Digital Health Adoption Among Professionals in Abu Dhabi's Public Hospitals

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Candidate Declaration

I hereby declare that:

1. I have not been enrolled for another award of the University, or other academic or professional organisation, whilst undertaking my research degree.

2. None of the material contained in the thesis has been used in any other submission for an academic award.

3. I certify that this thesis is my own work. The use of all published or other sources of material consulted have been properly and fully acknowledged.

4. The work undertaken towards the thesis has been conducted in accordance with the SHU Principles of Integrity in Research and the SHU Research Ethics Policy, and ethics approval has been granted for all research studies in the thesis.

5. The word count of the thesis is 71671.

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Abstract

This research investigates the adoption and acceptance of Digital Health (DH) applications among healthcare professionals in public hospitals in Abu Dhabi (AD). The study is based on the Unified Theory of Acceptance and Use of Technology (UTAUT), and the researcher proposes additional elements to improve the model's applicability in the context of adopting DH applications. Using a quantitative research method, this study examines the factors affecting the behavioural intention (BI) and actual usage (USE) of applications that include electronic health records (EHR) and electronic medical records (EMR). The study sample comprises 364 healthcare professionals.

The results indicate a strong preference for implementing DH applications, as 44.0% of the participants actively use these solutions. Nevertheless, adoption rates decline as applications become more advanced, suggesting the existence of an innovation-adoption gap. The study confirmed that personal and demographic factors such as age, education and DH experience are important elements that greatly influence the use of technology, but gender, position, work experience, IT skills and training had no significant impact on the intention to use DH applications. The original UTAUT model elements, performance expectancy (PE) and effort expectancy (EE), were found to have no impact on behavioural intentions (BI) to use DH applications in AD public hospitals. In contrast, social influence (SI) from the original UTAUT model, along with the new proposed constructs by the researcher, self-efficacy (SE), and management and leadership involvement (MLI) significantly influenced these intentions. For usage intention (USE), the original UTAUT model elements, facilitating conditions (FC) and intention behaviour (BI) showed no effect.

The study determines that effective deployment of DH requires a user-centric strategy, strong infrastructure, supportive leadership, and thorough training programmes. Additionally, it emphasises the importance of user-friendly solutions, peer influence, continuous support, and collaboration with technology providers as important factors for successfully integrating DH applications in AD’s healthcare sector. This study enhances comprehension of the adoption of DH applications in public hospitals in AD, offering valuable insights for focused initiatives to improve patient care and operational effectiveness using DH technology.

Keywords: Digital health, UTAUT, Healthcare Professionals, Abu Dhabi, Technology Adoption, Public hospitals

Abbreviations

AD	Abu Dhabi
AI	Artificial Intelligence
CFA	Confirmatory Factor Analysis
DH	Digital Health
DHA	Dubai Health Authority
DoH	Department of Health- Abu Dhabi
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
eHealth	Electronic Health
HER	Electronic Health Records
EHS	Emirates Health Services
EMR	Electronic Medical Records
FC	Facilitating Conditions
FDA	Food and Drug Administration
FMoH	The Federal Ministry of Health
HC	Healthcare
HCP	Healthcare Professional
HIE	Health Information Exchange
HIS	Hospital Information System
HIT	Health Information Technology
ICT	Information and Communication Technology
IMI	Internet and Mobile-Based Treatments
IoT	Internet of Things
IT	Information Technology
mHealth	Mobile Health
PE	Performance Expectancy
PLS	Partial least squares
QS	Quantified Self
RPM	Remote Patient Monitoring
SEM	Structural Equation Modelling
SI	Social Influence

TAM	Technology Acceptance Model
UAE	United Arab Emirates
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

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Dedication

To my dear mother

Suhaila to whom I am indebted for the rest of my life

To the soul of my honourable father **Awad**

To my loyal Wife

Aysha Alketbi for her support and encouragement

To my sweet daughters **Fatima, Hamda, Shaikha and Mouza**

To all those who stood with me in my Study Journey

Khalfan Alnuaimi

Chapter 1 : Introduction

1.1. Background to the Research

The healthcare industry has undergone a significant transformation driven by digital technology. These advancements have redefined how healthcare services are delivered and how patients engage with healthcare providers. In Abu Dhabi (AD), the capital of the United Arab Emirates (UAE), public hospitals are at the forefront of adopting these applications, guided by the perspectives of healthcare professionals on the benefits and challenges. In recent years, the demand for healthcare services has prompted substantial progress globally in the DH domain. The UAE has demonstrated its commitment to adopting and integrating DH solutions to stay abreast of global trends. This commitment is reflected in increasing interest in and implementation of DH systems, which have proven invaluable, especially during the COVID-19 pandemic, ensuring the continuity of high-quality patient care through remote interactions.

Integrating DH applications, such as telemedicine, electronic health records (EHRs), and big data analytics into public hospitals presents a promising avenue for enhancing healthcare delivery and patient care. However, the assimilation of such applications is not without difficulties. This research delves into the technological, economic, regulatory, and cultural barriers that healthcare professionals encounter when implementing DH solutions. Utilising the Unified Theory of Acceptance and Use of Technology (UTAUT) model, this thesis analyses factors such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), which significantly affect the adoption process of DH. Furthermore, the research investigates several components, including self-efficacy (SE), management and leadership involvement (MLI), and personal and demographic variables, to understand better the various influences on adopting DH.

By offering insights into these elements, this study aims to contribute to developing effective strategies that can foster the adoption and maximise the benefits of DH in AD, potentially influencing practices across the region. Furthermore, the study recognises the UAE's initiative to integrate sustainability through DH tools, contributing to a circular economy. By providing a comprehensive understanding of the current state of DH adoption in AD public hospitals and examining the influence of personal and demographic factors and technological competence, this thesis contributes to both academic knowledge and practical application in the healthcare sector. It aims to advise policies and management strategies that can help navigate the complexities of DH implementation, ultimately enhancing the efficiency and effectiveness of health services in the region.

