation oversight, and resource allocation decisions, providing

insights into the factors influencing MHS adoption (Sim, 2019). The demographic distribution of the population spans various healthcare settings across the United States, ensuring diverse perspectives on technology adoption challenges and opportunities. The population's involvement in Information Technology departments ensures familiarity with technological innovations and implementation challenges, making their responses particularly relevant to the objectives of this study (Sim, 2019).

Appropriateness of the Population to Study's Problem, Purpose, and Research Questions

The selection of healthcare provider decision-makers across the United States as the target population demonstrates exceptional alignment with the study's problem of insufficient understanding regarding Mobile Health Services (MHS) adoption factors. These decision-makers, particularly those within Information Technology departments, represent the primary stakeholders responsible for evaluating, selecting, and implementing technological solutions within healthcare organizations (Sim, 2019). The population's direct involvement in technology adoption decisions makes them uniquely positioned to provide insights into the factors influencing MHS implementation strategies (Sim, 2019). Their professional expertise and decision-making authority ensure that the data collected will reflect actual organizational considerations rather than theoretical perspectives (Sim, 2019). The selection of this population directly addresses the knowledge gap identified in the literature regarding factors predicting MHS adoption among healthcare decision-makers (Istepanian, 2022; Niaz & Nwagwu, 2023). Furthermore, this population's involvement in strategic technology decisions makes them ideal for examining the UTAUT framework's variables within the healthcare context (Sim, 2019).

The chosen population demonstrates remarkable congruence with the study's purpose of investigating and determining which UTAUT variables predict healthcare provider decision-

makers' MHS adoption factors in the United States. The professional positioning of these decision-makers enables them to provide comprehensive insights into Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions from an organizational perspective (Istepanian, 2022; Niaz & Nwagwu, 2023). Their strategic role in technology adoption decisions ensures that their responses will reflect the complex interplay of factors influencing MHS implementation at the institutional level (Sim, 2019). The population's expertise in healthcare operations and technology implementation makes them uniquely qualified to evaluate the practical implications of MHS adoption (Istepanian, 2022; Niaz & Nwagwu, 2023). Their involvement in resource allocation and strategic planning provides valuable context for understanding facilitating conditions and organizational constraints (Istepanian, 2022; Niaz & Nwagwu, 2023). Additionally, their experience with previous technology implementations offers crucial insights into the relationships between UTAUT variables and MHS adoption (Istepanian, 2022; Niaz & Nwagwu, 2023).

The research questions focus on predictive relationships between UTAUT variables and MHS adoption, which necessitates a population with a comprehensive understanding of both technological and organizational factors affecting MHS implementation. Healthcare provider decision-makers possess the requisite knowledge and experience to evaluate the potential impact of various UTAUT components on adoption decisions within their organizational context (Istepanian, 2022; Niaz & Nwagwu, 2023). Their strategic position enables them to assess technical and operational considerations influencing MHS adoption intentions (Sim, 2019). The population's involvement in technology evaluation and selection processes suits them to provide insights into the relative importance of different UTAUT variables (Istepanian, 2022; Niaz & Nwagwu, 2023). Their understanding of organizational dynamics and constraints ensures that

their responses will reflect realistic considerations rather than theoretical ideals (Istepanian, 2022; Niaz & Nwagwu, 2023). Moreover, their professional expertise enables them to evaluate the potential moderating effects of organizational and environmental factors on MHS adoption (Sim, 2019).

Sample Description

The sample for this quantitative correlational study encompassed a statistically determined minimum of 98 healthcare provider decision-makers, derived through a comprehensive G*Power3 analysis to ensure sufficient statistical power, specifically targeting Information Technology department leaders across diverse healthcare institutions in the United States. The participants were recruited from a Facebook group named Information Technology and Software Professionals, with over 2,900 members. The group's administrators issued written authorization to share their members' directories and allow for contact with them (Appendix B). All participants were purposively chosen from across the United States without limitations based on city, state, or organization (Baldwin, 2018). Chi-square goodness of fit was used to detect sampling biases, while inverse probability weighting will be implemented to correct these identified disparities. As a result, the findings from this study can be generalized to healthcare decision-makers throughout the United States.

The sample composition was restricted to qualified professionals who possess a minimum of an associate degree, demonstrate at least three years of substantive experience in healthcare technology implementation decision-making roles, and meet the age requirement of eighteen years or older, thereby ensuring a baseline of educational and professional competency among participants. The sampling framework deliberately incorporated decision-makers from various healthcare delivery environments. Thus, facilitates a comprehensive examination of

Mobile Health Services (MHS) adoption factors across varied institutional contexts. The selected participants exclusively comprised individuals who maintain direct involvement in the evaluation, selection, and implementation of system functionalities, modules, user interfaces, and interoperability mechanisms within MHS deployments, as these professionals possess the requisite technical expertise and organizational insight necessary for meaningful analysis of the UTAUT variables under investigation (Istepanian, 2022; Niaz & Nwagwu, 2023).

Appropriateness of the Sample to the Study Problem, Purpose, and Research Question

The sample of 190 purposively selected healthcare provider decision-makers from Information Technology departments across the United States demonstrated reasonable alignment with investigating the association between UTAUT constructs and Mobile Health Services (MHS) adoption, as these professionals influence and execute technology implementation decisions within their organizations (Sim, 2019). This sample size, determined through G*Power3 analysis, ensures sufficient statistical power to examine the association between UTAUT variables and adoption intentions. This directly addressed the problem of insufficient understanding regarding the factors associated with the adoption of MHS among healthcare provider decision-makers in the US (Istepanian, 2022; Niaz & Nwagwu, 2023). The purposeful selection of IT decision-makers with minimum qualifications (associate degree and three years of experience) ensured participants possess the necessary expertise to evaluate Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions within their organizational contexts, supporting the purpose of the study examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS (Niaz & Nwagwu, 2023; Sun et al., 2013). The diverse representation across healthcare settings provides insights into adoption factors across varied institutional environments, strengthening the

ability of the study to address research questions regarding the extent of the association between UTAUT variables and MHS adoption. The sample's professional positioning enables participants to provide informed responses about technical and organizational factors affecting MHS implementation (Niaz & Nwagwu, 2023). Furthermore, the sample's direct involvement in technology evaluation and selection processes makes it uniquely qualified to assess the relative importance of UTAUT variables, thereby supporting the investigation of research questions regarding their association with MHS adoption.

Type of Sampling Used

The researcher used purposive sampling as the primary method for participant selection. The researcher imposed specific delimitations on the target population to address the practical constraints of participant recruitment. Rather than attempting to reach every qualified healthcare IT decision-maker in the United States, the researcher focused exclusively on decision-makers who are members of the Facebook group Information Technology and Software Professionals. Because the researcher relied on purposive sampling, the findings cannot be generalized to the broader population of U.S. healthcare provider decision-makers. The results reflect the perspectives of a targeted group selected for their specific experience, which limits the ability to draw population-level conclusions. As a result, the statistical patterns observed should be interpreted as context-bound insights rather than evidence of trends applicable to all healthcare organizations.

Initially, members with a minimum of an associate degree and three years of experience as an IT decision maker in the healthcare sector in the United States were identified from the directories provided by the group's administrators. One thousand potential participants were then selected from the filtered list using “SAMPLE 1000 FROM ALL” in SPSS and invitations and

consent forms were sent to these members. Based on an anticipated response rate of 40%, approximately 400 members are expected to participate, but 190 responses were received. The purposive selection process was documented and replicable, adhering to the methodological requirements for quantitative research.

The researcher used purposive sampling to target healthcare provider decision-makers knowledgeable about MHS adoption. Purposive sampling allows deliberate inclusion of respondents from diverse healthcare settings, organizational sizes, and geographic regions to ensure coverage of key subgroups relevant to UTAUT constructs (Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, Facilitating Conditions, Behavioral Intention) and their association with MHS Adoption. By selecting participants based on explicit inclusion criteria and expertise, the approach supports data collection from the population of interest and facilitates examination of association using multiple regression and correlational analyses (Ünalan, 2021; Werme et al., 2022). While purposive selection does not provide probability-based estimates or formal sampling-error calculations, the researcher maintained transparent selection criteria (Riley et al., 2021; Wang, 2024).

The power analysis conducted using software determined the minimum required sample size of 98 participants based on key statistical parameters for this quantitative study. The analysis incorporated a medium effect size ($f^2 = .15$) to detect meaningful associations between variables while maintaining practical feasibility (Abdullahia, 2025). An alpha level of .05 was selected to maintain the conventional threshold for statistical significance in social science research (Rubin, 2021). The power level ($1 - \beta$) was set at .80, representing an 80% probability of detecting a true effect when present, which is the standard accepted power level in behavioral research (Giner-Sorolla et al., 2024). The calculation accounted for six variables (Performance Expectancy,

Effort Expectancy, Social Influence, Self-Concept, Facilitating Conditions, and Behavioral Intention) in the multiple regression analysis. To ensure adequate statistical power and account for potential incomplete responses, the researcher recruited 190 participants, exceeding the minimum required sample size of 98 (Serdar et al., 2021).

Recruitment Process

A recruitment strategy was implemented targeting healthcare provider decision-makers within Information Technology departments through the established Facebook group, Information Technology and Software Professionals, with over 2,900 members, spanning various technological and clinical domains in the United States. SPSS was utilized for participant filtering, which involved a multi-step process to identify eligible survey candidates from the Facebook group membership directories provided by the group administrator (Appendix B). First, the researcher imported the raw membership data into SPSS and performed data cleaning using the Data Editor, ensuring consistent formatting of variables like age, country, position, sector, and years of experience. To address the age requirement, the researcher executed the command "SELECT IF (Age >= 18)" to retain only adult participants. For geographical criteria, the researcher would apply "SELECT IF (Country = 'United States')" to isolate US-based members. The experience threshold was implemented through "SELECT IF (Years_Experience >= 3)" to ensure participants have a sufficient professional background. For identifying healthcare IT decision-makers, the researcher used the SPSS String functions to create a new variable that flags relevant positions: "COMPUTE Decision_Maker = 0. IF (UPCASE(Position) CONTAINS 'DIRECTOR' OR UPCASE(Position) CONTAINS 'CHIEF' OR UPCASE(Position) CONTAINS 'MANAGER' OR UPCASE(Position) CONTAINS 'ADMINISTRATOR' OR UPCASE(Position) CONTAINS 'SUPERVISOR' OR UPCASE(Position) CONTAINS 'HEAD'

OR UPCASE(Position) CONTAINS 'LEAD' OR UPCASE(Position) CONTAINS 'COORDINATOR') AND (UPCASE(Sector) CONTAINS 'HEALTH') COMPUTE Decision_Maker = 1." Finally, the researcher applied "SELECT IF (Decision_Maker = 1)" to retain only qualified participants, followed by "SAMPLE 1000 FROM ALL" to select 1000 eligible candidates for survey distribution.

Instrumentation

This research employed the questionnaire developed by Azam et al. (2023) as the instrument for data collection. The approval to use this instrument can be found in Appendix E. The psychometric properties of the measurement scales were validated through a systematic process that included content validity assessment by a panel of three experts from information management, public health, and health communication. The questionnaire consisted of two parts. The first part collected demographic information, including gender, age, and professional experience. The second part comprised seven sub-scales with 34 statements measuring Performance Expectancy (6 items), Effort Expectancy (5 items), Facilitating Conditions (4 items), Social Influence (4 items), Self-Concept (5 items), Behavioral Intention (5 items), and MHS Adoption (5 items).

The measurement items were adapted from well-established scales in prior literature, including Technology Acceptance Model (TAM) scales (Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) measures (Venkatesh et al., 2003), and Protection Motivation Theory (PMT) (Rogers, 1983) constructs, which have demonstrated strong validity and reliability across numerous empirical studies in information systems research. Operational Definition of Variables. The final instrument by Azam et al. (2023) demonstrated robust psychometric properties with Cronbach's alpha values of 0.890 for Performance Expectancy,

0.893 for Effort Expectancy, 0.839 for Facilitating Conditions, 0.862 for Social Influence, 0.885 for Self-Concept, 0.885 for Behavioral Intention, and 0.673 for mHealth Adoption. The overall Cronbach's alpha for all 34 statements across seven constructs was 0.966, indicating strong reliability.

The construct validity was established through confirmatory factor analysis (CFA), which confirmed the hypothesized factor structure with acceptable model fit indices ($\chi 2 = 3.206$; df = 254; $p = 0.000$; RMSEA = 0.084; CFI = 0.893; IFI = 0.894; TLI = 0.874). The latent variables' path coefficient values were found to be moderate-to-high, ranging from $\beta = 0.49$ to $\beta = 0.85$. The structural equation modeling validated the UTAUT model with an additional construct of self-concept, confirming that performance expectancy and self-concept were the main predictors influencing behavioral intention toward mHealth adoption among healthcare professionals.

The dependent variable in this study was the adoption of Mobile Health Services (MHS) measured by healthcare provider decision-makers' behavioral intention to adopt MHS. Independent variables will be the core constructs from the UTAUT framework: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), and Facilitating Conditions (FC) (Azam et al., 2023). The UTAUT framework was selected over alternative frameworks due to its comprehensive nature and empirical validation across diverse technological domains, particularly within healthcare contexts (Venkatesh et al., 2003; Alqahtani & Erfani, 2021; Sun et al., 2013). These constructs addressed individual perceptions and incorporated organizational and contextual factors associated with MHS adoption (Azam et al., 2023). The researcher utilized self-administered questionnaires developed by Azam et al. (2023) to collect data from purposively selected healthcare provider decision-makers across the United States, examining the relationships between these variables and MHS adoption.

Performance Expectancy (PE)

PE measured decision-makers' anticipated benefits from MHS implementation, focusing on operational optimization and enhanced patient care outcomes (Azam et al., 2023). PE was measured using six questionnaire items (PE1- PE6) as a independent variable on a seven-point Likert scale (1=strongly disagree, 7=strongly agree). The final PE score represented the average of these six measurements on an interval scale.

Effort Expectancy (EE)

PE measured the healthcare decision-makers' perceived ease of MHS integration into existing healthcare systems and workflows (Azam et al., 2023). On a seven-point Likert scale, this independent variable employed five questionnaire items (EE1-EE5). The EE score was calculated as the average of these five interval-scale measurements (Azam et al., 2023).

Social Influence (SI)

SI measured how peer opinions, professional recommendations, and industry expectations impact healthcare decision-makers' intention to adopt MHS (Azam et al., 2023). This independent variable used four questionnaire items (SI1-SI4) on a seven-point Likert scale, with the final SI score derived from their average (Azam et al., 2023).

Self-Concept

Self-Concept (SC) measured how healthcare professionals' self-perceptions, beliefs, and internal assessments regarding the significance of MHS impact their intention to adopt MHS. This indendent variable used five questionnaire items (SC1-SC5) on a seven-point Likert scale, with the final SC score derived from their average (Azam et al., 2023).

Facilitating Conditions (FC)

FC measured the healthcare decision-makers' perceived availability of organizational support systems, including technical infrastructure, training resources, and implementation support (Azam et al., 2023). This independent variable comprised four questionnaire items (FC1-FC4), measured on a seven-point Likert scale. The FC score represented the average of these four interval measurements.

Behavioral Intention (BI)

BI measured healthcare decision-makers' individualistic probability and willingness to adopt MHS. This dependent variable used five questionnaire items (BI1-BI5) on a seven-point Likert scale, with the final BI score derived from their average (Azam et al., 2023).

MHS Adoption (AD)

AD will measure healthcare decision-makers’ acceptance and integration of MHS and applications in their healthcare delivery systems. This outcome variable will use five questionnaire items (AD1-AD5) on a seven-point Likert scale, with the final adoption score derived from their average (Azam et al., 2023).

Study Procedure

The researcher collected data by distributing validated questionnaires developed by Azam et al. (2023) to purposively selected healthcare provider decision-makers within Information Technology departments in the United States. Participants were recruited through professional healthcare networks through established Facebook groups, including Information Technology and Software Professionals, with over 2,900 members, utilizing a purposive sampling approach to ensure geographical representation while maintaining the minimum required sample size of 98 participants, as determined through G*Power3 analysis. The questionnaire was administered via

Qualtrics, incorporating established measurement scales for Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), Facilitating Conditions (FC), Behavioral Intention (BI), and MHS Adoption (AD) with responses recorded on a seven-point Likert scale ranging from "strongly disagree" to "strongly agree." The target population was specifically comprised of healthcare provider decision-makers who possess a minimum associate degree, demonstrate at least three years of experience in healthcare technology implementation decision-making roles, and meet the age requirement of eighteen years or older.

The researcher used the Statistical Package for the Social Sciences (SPSS) to filter participants, and the process involved several steps to identify eligible candidates from the Facebook group directories. Initially, the raw membership data were imported into SPSS, followed by data cleaning to ensure consistent formatting of key variables such as age, country, position, sector, and years of experience. To meet the age requirement, participants aged 18 and above are selected with the command "SELECT IF (Age >= 18)." For geographical filtering, only those from the United States are isolated using "SELECT IF (Country = 'United States')." A minimum experience threshold of three years is enforced with "SELECT IF (Years_Experience >= 3)." To identify healthcare IT decision-makers, a new variable is created using string functions to flag relevant positions, marking them as decision-makers if their titles contain specific terms related to leadership in the healthcare sector. Finally, only these qualified participants are retained with "SELECT IF (Decision_Maker = 1)," followed by "SAMPLE 1000 FROM ALL" to select eligible candidates for survey distribution.

The researcher implemented data collection protocols that incorporated validation checks via Qualtrics' advanced features, including mandatory responses for all items, progress-saving capabilities, and branching logic to ensure data quality and completeness (Stokes et al., 2019).

The collected data were automatically encrypted and stored in Qualtrics' secure servers, which maintain compliance with healthcare privacy regulations and institutional review board requirements. The researcher assigned unique identification codes to participants while removing personal identifiers to maintain confidentiality throughout data collection and analysis. The questionnaire administration was conducted exclusively online, enabling participants to complete the survey conveniently while ensuring consistent data collection procedures across all geographical regions. The data collection methodology has been designed to facilitate replication, with detailed documentation of sampling procedures, participant selection criteria, and questionnaire administration protocols that were maintained throughout the research process.

Data Analysis

The data analysis process commenced with systematic coding in SPSS version 30.0.0, in which responses were numerically coded using a comprehensive codebook, with Likert-scale items coded from 1 (strongly disagree) to 7 (strongly agree). Prior to conducting the primary analysis, data cleaning procedures were implemented, including assessments for missing values (coded as -999), outliers identified through multiple methods, including Mahalanobis distance calculations (values > 20.52) (Pallant, 2011), Cook's distance (values > 1), and standardized residuals (±3), the potential outliers were evaluated individually for their impact on the analysis results. The Chi-square goodness-of-fit test was used to detect sampling biases, while inverse probability weighting was implemented to correct these identified disparities. The researcher used Pearson correlation analysis to determine the relationships between the independent and criterion variables. Hierarchical multiple regression analysis and independent samples t-tests were used to determine the extent to which PE, EE, SI, and SC is associated with the BI of MHS and the extent to which FC and BI is associated with AD. Reliability testing was conducted

through Cronbach's alpha coefficients (with acceptable values set at > .70) and validity assessment through factor analysis, and Average Variance Extracted (AVE). The researcher incorporated descriptive statistics and data visualization techniques, including Normal P-P plots to assess normality by comparing observed values with expected normal distribution values, alongside scatter plots, box plots, and residual plots to identify potential trends, relationships among variables, and confirm outlier detection.

The researcher employed statistical analyses including hierarchical multiple regression and independent-samples *t*-tests to evaluate each hypothesis. The regression models assessed the extent to which the UTAUT dependent variables were associated with healthcare provider decision-makers' adoption of mobile health services (MHS), using a significance threshold of $p < .05$.

Assumption testing encompassed assessments of multicollinearity through Variance Inflation Factor (VIF) analysis (with values > 10 indicating potential issues), normality through examination of Normal P-P plots (showing cumulative probability of a variable against the cumulative probability of a normal distribution), homoscedasticity through Breusch-Pagan tests, and Levene's test for equality of variances for t-tests. Power analysis using G*Power 3.1 has confirmed that the sample size of 98 participants provides adequate statistical power (0.80) to detect medium effect sizes ($f^2 = .15$ for regression, $d = .50$ for t-tests) at $\alpha = .05$. The findings were reported using standardized beta coefficients for regression analyses and Cohen's d effect sizes for t-tests to determine the relative associtation of each independent variable in explaining variance in adoption intentions, with R^2 values indicating the overall model fit and addressing the primary research objective of understanding MHS adoption factors.

Assumptions

This research relied on a series of foundational assumptions. Firstly, it was anticipated that each potential participant would be able to read and understand the survey requirements, willingly agree to participate in the online survey by clicking the provided link, and do so without any pressure (Nayak & Narayan, 2019). Secondly, all survey questions were designed to ensure clarity and eliminate ambiguity. Thirdly, it was assumed that each participant would adequately comprehend the survey questions and possess the professional knowledge to provide informed responses. Fourthly, all participants were expected to answer each question in the self-administered online survey honestly and from a personal perspective (Andrade, 2020). Fifthly, measures will be taken to guarantee that the data collection and storage processes are devoid of human error or intentional misrepresentation, thereby preserving the accuracy and integrity of the survey responses.

Limitations

As with all empirical investigations, this study will acknowledge several limitations that must be carefully considered in interpreting the findings. The primary limitation was the use of the purposive sampling method; inferential results must be interpreted with caution, as sampling-related assumptions supporting population-level generalization are not fully met. Another limitation stems from potential participant hesitancy in providing candid responses to the self-administered questionnaires due to privacy concerns, particularly given the sensitive nature of healthcare technology adoption decisions. Although data protection protocols and confidentiality measures were implemented through the Qualtrics platform, healthcare decision-makers may be hesitant to share strategic insights on Mobile Health Services (MHS) adoption intentions. Additionally, participants expressed concerns about potential implications for their

organizational relationships or institutional protocols, despite explicit assurances of data anonymization and secure storage, in compliance with healthcare privacy and Institutional Review Board (IRB) regulations. A methodological limitation arose from the non-experimental correlational design, which, while appropriate for examining relationships between UTAUT variables and adoption intentions, precludes the establishment of causal relationships between Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC) and Facilitating Conditions (FC), and healthcare provider decision-makers' Behavioral Intentions and MHS adoption. This limitation is inherent in correlational research designs, as they examine covariation between variables without manipulating independent variables or controlling for all potential confounding factors.

To mitigate these limitations, several measures were implemented. Firstly, the interpretation of all findings was strictly within the boundaries of the purposively selected sample, and claims of generalizability beyond this specific group of healthcare decision-makers were avoided. The researcher employed encryption protocols within the Qualtrics platform to address privacy concerns, ensuring that all collected data was securely stored and transmitted. Participant identifiers were removed and replaced with unique codes to maintain strict confidentiality while facilitating potential follow-up communications if necessary. The researcher utilized validated questionnaires developed by Azam et al. (2013), which have demonstrated psychometric properties with Cronbach's alpha values exceeding .80 and composite reliability scores above .70, thereby enhancing measurement reliability. To strengthen the correlational design validity, the researcher implemented statistical controls, including assumption testing, assessments of multicollinearity, normality evaluations, and outlier analyses. However, the purposive sampling approach reduced the generalizability of findings.

Delimitations

The delimitations of this study were intentionally set to align with the problem, purpose, research questions, and the established theoretical framework. Firstly, the study is delimited to healthcare provider decision-makers within Information Technology departments across the United States, as these individuals possess the requisite expertise and decision-making authority to provide valuable insights into the factors influencing Mobile Health Services (MHS) adoption. This population was purposively recruited from an established Facebook group, including Information Technology and Software Professionals. This population selection is consistent with the problem statement, associated with the adoption of MHS among healthcare provider decision-makers in the US, resulting in inconsistent adoption despite its potential benefits, a gap identified in the existing literature (Istepanian, 2022; Niaz & Nwagwu, 2023). Additionally, the UTAUT framework, which serves as the guiding theoretical model, focuses on technology acceptance behaviors at the individual and organizational levels, making the chosen population an appropriate fit (Alqahtani & Erfani, 2021; Azam et al., 2023; Sun et al., 2013; Venkatesh et al., 2003). Secondly, the study is delimited to examine the five UTAUT constructs, Performance Expectancy, Effort Expectancy, Social Influence, Self-Concept, and Facilitating Conditions as predictors of MHS adoption (Azam et al., 2023; Sun et al., 2013; Venkatesh et al., 2003). This delimitation ensured that the researcher focused on the established theoretical underpinnings, enabling an investigation of the associations between these variables and the dependent variables, as outlined in the purpose statement and research questions. Finally, the quantitative, correlational design of the study was a deliberate delimitation, as it aligns with the need to quantify the strength and significance of the associations, addressing the problem of insufficient understanding through statistical analysis.

Ethical Assurances

Before data collection, this researcher obtained approval from National University's Institutional Review Board (IRB) to ensure compliance with ethical research standards and participant protection protocols. The risk to participants was considered minimal as the study involves a standard questionnaire about technology adoption, with no experimental manipulation or sensitive personal information collection required. Confidentiality and anonymity were maintained through multiple safeguards, with data collection administered through Qualtrics, encryption protocols, and secure data storage compliant with the National University's IRB and healthcare privacy regulations. All participant identifiers were removed and replaced with unique codes during data processing, and healthcare provider decision-makers were recruited from the Facebook group Information Technology and Software Professionals, which has members across all geographical regions of the United States. Data security adhered to IRB requirements, with all collected data stored on Qualtrics' secure servers with strict access controls, and only the researcher will have access to the encrypted data through a password-protected account.

The researcher's role in this study was to design and implement the research methodology, coordinate data collection, and analyze results while maintaining objectivity. The researcher used the validated questionnaire developed by Azam et al. (2023) rather than creating new instruments that might reflect researcher bias, and implemented standardized data collection procedures in Qualtrics to ensure a consistent participant experience. The researcher followed established statistical procedures for data analysis with clear documentation of all analytical decisions to ensure objectivity. Detailed research logs were maintained to document decision-making processes and potential bias considerations.

The researcher used the questionnaire developed by Azam et al. (2023) in Appendix F, with some modifications, and found robust psychometric properties, with all constructs achieving strong validity and reliability. All findings were reported honestly and impartially, with clear acknowledgment of any limitations or constraints identified during the research process. The research adhered strictly to ethical data collection, analysis, and reporting guidelines, ensuring transparency and credibility throughout the research process. The researcher ensured representation and minimized potential bias in responses by maintaining no direct contact between researchers and participants during recruitment and data collection.

Summary

This quantitative correlational study investigated factors influencing healthcare provider decision-makers' adoption of Mobile Health Services (MHS) in the United States. The researcher used the UTAUT variables (Performance Expectancy, Effort Expectancy, Social Influence, Self Concept, and Facilitating Conditions) to predict MHS adoption. The researcher incorporated validated questionnaires developed by Azam et al. (2023) administered through Qualtrics to ensure data security and standardization. The target population comprised healthcare provider decision-makers in Information Technology departments, with a sample size of 190, although 98 participants were the minimum required sample size determined through G*Power3 analysis.

The researcher implemented a data collection process, including participant screening, informed consent procedures, and purposive sampling across geographical regions to ensure representative data. The researcher employed Pearson correlation, hierarchical multiple regression, and t-tests to examine relationships between variables while maintaining ethical standards and IRB compliance. The researcher incorporated assumption testing to ensure statistical validity, including assessments of multicollinearity, normality, and outliers.

The established theoretical framework provided a foundation for investigating the factors associated with MHS adoption among healthcare decision-makers that was purposively selected, addressing the identified knowledge gap in the literature. The data collection and analysis approach, combined with validity, reliability, and ethical considerations, positioned the study to generate meaningful insights into technology adoption in healthcare settings among the selected sample. The next chapter will present the findings, revealing the associations between UTAUT variables and MHS adoption. The results will illuminate the relative importance of each variable in explaining the variance in MHS adoption. The findings were intended to contribute to the scholarly discourse by offering exploratory, theory-informing evidence that may guide future research employing probability-based sampling or alternative methodological approaches.

Chapter 4: Findings

The problem addressed in this study was the insufficient understanding of the factors associated with the adoption of MHS among healthcare provider decision-makers in the US, resulting in inconsistent adoption despite its potential benefits. (Istepanian, 2022; Niaz & Nwagwu, 2023). The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States. Rather than seeking generalizable findings, the researcher aimed to explore patterns of association within a targeted group of individuals with direct experience and responsibility in technology-related decision-making. By focusing on this knowledgeable subset, the researcher sought to provide context-specific insights into how UTAUT constructs manifest in organizational environments and how these relationships may inform theoretical understanding of technology adoption in healthcare settings.

The researcher recruited participants (N = 190) purposively for roles and experience relevant to MHS decision-making (≥18 years old, ≥ associate degree, ≥3 years of IT decision-making experience in healthcare and lives in the USA). Purposive recruitment facilitated access to knowledgeable respondents but does not produce a probability sample. Consequently, demographic and descriptive statistics describe the characteristics of this specific purposive cohort and should not be treated as representative estimates for all U.S. healthcare decision-makers.

The researcher began by examining the validity of the UTAUT instrument through factor analysis, Average Variance Extracted (AVE), and reliability analysis using Cronbach's alpha coefficients (acceptable values exceeded 0.70). Next, assumption testing was conducted to

validate the appropriateness of the planned statistical procedures. This involved assessing multicollinearity through Variance Inflation Factor (VIF) analysis, where values greater than 10 indicated potential issues. Normality was examined using distribution plots. Homoscedasticity was tested, and heteroscedasticity was evaluated using the Breusch-Pagan test. The calculations of Mahalanobis distance revealed that the highest value is .875, which is below 3. Meanwhile, Cook's distance has a maximum value of 0.0076, suggesting no potential outliers in the data (Erpurini et al., 2023).

The primary statistical analyses began with Pearson correlation analyses to explore relationships among variables, followed by hierarchical multiple regression and independent-samples t-tests to determine how UTAUT variables are associated with MHS adoption intentions. Finally, results reporting utilized standardized beta coefficients for regression analyses, Cohen's d effect sizes for t-tests, and R^2 values to indicate overall model fit, providing insights into the relative importance of each variable in explaining variance in adoption intentions. This chapter presents the statistical analysis tables and figures in alignment with the research questions and hypotheses. Consequently, the findings and insights obtained from the statistical tests enable the addressing of the research questions.

Validity and Reliability of the Data

In this study, the constructs were evaluated using responses recorded on a 7-point Likert scale. The objective was to determine the effectiveness of these items in measuring MHS Adoption Intention, using factor loadings and cross-loadings in SPSS. However, because the dataset derives from purposive rather than random sampling, key inferential assumptions underlying parametric tests and population-level generalizations (independence and random selection from the target population) are not met. Thus, reported p-values, confidence intervals,

and regression inferential claims will be understood as conditional on this purposive sample; they indicate associations within the study sample but cannot be straightforwardly extrapolated to the broader population.

Initially, the items were input into the dimension reduction function in SPSS, where KMO and Bartlett's test were selected for descriptive statistics, a Scree Plot was used for extraction, and Promax rotation was applied. The expectation was that the items measuring each construct would exhibit high loadings (preferably above 0.6) in their designated column while displaying low loadings in other constructs. Any items that showed substantial loadings in unintended constructs were removed from the analysis, and this process was repeated until satisfactory results were achieved.

Upon completing the factor analysis, the output from the Pattern Matrix was examined to identify factor loadings and cross-loadings. The output was formatted to enhance clarity, making it easier to identify items that measured the constructs. Items that did not meet the loading threshold of 0.6 were excluded from the analysis. In selecting the items, the researcher focused on those with the highest factor loadings, ensuring they were strong indicators of the construct being measured. Additionally, the researcher verified that the selected items did not exhibit high loadings on other constructs, which could compromise their relevance. Table 1 shows the factor loadings and cross-loadings. The selected items were then used to determine descriptive statistics and conduct further analysis (Venkatesh et al., 2003).

Table 1

Factor loading and cross-loading result

Construct	Item	PE	EE	SI	SC	FC	BI	AD
	PE4	**.882**	-.033	-.448	-.443	.332	-.544	.156
PE	PE5	**.873**	.294	-.332	.133	.334	-.139	-.432
	PE6	**.976**	.335	.423	.443	-.566	-.434	-413
	EE1	**.953**	-.224	.024	-.331	-.577	.113	-.332
EE	EE2	-.076	**.899**	.032	.044	-.323	-.223	-.004
	EE5	-.032	**.988**	-.453	.298	-.545	-.044	-.335
	SI2	.377	-.213	**.933**	-.221	.323	-.243	-.244
SI	SI3	.432	-.222	**.899**	.134	-.432	-.044	-.086
	SI4	.371	-.044	**.988**	.432	-.332	-.012	-.034
	SC2	-.213	-.331	-.434	**.934**	-.333	-.122	.532
SC	SC4	.043	.044	.098	**.832**	-.443	.445	-.443
	SC5	.434	.298	.044	**.988**	.455	.632	-.449
FC	FC1	.323	-.443	-.112	-.334	**.949**	-.033	.445
	FC4	.322	-.213	-.439	.421	**.884**	-.433	-.334
BI	BI1	-.344	.044	-.044	-.443	-.334	**.833**	.043
	BI3	.044	.032	-.344	-.322	-.114	**.899**	-.443
	AD1	.443	-.455	-.644	.054	-.445	.114	**.823**
AD	AD2	-.332	-.604	.043	-.432	-.112	-.423	**.954**
	AD5	-.044	-.443	.043	-.341	-.455	-.342	**.855**

Note. The table displays the factor loading and cross-loading of the selected items, highlighting those with high factor loading and low cross-loading.

The researcher ensures the validity and reliability of the data collected. As the power analysis indicated that the minimum required number of responses was 98, the final dataset comprised 190 complete responses, which can be considered a valid and adequate sample size for the reliability and validity analysis. Reliability is a crucial aspect of quantitative data analysis and correlational research, as it ensures the repeatability and consistency of the measurement instruments (Duckett, 2021). In this study, Cronbach's alpha was calculated to assess the reliability of the selected UTAUT items. The overall Cronbach's alpha for the 19 items across the seven constructs was .875, which falls into the optimum range of .7 to .95 (Kennedy, 2022).

Table 2 shows that the items within each UTAUT construct were consistent with one another, indicating that the survey questions for each construct worked together in a stable manner for this sample. These reliability values indicate that the constructs were measured with limited random variation, allowing the researcher to examine relationships among the variables with greater clarity. These results simply show that each group of questions measured the same general idea. This consistency is important because it supports the accuracy of the later analyses that explore how the UTAUT constructs is associated with Mobile Health Services adoption. By confirming that each construct was measured reliably, Table 2 helps address the research questions by ensuring that the variables used in the correlation and regression analyses were measured reliably.

Table 2

Cronbach's alpha for each UTAUT Construct

Construct	Cronbach's alpha
Performance Expectancy	.965
Effort Expectancy	.930
Social Influence	.832
Self-Concept	.775
Facilitating Conditions	.891
Behavioral Intention	.775
MHS Adoption	.856

Note. This table displays the computation results of the reliability analysis. Values from Cronbach's alpha for each UTAUT construct.

Validity is a fundamental aspect to consider in non-experimental correlational studies. In this study, validity denotes the degree to which the UTAUT instrument effectively measures what it is intended to, without being influenced by biases or unrelated variables (Sürücü & Maslakci, 2020). To evaluate validity, the researcher employed confirmatory factor analysis was performed, and Average Variance Extracted (AVE) to assess the validity of the dataset (Sujati & Akhyar, 2020). The analysis utilized KMO and Bartlett's test as statistical methods to examine the quality of variance within the data samples and determine the appropriateness of factor analysis. A KMO value greater than .5 and a p-value from Bartlett's test below .05 indicate the presence of significant common variance, affirming the relevance of factor analysis (Erpurini et al., 2023). These results indicate that the survey items aligned with the ideas they were designed to measure. By confirming that the constructs were valid representations of the UTAUT framework, Table 3 supports the study's ability to answer the research questions because it

verifies that the variables used in the analyses reflect the concepts being examined. Table 3 shows the result of the validity test.

Table 3

Result of Validity Test

Indicator	Value	Good Range	Within Good Range?
KMO Value	.861	>= .5	Yes
Bartlett's *p*-value	.001*	<= .05	Yes
AVE (Component 1)	.726	>=.012	Yes
AVE (Component 2)	.526	>=.012	Yes

Note. This table shows the result of the validity analysis. The KMO Bartlett's test and the AVE proved the validity of the collected data. * $p<.05$.

The Average Variance Extracted (AVE) was calculated using factor analysis based on Principal Component Analysis (PCA) with two components and the Oblimin rotation method with Kaiser normalization (Shrestha, 2021). To improve clarity in the factor structure, smaller coefficients were suppressed using an absolute value threshold of 0.4, following Field's (2013) recommendation for reducing noise in factor loadings. Using this approach, the AVE values for the two components were .726 and .526. Both values were higher than the squared correlation of .012, indicating that the constructs measured by the UTAUT instrument captured a meaningful amount of variance relative to shared variance with other constructs. This level of validity is relevant to the research questions because it confirms that the variables used to examine associations among UTAUT constructs and Mobile Health Services adoption were measured in ways that reflect the intended concepts. Since the sample was purposive, these validity indicators apply to this specific group, and additional testing with a probability-based or more diverse sample would be needed to determine whether the measurement properties extend to broader populations.

Result

Demographic of the Responses

This quantitative correlational study included 190 complete responses from healthcare decision-makers across the United States. Participants were required to be at least 18 years old, possess a minimum of an associate degree, and have a minimum of three years of experience in IT decision-making within healthcare. The collected data surpassed the minimum sample size of 98, calculated using G*Power3 analysis. The average method was applied to analyze the values of each variable among the 190 valid responses, with each independent and dependent variable represented by a decimal value ranging from 1 to 7.

Descriptive Analysis, Data Visualization, and Exploration

Table 4 presents the descriptive statistics for the variables in this study. The range, minimum, maximum, mean, median, standard deviation, variance, and skewness are reported for each variable. The ranges of the variables were calculated by subtracting the minimum value from the maximum value. The minimum values for all the variables from all responses are 1, and the maximum values are 7, indicating that the maximum value was reached for each variable. The range of responses for all constructs is 6. The mean values range from 3.811 to 4.424, with SC having the highest mean at 4.424 and AD having the lowest mean at 3.811. The medians of EE, FC, and AD are 4.000, the medians of PE and BI are 4.500, and the median of SI is 5.000.

The standard deviation values vary considerably, ranging from 1.163 to 2.232. EE has the highest standard deviation at 1.494, while FC has the lowest standard deviation at 1.078. The variance values range from 1.163 to 2.232 with EE having the highest variance at 2.232 and FC having the lowest variance at 1.163. The skewness values provide information about the symmetry of the variable distributions (Mishra et al., 2019). All the variables have skewness

values near 0, indicating relatively symmetric distributions. However, BI has a skewness value of -.382, suggesting a negatively skewed distribution.

These descriptive statistics establish the foundational patterns in how the purposively selected healthcare decision-makers perceive the factors associated with MHS adoption, which is essential for interpreting later analytical results. By showing that all variables use the full response scale and have reasonable central tendencies, the table confirms that the dataset is suitable for examining relationships among the constructs in the research model. The relatively high means for constructs like SC and PE suggest that respondents generally view MHS favorably, which provides early insight into potential associations with behavioral intention. The variability measures indicate where perceptions are more or less consistent across respondents, helping explain why certain constructs may emerge as stronger or weaker in later inferential analyses. Overall, Table 4 lays the groundwork for answering the research question by clarifying the distribution and characteristics of each variable before testing how they are associated with MHS adoption. Overall, the descriptive statistics presented in Table 4 provide a comprehensive overview of the characteristics of the variables in this study, while Table 5 shows the SPSS output.

Table 4

Descriptive Statistics for the Variables

Descriptive Statistics	Variable (s)	Values
Range	All variables	6.000
Mean	SC	4.424 (largest)
	AD	3.811 (smallest)
Median	EE, FC, AD	4.000
	PE, SC, BI	4.500
	SI	5.000
Minimum	All variables	1.000
Maximum	All variables	7.000
Standard Deviation	EE	1.494 (largest)
	FC	1.078 (smallest)
Variance	AD	2.811 (largest)
	FC	1.078 (smallest)
Skewness	PE5	.573 (largest positive)
	SC	-.382 (smallest negative)

Note. This table shows the range, mean, median, minimum, maximum, standard deviation, variance, and skewness value for each variable.

Table 5

SPSS output of the descriptive statistics.

		PE	EE	SI	SC	FC	BI	AD
N	Valid	190	190	190	190	190	190	190
	Missing	0	0	0	0	0	0	0
Mean		4.2079	4.2737	4.3105	4.4237	4.0026	4.3447	3.8105
Median		4.5000	4.0000	5.0000	4.5000	4.0000	4.5000	4.0000
Std. Deviation		1.24172	1.49385	1.30967	1.22937	1.07828	1.40703	1.39002
Variance		1.542	2.232	1.715	1.511	1.163	1.980	1.932
Skewness		.573	.222	.644	.457	.202	-.382	.177
Std. Error of Skewness		.176	.176	.176	.176	.176	.176	.176
Range		6.00	6.00	6.00	6.00	6.00	6.00	6.00
Minimum		1.00	1.00	1.00	1.00	1.00	1.00	1.00
Maximum		7.00	7.00	7.00	7.00	7.00	7.00	7.00
Sum		799.50	812.00	819.00	840.50	760.50	825.50	724.00

Note. This table displays the range, mean, median, minimum, maximum, standard deviation, variance, and skewness, as well as the standard error of skewness, for each variable.