1.2. Thesis Key Terms and Definitions

In this thesis, several key terms are utilised, which are elucidated below to ensure precision and coherence in the discourse:

Technology Acceptance encapsulates the willingness and intention of individuals to adopt and implement new applications within their professional sphere or everyday life. Specifically, in healthcare settings, acceptance is related to healthcare professionals embracing DH applications, which is pivotal to the effective deployment and application of these applications. The UTAUT model, introduced by Venkatesh et al. (2003), outlines the key constructs that affect the adoption process, such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC).

Digital Health (DH) signifies the use of integrated digital applications, including information and communication applications (ICT), in providing healthcare services. This broad spectrum includes, but is not limited to, EHRs, telemedicine, mobile health (mHealth) apps, wearable devices, artificial intelligence (AI), and data analytics. DH aims to augment care accessibility, improve patient outcomes, enhance efficiency, and foster active patient participation in health management (Brice & Almond, 2020; Sui & Facca, 2020; Patel et al., 2022).

Healthcare Professionals encompass a wide array of practitioners who render medical services to patients, including doctors, nurses, pharmacists, therapists, and other allied health workers. Their roles extend beyond clinical care to patient education, health promotion, and advocacy. They are entrusted with the critical competencies of communication and collaboration, which are essential for delivering patient-centred care and optimising health outcomes (Suter et al., 2009; Hou et al., 2018).

1.3. Statement of the Research Problem

The healthcare industry has been transformed by innovative digital applications and patient management systems. EHRs, telemedicine, AI diagnostics, and mobile health apps have the potential to transform healthcare by enhancing patient outcomes and improving operational efficiency and coverage. Regrettably, several obstacles must be confronted when adopting such systems in public hospitals in AD, including technical challenges, economic restrictions, regulatory concerns, and cultural disparities (Alrahbi et al., 2022). Despite the significant impact these tools can have on patient care, the adoption of these applications is hindered by issues around data privacy, security risks, and resistance to change among healthcare professionals. In AD’s public hospitals, these challenges are further shaped by the emirate’s unique cultural, regulatory, organizational, and economic contexts, making implementation both complex and full of opportunities, which make such implementation both challenging while simultaneously rife with feasible opportunities. AD's reality as a multicultural environment encompassing Emirati nationals and a robust expatriate population necessitates digital solutions that cater to the different linguistic, cultural, and technological proficiency among diverse peoples. In their emphasis of the importance of collectivist norms existing in the UAE commonly characterized by prioritization of familial and community decision making, Drissi et al. (2022) argue that perceptions of DH adoption are shaped by such cultural dimensions, and even more so for sensitive applications, including mental health digital tools and solutions. Inadequate Arabic language content and culturally informed scepticism about digital solutions, especially privacy concerns, are among the leading barriers identified that require culturally adapted strategies (Drissi et al., 2022). Regarding AD's unique regulatory context, Jain (2023) finds a current lack of explicit telehealth legislation and digital consent concerns as limiting trust and the overall realization of DH opportunities and potential. Thus, AD is characterized by gaps that require stronger regulatory frameworks put in place to protect patients’ data and facilitate compliance with global standards while accounting for local nuances.

Additionally, from the organizational point of view, AD's centralized healthcare governance also influences DH adoption considerably, elevating the need to understand the unique role of organizational leadership in supporting DH adoption in UAE public hospitals. In Aburayya et al. (2020), the researchers highlight the importance of a leadership commitment and a culture of continuous improvement to navigate these organizational challenges. This complexity is compounded further by the economic forces at play, which El Khatib et al. (2022) note pose complications for smaller facilities in AD having to deal with the high costs of DH infrastructure, alongside little financial incentive for adoption. Economies of scale and governmental support benefit larger hospitals; however, resource allocation and unequal ecosystem adoption disadvantages the allocation of resources to smaller hospitals. These factors aggregate in a collective way to emphasize the need for a tailored DH adoption framework that incorporates AD's unique cultural sensibilities, governance requirements, organizational set up and leadership, and the relevant economic aspects.

Furthermore, it is crucial to address the lack of literature on the unique factors and obstacles that impact healthcare workers in AD, which might impede the implementation of DH. This clarification is essential for understanding how to use these applications effectively in this context. The study addresses this lack of knowledge by conducting a comprehensive literature analysis and identifying the factors that influence the implementation of DH in public hospitals in AD. Identifying these elements is crucial for developing strategies to overcome obstacles and make use of the factors that contribute to the effective implementation of DH applications in healthcare delivery systems. This research aids policymakers, healthcare providers, and technology innovators in making well-informed choices to enhance the healthcare services in AD and support the UAE's sustainable healthcare innovation and development plan.

1.4. Research Aim

To analyse and understand the factors influencing the acceptance and usage of DH applications among healthcare professionals in AD public hospitals, guided by the UTAUT model.

1.5. Research Objectives

This study set out to achieve the following objectives:

- Evaluate the impact of personal and demographic factors on the intention of healthcare professionals to use DH applications.
- Investigate how the core constructs of the UTAUT model—PE, EE, SI, and FC—affect the adoption of DH applications.
- Assess how healthcare professionals' belief in their ability to use DH systems (self-efficacy) and the involvement of management and leadership impact the usage of DH systems.
- Offer practical recommendations that support healthcare digitalisation in AD public hospitals based on the findings of this study.

1.6. Principal Research Questions

This study answers the following research questions:

1. To what extent and why do personal and demographic factors explain the variances in the actual usage of DH applications in AD public hospitals?
2. To what extent and why do PE, EE, SI, and FC explain the variances in behavioural intention (BI) and actual usage of DH applications in AD public hospitals?
3. To what extent and why do SE and MLI impact the behavioural intention to use DH applications?
4. How can the UTAUT model be used to understand better what healthcare professionals in AD public hospitals perceive they need to adopt DH applications effectively?