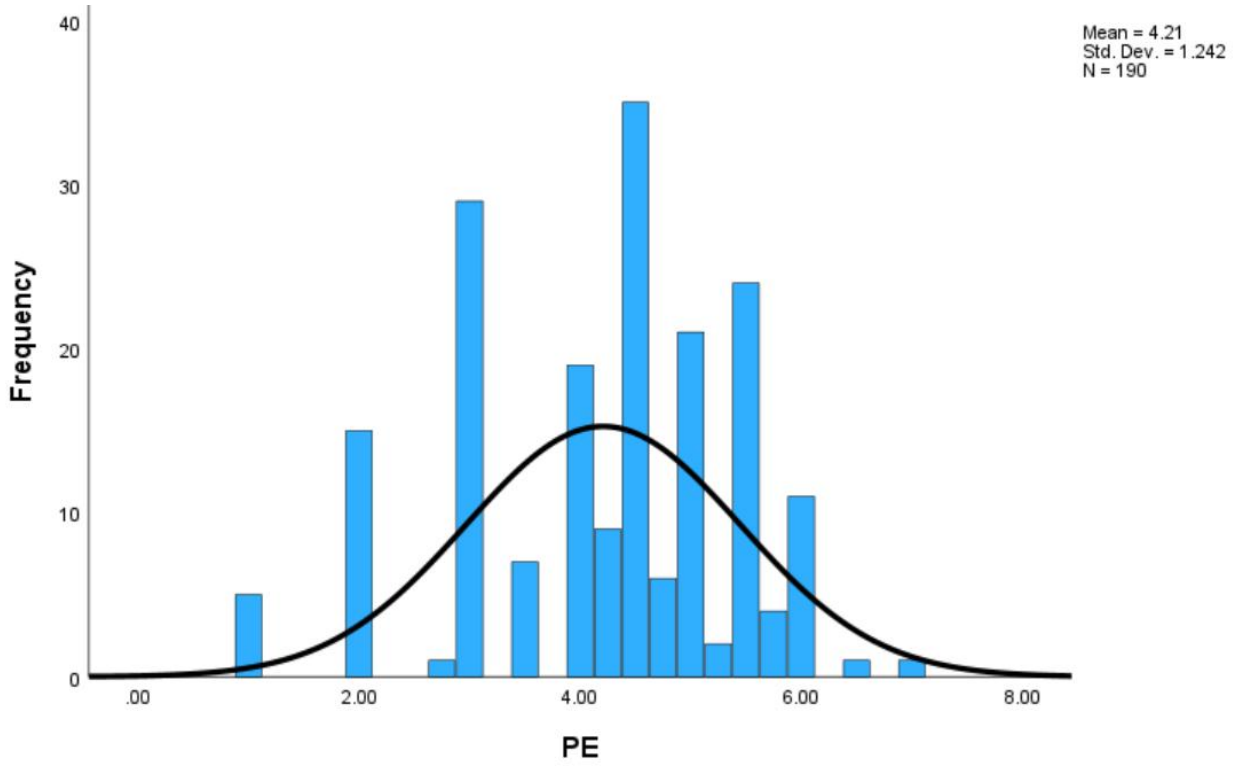
Figures 2 to 8 provide visual representations of the data distribution for each variable through histograms and distribution curves. The data generally exhibits symmetric or slightly skewed distributions across the variables.

Within this purposively selected sample, the distribution for Performance Expectancy was generally symmetric, with most responses concentrated around moderate levels. Fewer

participants selected values at the lower or higher ends of the scale, indicating limited dispersion. This pattern reflects the range of perceptions about the usefulness of mobile health services among the individuals included in the study. These observations apply only to this sample and provide context for interpreting how PE aligns with the research questions. Figure 2 shows the histogram and distribution curve for PE.

Figure 2

Histogram and Distribution Curve for Performance Expectancy (PE)



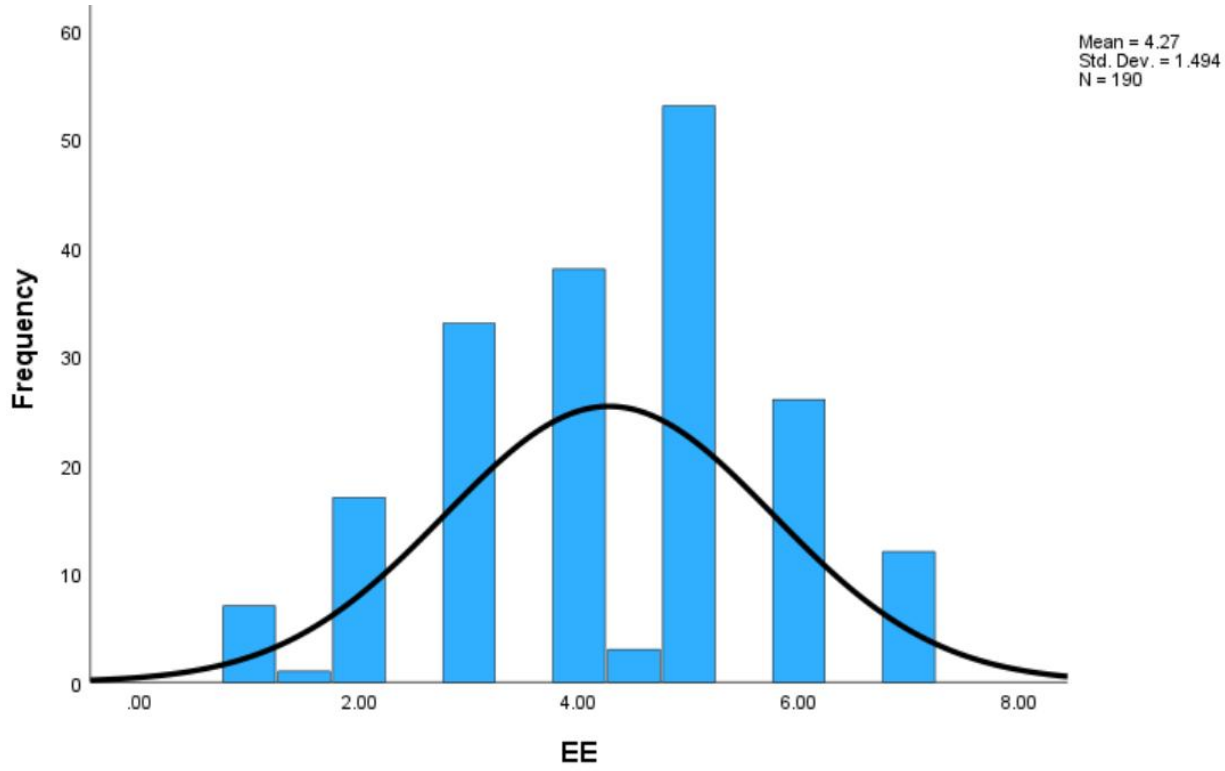
Note. The histogram is the blue bars, and the distribution curve is the black line for Performance Expectancy (PE).

In this purposively selected sample, Effort Expectancy displayed a balanced distribution, with responses primarily located near the midpoint of the scale. Extreme values were limited, indicating relatively consistent perceptions of ease of use among participants. This pattern

reflects the usability views held by individuals in the sample without implying broader population trends. These findings help situate EE within the study's analytical framework. Figure 3 shows the histogram and distribution Curve for EE

Figure 3

Histogram and Distribution Curve for Effort Expectancy (EE)



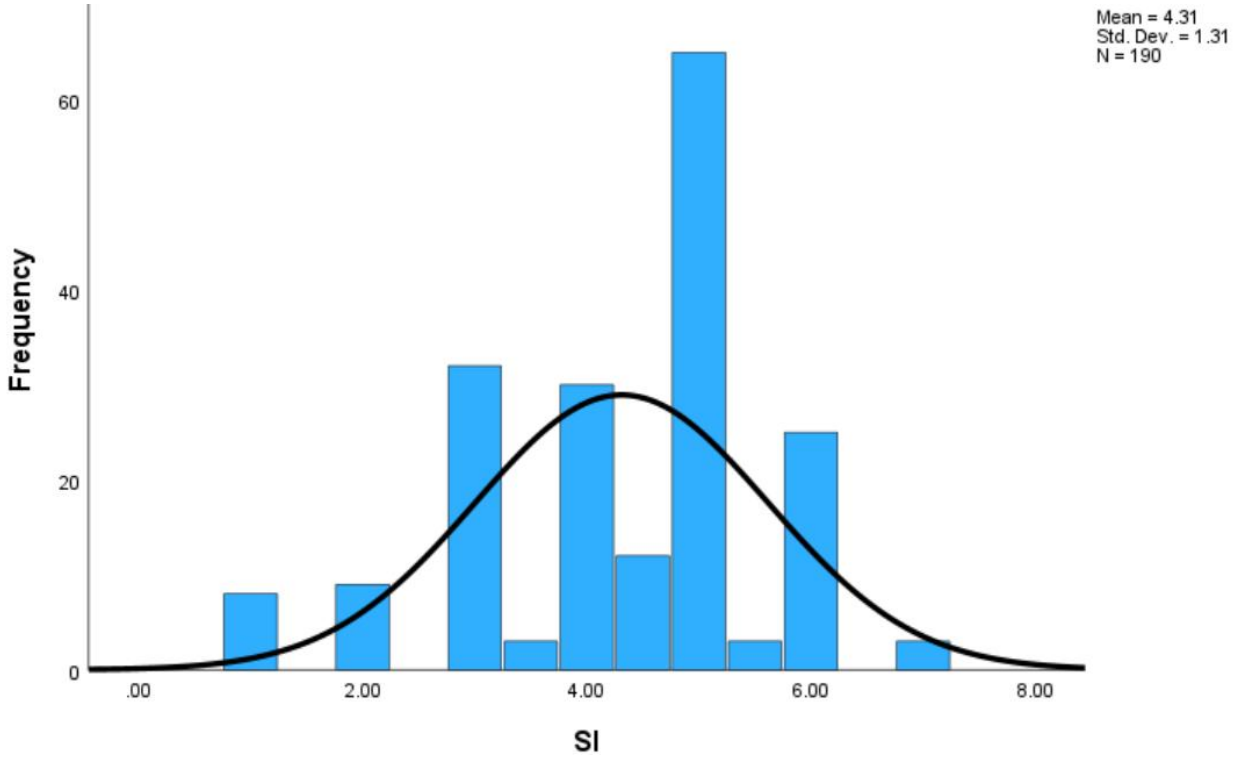
Note. The histogram is the blue bars, and the distribution curve is the black line for Effort Expectancy (EE).

The distribution for Social Influence in this purposively selected sample was mostly centered, with participants reporting similar levels of perceived expectations or encouragement from others regarding mobile health adoption. Most responses were located near the middle of the scale, with fewer observations at the extremes. This pattern reflects moderate levels of perceived social expectations within the sample. These results are specific to this group and

support the interpretation of SI in relation to the research questions. Figure 4 shows the histogram and distribution curve for SI.

Figure 4

Histogram and Distribution Curve for Social Influence (SI)

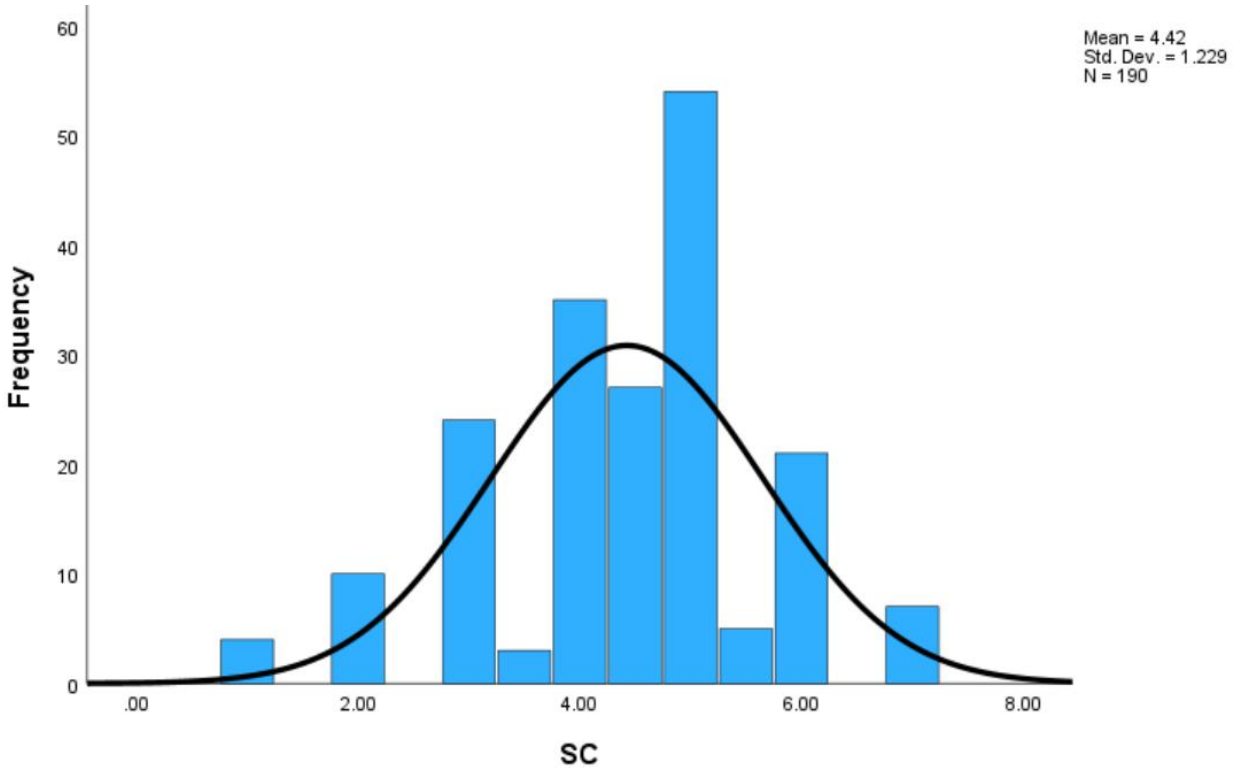


Note. The histogram is the blue bars, and the distribution curve is the black line for Social Influence (SI).

Self-Concept demonstrated a slightly skewed but generally stable distribution within this purposively selected sample. Participants varied in their perceptions of their technological capability, with many reporting moderate levels and fewer reporting lower levels. This variation reflects the range of self-evaluations present among individuals included in the study. These observations are not intended for generalization but provide context for understanding how SC relates to the study's analytical outcomes.

Figure 5

Histogram and Distribution Curve for Self-Concept (SC)

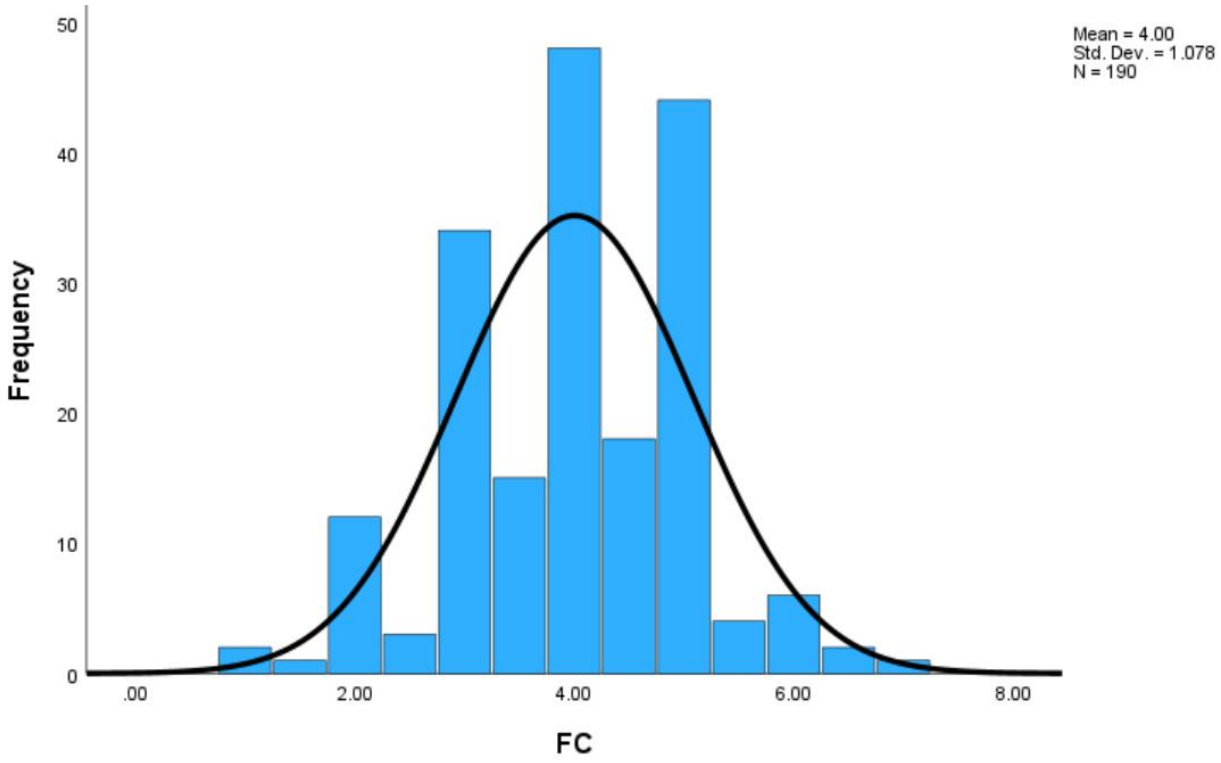


Note. The histogram is the blue bars, and the distribution curve is the black line for Self-Concept (SC).

Facilitating Conditions exhibited a relatively narrow distribution in this purposively selected sample, with most responses concentrated near the center of the scale. Participants reported similar levels of access to resources and support for using mobile health services, with limited representation at the extremes. This pattern reflects the environmental conditions experienced by individuals in the sample. These findings help position FC within the broader interpretation of the study's results. Figure 6 shows the histogram and distribution curve for FC

Figure 6

Histogram and Distribution Curve for Facilitating Condition (FC)

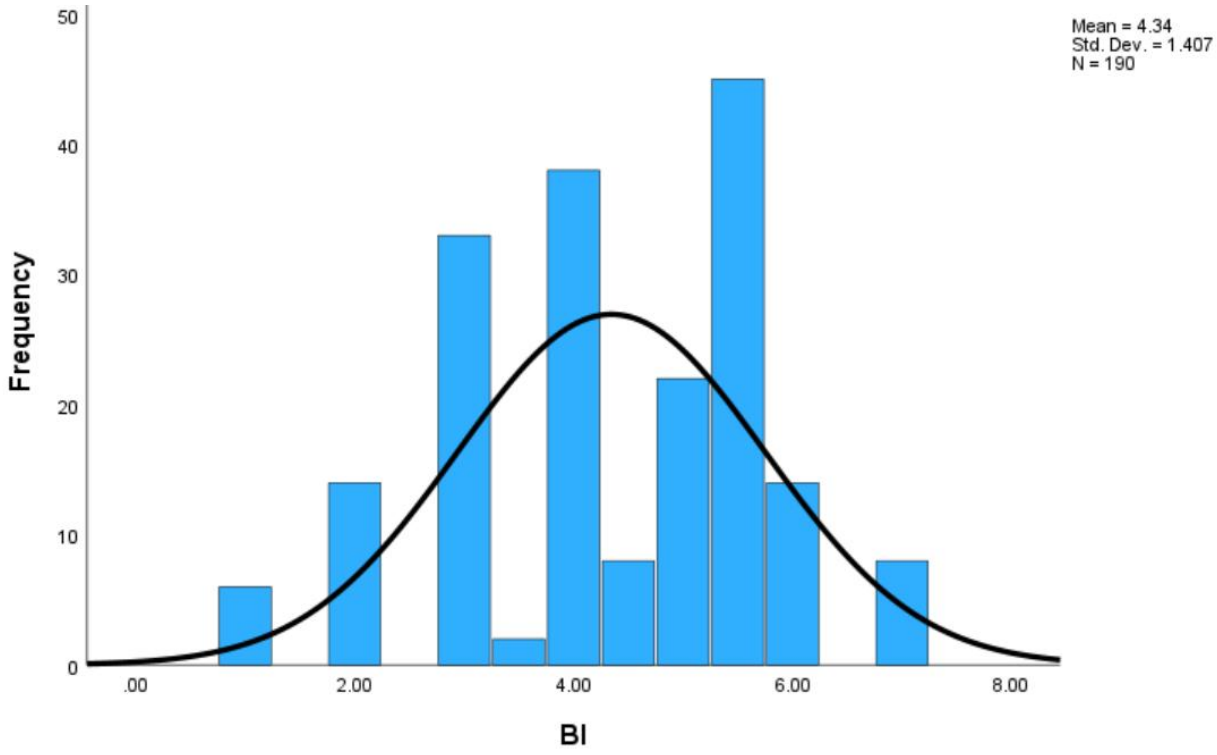


Note. The histogram is the blue bars, and the distribution curve is the black line for Facilitating Condition (FC).

Behavioral Intention displayed a centered distribution within this purposively selected sample, with participants reporting moderate to moderately high intentions to adopt mobile health services. Extreme values were less common, indicating limited variability in adoption-related intentions. These observations apply only to this sample and are not intended for generalization. The distribution provides context for understanding BI as an outcome variable in the study. Figure 7 shows the histogram distribution curve for BI.

Figure 7

Histogram and Distribution Curve for Behavioral Intention (BI)

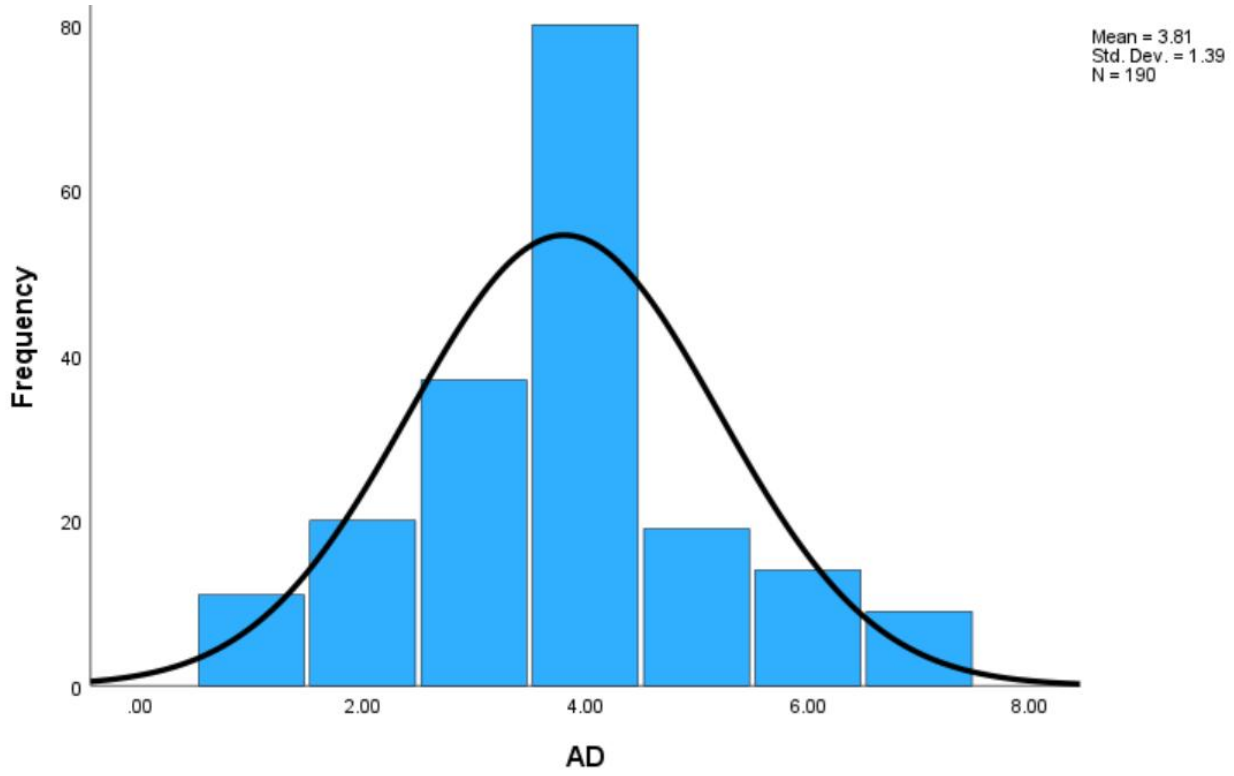


Note. The histogram is the blue bars, and the distribution curve is the black line for Behavioral Intention (BI).

Adoption Intention showed a slightly skewed distribution in this purposively selected sample, indicating variation in participants' readiness to adopt mobile health services. Some respondents selected higher values, while others indicated lower levels of intention, resulting in a wider spread of responses. This variation reflects the range of adoption attitudes within the sample. These findings help contextualize how AD aligns with the study's research questions. Figure 8 shows the histogram and distribution curve for AD.

Figure 8

Histogram and Distribution Curve for Adoption Intention (AD)



Note. The histogram is the blue bars, and the distribution curve is the black line for Adoption Intention (AD).

Multi-collinearity

Multi-collinearity is a condition where two or more independent variables in a regression model are highly correlated with each other. This can lead to unstable and unreliable estimates of the regression coefficients, making it difficult to determine the unique contribution of each independent variable to the dependent variable (Montgomery et al., 2021). The absence of collinearity is an important assumption in multiple linear regression because it ensures that the independent variables are measuring distinct and independent concepts (Montgomery et al., 2021). If collinearity is present, the regression model may not be able to determine the individual effects of the independent variables on the dependent variable, as the effects can become

confounded and difficult to disentangle. Violating the assumption of no collinearity can lead to inflated standard errors, unstable regression coefficients, and reduced overall explanatory power of the regression model (Montgomery et al., 2021). Therefore, it is essential to assess and address any potential collinearity issues before proceeding with the regression analysis to ensure the validity and reliability of the results.

The collinearity statistics presented in Table 6 provide valuable information about the degree of multicollinearity in the data. Specifically, the Variance Inflation Factor (VIF) is a commonly used metric to detect collinearity (Montgomery et al., 2021). A VIF value greater than 10 is generally considered an indication of severe multicollinearity, suggesting that the independent variables are highly correlated and their individual effects on the dependent variable cannot be reliably estimated. In this study, the collinearity statistics reported in Table 5 do not indicate the presence of any severe multicollinearity issues, as all VIF values are well below the threshold of 5. FC has the lowest VIF value of 1.378, and PE has the highest VIF value of 3.291. This suggests that the independent variables measure distinct and independent concepts.

Table 6

Result of Collinearity Statistics

Construct	VIF	Tolerance
PE	3.291	.304
EE	2.613	.383
SI	2.391	.418
SC	2.882	.348
FC	1.378	.726
BI	3.018	.331

Note. This figure displays the value of VIF and Tolerance to detect multicollinearity.

Multivariate Normality

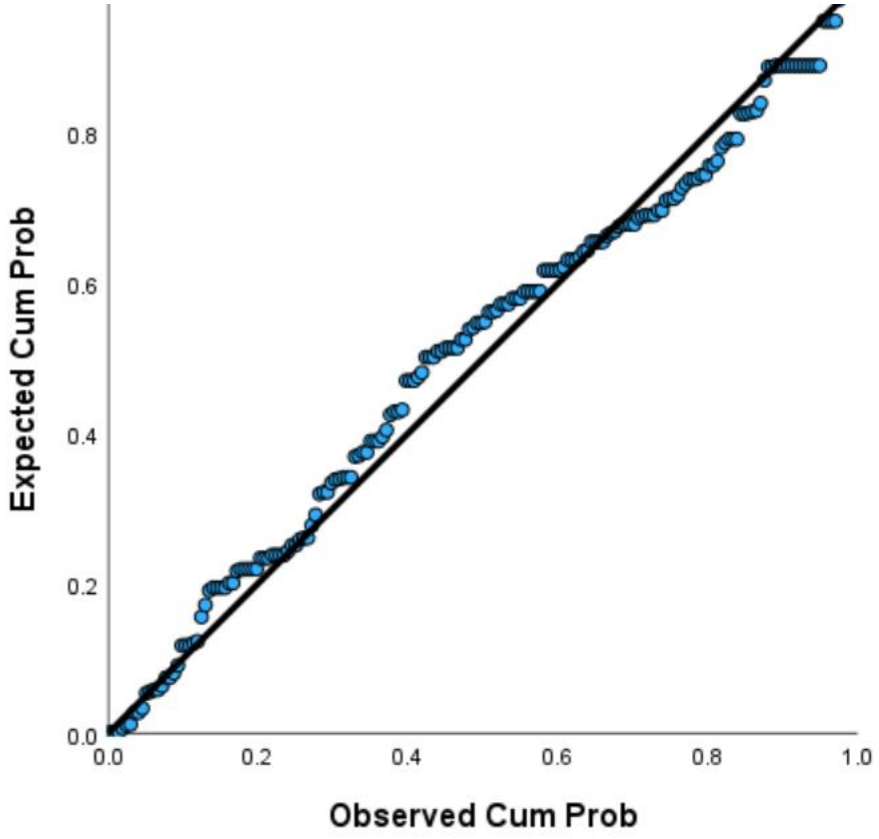
Multivariate normality refers to the condition where the residuals, or error terms, in a regression analysis are distributed according to a normal distribution. This means that the discrepancies between the observed and predicted values of the dependent variable should align with a normal distribution. Achieving multivariate normality is a crucial assumption in multiple linear regression analysis. To assess this condition, both a normal Probability-Probability (P-P) plot and the Shapiro-Wilk test were utilized. In the P-P plot, if the points are closely and uniformly aligned along the 45-degree diagonal line, the cumulative probability of the observed regression residuals closely matches that of the anticipated normal distribution (Montgomery et al., 2021). The blue dots representing the expected versus observed cumulative probabilities are evenly and tightly distributed around both sides of the 45-degree diagonal line. This pattern indicates that the distribution of the regression residuals closely resembles the expected normal distribution (Montgomery et al., 2021).

The collinearity statistics in this purposively selected sample indicate that the independent variables do not overlap to a degree that would interfere with estimating their individual relationships with the dependent variable. The VIF values fall within commonly accepted ranges, suggesting that each construct contributes a distinct source of information to the regression model. The assessment of multivariate normality shows that the residuals align with the expected pattern for a normal distribution, as reflected in the P-P plot. This alignment supports the assumption that the model's error structure is appropriate for multiple regression. Together, these results indicate that the analytical procedures are suitable for examining the relationships addressed in the research questions within this purposively selected sample. Figure

9 illustrates the normal P-P plot comparing the expected cumulative probabilities against the observed cumulative probabilities of the regression standardized residuals in this study

Figure 9

Normal P-P Plot of Regression Standardized Residuals



Note. This plot shows the expected cumulative probability vs the observed cumulative probability for regression standardized residuals.

Additionally, the Shapiro-Wilk test serves as a statistical method for assessing normality, determining whether a dataset adheres to a normal distribution (González-Estrada et al., 2022). In this analysis, the Shapiro-Wilk test was performed to evaluate the normality of the regression residuals. The resulting p-value was .825, which exceeds the threshold of .05. This indicates that there is insufficient evidence to conclude that the regression residuals deviate from a normal distribution. Consequently, it can be inferred that the regression residuals conform to a normal

distribution at the .05 significance level, meeting the multivariate normality requirement. This result is relevant to the study because meeting the normality assumption supports the use of multiple regression to examine the associations addressed in the research questions within this purposively selected sample.

Homoscedasticity

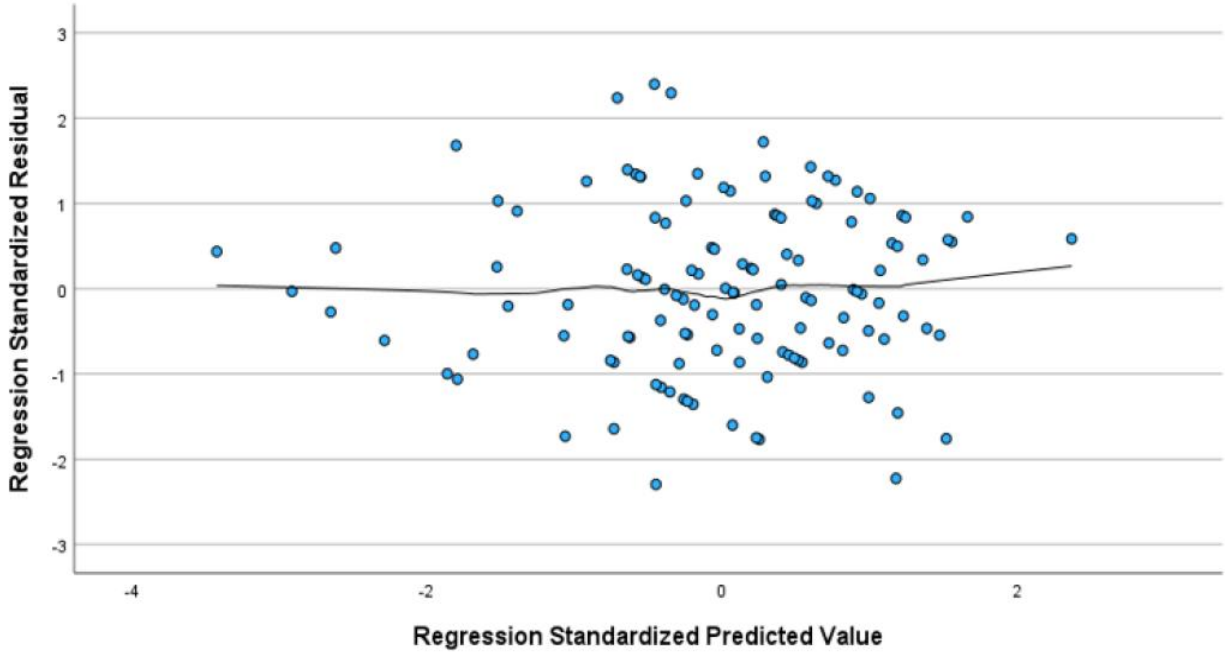
Homoscedasticity refers to the consistency of random disturbances or errors in the linear relationship between independent and dependent variables across all levels of the independent variables. This concept is a crucial assumption in multiple linear regression analysis. In contrast, heteroscedasticity signifies that the variance of the residuals (or error terms) varies considerably with the independent variables within the regression model (Z. Li & Yao, 2019). A rise in heteroscedasticity typically indicates a greater violation of the homoscedasticity assumption. Figure 10 presents a scatterplot comparing the actual values of regression standard residuals against predicted values to assess homoscedasticity. The central black curve represents the Locally Estimated Scatterplot Smoothing (LOESS) fitted line (Montgomery et al., 2021). This LOESS curve is notably flat and smooth, indicating that the residual variance remains roughly parallel to it. This observation suggests no significant evidence of heteroscedasticity, supporting the presence of homoscedasticity in the multiple linear regression analysis.

Additionally, the Breusch-Pagan test serves as a statistical method to determine the existence of heteroscedasticity in multiple regression models (Montgomery et al., 2021). In this study, the Breusch-Pagan test yielded a p-value of .455, exceeding the significance threshold of .05. This result indicates that heteroscedasticity was not detected in the multiple regression model at the .05 significance level, thereby confirming adherence to the homoscedasticity assumption. In conclusion, this study successfully met the prerequisites for multiple linear

regression analysis, including the absence of multicollinearity, maintenance of multivariate normality, and confirmation of homoscedasticity (Paiola, 2021). The results from the scatterplot and the Breusch-Pagan test indicate that the variance of the residuals remains consistent across predicted values within this purposively selected sample, supporting the homoscedasticity assumption. This finding is relevant because meeting the homoscedasticity requirement strengthens the suitability of multiple regression for examining the relationships addressed in the study's research questions.

Figure 10

Scatter Plots for Homoscedasticity Test



Note. This figure shows the scatter plot of regression standard residual actual vs regression standard residual predicted values with an LOESS fit curve for the homoscedasticity test.

Pearson's Correlation Coefficient and Multiple Hierarchical Regression

The analysis of the correlation coefficient reveals that PE, EE, and SI show a moderate positive correlation with BI, and SC shows a strong positive correlation with BI. FC shows a

moderate positive correlation with AD, and BI shows a strong positive correlation with AD. The correlations in this purposively selected sample indicate that several constructs share meaningful linear associations with Behavioral Intention and Adoption Intention. The positive correlations suggest that higher levels of each predictor tend to align with higher levels of the corresponding outcome variables, although these associations do not imply causation. These results help clarify which constructs may contribute more prominently to the regression models that follow. The statistically significant p-values indicate that the observed relationships are unlikely to be due to random variation within this sample. Overall, the correlation patterns provide an initial foundation for understanding how the study variables relate to the research questions. Table 7 shows the results of the Pearson's Correlation analysis, which reveals several significant correlations among the variables. All variables show a significance level of $p < .05$.

Table 7

Result of Pearson's Correlation Analysis

Variables	r	p
PE and BI	.669	.00027*
EE and BI	.604	.00036*
SI and BI	.670	.00022*
SC and BI	.765	.00041*
FC and AD	.572	.00043*
BI and AD	.740	.00024*

Note. This table shows the Pearson's Correlation results, indicating the variables' correlations. *p<.05.

Descriptive analysis, data visualization, and exploratory techniques confirmed the absence of multicollinearity, multivariate normality, and homoscedasticity, which are essential for

conducting linear regression analysis (Shrestha, 2020). The regression summary for this purposively selected sample shows that each block of predictors adds explanatory value to the model, as reflected in changes in R^2 and adjusted R^2. The coefficients indicate the direction and relative magnitude of each variable's association with the outcomes. The statistically significant t-tests and F-tests demonstrate that the constructs contribute meaningfully to the model at the .05 level. These results help clarify how the constructs relate to Behavioral Intention and Adoption Intention when examined simultaneously rather than individually. Together, the findings support the relevance of the constructs to the study's research questions.

A multiple linear regression model was developed based on the principle of minimizing the sum of squared residuals (Montgomery et al., 2021). To assess the existence of a statistically significant relationship between each independent and dependent variable, two-tailed t-tests and F-tests were performed, utilizing a significance level of .05. The researcher employed Coefficient of Determination (R^2) and adjusted R^2 to determine the percentage of variance in the dependent variable that could be explained by the independent variables and to evaluate the overall fit of the linear regression model (Montgomery et al., 2021). Table 8 presents a summary of the hierarchical multiple regression, while Tables 9 and 10 display the SPSS output for the Hierarchical multiple regression. It was observed that BI had the highest positive correlation with AD, at .592, and PE had the lowest positive correlation with BI, at .128. The p-values of all the variables were less than .05.

Table 8

Summary of the Hierarchical Multiple Regression

Statistics	Variable(s)	Value	Implication
Regression Coefficient	PE, EE, SI	.128, .159, .156	Positive weak correlation with BI
	SC	.584	Positive moderate correlation with BI
	FC and BI	.527 and .592	Positive, moderate correlation with AD.
p-value of *t-statistic*	PE, SC, FC and BI	.001*	Statistically significant (<= .05)
	EE and SI	.014* and .029*	Statistically significant (<= .05)
p-value of F-statistics		.001*	Statistically significant (<= .05)
R^2		.851	Strong positive correlation
Adjusted R^2		.843	Strong positive correlation

Note. This table shows the summary results of the regression coefficient, *p*-value, *t*-statistics, F-statistics. R^2, Adjusted R^2. *p<.05.

The regression model for Behavioral Intention in this purposively selected sample indicates that the constructs maintain statistically associations with. The standardized coefficients show the relative contribution of each construct, with some variables demonstrating stronger associations

than others. The significance levels suggest that these relationships are unlikely to be due to chance within this sample. These results help clarify which constructs may play a more prominent role in shaping Behavioral Intention in the context of mobile health adoption. The model provides insight into how the study variables align with the research questions concerning predictors of BI. Table 9 shows the coefficients and t-statistics for BI.

Table 9

Coefficient and t-Statistics of Multiple Linear Regression Model for Behavioral Intention

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.330	.285		11.690	.001
	Gender	.783	.204	.272	3.840	.001
	Age	.057	.123	.063	.459	.647
	Experience	.137	.121	.155	1.135	.258
2	(Constant)	.033	.259		.127	.899
	Gender	.097	.134	.033	.721	.472
	Age	-.136	.078	-.152	-1.745	.083
	Experience	.090	.075	.102	1.201	.231
	PE	.128	.086	.113	1.495	.001*
	EE	.159	.064	.169	2.482	.014*
	SI	.156	.070	.145	2.207	.029*
	SC	.584	.073	.510	8.036	.001*

Note. This table displays the regression coefficients, coefficients standard error, *t*-statistics,

significance value (*p*-value) for Behavioral Intention (BI). *$p<.05$.

The regression model for Adoption Intention in this purposively selected sample indicates that both Facilitating Conditions and Behavioral Intention have statistically significant associations with AD when controlling for demographic factors. The standardized coefficients show that these predictors contribute meaningfully to explaining variation in AD. These findings help clarify which constructs are most relevant to understanding adoption-related outcomes in the study. The results support the research questions by identifying the construct that associates most closely with Adoption Intention. Table 10 shows the coefficients and t-statistics for AD.