1.7. Research Significance

The increasing significance of DH applications in the healthcare industry signifies a crucial change towards improving the quality and effectiveness of delivering care. This research highlights the significant impact of DH on the transformation of healthcare systems, drawing on findings that underscore the role of DH in enhancing patient outcomes and healthcare efficiency (WHO, 2020; Brice & Almond, 2020). Healthcare facilities strive to enhance patient care by incorporating advances in digital applications, including electronic health records (EHRs), telemedicine, mobile health (mHealth), and data-driven solutions (AlQudah et al., 2021; Sui & Facca, 2020). The World Health Organization's Global Strategy on DH 2020-2025 highlights the importance of integrating DH into healthcare priorities, emphasizing its potential to ethically, safely, securely, and equitably serve populations (WHO, 2020).

Although the promise of DH applications is widely acknowledged, health practitioners face hurdles in accepting them. An important obstacle to adoption is the need for a significant change in thinking among healthcare staff. Health professionals must view DH as a resource that improves access to patient information, enables seamless provider communication, and facilitates evidence-based decision-making (Carter et al., 2018; Nakrem et al., 2018). Overcoming these barriers requires specific educational initiatives and targeted training programs to equip healthcare professionals with the skills and confidence to use DH systems effectively (Brice & Almond, 2020).

This research enhances current knowledge by examining the variables that impact the acceptance or rejection of DH applications in AD's public healthcare system. It focuses on understanding why some healthcare professionals embrace these technologies while others resist them. By addressing these questions, the study fills existing gaps in understanding technology acceptance, specifically within DH, as applied to public hospitals in AD (Alrahbi et al., 2022; Saleh et al., 2016).

The conclusions of this research have practical implications for healthcare practitioners, policymakers, and technology developers. Understanding the factors influencing DH adoption enables stakeholders to develop supportive environments that encourage healthcare professionals to integrate digital solutions into their practice. Identifying barriers, such as lack of training, resistance to change, and concerns over data security, allows targeted solutions to be implemented, such as improved regulatory frameworks, ongoing technical support, and user-friendly system designs (Nakrem et al., 2018; Saleh et al., 2016). Consequently, this research provides recommendations for health policy and practice that promote successful DH implementation, improving patient care quality, operational efficiency, and preparedness for public health crises (AlQudah et al., 2021; WHO, 2020). In conclusion, this study lays a foundation for future research on integrating advanced digital technologies seamlessly into healthcare systems.

1.8. Contributions to Knowledge

Epistemologically, this thesis contributes to new knowledge creation and expansion by advancing the theoretical understanding of DH adoption within AD’s public hospitals, particularly by utilizing a customized and extended UTAUT framework. It extends the generic UTAUT framework by incorporating dimensions such as leadership involvement, self-efficacy, and infrastructure readiness, thereby expanding the model’s applicability in non-Western, resource-diverse settings (Reixach et al., 2022). The feasibility of this extended version of the UTAUT is demonstrated using an evidence-based approach that relies on empirical insights from robust quantitative research, filling the scarcity of comprehensive studies on DH in AD and the wider Middle East context. In this regard, the study is also significant because it addresses most of the abovementioned underexplored aspects affecting DH adoption in AD's unique context, including the identified regulatory, organizational, and economic characteristics. The inclusion of an evidence-based analysis focused on these domains and factors remedies gaps in current DH adoption frameworks that are not effectively tailored to the DH adoption context in the AD. In this way, the thesis addresses gaps in the literature regarding how these local factors influence healthcare professionals' acceptance and use of DH.

In practice, the findings offer actionable strategies for policymakers, healthcare administrators, and technology developers addressing the currently limited literature on DH implementation in AD public hospitals. The developed, evidence-based recommendations will address barriers such as limited infrastructure, cultural resistance, and regulatory ambiguities, enabling tailored interventions to enhance DH integration, particularly by focusing on AD's unique environment to equip stakeholders with localized strategies to navigate challenges, thereby supporting the UAE's broader digital transformation and health innovation goals (El Khatib et al., 2022). As such, this research represents a unique contribution to understanding the key factors associated with improving the success rate of DH implementation in public hospitals. Also, the thesis will identify the key success factors for adoption by similar healthcare organisations in other parts of the UAE. Furthermore, this study makes practical recommendations to help public hospitals in AD implement DH applications more efficiently and effectively.

1.9. Research Structure

The research structure of this thesis on **Digital Health Adoption Among Professionals in Abu Dhabi Hospitals** is subdivided into chapters, with each either adding to the research or presenting a milestone, as follows:

Chapter 1: This chapter introduces the study's purpose and outlines the background and significance of DH in AD. It has provided the research questions and aims, thus aiding navigation.

Chapter 2: This literature review chapter surveys and critically analyses existing research on DH adoption using the UTAUT model. It thus reviews several pieces of research outlining the key technological and human factors that have affected the adoption of DH, especially within the health sector in AD.

Chapter 3: This is the theoretical framework chapter focused on developing and justifying the study's research model. Building on the insights derived from the review of empirical research in Chapter 2, Chapter 3 discusses the original form of the UTAUT model and then proposes an evidence-based extension of the original model to achieve a reconfiguration that fits this study's context.

Chapter 4: This methodology chapter describes the scientific research process and set-up, describing a quantitative research model and explaining the methods and techniques used for collecting data and samples and analysis guided by the Saunders onion model for research.

Chapter 5: The analysis chapter presents the outcomes of the analysis of the collected research data, indicating the effect of personal and demographic variables on DH applications, which are mainly related to AD's public hospital setting. The analysis of the four UTAUT constructs (PE, EE, SI, and FC) is highlighted and supported by SE and MLI.

Chapter 6: This discussion chapter interprets the research outcomes, comparing them with the available literature. It discusses the implications of the study's findings for current and future healthcare settings, stakeholders, and future research.

Chapter 7: The conclusion and recommendations chapter are the final chapter concluding the research by summarising the research outcomes and making recommendations to future healthcare administrators and IT professionals in the public health facilities in AD.

The outlined structure thus presents a holistic approach to the presentation and recommendation of the facts that could be useful in understanding the factors leading to DH technological outcomes that may accelerate wider DH implementation in AD.

1.10. Summary

This chapter provides definitions and concepts necessary to characterise the adoption and implementation process of DH in AD public hospitals, followed by clarification of important terminology in DH, laying the groundwork for the coming chapters. The chapter provides an overview of the main objective of the research, which is to examine the variables that impact the willingness of healthcare professionals at public hospitals in AD to adopt DH. The objective highlights the need to examine the factors that promote and hinder the successful incorporation of digital application into the healthcare system. Furthermore, this chapter introduces the UTAUT model that directed this study, allowing the systematic evaluation of elements involved in adopting technology. Chapter 1 outlines this study's extent, importance, and research structure, ensuring readers have the necessary background knowledge. The next chapter provides an extensive literature review on DH, technology acceptance models, and the unique aspects of AD's healthcare system, serving as the theoretical and contextual foundation for subsequent analysis.

Chapter 2 : Literature Review

2.1. Abu Dhabi (AD) Profile

The Emirate of AD is the largest of the seven emirates that make up the UAE and is distinguished by its different geographical sections, which include the Central Capital District, the Eastern Region, and the Western Region (Paulo, 2017). AD, situated in the southeastern part of the Arabian Peninsula, is bounded to the north by the Persian Gulf (also known as the Arabian Gulf), to the south by Saudi Arabia, and to the southeast by Oman as shown in figure 2.1 below.

Figure 2.1 **Abu Dhabi's Location**: This figure illustrates the geographic location of AD and UAE in relation to neighbouring countries. Adapted from "United Arab Emirates," by Britannica, n.d., Britannica Website (https://www.britannica.com/place/United-Arab-Emirates#/media/1/615412/208693).

According to Paulo et al. (2019), AD has the greatest area and population among the emirates and has a geographically advantageous position, functioning as a pivotal point connecting the Eastern and Western regions. Consequently, it plays a crucial role as a central hub for facilitating trade and business (AlOwais, 2019) (see Figure 2.2).

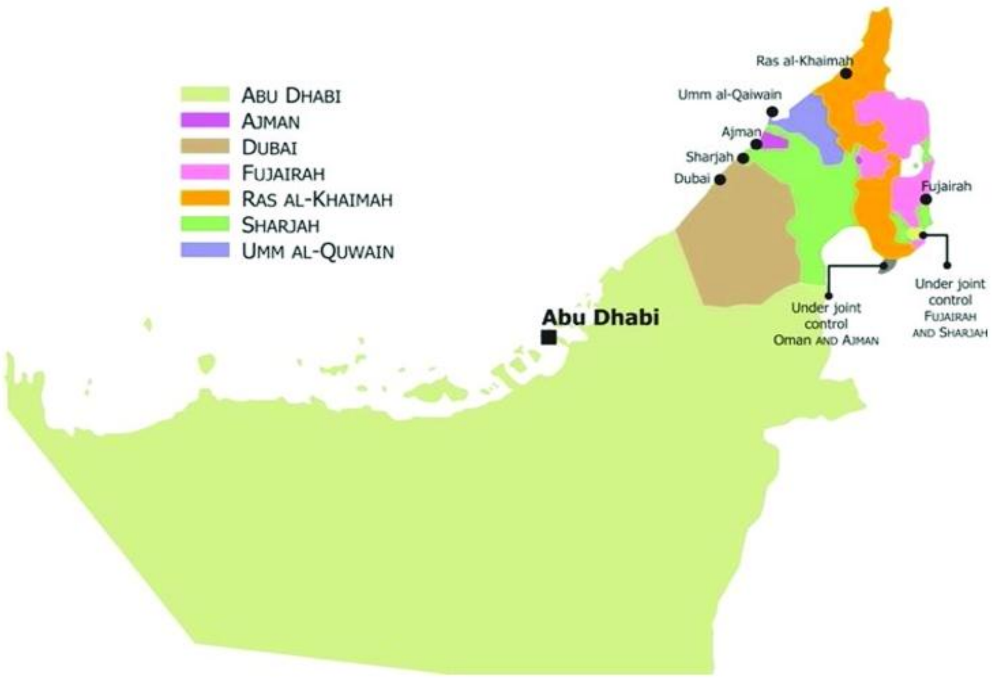

Figure 2.2 **Abu Dhabi (AD) Emirate location**: This figure provides a detailed map of AD Emirate, highlighting other emirates and city's location. Adapted from https://www.researchgate.net/figure/Map-of-the-seven-states-of-the-United-Arab-Emirates-Used-with-permission-from_fig1_372048012

With its advantageous geographical position, varied population, strong relationships with other emirates, and vast healthcare infrastructure, AD has a vital position within the UAE. To fully comprehend the wider socio-economic and cultural environment of the UAE, it is critical for scholars, policymakers, and the public to have a thorough awareness of these facets of the emirate. AD has undergone a substantial population expansion in recent years. According to Talib et al. (2015), the population is expected to increase fourfold by 2030. The emirate hosts a demographically rich population, comprising not only the Emiratis but also expatriates who live in the region (Younies et al., 2008). The healthcare system in AD has been working to keep pace with the needs of this growing population.

2.2. UAE Healthcare System

The UAE healthcare system is designed to offer a wide spectrum of public and private healthcare facilities operating in accordance with international requirements. The healthcare system in the UAE is evolving, with the foundation of new hospitals, medical facilities, and special hospitals (El Khatib et al., 2022). The public healthcare system in the UAE is free or heavily funded for UAE nationals, thus making healthcare in government facilities accessible to the general population. For residents, the services of public hospitals are nominally priced; moreover, employers are required to provide mandatory health insurance, which further drives down the costs.

With private healthcare providers, UAE nationals and other residents may face additional expenses, as government financial support does not normally encompass treatment in private healthcare facilities. Healthcare insurance usually covers treatment by private healthcare providers, with pre-authorisation to go ahead with procedures such as surgery. However, the extent to which treatment costs are covered and the specifics of the process vary in each case. The Federal Ministry of Health (FMoH) is one of the most important government bodies, providing a nationwide network of medical resources for the public (Bodolica & Spraggon, 2021). This institution controls and regulates everything related to public health and healthcare in the UAE, cooperating with other entities such as the AD and Dubai Departments of Health.