Table 10

Coefficient and t-Statistics of Multiple Linear Regression Model for Adoption Intention

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.412	.273		8.836	.001
	Gender	.844	.195	.296	4.320	.001
	Age	.202	.118	.228	1.711	.089
	Experience	.084	.116	.096	.725	.469
2	(Constant)	-1.384	.251		-5.512	.001
	Gender	.291	.114	.102	2.543	.012
	Age	.067	.067	.075	.995	.321
	Experience	.045	.066	.051	.683	.495
	FC	.527	.051	.409	10.330	.001*
	BI	.592	.041	.599	14.612	.001*

Note. This table displays the regression coefficients, coefficients standard error, *t*-statistics, significance value (*p*-value) for Adoption Intention (AD). *$p<.05$.

Table 11 presents the SPSS output of the Analysis of Variance (ANOVA), which includes the F-statistics and corresponding p-values for the constructed multiple linear regression model. The ANOVA results for this purposively selected sample indicate that the regression model explains a statistically significant portion of variance in the dependent variable compared to a model without the constructs. The significant F-statistic indicates that the constructs collectively contribute explanatory power. This finding supports the use of multiple regression as an appropriate analytical approach for the study. The results also reinforce the relevance of the selected variables to the research questions. Overall, the ANOVA output confirms that the model provides a meaningful representation of the relationships examined in the study. The value of the F-statistic was 114.102 and *p*-value was .001, signifying statistical significance ($p<.05$). It can be concluded that this linear regression model is a better fit for the collected data when compared to a model that did not include independent variables.

Table 11

ANOVA of Multiple Linear Regression Model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56.585	3	18.862	11.369	.001*
	Residual	308.594	186	1.659		
	Total	365.179	189			
2	Regression	310.716	9	34.524	114.102	.001*
	Residual	54.463	180	.303		
	Total	365.179	189			

a. Predictors: (Constant), Experience, Gender, Age

b. Predictors: (Constant), Experience, Gender, Age, FC, BI, SI, EE, SC, PE

Note. This table displays the result of Analysis of Variance (ANOVA), including sum of squares, degree of freedom, mean square, *F*-statistics, and significance value (*p*-value).

* $p<.05$.

Table 12 presents the SPSS output for additional metrics, including R, R^2, adjusted R^2, the standard error of estimate, degrees of freedom (*df*), and the p-value for the multiple linear regression model. The model summary for this purposively selected sample indicates that the constructs collectively account for a substantial proportion of variance in the dependent variable. The adjusted R^2 value shows that the model maintains its explanatory strength even after accounting for the number of constructs. The change statistics demonstrate that adding the main study variables meaningfully improves the model. These results help clarify the extent to which the constructs contribute to explaining the outcomes addressed in the research questions. The overall pattern supports the suitability of the regression approach for this study.

The model demonstrates an R^2 value of .851, indicating a fit, as over 85.1% of the variance in the dependent variable is explained by the independent variables. The adjusted R^2 is 0.843, indicating the model's validity given the number of predictors utilized. Both R^2 and adjusted R^2 fall within the acceptable threshold of 0.4 for linear regression, indicating the integrity of this constructed model.

Table 12

Summary of Hierarchical Multiple Regression Model

				Std. Error of	Change Statistics				
Model	R	R Square	Adjusted R Square	the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.394[a]	.155	.141	1.28806	.155	11.369	3	186	.001*
2	.922[b]	.851	.843	.55007	.696	139.984	6	180	.001*

a. Predictors: (Constant), Experience, Gender, Age

b. Predictors: (Constant), Experience, Gender, Age, FC, BI, SI, EE, SC, PE

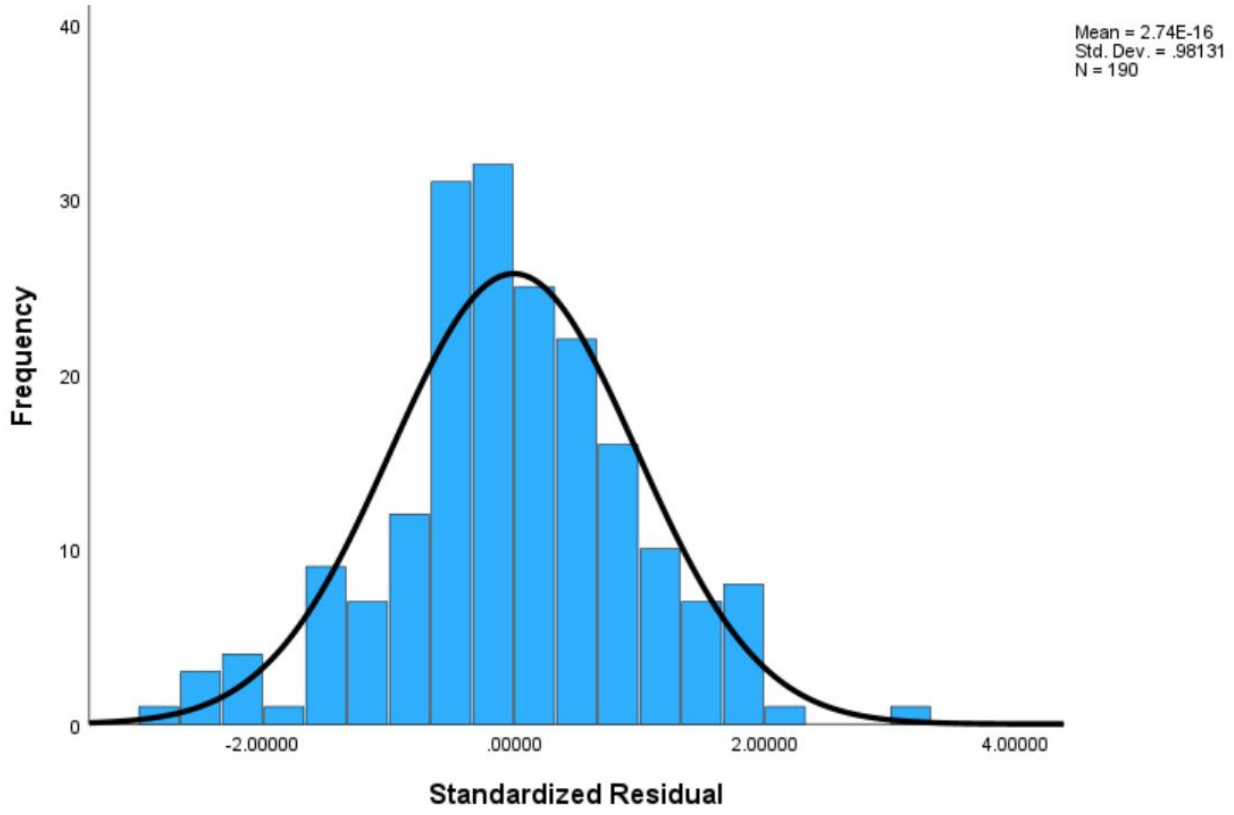
Note. This table displays the summary multiple linear regression model, including R, R^2, adjusted R^2, standard error of estimate, F-statistics, degree of freedom (df), and p-value. *p<.05.

Figure 11 shows the histogram and distribution of the standardized regression residuals, revealing a distribution curve closely centered around zero. Additionally, Figure 11 indicates that the standardized residuals have a mean value of 2.74* e^{-16}, nearly zero, and a standard deviation of 0.98131, which approximates one. The standardized regression residuals are centered around zero and fall within a range that is consistent with a normal distribution. The mean of the residuals is extremely close to zero, and the standard deviation is close to one, which aligns with the characteristics of a standard normal distribution. These values indicate that the residuals follow the pattern expected under the normality assumption. Meeting this assumption supports the use of

multiple regression in this purposively selected sample. Overall, the distribution of residuals is appropriate for interpreting the regression results. The results of this analysis are aimed to provide context-specific insights into how UTAUT constructs manifest in organizational environments and how these relationships may inform theoretical understanding of technology adoption in healthcare settings.

Figure 11

Histogram and Distribution of Regression Standardized Residual



Note. This figure shows the frequency and probability density of the regression standardized residual.

Research Question 1/ Hypothesis

To what extent, if any, is performance expectancy associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

$H1_0$

There is no statistically identifiable association between performance expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

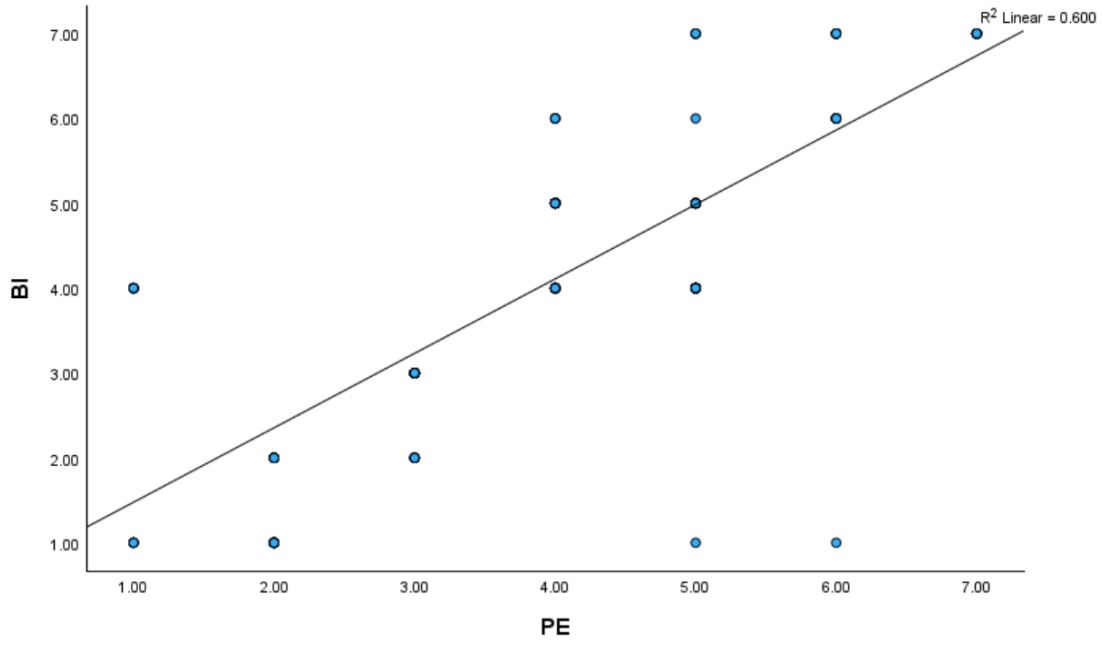
$H1_a$

There is a statistically identifiable association between performance expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

The multiple linear regression analysis indicated that Performance Expectancy (PE) was associated with Behavioral Intention (BI) within this purposively selected sample, with $t = 1.495$ and $p = .001$. The standardized coefficient ($\beta = .128$) reflects a weak positive association between the two constructs. Based on these results, the null hypothesis was rejected. The observed pattern suggests that higher levels of PE corresponded with higher levels of BI among individuals in this sample. These findings represent associations within this context-specific group rather than generalizable trends. Figure 12 shows the regression graph for the association between PE and BI. The regression graph for Performance Expectancy and Behavioral Intention shows a weak positive slope, indicating that increases in PE were associated with slight increases in BI within the purposive sample. This visual pattern directly relates to RQ1 by illustrating the nature of the association between PE and BI as identified in the statistical results. The graph supports the conclusion that PE demonstrated a statistically identifiable, though weak, relationship with BI, consistent with the rejection of the null hypothesis. The R^2 value of .6 shows the proportion of variation in Behavioral Intention explained by Performance Expectancy in this sample. The low R^2 aligns with the shallow slope in the graph, indicating that PE plays only a limited role in addressing the research question.

Figure 12

Regression graph for the association between PE and BI



Note. This figure shows the regression graph that represents the association between PE and BI.

RQ2

To what extent, if any, is effort expectancy associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

$H2_0$

There is no statistically identifiable association between effort expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

$H2_a$

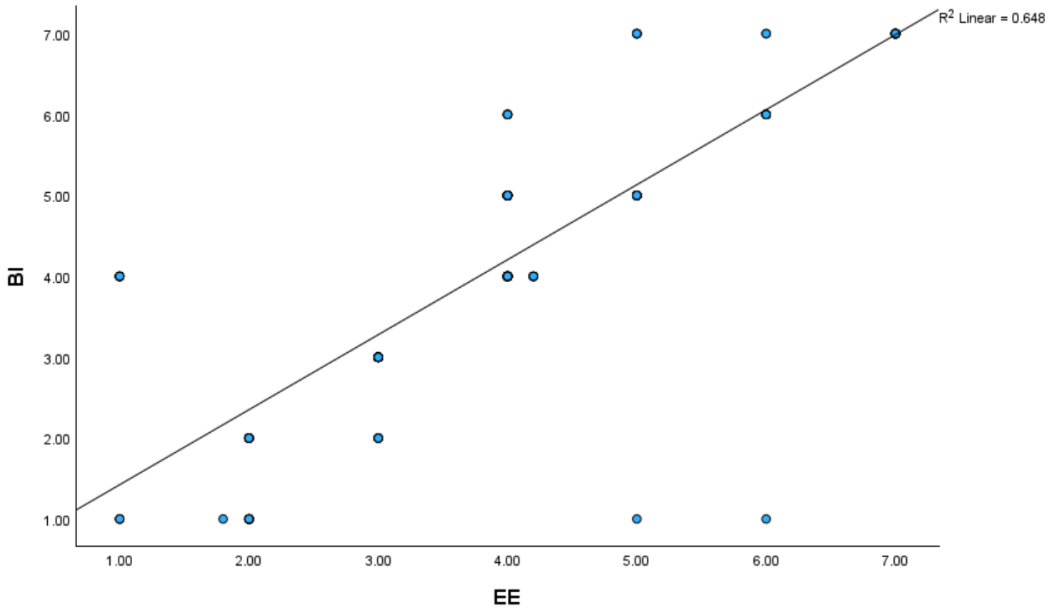
There is a statistically identifiable association between effort expectancy and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

Effort Expectancy (EE) demonstrated a statistically identifiable association with Behavioral Intention (BI), with $t = 2.482$ and $p = .014$. The standardized coefficient ($\beta = .159$)

indicates a weak positive relationship between EE and BI in this purposively selected sample. The null hypothesis was rejected. The results suggest that higher levels of EE corresponded with higher levels of BI within this group. These findings reflect patterns observed in the sample and are not intended to imply population-level inference. Figure 13 shows the regression graph of the association between EE and BI. The regression graph for Effort Expectancy and Behavioral Intention shows a modest upward trend, indicating that higher EE scores correspond to slightly higher BI. This visual representation addresses RQ2 by depicting the weak positive association observed between EE and BI in the analysis. The graph reinforces the statistical finding that EE had a statistically identifiable relationship with BI, supporting the decision to reject the null hypothesis. The R^2 value of .648 reflects the proportion of Behavioral Intention explained by Effort Expectancy. The low R^2 corresponds with the weak upward trend in the graph, demonstrating that EE contributes modestly to answering the research question.

Figure 13

Regression graph for the association between EE and BI



Note. This figure shows the regression graph that represents the association between PE and BI.

RQ3

To what extent, if any, is social influence associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

$H3_0$

There is no statistically identifiable association between social influence and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

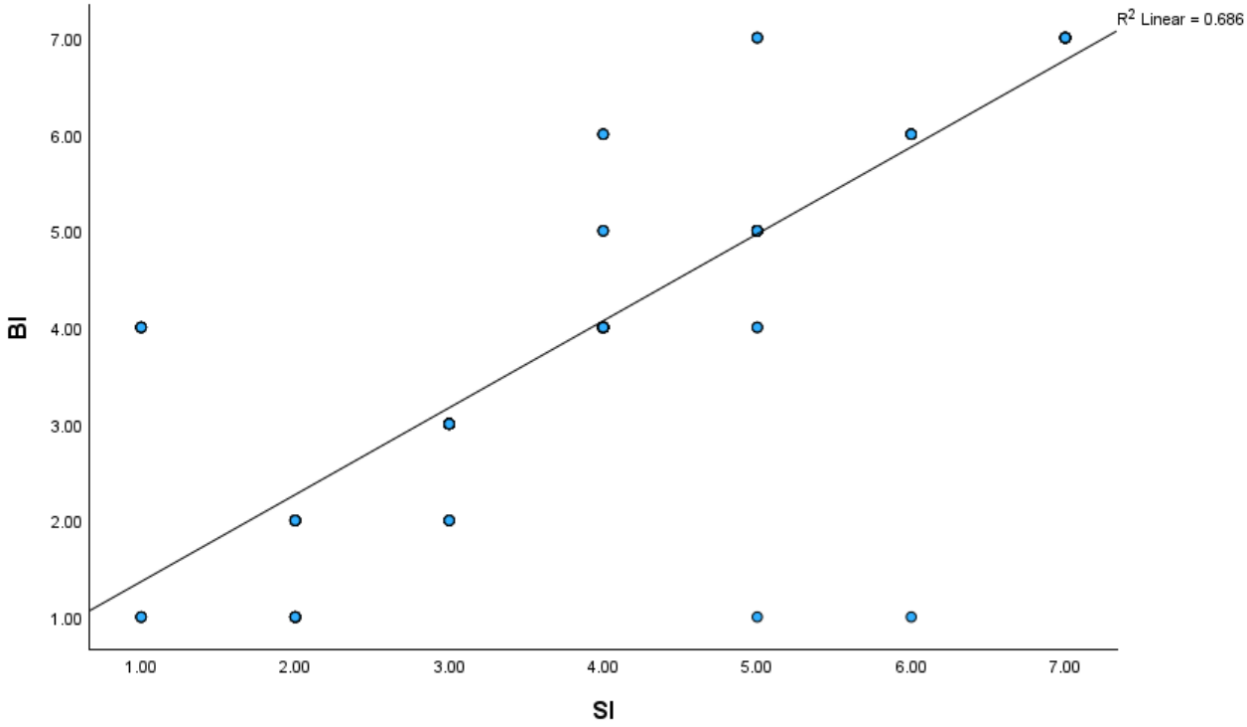
$H3_a$

There is a statistically identifiable association between social influence and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

Social Influence (SI) was associated with Behavioral Intention (BI), with $t = 2.207$ and $p = .029$. The standardized coefficient ($\beta = .156$) reflects a weak positive association between SI and BI in this purposively selected sample. The null hypothesis was rejected. The results indicate that higher levels of SI corresponded with higher levels of BI among participants in this study. These findings represent context-bound associations rather than generalizable conclusions. Figure 14 shows the regression graph of the association between SI and BI. The regression graph for Social Influence and Behavioral Intention shows a slight positive slope, indicating that increases in SI were associated with small increases in BI. This pattern directly relates to RQ3 by visually demonstrating the weak positive association identified between SI and BI in the sample. The graph supports the conclusion that SI had a statistically identifiable relationship with BI, consistent with the rejection of the null hypothesis. The R^2 value indicates how much of the variation in Behavioral Intention is accounted for by Social Influence. The low R^2 matches the slight slope in the graph, showing that SI explains only a small portion of BI in relation to the research question.

Figure 14

Regression graph for the association between SI and BI



Note. This figure shows the regression graph that represents the association between SI and BI.

RQ4

To what extent, if any, is self-concept associated with healthcare provider decision-makers' behavioral intention to adopt MHS in the US?

$H4_0$

There is no statistically identifiable association between self-concept and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

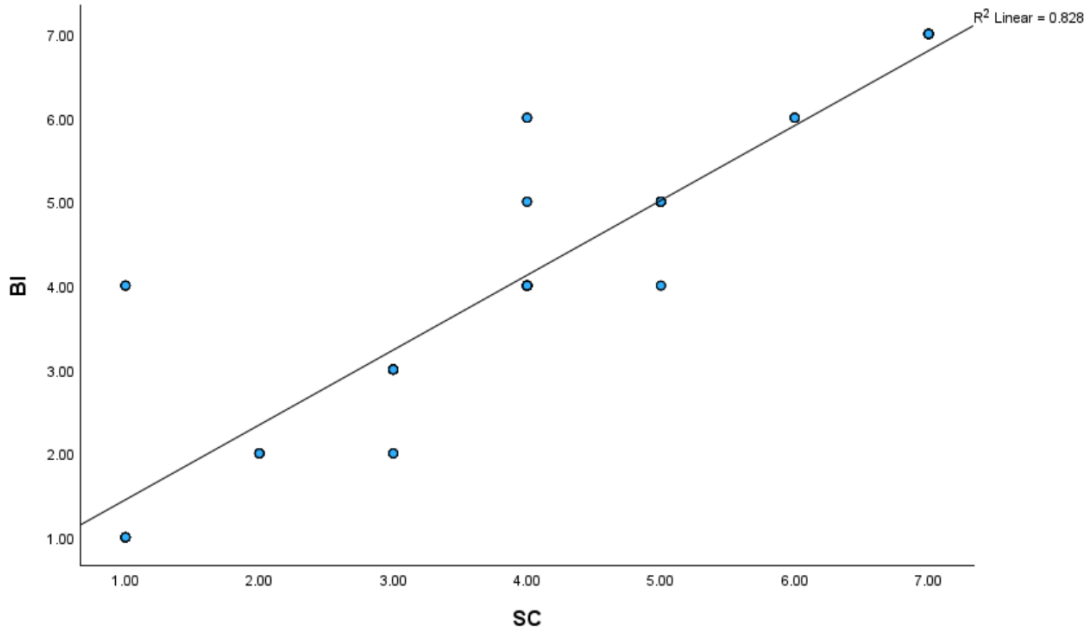
$H4_a$

There is a statistically identifiable association between self-concept and healthcare provider decision-makers' behavioral intention to adopt MHS in the US.

Self-Concept (SC) demonstrated a statistically identifiable association with Behavioral Intention (BI), with $t = 8.036$ and $p = .001$. The standardized coefficient ($\beta = .584$) indicates a moderate positive association within this purposively selected sample. The null hypothesis was rejected. The results suggest that higher levels of SC corresponded with higher levels of BI among individuals in this group. These findings reflect patterns observed in the sample and are interpreted as exploratory rather than predictive. Figure 15 shows the regression graph of the association between SC and BI. The regression graph for Self-Concept and Behavioral Intention shows a noticeably steeper positive slope compared to the other constructs, reflecting a moderate association between SC and BI. This visual trend addresses RQ4 by illustrating the strength and direction of the relationship between SC and BI within the purposive sample. The graph supports the statistical finding that SC had the strongest association with BI, reinforcing the rejection of the null hypothesis and highlighting its prominence among the constructs. The R^2 value of .828 represents the extent to which Self-Concept explains variation in Behavioral Intention. The higher R^2 aligns with the steeper slope in the graph, demonstrating that SC plays a moderate role in addressing the research question.

Figure 15

Regression graph for the association between SC and BI



Note. This figure shows the regression graph that represents the association between SC and BI.

RQ5

To what extent, if any, are facilitating conditions associated with healthcare provider decision-makers' intention to adopt MHS in the US?

$H5_0$

There is no statistically identifiable association between facilitating conditions and healthcare provider decision-makers' adoption of MHS in the US.

$H5_a$

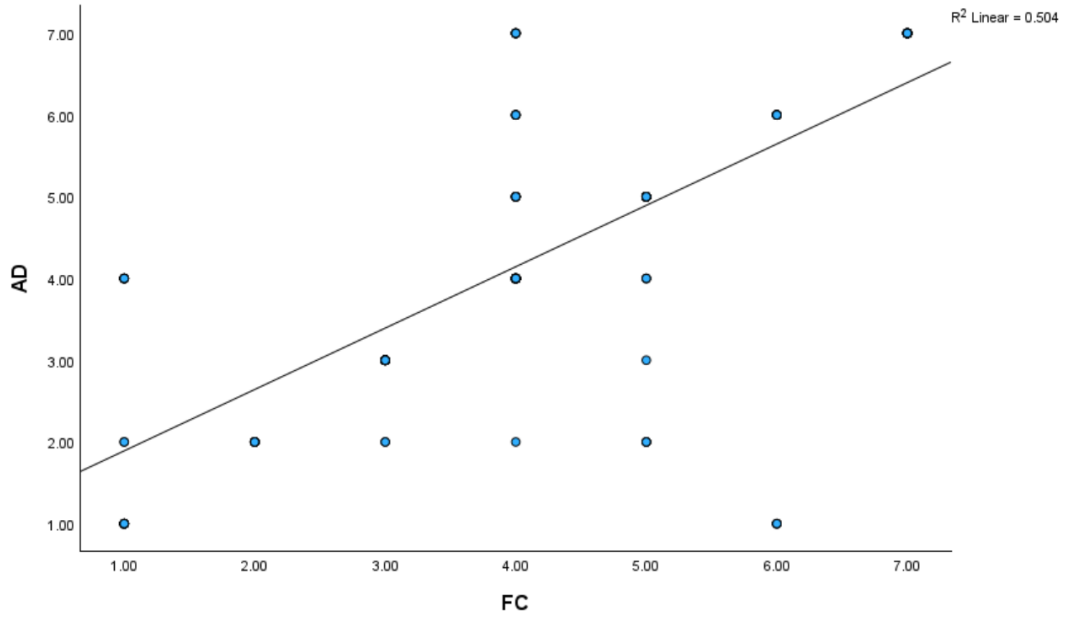
There is a statistically identifiable association between facilitating conditions and healthcare provider decision-makers' adoption of MHS in the US.

Facilitating Conditions (FC) were associated with Adoption Intention (AD), with t = 10.330 and p = .001. The standardized coefficient (β = .527) reflects a moderate positive association within this purposively selected sample. The null hypothesis was rejected. The results

suggest that higher levels of FC corresponded with higher levels of AD among participants. These findings represent context-specific patterns rather than generalizable effects. Figure 16 shows the regression graph of the association between FC and AD. The regression graph for Facilitating Conditions and Adoption Intention presents a positive slope, indicating that higher FC levels corresponded with higher AD. This visual pattern directly addresses RQ5 by depicting the moderate association between FC and AD identified in the statistical analysis. The graph supports the conclusion that FC had a statistically identifiable relationship with AD, consistent with the rejection of the null hypothesis. The R^2 value of .504 shows how much of the variation in Adoption Intention is explained by Facilitating Conditions. The moderate R^2 is consistent with the positive slope in the graph, indicating that FC moderately contributes to answering the research question.

Figure 16

Regression graph for the association between FC and AD



Note. This figure shows the regression graph that represents the association between FC and AD.

RQ6

To what extent, if any, are behavioral intention associated with healthcare provider decision-makers' intention to adopt MHS in the US?

$H6_0$

There is no correlation between behavioral intention and healthcare provider decision-makers' adoption of MHS in the US.

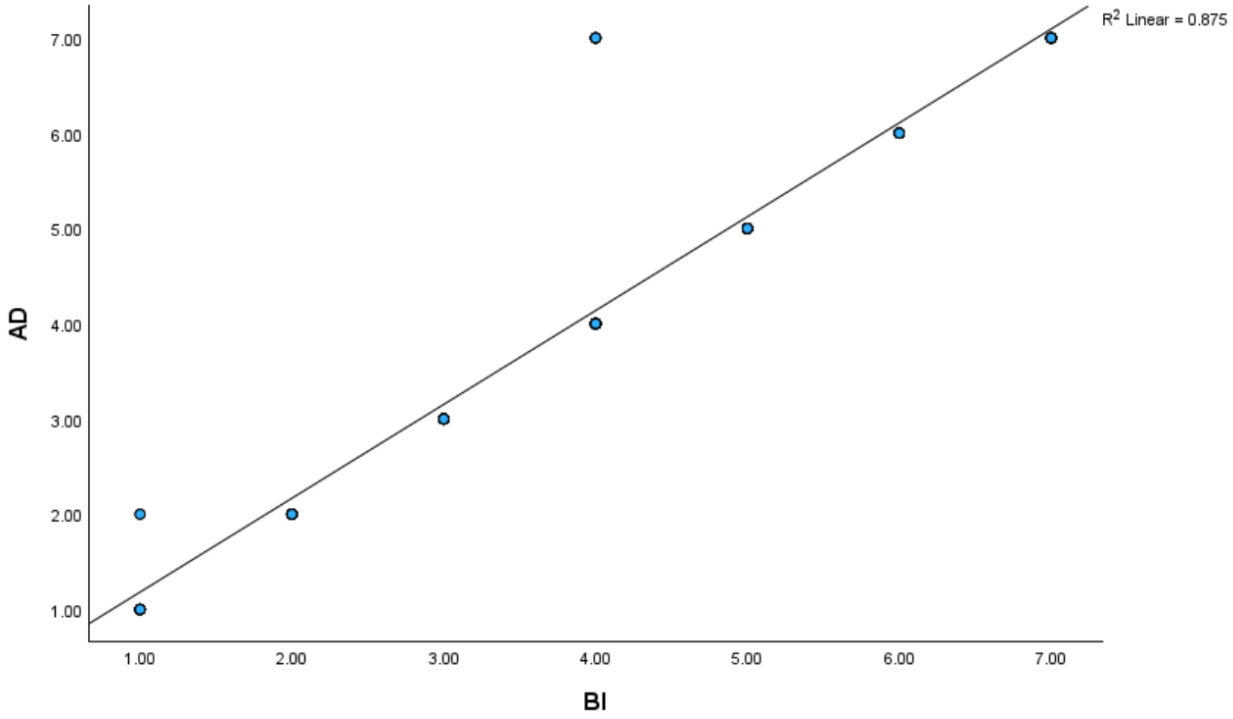
$H6_a$

There is a statistically identifiable association between behavioral intention and healthcare provider decision-makers' adoption of MHS in the US.

Behavioral Intention (BI) demonstrated a statistically identifiable association with Adoption Intention (AD), with $t = 14.612$ and $p = .001$. The standardized coefficient ($\beta = .592$) indicates a moderate positive association within this purposively selected sample. The null hypothesis was rejected. The results suggest that higher levels of BI corresponded with higher levels of AD among individuals in this group. These findings are interpreted as exploratory indicators of association rather than population-level predictors. Figure 17 shows the regression graph of the association between BI and AD. The regression graph for Behavioral Intention and Adoption Intention shows a strong positive slope, indicating that increases in BI were associated with higher AD within the sample. This visual trend relates to RQ6 by illustrating the strength of the association between BI and AD found in the analysis. The graph reinforces the statistical conclusion that BI significantly predicted AD, supporting the rejection of the null hypothesis. The R^2 value of .875 reflects the proportion of Adoption Intention explained by Behavioral Intention. The high R^2 aligns with the strong slope in the graph, demonstrating that BI is a moderate explanatory factor in addressing the research question.

Figure 17

Regression graph for the association between BI and AD



Note. This figure shows the regression graph that represents the association between BI and AD.

The regression and correlation results indicated associations among UTAUT constructs and between behavioral intention and adoption intention within this dataset. Given the purposive, nonrandom sampling strategy, these findings should be framed as sample-specific; they document patterns among the recruited decision-makers but do not establish population-level effect estimates. The lack of random sampling reduces external validity and increases the risk that sample selection biases influenced observed effect sizes and p-values. Accordingly, conclusions about the significance of these relationships in the wider population of U.S. healthcare decision-makers must be tempered.

Comparison of the Results to the Literature Review

The findings related to Performance Expectancy (PE) in this study are consistent with prior research emphasizing the role of perceived usefulness in technology adoption. The positive association between PE and Behavioral Intention (BI) aligns with the work of Istepanian (2022) and Niaz and Nwagwu (2023), who reported that healthcare decision-makers tend to support Mobile Health Services (MHS) when they perceive operational or clinical benefits. The pattern observed in this sample also reflects the conclusions of Rodić et al. (2024), who identified PE as an important factor in shaping adoption-related attitudes. Williams and Radnor (2022) noted that the influence of PE can vary across organizational contexts, which is consistent with the weak association observed in this study. Overall, the findings support the broader literature while indicating that the strength of the association may depend on contextual factors.

The results for Effort Expectancy (EE) show a statistically identifiable but weak positive association with BI, which aligns with research highlighting the relevance of perceived ease of use in technology adoption (Paul & Criado, 2020; Sun et al., 2013). The positive association observed in this sample is consistent with Alqahtani and Erfani (2021), who found that ease of use can support adoption intentions among healthcare decision-makers, particularly those with limited technological experience. However, Van Biesen et al. (2022) suggested that the influence of EE may diminish as individuals become more familiar with similar technologies, which may help explain the weaker association identified in this study. These findings indicate that EE remains relevant but may vary depending on prior exposure and organizational conditions.

The weak positive association between Social Influence (SI) and BI observed in this study aligns with literature describing the role of social and professional networks in shaping technology-related decisions. Duarte and Pinho (2019) emphasized that peer input and

professional expectations can influence adoption-related attitudes, which is consistent with the pattern identified in this sample. The findings also align with Heavey et al. (2020), who noted that social support can contribute to acceptance of new technologies. At the same time, Kosiol et al. (2024) cautioned that excessive social pressure may lead to limited or superficial engagement, suggesting that SI may operate differently across contexts. The results of this study contribute to this discussion by showing that SI is associated with BI, though the strength of the association remains modest.

The results related to Self-Concept (SC) indicate a moderate positive association with BI, suggesting that decision-makers' self-perceptions are relevant to their adoption-related attitudes. This finding aligns with Azam et al. (2023), who reported that positive self-perception can support openness to new technologies. The results also reflect the work of Dwivedi et al. (2016), who noted that alignment between a technology and an individual's professional identity can support adoption intentions. The pattern observed in this sample highlights the importance of SC as a factor that may shape decision-makers' views of MHS. These findings contribute to the literature by illustrating how SC may operate within organizational decision-making contexts.

The findings regarding Facilitating Conditions (FC) show a moderate positive association with Adoption Intention (AD), consistent with research emphasizing the importance of organizational resources and support structures. Venkatesh et al. (2003) and Al-Rawashdeh et al. (2022) noted that adequate infrastructure and training can support technology adoption, which aligns with the pattern observed in this sample. Niaz and Nwagwu (2023) also highlighted that resource limitations can restrict adoption efforts, suggesting that FC may vary across settings. The results of this study reinforce the relevance of FC within the technology acceptance

framework and indicate that supportive conditions may contribute to adoption-related attitudes in this sample.

The moderate positive association between Behavioral Intention (BI) and Adoption Intention (AD) aligns with literature identifying BI as a central component of technology acceptance models. The pattern observed in this sample is consistent with Venkatesh et al. (2003) and Yang et al. (2024), who reported that stronger intentions are associated with greater likelihood of adoption. The findings also align with Alqahtani and Erfani (2021), who noted that intention is often linked to subsequent behavior. The results of this study support the role of BI as an important factor associated with AD within this purposively selected sample. These findings contribute to the broader literature by illustrating how BI may function in decision-making contexts related to MHS.

Summary

Chapter 4 presents the findings of this quantitative correlational study examining the extent to which UTAUT constructs were associated with the adoption of Mobile Health Services (MHS) within a purposively selected group of healthcare provider decision-makers in the United States. Reliability and validity of the research instrument were supported through factor analysis and Cronbach's alpha, indicating internal consistency across the UTAUT constructs used in the analysis. Because purposive sampling limits external validity, all inferential statements apply only to the individuals included in this sample, and any broader interpretations should be considered tentative until examined with probability-based samples. Pearson's correlation analysis showed that Self-Concept demonstrated the strongest association with Behavioral Intention, followed by Social Influence, while Performance Expectancy and Effort Expectancy also showed positive associations of smaller magnitude. These patterns align with the UTAUT

framework and indicate that multiple constructs were related to Behavioral Intention and MHS Adoption within this sample.

The multiple linear regression analyses further indicated that each UTAUT construct demonstrated a statistically identifiable association with Behavioral Intention or Adoption Intention, with the overall model explaining a substantial proportion of variance in the outcomes. Behavioral Intention showed a notable association with Adoption Intention, indicating that intention played an important role in understanding adoption-related attitudes within this group. These results reflect patterns observed in this context-specific sample rather than predictive relationships generalizable to the broader population. Overall, the chapter highlights the multifaceted nature of MHS adoption and the ways in which decision-makers' perceptions were associated with their reported intentions in this study.

Chapter 5 will expand on these findings by organizing the discussion around the major results and interpreting them in relation to the research questions, theoretical framework, and existing literature. The chapter will also examine contextual factors that may influence interpretation, including the implications of purposive. Alignment between the study's findings and prior research will be evaluated, and limitations will be addressed to clarify the boundaries of the study's contributions. Finally, Chapter 5 will outline practical implications, identify areas for future research, and discuss how the findings may inform ongoing efforts to understand MHS adoption among healthcare decision-makers.

Chapter 5: Discussion, Recommendations, and Study Summary

The problem addressed in this study was the insufficient understanding of the factors associated with the adoption of MHS among healthcare provider decision-makers in the US, resulting in inconsistent adoption despite its potential benefits. (Istepanian, 2022; Niaz & Nwagwu, 2023). The purpose of this non-experimental, quantitative correlational study was to examine the extent to which the constructs of UTAUT were associated with adoption intention for MHS among a purposively selected group of healthcare provider decision-makers in the United States.

The researcher employed a quantitative correlational research design to investigate the factors associated with healthcare provider decision-makers' adoption of Mobile Health Services (MHS). Utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, the researcher focused on key variables, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Self-Concept (SC), Facilitating Conditions (FC), and Behavioral Intention (BI). Purposive data collection was facilitated through self-administered questionnaires developed by Azam et al. (2023) and distributed to healthcare decision-makers across Information Technology departments in the United States. One thousand participants were purposively recruited from a Facebook group to complete the survey, and 190 participants completed the questionnaire. The sample was non-probabilistic and chosen for relevance to the research question rather than for representativeness. This purposive approach facilitated access to experienced IT decision-makers but constrains population-level inference.

The correlational design enabled the examination of relationships between independent variables and dependent variables. The researcher employed a seven-point Likert scale questionnaire. Statistical analyses, including Pearson correlation and multiple linear regression,

were conducted to assess the strength and associations of the UTAUT construct with MHS adoption within the purposive sample. Assumption testing, including checks for multicollinearity, normality, and homoscedasticity, was incorporated into the study to ensure the validity of the results. This approach enabled the researcher to draw meaningful conclusions about the association of UTAUT construct with MHS adoption among healthcare provider decision-makers within the purposive sample.

The results of Pearson's correlation revealed that PE, EE, SI, and SC showed positive association with Behavioral Intention (BI), with SC exhibiting the strongest association at .765. Facilitating Conditions (FC) had a moderate positive association with Adoption Intention (AD), while BI demonstrated a strong positive association with AD at .740. The Multiple linear regression analysis indicated that PE, EE, SI, and SC are associated with BI. Additionally, FC and BI were found to be associated with AD. Overall, the findings underscore the likelihood that these constructs are associated with healthcare provider decision-makers' intentions to adopt Mobile Health Services.

Despite the study's strengths, several limitations must be acknowledged. One primary limitation is the reliance on self-reported data, which may introduce biases such as social desirability or response bias, potentially affecting the reliability of participants' responses. Importantly, the use of purposive (non-probability) sampling. The purposive sampling used in this study limits external validity: the findings cannot be generalized to all U.S. healthcare provider decision-makers. Inferential statistics applied to this sample should be interpreted cautiously because standard generalization and significance claims presuppose random sampling. Consequently, effect estimates and reported associations reflect relationships within this purposive sample and may not replicate in probability-based samples or broader contexts. The

correlational design precludes the establishment of causal relationships, limiting the ability to infer direct effects of the UTAUT constructs on MHS adoption. The participants were purposively selected from a specific Facebook group, which may not fully represent the broader population of healthcare provider decision-makers in the United States, thereby affecting the generalizability of the findings. Finally, the study's focus on a single point in time may overlook the dynamic nature of technology adoption, necessitating longitudinal research to capture changes in perceptions and behaviors over time.

This chapter will focus on major findings from the study, emphasizing how these results address the research problem and contribute to existing literature. Factors influencing the interpretation of results will be considered, along with the consistency of findings with current research and theory, including explanations for any unexpected outcomes. Recommendations for practice will be framed within the context of the study's findings and existing literature, ensuring not to overstate applicability. Lastly, suggestions for future research will be presented, including ways to build upon this study and address its limitations, as well as outlining the next logical steps in the research trajectory.

Discussion

Performance Expectancy (PE)

The multiple linear regression analysis indicated that Performance Expectancy (PE) was positively associated with Behavioral Intention (BI) within this purposively selected sample ($\beta = .128$, $p = .001$). Descriptive statistics showed that PE had a mean of 4.208 and a standard deviation of 1.242, reflecting moderate variation in participants' perceptions of the anticipated benefits of MHS. Factor analysis produced loading values of .882, .873, and .976 for the PE items, supporting the construct's measurement validity and its distinction from other UTAUT

variables. Reliability analysis yielded a Cronbach's alpha of .965, indicating internal consistency among the PE items. The weak association between PE and BI suggests that perceived performance benefits contributed to decision-makers' adoption-related intentions, though these perceptions functioned as one component within a broader set of considerations.

The histogram of PE responses showed a positively skewed distribution (skewness = .573) centered near the median value of 4.500, indicating generally favorable views of MHS performance benefits among participants. Correlation analysis positioned PE within a network of relationships among the UTAUT constructs while maintaining its distinct measurement properties, suggesting that performance perceptions operate as part of an integrated evaluative process rather than as an isolated factor. The regression coefficient indicates that each one-unit increase in PE corresponded with a .128-unit increase in BI, reflecting the modest contribution of performance perceptions to intention formation. Multicollinearity testing produced a Variance Inflation Factor of 3.291, indicating that PE was statistically independent from other factors while still conceptually related to them. Overall, the findings suggest that assessments of MHS performance capabilities contributed to adoption-related intentions within this sample, operating alongside other psychological and organizational factors that shape decision-making.