The FMoH is responsible for formulating policies, devising strategic plans, overseeing progress and carrying out assessments, providing funding, delivering training, enhancing capabilities, developing human resources, and fostering institutional growth. Furthermore, it oversees procurement inside the ministry, completing a study to assess performance at least once every four years. The UAE has specific government bodies, including the AD Department of Health (DoH) and the Dubai Health Authority (DHA), which regulate and evaluate competent performance in public and private healthcare organisations in their emirates. These departments in each emirate focus solely on improving health standards, plans and services for their populations. It is the responsibility of health authorities to develop and improve the health sector in collaboration with different entities and stakeholders, ensuring they provide quality healthcare services across the nation. There were 971 private and public hospitals in the UAE as of 2021. There has been a rise in the number of hospitals from 789 in 2014 (Bodolica & Spraggon, 2021) (Figure 2.3).

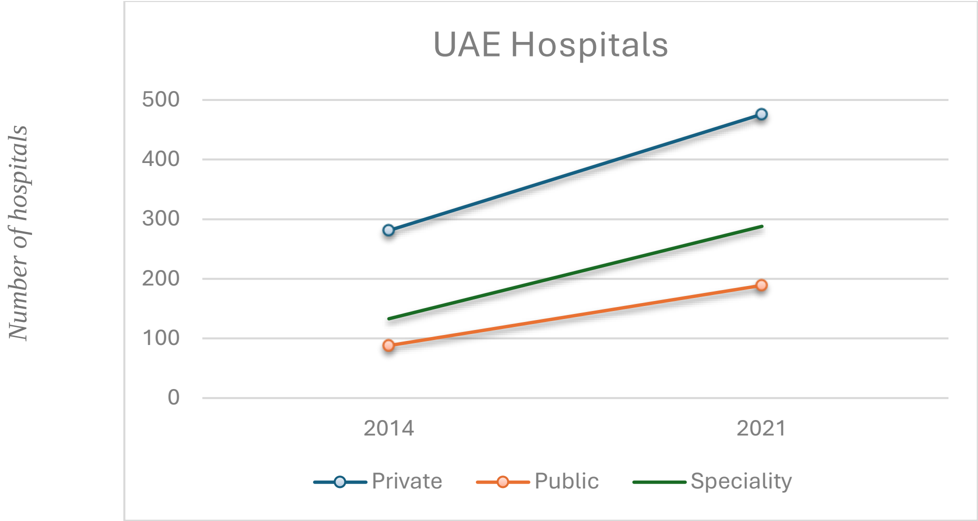

Figure 2.3 **Total Number of Hospitals in the UAE**: This figure compares the number of public and private hospitals across different years. Adapted by Bodolica & Spraggon (2021).

The healthcare system in the UAE is characterised by rapid speed development and a significant degree of technical improvement (Bodolica & Spraggon, 2021). Integrating technology has great potential to accelerate progress and innovation in healthcare nationwide. While the FMoH has led the nationwide implementation of cutting-edge medical solutions, maximising existing resources and introducing novel treatment centres will require balanced investments over time. As shown in Figure 2.4, designated funding continues to support establishing upgraded infrastructure and new facilities, with the aim of expanding equitable access to quality care.

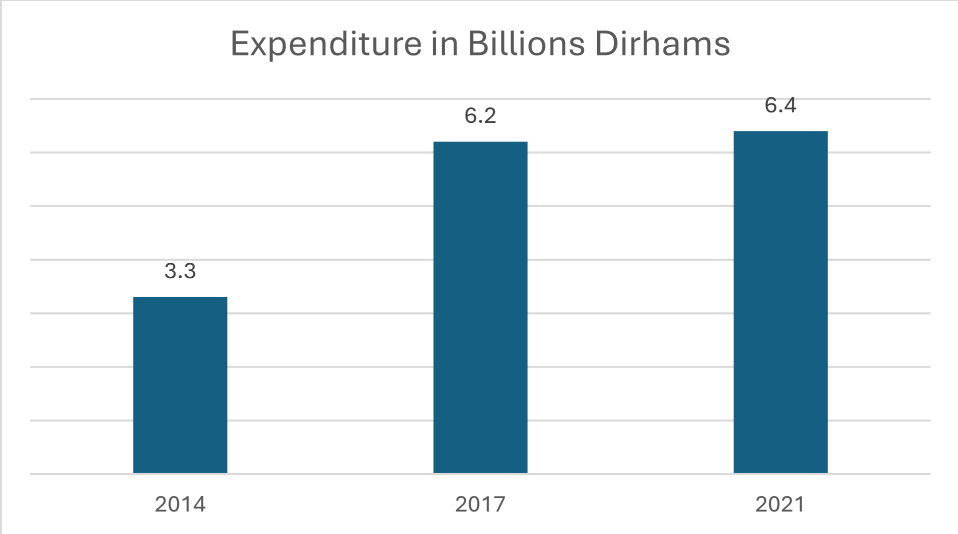

Figure 2.4 **Expenditure by the UAE Government on Healthcare (2014,2017 and 2021)**: This figure displays government spending trends on healthcare over time, indicating investment growth in DH initiatives.

The government's allocation of resources to the health sector has been motivated by several factors, such as the need to provide equal access to healthcare services, respond to advances in technology and medical research, and reflect overall economic progress and increases in per capita income.

2.3. Healthcare System in AD

AD's healthcare system forms part of wider UAE healthcare, which comprises seven emirates with distinct healthcare systems (Sadek et al., 2016). Changes have been implemented in AD's healthcare system to improve accessibility and quality of health services (Koornneef et al., 2017).

The healthcare system in AD is characterised by a combination of public and private healthcare services, with the goal of providing complete treatment to the population. Public healthcare services are specifically intended to guarantee that everyone can readily receive high-quality, sustainable medical care over time.

These services emphasise preventative care and include specialist care and emergency services. Progress in the overall ability and quality of public health is also attributed to investments in healthcare infrastructure, workforce training, and the organisational systems for delivering care. Investments in the healthcare infrastructure of AD have been extensive, with premier hospitals and medical facilities brought to middle-income areas (Paulo et al., 2019). According to Paulo et al. (2019), the emirate has a greater density of physicians and nurses per person than other regions of the UAE, enhancing the availability of healthcare services to residents.