Effort Expectancy (EE)

The multiple regression analysis indicated that Effort Expectancy (EE) was positively associated with Behavioral Intention (BI) within this purposively selected sample ($\beta = .159$, $p = .014$). Descriptive statistics showed that EE had the highest standard deviation (1.494) and variance (2.232) among the constructs, reflecting variation in participants' perceptions of the ease of implementing and using MHS technologies. Factor analysis produced loading values of .953, .899, and .988 for the EE items, supporting the construct's measurement validity and its

distinction from other UTAUT variables. Reliability analysis yielded a Cronbach's alpha of .930, indicating internal consistency among the EE items. The weak association between EE and BI suggests that perceptions of ease of use contributed to adoption-related intentions, although these perceptions represented only one component of the broader decision-making process.

The distribution of EE responses showed a symmetric pattern centered around the median value of 4.000, indicating balanced views regarding the effort required to use MHS across participants. Correlation analysis positioned EE within a network of relationships among the UTAUT constructs while maintaining its distinct measurement properties, suggesting that ease-of-use considerations functioned as part of an integrated evaluative framework rather than as an isolated factor. Overall, the findings indicate that perceptions of implementation effort contributed to BI within this sample, operating alongside other psychological and organizational influences relevant to MHS adoption.

Social Influence (SI)

The multiple linear regression analysis indicated that Social Influence (SI) was positively associated with Behavioral Intention (BI) within this purposively selected sample ($\beta = .156$, $p = .029$). Descriptive statistics showed that SI had the highest median value (5.000) among the constructs, reflecting generally favorable perceptions of professional and peer support for MHS adoption. Factor analysis produced loading values of .933, .899, and .988 for the SI items, supporting the construct's measurement validity and its distinction from other UTAUT variables. Reliability analysis yielded a Cronbach's alpha of .832, indicating internal consistency among the SI items. The weak association between SI and BI suggests that social and professional input contributed to adoption-related intentions, though these influences represented one component of a broader decision-making process.

Correlation analysis positioned SI within a network of relationships among the UTAUT constructs while maintaining its distinct measurement properties, indicating that social considerations functioned as part of an integrated evaluative framework rather than as isolated influences. The regression coefficient indicates that each one-unit increase in SI corresponded with a .156-unit increase in BI, reflecting the specific contribution of social dynamics to intention formation. Multicollinearity testing produced a Variance Inflation Factor of 2.391, indicating that SI was statistically independent from other predictors while still conceptually related to them. Overall, the findings suggest that perceptions of social and professional support contributed to BI within this sample, operating alongside other psychological and organizational factors relevant to MHS adoption.

Self-Concept (SC)

The multiple linear regression analysis indicated that Self-Concept (SC) was positively associated with Behavioral Intention (BI) within this purposively selected sample ($\beta = .584$, $p = .001$). Descriptive statistics showed that SC had the highest mean value (4.424) among the constructs, reflecting generally favorable perceptions of technological compatibility among participants. Factor analysis produced loading values of .934, .832, and .988 for the SC items, supporting the construct's measurement validity and its distinction from other UTAUT variables. Reliability analysis yielded a Cronbach's alpha of .775, indicating acceptable internal consistency among the SC items. The moderate association between SC and BI suggests that participants' self-perceptions regarding their technological identity and capabilities contributed meaningfully to their adoption-related intentions.

Correlation analysis positioned SC within a network of relationships among the UTAUT constructs while maintaining its distinct measurement properties, indicating that self-perception

functioned as part of an integrated evaluative framework. The regression coefficient shows that each one-unit increase in SC corresponded with a .584-unit increase in BI, reflecting the specific contribution of self-perception to intention formation. Multicollinearity testing produced a Variance Inflation Factor of 2.882, indicating that SC was statistically independent from other constructs while still conceptually related to them. Overall, the findings suggest that SC played an important role in shaping BI within this sample, operating alongside other psychological and organizational factors relevant to MHS adoption.

Facilitating Conditions (FC)

The multiple linear regression analysis indicated that Facilitating Conditions (FC) were positively associated with Adoption Intention (AD) within this purposively selected sample ($\beta = .527$, $p = .001$). Factor analysis produced loading values of .949 and .884 for the FC items, supporting the construct's measurement validity and its distinction from other UTAUT variables. Reliability analysis yielded a Cronbach's alpha of .891, indicating internal consistency among the FC items. The moderate association between FC and AD suggests that organizational infrastructure and support resources contributed to adoption-related intentions, although these factors represented one component of a broader decision-making process.

The distribution of FC responses showed a relatively symmetric pattern centered around the median value of 4.000, indicating balanced perceptions of organizational support across participants. Correlation analysis positioned FC within a network of relationships among the UTAUT constructs while maintaining its distinct measurement properties, suggesting that organizational support functioned as part of an integrated evaluative framework rather than as an isolated factor. The regression coefficient indicates that each one-unit increase in FC corresponded with a .527-unit increase in AD, reflecting the specific contribution of

organizational support to intention formation. Multicollinearity testing produced a Variance Inflation Factor of 1.378, indicating that FC was statistically independent from other predictors while still conceptually related to them. Overall, the findings suggest that FC contributed to AD within this sample, operating alongside other psychological and organizational influences relevant to MHS adoption.

Behavioral Intention (BI)

The multiple regression analysis indicated that Behavioral Intention (BI) was positively associated with Adoption Intention (AD) within this purposively selected sample ($\beta = .592$, $p = .001$). Descriptive statistics showed that BI had a median value of 4.500 and a negatively skewed distribution (skewness = –.382), reflecting generally favorable adoption intentions among participants. Factor analysis produced loading values of .833 and .899 for the BI items, supporting the construct's measurement validity and its distinction from other UTAUT variables. Reliability analysis yielded a Cronbach's alpha of .775, indicating acceptable internal consistency among the BI items. The moderate association between BI and AD aligns with the UTAUT framework, which identifies intention as an important factor related to adoption-related behaviors.

The regression coefficient indicates that each one-unit increase in BI corresponded with a .592-unit increase in AD, reflecting the specific contribution of intention to adoption-related outcomes within this sample. Correlation analysis positioned BI within a network of relationships among the UTAUT constructs, suggesting that intention functioned as part of an integrated evaluative framework. Multicollinearity testing produced a Variance Inflation Factor of 3.018, indicating that BI was statistically independent from other constructs while still conceptually related to them. Overall, the findings suggest that BI contributed to AD within this

sample, operating alongside other psychological and organizational factors relevant to MHS adoption.

Factors influencing the interpretation of results

The self-reported nature of the data-collection methodology may introduce response bias, as healthcare provider decision-makers may have presented socially desirable responses rather than their authentic perspectives on MHS adoption. The cross-sectional design captures participants' perceptions at a single point in time, failing to account for the dynamic and evolving nature of technology acceptance processes that unfold longitudinally within healthcare organizations. Because the sample was purposive, caution is warranted when interpreting correlations and regression coefficients as evidence of generalizable patterns. These sampling characteristics may inflate or attenuate estimated relationships among UTAUT constructs and Behavioral Intention. Thus, reported p-values and model fit indices should be treated as sample-specific indicators of correlation rather than definitive evidence of population-level effects. Statistical limitations, particularly the relatively weak correlations observed for Performance Expectancy (β=.128), Effort Expectancy (β=.159), and Social Influence (β=.156), suggest that these constructs explain only modest variance in Behavioral Intention, necessitating cautious interpretation of their associative significance.

The organizational contexts in which participants operate were not comprehensively captured, which limits the ability to determine how institutional characteristics such as organizational size, resource availability, regulatory requirements, and strategic priorities may influence or moderate the relationships between UTAUT constructs and adoption intentions. The exclusive use of a quantitative design, while providing statistical structure, did not allow for the contextual depth that qualitative methods could have contributed to understanding the decision-

making processes surrounding MHS adoption. The operationalization of constructs through standardized measurement items may not fully reflect the nuanced ways in which healthcare provider decision-makers interpret and evaluate technological innovations within their specific professional environments. Although multicollinearity was not severe based on Variance Inflation Factor values (with the highest VIF at 3.291 for Performance Expectancy), the presence of intercorrelations among the constructs indicates some overlap in construct variance, which may influence the precision with which variance is attributed to individual UTAUT components. Additionally, reliance on the UTAUT framework, while theoretically grounded, may have excluded other relevant factors specific to healthcare settings that fall outside the scope of the model.

The generalizability of findings is constrained by the geographical focus of this study on the United States healthcare system, which operates under unique regulatory, financial, and structural conditions that may not translate to other national contexts. The technological landscape of MHS is rapidly evolving, with continuous innovations potentially rendering the findings in this study less applicable to emerging technologies and implementation approaches not captured during the data collection period. Participant characteristics, particularly their technological literacy, prior experiences with similar systems, and professional roles within their organizations, may have systematically influenced their responses in ways not fully accounted for in this study.

Contextualizing the result of the study

Finally, the study contributes to the broader literature by demonstrating the usefulness of correlational analysis for examining healthcare technology (Reed et al., 2021; Varpio et al., 2020). The validation procedures, including factor analysis and reliability testing, support the

psychometric properties of the UTAUT constructs within this purposively selected sample, addressing methodological gaps in prior research that often assumed construct validity without empirical verification (Sürücü & Maslakci, 2020; Kennedy, 2022). The hierarchical regression approach offers insight into how different factors relate to adoption intentions (Montgomery et al., 2021; Shrestha, 2020).

In keeping with the exploratory nature of the study, these findings are interpreted as context-specific indicators rather than generalizable associations. Rather than claiming broad explanatory or predictive power, the study contributes by illustrating how UTAUT constructs manifested among actual healthcare decision-makers and by identifying patterns of association that may guide future research using probability-based sampling or mixed-method designs. The results also highlight practical considerations for organizations exploring MHS adoption, including the potential relevance of professional identity and organizational support. This positioning frames the study as a theory-informing contribution that offers context-bound insights into technology adoption processes in healthcare settings, while acknowledging that the findings are limited to the purposively selected sample and should be interpreted cautiously when applied to broader populations.

Consistency with existing research and theory and explanations for unexpected results

The findings from this study demonstrate alignment with existing theoretical perspectives while also revealing several patterns that extend current understanding of healthcare technology adoption within this purposively selected sample. The association between Self-Concept (β = .584, p = .001) and Behavioral Intention is consistent with Azam et al.'s (2023) proposition that healthcare professionals' self-perceptions influence technology acceptance. This relationship also reflects Dwivedi et al.'s (2016) view that professional identity considerations contribute to

technology-related evaluations in healthcare settings. The association between Facilitating Conditions and MHS Adoption (β = .527, p = .001) aligns with Istepanian's (2022) emphasis on organizational infrastructure as an enabling factor, while the relationship between Behavioral Intention and MHS Adoption (β = .592, p = .001) corresponds with the central pathway proposed in the UTAUT framework (Venkatesh et al., 2003).

The weak associations observed for Performance Expectancy (β = .128, p = .001), Effort Expectancy (β = .159, p = .014), and Social Influence (β = .156, p = .029) represent a departure from traditional UTAUT findings, which often identify Performance Expectancy as the strongest correlate of adoption intentions (Sun et al., 2013; Venkatesh, 2022). Within this sample, the weaker association may reflect the professional context in which healthcare decision-makers operate, where evaluations of technology may be shaped more by alignment with professional identity than by utilitarian assessments of performance benefits. This interpretation is consistent with Williams and Radnor's (2022) observation that healthcare technology evaluations differ from those in commercial environments. Additionally, the established presence of digital tools in healthcare may have normalized performance expectations, reducing the extent to which these expectations differentiate adoption intentions compared to earlier studies conducted during periods of technological novelty.

The weak association between Effort Expectancy and Behavioral Intention diverges from findings reported by Paul and Criado (2020), who identified ease of use as a meaningful factor in healthcare technology adoption. This pattern may reflect participants' extensive experience with digital systems, which could reduce the relevance of implementation effort in their evaluations. This interpretation aligns with Alqahtani and Erfani's (2021) observation that the influence of Effort Expectancy diminishes as users gain familiarity with similar technologies. The specialized

nature of healthcare technologies may also contribute to expectations of implementation complexity, reducing the weight placed on ease of use. Additionally, decision-makers' responsibilities often involve overseeing implementation rather than directly operating systems, which may shift their focus toward organizational and clinical considerations rather than personal usability.

The weak association between Social Influence and Behavioral Intention contrasts with Duarte and Pinho's (2019) findings regarding the influence of professional networks. This result may reflect the autonomy associated with decision-making roles, which could reduce susceptibility to peer influence compared to frontline clinicians. The finding is consistent with Heavey et al.'s (2020) observation that social pressures may contribute to surface-level adoption rather than substantive integration, suggesting that decision-makers may moderate the influence of social dynamics when evaluating new technologies. Additionally, as technology adoption becomes more standardized within healthcare organizations, the influence of social endorsement may diminish relative to earlier periods of digital transformation.

The explanatory power of the overall model ($R^2 = .851$) exceeds values commonly reported in UTAUT studies, which often range from .40 to .70 (Venkatesh, 2022). This result may reflect the purposive nature of the sample and the inclusion of Self-Concept, which captured a dimension of decision-making that appears relevant in this professional context. The focused nature of the sample—healthcare provider decision-makers rather than general healthcare personnel may have reduced variability associated with diverse roles, thereby strengthening model fit. This pattern aligns with Azam et al.'s (2023) theoretical extension of UTAUT and demonstrates the model's applicability to decision-makers in healthcare settings.

The prominence of Self-Concept within this sample diverges from the traditional UTAUT hierarchy but aligns with emerging perspectives emphasizing professional identity in healthcare technology adoption (Azam et al., 2023). This finding suggests that decision-makers' evaluations of MHS may be shaped by perceptions of compatibility with professional identity rather than by utilitarian assessments alone. This interpretation is consistent with Gao et al.'s (2015) theoretical argument regarding the role of professional identity in technology acceptance. The prominence of Self-Concept may reflect characteristics of healthcare environments in which professional values and identity are closely linked to practice norms, creating a distinct evaluative framework for MHS adoption that differs from those observed in commercial or general organizational contexts.

Significant implications and consequences of the study

The most meaningful societal implication of this study emerges from the observed association between Self-Concept and Behavioral Intention within this purposively selected sample. This pattern suggests that implementation strategies emphasizing alignment with healthcare professionals' professional identity may support Behavioral Intention more effectively than approaches focused solely on technological performance. Such strategies may contribute to more effective technology implementation by shifting attention from traditional performance-based arguments toward messaging that resonates with how healthcare professionals perceive their roles and responsibilities. The association between Facilitating Conditions and MHS Adoption further indicates that organizational infrastructure, training, and technical support represent important areas for investment among healthcare organizations seeking to strengthen adoption-related intentions. While these findings offer insight into potential implementation approaches, they should be interpreted cautiously, as improvements in intention

alone are unlikely to address broader structural challenges—such as interoperability limitations, regulatory requirements, and resource constraints—that extend beyond the influence of individual decision-makers. The study's contribution is framed as theory-informing rather than predictive, consistent with its exploratory design. Instead of making broad generalizations, the findings offer insight into how UTAUT constructs appeared among the healthcare decision-makers in this purposive sample and identify patterns that may guide future research using probability-based or mixed-method approaches. The results also point to practical considerations for organizations exploring MHS adoption, particularly the roles of professional identity and organizational support. Overall, the study provides context-specific understanding of technology adoption in healthcare settings while acknowledging that its conclusions are limited to the sampled population.

Recommendation for Practice

The findings in this study suggest that within this purposively selected sample, Self-Concept demonstrated the strongest association with Behavioral Intention ($\beta = .584$, $p = .001$), indicating that healthcare organizations may benefit from implementation strategies that emphasize alignment with healthcare decision-makers' professional identities and values rather than relying primarily on technical capabilities or operational benefits. This interpretation aligns with prior research highlighting the role of professional identity in healthcare technology acceptance (Dwivedi et al., 2016; Gao et al., 2015; Azam et al., 2023). Technology developers may therefore consider incorporating professional identity considerations into system design, while implementation teams may frame MHS adoption as enhancing rather than replacing professional judgment. The relatively weaker association of Performance Expectancy ($\beta = .128$) suggests that identity-congruent messaging may be more influential than performance-based

arguments within this sample. Educational programs may also benefit from addressing how new technologies intersect with and potentially reshape professional identity, preparing future decision-makers for the psychological dimensions of technology adoption.

The significant association between Facilitating Conditions and MHS Adoption (β = .527, p = .001) indicates that organizations may need to invest in support infrastructures such as training, technical resources, and implementation assistance, consistent with Al-Rawashdeh et al.'s (2022) emphasis on organizational readiness. The relationship between Behavioral Intention and Adoption (β = .592, p = .001) further suggests that organizations may need to assess decision-makers' attitudes before committing substantial resources, aligning with the UTAUT framework's emphasis on intention as a mediating mechanism (Venkatesh et al., 2003). Because Performance Expectancy, Effort Expectancy, and Social Influence showed weaker associations with Behavioral Intention, implementation strategies may require multifaceted approaches rather than relying solely on operational benefits, consistent with theoretical perspectives emphasizing the complex interplay of adoption factors (Istepanian, 2022; Niaz & Nwagwu, 2023). Policy development may also need to consider the psychological and identity-related dimensions of technology adoption, recognizing that professional identity exerted greater influence on Behavioral Intention than traditional UTAUT constructs, consistent with Williams and Radnor's (2022) observation that healthcare technology evaluations differ from those in commercial sectors.

In keeping with the exploratory nature of the study, the contribution to the body of knowledge is framed as theory-informing rather than predictive. Rather than seeking generalizable findings, the researcher aimed to explore patterns of association within a targeted group of individuals with direct responsibility for technology-related decision-making. By

focusing on this knowledgeable subset, the result of the study provides context-specific insights into how UTAUT constructs manifested in organizational environments and how these relationships may inform theoretical understanding of technology adoption in healthcare settings. The findings offer preliminary evidence that may guide future research employing probability-based sampling or alternative methodological approaches, while also highlighting practical considerations for organizations exploring MHS adoption, including the potential relevance of professional identity and organizational support. This positioning reflects the study's intent to contribute to scholarly discourse by offering exploratory, context-bound insights while acknowledging that the results are limited to the purposively selected sample.

Recommendation for Future Research

Future researchers may consider conducting longitudinal investigations to examine how relationships among UTAUT constructs and MHS adoption evolve over time, addressing the cross-sectional limitation of this study and enabling stronger causal inferences about the adoption process. Such designs could extend Venkatesh et al.'s (2003) theoretical framework by capturing the dynamic nature of technology acceptance, including how Self-Concept, identified in this study, had the strongest association with Behavioral Intention ($\beta = .584$, $p = .001$), may shift as decision-makers gain experience with emerging technologies. Mixed-methods approaches that integrate quantitative measurement with qualitative exploration of decision-makers' reasoning processes would also provide deeper insight into why Self-Concept is associated with Behavioral Intention, addressing the limitation of relying exclusively on quantitative self-report data. Future studies may also investigate potential moderating variables such as organizational size, resource availability, and healthcare specialization, which could help explain contextual variations in the relationships among UTAUT constructs and MHS adoption. This direction

aligns with Williams and Radnor's (2022) observation that implementation contexts significantly shape adoption patterns. Cross-cultural comparative research would further clarify whether the prominence of Self-Concept association with Behavioral Intention generalizes across different healthcare systems and cultural environments, addressing this study's focus on the United States. Researchers may also develop and validate more refined measurement instruments for Self-Concept in healthcare technology contexts, building on this study's findings while addressing potential limitations in the current operationalization.

Methodological improvements could include random sampling across diverse healthcare settings to enhance representativeness and enable broader generalization. Such sampling strategies may also reveal how organizational characteristics moderate the relationships identified in this study, consistent with Istepanian's (2022) emphasis on contextual influences in healthcare technology adoption. Experimental or quasi-experimental designs that manipulate specific aspects of MHS implementation, particularly those targeting professional identity considerations, would help establish causal relationships beyond the association patterns observed in this study. Longitudinal intervention studies may also examine whether strategies designed to address Self-Concept concerns yield stronger Behavioral Intention outcomes than approaches focused primarily on performance benefits.

A logical next step in this research trajectory involves developing and empirically testing an expanded theoretical model that more fully integrates psychological identity processes with traditional UTAUT constructs in healthcare technology contexts. This direction responds to the unexpected finding that Self-Concept demonstrated the strongest association with Behavioral Intention and aligns with Azam et al.'s (2023) call for more conceptual frameworks in healthcare technology acceptance. Future research may explore the mechanisms through which

Self-Concept influences Behavioral Intention, including potential mediating psychological processes, and examine how different dimensions of professional identity—such as clinical expertise, patient relationships, and technological proficiency—contribute to the overall effect of Self-Concept. Researchers may also design and evaluate targeted interventions that address the psychological dimensions of MHS adoption, reflecting this study's finding that identity considerations outweighed performance expectations in the purposively selected decision-makers' evaluations. Ultimately, these efforts may support the development of comprehensive implementation frameworks that integrate technical, organizational, and psychological dimensions of healthcare technology adoption, addressing the complex interplay of factors revealed in this study.