AD has recently prioritised enhancing the availability of healthcare personnel (Paulo et al., 2019). Attempts have been made to attract and retain healthcare professionals, such as physicians and nurses, to fulfil increasing needs for healthcare services (Paulo et al., 2019). The emirate has used a variety of measures to augment the expertise and capabilities of its healthcare professionals (Alhajeri, 2021).

AD has been working on major reforms to upgrade its healthcare infrastructure to keep pace with the growing population. AD has invested in expanding through several initiatives its healthcare workforce, which underpins the wellbeing of its people (Paulo et al. 2019). The healthcare system in AD adopts a progressive outlook, exploiting technology-based interventions as its digital pillar. The Malaffi health information exchange platform (Balasubramanian et al., 2023) is an example of the emirate-wide digital transformation of healthcare. The utilisation of digital infrastructure is considerable and improves the effectiveness of operational and administrative processes and assists in telehealth delivery using data-driven decision support tools (Mahdi et al., 2023). While some progress has been made, there are bottlenecks in the DH ecosystem, such as data security, interoperability and digital literacy among healthcare professionals and patients. Therefore, continuous efforts are required to improve the situation (Jain, 2023).

In AD, the healthcare system is at a critical juncture where enhancement and expansion of the digital infrastructure could significantly impact health provision and service operations. At this point, the emirate is making strides in using healthcare technology that benefits patient care and data privacy, while encouraging innovation. The challenges AD thus faces in realising its aspiration of a technology-enabled healthcare system designed to meet the needs of its diverse population, are clear.

2.4. Contextual Factors Influencing DH Adoption in AD

The implementation of DH technologies in AD’s public hospitals reflects the complexity of operating within a unique blend of cultural, regulatory, organizational, and economic contexts. While these factors create significant challenges, they also offer opportunities for innovation and growth. As the capital of the UAE and a hub of multiculturalism, AD faces the challenge of ensuring its DH ecosystem meets the needs of both Emirati nationals and expatriates. This analysis explores these factors in detail, providing a comprehensive view of their impact on DH adoption.

The cultural environment in AD exerts a profound influence on DH adoption, shaping both professional and patient attitudes toward digital tools. Cultural norms in the UAE emphasize privacy, trust, and collective decision-making, which create both barriers and opportunities for DH technologies. AD's healthcare system serves a diverse population comprising Emirati nationals and a significant expatriate workforce. This multicultural environment necessitates digital solutions that are inclusive and adaptable. Tools must cater to various linguistic needs, as healthcare professionals often face language barriers when treating patients whose first language is neither Arabic nor English. Creating multilingual systems with user-friendly interfaces is essential for addressing these difficulties. Digital technologies that provide Arabic language options, alongside interfaces in English and other prevalent languages, can enhance accessibility and usefulness for the patient demographic (Shemeili et al., 2016; Drissi et al., 2022).

The cultural focus on privacy and trust influences the perception of DH technologies. Insufficient security for privacy could cause distrust among healthcare practitioners and patients. Technologies such as telemedicine, although advantageous in terms of convenience, frequently face opposition due to concerns over data breaches and the impersonal nature of remote consultations. Drissi et al. (2022) highlight that, for sensitive applications such as mental health tools, culturally informed strategies are necessary to build trust and acceptance.

Another challenge lies in the preference for traditional, in-person consultations. Many patients and professionals in AD view face-to-face interactions as the gold standard for care, which limits the adoption of telemedicine and virtual health services. In order to resolve this issue, telemedicine initiatives must underscore their capacity to enhance traditional care, rather than to supplant it. For instance, the integration of telemedicine with hybrid care models or in-person follow-ups could alleviate concerns while simultaneously demonstrating its advantages (Rodrigues et al., 2024). Additionally, family members are frequently involved in healthcare decisions due to the collectivist norms that are prevalent in Emirati culture. Digital tools that facilitate collaborative decision-making and provide family members with access to patient records can enhance acceptance. Gender dynamics also contribute to the process; for instance, female patients may favour consulting female healthcare providers. The development of telemedicine platforms that are compatible with these preferences has the potential to increase their adoption (Rodrigues et al., 2024).

The regulatory framework in AD presents a dual-edged sword for DH adoption. While strong policies exist to protect patient data, gaps in specific areas such as telehealth legislation create challenges that hinder widespread implementation. The UAE's Personal

Data Protection Law (PDPL) offers robust safeguards for patient confidentiality, ensuring that DH solutions meet high security standards. However, these regulations also impose significant compliance requirements on healthcare providers. New technologies must undergo rigorous evaluations, delaying their implementation and increasing costs (Jain, 2023; Khatib et al., 2022). Telemedicine represents a cornerstone of DH innovation, but AD's regulatory landscape lacks explicit telehealth policies. This creates ambiguity among healthcare practitioners, constraining trust and excitement for implementation. Jain (2023) emphasizes that persistent concerns around digital consent and liability exacerbate these difficulties. Policymakers must prioritize the formulation of telehealth policies that balance innovation with patient safety.

One of the most pressing challenges in AD's public hospitals is the lack of interoperability among DH systems. Many hospitals operate disparate electronic medical record (EMR) platforms, which often lack standardized communication protocols, making data sharing and cross-institutional collaboration difficult (Mahdi et al., 2023). While initiatives like Malaffi Health Information Exchange have improved data integration, the reliance on legacy systems in certain hospitals has created barriers to real-time information access (Balasubramanian et al., 2023). These interoperability challenges lead to data silos, which hinder the continuity of care and increase administrative burdens for healthcare professionals. Addressing this issue requires a standardized digital infrastructure, promoting seamless integration across all healthcare institutions.

Despite these limitations, governmental programs such as the Malaffi Health Information Exchange have achieved considerable progress in promoting the usage of DH. Malaffi links healthcare professionals around AD, facilitating effortless access to patient records and enhancing continuity of service. The efficacy of such programs is heavily dependent upon the capacity of healthcare personnel to adapt to these systems. Ongoing training and technical support are critical to ensuring their effectiveness (Khatib et al., 2022; Nahal et al., 2018).

Organizational factors, including leadership, infrastructure, and workforce readiness, are pivotal to the success of DH technologies in AD's public hospitals. Effective leadership is essential for facilitating digital transformation. Hospitals led by visionary managers who actively advocate for the implementation of DH are more likely to achieve success. Institutions like Cleveland Clinic AD have adopted modern technology, including ePathology, establishing precedents for others. Leadership commitment cultivates an innovative culture, prompting employees to perceive digital tools as facilitators rather than obstacles (Nahal et al., 2018; Aburayya et al., 2020).

Resistance among healthcare professionals remains a persistent issue. Concerns about increased workloads, disruptions to established workflows, and a lack of familiarity with digital tools contribute to hesitation. Effective leadership must address these concerns by engaging staff early in the decision-making process, ensuring they understand the value of these tools in enhancing patient care (Khatib et al., 2022). Disparities in infrastructure readiness across public hospitals create unequal opportunities for DH adoption. While some facilities boast high-speed internet, advanced hardware, and integrated electronic medical records (EMRs), others lack these foundational elements. This uneven landscape underscores the need for targeted investments to bridge the gap and ensure equitable access to digital technologies across AD (Nahal et al., 2018). The capacity of the workforce is another essential factor. A significant number of healthcare professionals, especially senior personnel, lack the requisite technical abilities to utilize digital tools proficiently. Comprehensive training programs customized for varying expertise levels are necessary. These programs must encompass not just technical skills but also the psychological dimensions of adapting to new technology, fostering confidence among personnel (Drissi et al., 2022; Rodrigues et al., 2024).

Economic factors significantly influence DH adoption in AD, shaping decisions around resource allocation, cost management, and technology sustainability. AD's Vision 2030 has driven substantial investments in DH infrastructure, including AI-powered diagnostics and EMRs. These initiatives demonstrate the government's commitment to leveraging technology to improve healthcare outcomes. However, financial sustainability remains a challenge, particularly for smaller hospitals that struggle to bear the high costs of implementation and maintenance (Liang et al., 2021; Khatib et al., 2022). Larger hospitals benefit from economies of scale and greater government support, while smaller facilities face resource constraints. This unequal distribution of resources hinders uniform DH adoption across the emirate. Establishing cost-sharing mechanisms and allocating resources equitably are crucial to addressing this disparity (Rodrigues et al., 2024).

Public-private partnerships (PPPs) are becoming a key driver of DH adoption in AD, enabling the co-development of AI-driven diagnostics, telemedicine platforms, and integrated patient management systems. The UAE government's collaboration with technology firms and research institutions has led to significant advancements in DH infrastructure, particularly through the Malaffi initiative and AI-based predictive analytics in hospitals

(AlKnawy et al., 2023). However, PPPs also pose challenges related to data governance, financial sustainability, and ethical concerns regarding private-sector involvement in public healthcare decision-making. To maximize the benefits of PPPs, AD must establish clear regulatory frameworks, financial incentives for private investment, and transparent collaboration models to ensure digital health solutions are equitably implemented across public hospitals.

The variation in reimbursement schemes for telehealth services contributes to economic sustainability challenges. Professionals are less inclined to incorporate telehealth into their practice in the absence of explicit financial incentives. Policymakers must formulate reimbursement structures that encourage the utilization of DH technologies, guaranteeing advantages for both providers and patients (Jain, 2023; Drissi et al., 2022). Although digital tools can diminish long-term operating expenditures, their substantial initial costs burden hospital finances. Transitioning from conventional systems to digital platforms frequently necessitates substantial investment in hardware, software, and training. Economic models for gradual deployment can assist hospitals in managing expenses without compromising care (Liang et al., 2021).

The adoption of DH technologies in AD's public hospitals is deeply intertwined with the emirate's cultural, regulatory, organizational, and economic contexts. While these factors present substantial challenges, they also highlight opportunities for tailored solutions that align with AD's unique environment. By addressing issues related to culture, optimizing rules, promoting leadership involvement, and guaranteeing equal economic support, AD can establish a strong platform for DH innovation. These initiatives will not only improve patient care but also establish AD as a leadership in global health technology.

2.5. Importance of Digital Health

According to Silven et al. (2022), Digital Health (DH) refers to using digital application and data to deliver better health outcomes and includes telemedicine, wearable devices, and monitoring systems with AI-based diagnosis and treatment. These applications enable patients to be active players in their own health management and improve the efficiency and precision of healthcare delivery. Overall, DH can promote preventative health by informing people of their risk of morbidity at different ages, with proven effectiveness. DH tools and technology aim to enable the efficacy, access, and personalisation of healthcare services. Implementing DH solutions provides a multitude of advantages that have the potential to transform the healthcare sector. According to research published by the World Government

Summit and McKinsey et al. (2022), implementing DH applications can open a market worth $230 billion worldwide in the next five years, with the Middle East contributing $10 billion.

DH has emerged as a transformative tool in healthcare, offering a wide array of benefits. DH can potentially optimise operational efficiency, enhance patient experience, and improve patient outcomes (Olu et al., 2023). By leveraging DH solutions, healthcare providers can facilitate predictive modelling and offer individualised treatment plans through virtual human digital twins and wearable data (Akeju et al., 2022). This advance not only enhances the availability of medical services but also helps reduce healthcare costs (Akeju et al., 2022). Furthermore, DH can improve data sharing and compatibility, leading to a more comprehensive approach to patient care and better outcomes (Olu et al., 2023). Healthcare practitioners can enhance their skills and stay up to date with the latest innovations by utilising analytics and next generation learning tools (Teede, 2024). Implementing DH can result in significant improvements in healthcare delivery, ultimately benefiting individuals and communities (Olu et al., 2023).