Study Summary

The results of this quantitative correlational study identified factors associated with healthcare provider decision-makers' adoption of Mobile Health Services within this purposively selected sample, addressing the limited understanding that has contributed to inconsistent implementation despite the potential benefits of MHS. The findings indicate that Self-Concept ($\beta = .584$) demonstrated the strongest association with Behavioral Intention, exceeding the influence of traditional UTAUT constructs such as Performance Expectancy ($\beta = .128$), Effort Expectancy ($\beta = .159$), and Social Influence ($\beta = .156$). Facilitating Conditions ($\beta = .527$) and Behavioral Intention ($\beta = .592$) were also significantly associated with MHS Adoption. These patterns suggest that, within this sample, Behavioral Intention was shaped more by professional identity considerations than by utilitarian assessments of performance benefits, indicating that implementation strategies may need to emphasize alignment with healthcare professionals' self-perceptions. The explanatory power of the integrated model ($R^2 = .851$) further suggests that

the UTAUT framework, when extended to include Self-Concept, captures key cognitive processes underlying MHS adoption in this context.

Beyond theoretical contributions, the findings offer practical insights for healthcare organizations seeking to strengthen digital health integration. By highlighting the psychological dimensions of technology acceptance among healthcare decision-makers, the results of the study provides context-specific guidance for developing implementation strategies that address professional identity considerations alongside traditional infrastructure and training support. The results challenge the assumption that performance-based arguments are the primary drivers of adoption, suggesting that successful MHS implementation may require approaches that reinforce, rather than disrupt, healthcare providers' professional self-concept. These insights are framed as theory-informing and context-specific, offering preliminary evidence that may guide future research and organizational decision-making while acknowledging the limitations associated with the purposively selected sample.

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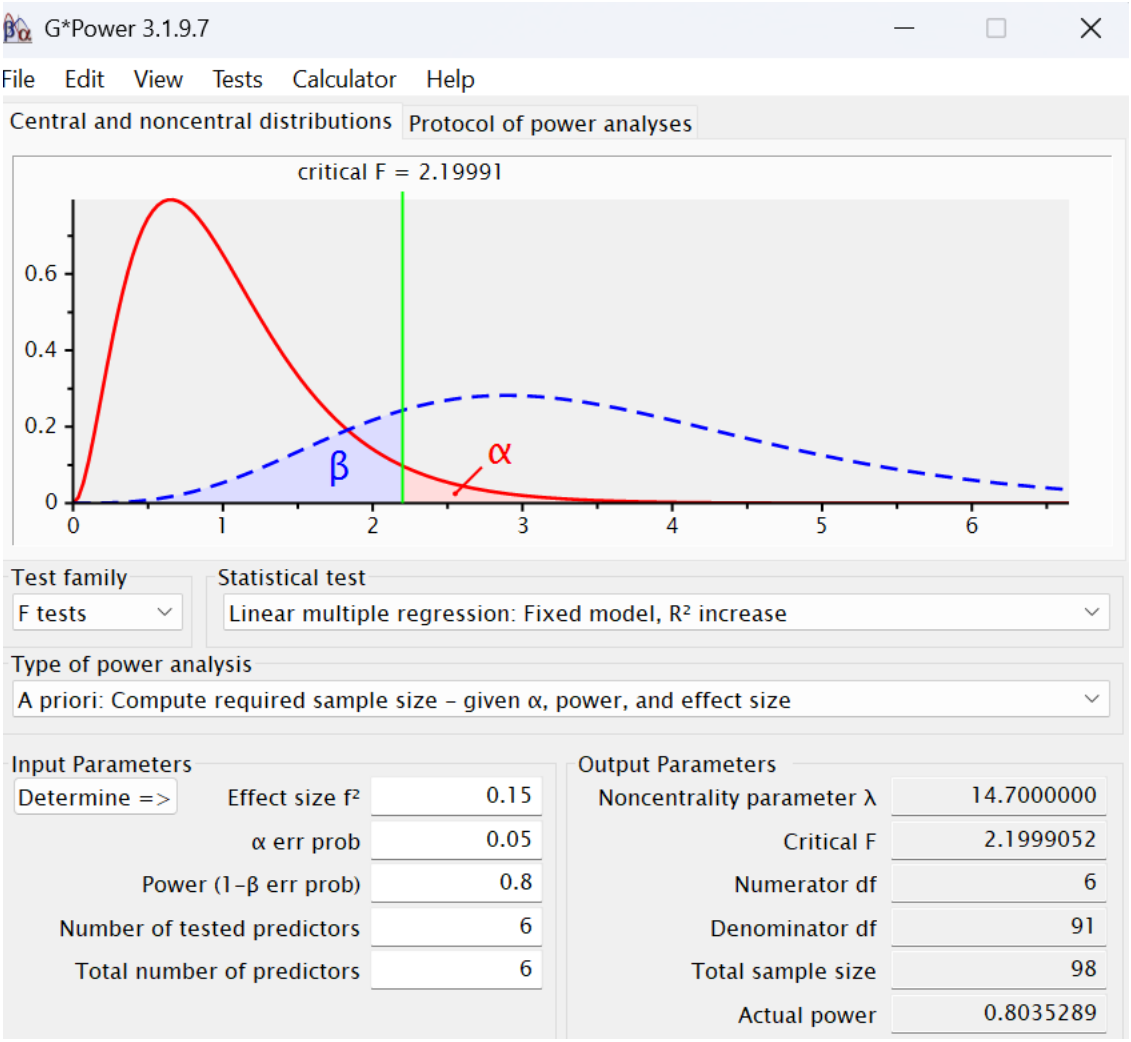
Appendices

Appendix A

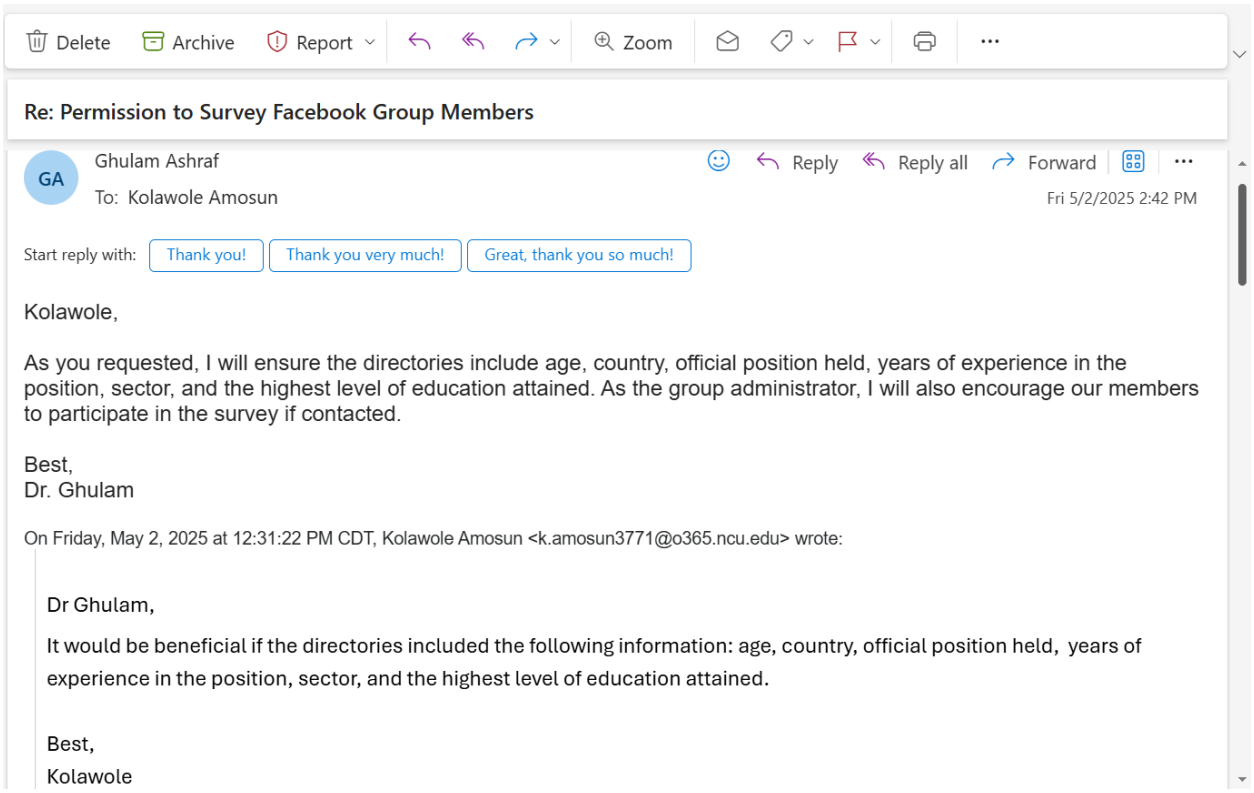
Parameter Values and Interface in Power Analysis



Note. This figure illustrates the specific parameter values and interface used for power analysis within the G-Power software.

Appendix B

Permission to Survey Group Members



Delete Archive Report Zoom

Re: Permission to Survey Facebook Group Members

GA

Ghulam Ashraf

To: Kolawole Amosun

Reply Reply all Forward

Fri 5/2/2025 2:42 PM

Start reply with: Thank you! Thank you very much! Great, thank you so much!

Kolawole,

As you requested, I will ensure the directories include age, country, official position held, years of experience in the position, sector, and the highest level of education attained. As the group administrator, I will also encourage our members to participate in the survey if contacted.

Best,
Dr. Ghulam

On Friday, May 2, 2025 at 12:31:22 PM CDT, Kolawole Amosun <k.amosun3771@o365.ncu.edu> wrote:

> Dr Ghulam,
>
> It would be beneficial if the directories included the following information: age, country, official position held, years of experience in the position, sector, and the highest level of education attained.
>
> Best,
> Kolawole

Appendix C

Recruitment Letter

Dear Prospective Participants,

I am Amosun Kolawole, a doctoral student at National University. I am writing to invite you to participate in my research study, which explores the factors influencing IT decision makers in healthcare adoption intentions of Mobile Health Services (MHS) in the United States of America: A Quantitative Analysis.

Your participation would involve completing a brief online survey related to this topic, which is expected to take about ten minutes. Please be assured that all responses will be treated with the utmost confidentiality.

I encourage you to take a moment to examine the informed consent form, as it outlines the ethical standards governing the research, including an assurance that participants' identities will remain anonymous in the final report.

If you have any questions regarding the study, please contact me via email at K.amosun3771@o365.ncu.edu.

Thank you for considering this opportunity to contribute to this research.

Sincerely,

Amosun Kolawole

Appendix D

Consent Form

Hello,
My name is Amosun Kolawole, and I am a doctoral student at National University. I am conducting an online survey to determine what factors influence healthcare leaders when they decide whether to adopt Mobile Health Services (MHS) in their organizations across the United States.

In order to participate, you are required to have the following qualifications:

i. You are 18 years of age or older.
ii. You live in the United States.
iii. You have a minimum associate degree.
iv. You have at least three years of experience as an IT decision-maker in healthcare.

Your participation in this study is voluntary. If you decide to participate, your responses will be anonymous, that is, recorded without any identifying information that is linked to you. If you have any questions regarding this survey, please contact me at k.amosun3771@o365.ncu.edu

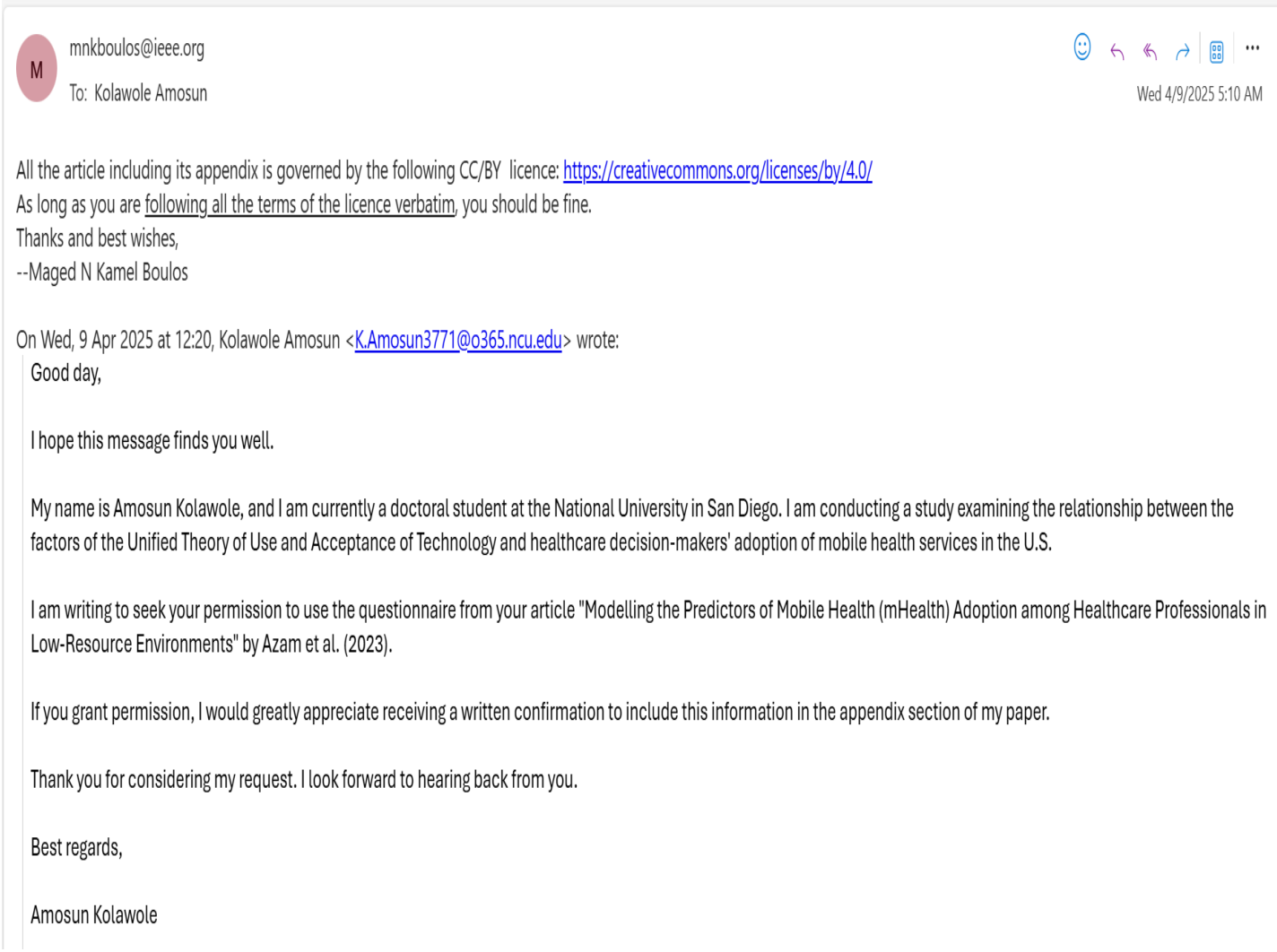
If you have any questions regarding your rights as a human subject and participant in this study, or to report research-related problems, you may email the National University IRB at irb@nu.edu.

By clicking the next button and completing the survey, you indicate that you have consented to participate in this research. If you do not want to participate, please close the browser.

- o Yes, I agree
- o No, I disagree

Appendix E

Permission to Use Survey Instrument



M

mnkboulos@ieee.org

To: Kolawole Amosun

Wed 4/9/2025 5:10 AM

All the article including its appendix is governed by the following CC/BY licence: https://creativecommons.org/licenses/by/4.0/
As long as you are following all the terms of the licence verbatim, you should be fine.
Thanks and best wishes,
--Maged N Kamel Boulos

On Wed, 9 Apr 2025 at 12:20, Kolawole Amosun <K.Amosun3771@o365.ncu.edu> wrote:

> Good day,
>
> I hope this message finds you well.
>
> My name is Amosun Kolawole, and I am currently a doctoral student at the National University in San Diego. I am conducting a study examining the relationship between the factors of the Unified Theory of Use and Acceptance of Technology and healthcare decision-makers' adoption of mobile health services in the U.S.
>
> I am writing to seek your permission to use the questionnaire from your article "Modelling the Predictors of Mobile Health (mHealth) Adoption among Healthcare Professionals in Low-Resource Environments" by Azam et al. (2023).
>
> If you grant permission, I would greatly appreciate receiving a written confirmation to include this information in the appendix section of my paper.
>
> Thank you for considering my request. I look forward to hearing back from you.
>
> Best regards,
>
> Amosun Kolawole

Appendix F

Survey Questions

Construct	Items	Measure
Performance Expectancy (PE)	PE1	I find MHS useful in daily life.
	PE2	I think MHS can help in providing timely medical advice to patients.
	PE3	I think MHS can help in accomplishing daily tasks more quickly.
	PE4	I think adopting MHS can increase clinical performance.
	PE5	I think MHS can reduce a considerable amount of hospital expenses on the provision of healthcare.
	PE6	I think MHS application allows healthcare professionals to be easily accessible and thereby enhances patient experience.
Effort Expectancy (EE)	EE1	I think learning how to monitor health issues through MHS is easy.
	EE2	I think interaction with patients through MHS app is clear and understandable.
	EE3	I think MHS apps are easy to use.
	EE4	I think no effort is needed to use MHS for patient care.
	EE5	I think it is easy to learn how to use MHS to receive, track, and evaluate medical data.
Social Influence (SI)	SI1	People who influence my behavior think that I should adopt MHS for clinical practice.
	SI2	People whose opinions that I value prefer that I adopt MHS for clinical practice.
	SI3	Professionals in my community who adopt MHS are more informed and active than those who do not.
	SI4	My mentors and senior professionals encourage me to adopt MHS for providing patient care.
Self-Concept (SC)	SC1	I think the application of MHS is necessary for clinical practice.
	SC2	I think there is strong evidence that supports the use of MHS in order to improve the quality of patient care.
	SC3	I feel adherence to MHS characteristics.
	SC4	I think my personal behavior is compatible with the MHS image.
	SC5	I think MHS can help in monitoring patients, issuing diagnoses, and treating diseases.
Facilitating Conditions (FCs)	FC1	I think my organization has access to the secured and trusted resources necessary to adopt MHS.

	FC2	I think I have gathered the knowledge necessary to adopt MHS.
	FC3	I think I can get help from my colleagues when I have difficulties adopting MHS.
	FC4	I think our hospital encourages and facilitates the adoption of MHS.
Behavioral Intention (BI)	BI1	I intend to adopt MHS in the future.
	BI2	I am interested in improving the skills necessary to incorporate MHS into clinical practice.
	BI3	If MHS brings convenience to patients, I am willing to continue incorporating it into our systems.
	BI4	I intend to inform my colleagues and other healthcare professionals to adopt MHS.
MHS Adoption for Healthcare	AD1	I think adopting MHS service will be a pleasant experience.
	AD2	I think MHS can provide an opportunity to respond to patients more quickly.
	AD3	I spend a lot of time using MHS applications.
	AD4	I think adopting MHS can enable faster access to patient data.
	AD5	I frequently use MHS.

Note. This survey instrument was adapted from Azam et al. (2023).

Appendix G

IRB Approval Letter

Dissertation

Dear Kolawole Amosun:

The study referenced above has been reviewed by the National University IRB. The IRB has determined your research is exempt from further review under 45 CFR 46.104, which means you will not need to renew your study and may begin your study effective immediately. However, if you find the need to change your study in any way, you will need to submit a modification to the IRB prior to implementing the changes. This will allow the IRB to determine whether or not the study still meets exemption criteria.

Please review your Post Approval Responsibilities here: Approved Documents Guidelines

For any questions regarding your protocol, please reach out to the IRB at irb@nu.edu.

Sincerely,

Dr. Joseph Marron, IRB Chair

Dr. Brianne Mongeon, Director, HRPP & IRB

Jenessa Eberhardt, Associate Director, HRPP & IRB

IRB-FY25-26-8 - Initial: Exempt from Further Review

National UNIVERSITY

9388 Lightwave Ave.
San Diego, CA 92123
irb@nu.edu

Notice of Exemption

July 28, 2025

To: Kolawole Amosun

Project Title: Factors Influencing Healthcare Provider Decision Makers' Adoption of Mobile Health Services (MHS) in the United States of America: A Quantitative Analysis
NU IRB Number: IRB-FY25-26-8
Determination: Exempt from further review 45 CFR 46.101 Category 2.(i). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met:
The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects;

Status: Active - Research activities may begin as of July 28, 2025