Digital transformation serves as a guiding light for beneficial change, lighting a road that leads to cost efficiency, improved quality of patient care, and the ability to respond to the expectations and demands of stakeholders, as shown by Rouidi et al. (2022). As noted by Moopen (2023), the healthcare business has been transformed greatly over recent years owing to digital technology, with improved accessibility to medical healthcare and increased treatment quality and has assisted healthcare professionals to work more efficiently.

Silven et al. (2022) highlighted the significant influence that DH may have on primary care by allowing patients to manage their own health efficiently and cost-effectively. Several DH solutions, including patient portals and drug ordering applications, have enabled access to health information with a single click and eased communication between patients and healthcare practitioners. Furthermore, there is an ongoing transition in healthcare towards the use of AI and the collection and subsequent utilisation of primary care data, leading to more precise individualised healthcare. During pandemics, digital application enables healthcare practitioners to quickly and efficiently adapt to changes. Specific DH rules that are custom-made are required to ensure that the benefits of DH can be accrued without compromising the quality of care provided.

According to Abernethy et al. (2022), DH is an important tool that could transform health care, allowing patient-centred and evidence-based treatment of diseases, thus improving the quality of life for patients and reducing healthcare costs. Digital applications assist doctors in diagnosing or treating their patients, supporting patients with self-care and health management as well as providing health information or services to people at a greater geographical distance from a care provider. Health data is monitored and analysed by adopting DH tools to identify trends, ascertain people at risk of certain conditions or diseases, and evaluate the efficiency and versatility of treatments.

As evidenced by Abernethy et al. (2022), the revolutionary change of practices to deliver more sophisticated and better care across the entire range of cared-for conditions and diseases is being achieved by integrating DH applications into the healthcare system. Sensors, 3D printing, robots, drones, the internet of things, and other advances provide substantial improvement to diagnostics and treatment or enable better management of supply chains.

Rouidi et al. (2022) state that integrating and using electronic health (eHealth) technology in the healthcare industry is becoming crucial to enhancing the quality of service and fostering effective communication between healthcare practitioners and patients. Nevertheless, the approval and effective execution of these applications by end users (namely healthcare professionals) is crucial for seamless integration. Implementing eHealth technology requires an intricate transformation of procedures for professionals at an individual level. Healthcare workers, as the end users, do not fully exploit the advantages of deploying such applications.

The global COVID-19 pandemic highlighted the importance of digital application in health (Glauner, 2021), triggering the adoption of digital solutions aimed at guaranteeing that care continues and improves during crises (Wang et al., 2021). Digitalisation in healthcare needs to change ways of managing across the sector in order to make services more agile and improve the future development of healthcare (Glauner, 2021). Communication of data plays a key role in the development of digital public health responses to pandemics, but healthcare systems may be able to use technology and applications to address day-to-day challenges (Wang et al., 2021). The digital transformation of healthcare is pivotal in directing innovation, improving patient outcomes, and reshaping the future of healthcare delivery in Europe and beyond (Glauner, 2021).

Mobile health platforms and DH services have greatly enhanced the effectiveness of medical treatment and the safety of patients. These treatments enable a prompt response from healthcare personnel, reducing the deterioration in health and enhancing patient quality of life. The use of digital application in healthcare has fundamentally transformed the dynamic between physicians and patients, as well as the overall results of healthcare, by facilitating the connection between patients and providers via mobile technology. This connection allows rapid access to up-to-date information (Srivastava, 2022). Moreover, digital platforms have shown their usefulness in low- and middle-income countries by optimising healthcare provider networks and tracking patient movements, thereby improving the transparency and effectiveness of healthcare delivery (Huisman et al., 2022).

DH tools like EHRs and telehealth services are used to improve the efficacy and availability of healthcare. These applications not only make the clinical processes more efficient but also extend healthcare to remote and less privileged communities. A comprehensive analysis of review studies on DH highlighted its capacity to enhance accessibility, patient safety, and efficiency in diverse healthcare systems (Ibrahim et al., 2022). Similarly, DH platforms served to remedy deficiencies in clinical care and enhance treatment coordination during the pandemic, as shown by the development of DH platforms specifically designed for psychiatric care, as described by Sigurðardóttir et al. (2024).

Healthcare data analytics and AI have created novel pathways for decision-making based on data, leading to enhanced patient-centric care and operational innovation. Digitalisation of accounting in health organisations is an example of how digital technology increases accurate financial calculations and provides high-quality healthcare services at the same time (Lin et al., 2023). More importantly, the failure of forecasting caregiver activity based on machine learning models emphasises the importance of using data-driven approaches to help enhance DH efficiency (Andersson & Sager, 2020).

DH plays a crucial role in contemporary medicine, enabling substantial progress in patient care, healthcare effectiveness, and the use of data-driven decision-making methods. The current digital revolution in healthcare offers the potential for improved health outcomes and the development of a more patient-focused, easily accessible, and efficient healthcare system. The integration of DH into clinical practice will inevitably increase as it continues to advance, ushering in a new age in healthcare delivery.

2.6. Advances in Digital Health Worldwide

Digital innovation in healthcare has progressively reduced the doctor-to-patient ratio worldwide (Abdulrahman Mohammed Al, M., Zakiuddin, A., & Abdullah, M. A. 2018). Consequently, conventional healthcare systems struggle to support a continuously growing number of patients. However, advances in DH have facilitated a rapid increase in healthcare provision. The onset of the COVID-19 pandemic in 2019 precipitated a transformation in digital applications. Systems were implemented to identify and monitor the impacted population and take action based on communication and mobility data (Budd et al., 2020).

Swift reactions to the pandemic used vast amounts of web data, smart devices, and sophisticated machine learning.

In a 2021 study conducted by Aghdam et al, it was found that the internet has facilitated the emergence of future sound trends practical use in improving healthcare, enabling individuals to get effective therapy regardless of their geographical location. To enhance the capacity of healthcare systems to provide efficient healthcare to a larger number of patients concurrently, there is a resultant enhancement in patient outcomes and the delivery of healthcare services, leading to a notable improvement in public health. DH has introduced several healthcare possibilities to overall healthcare operations. Based on the study results, it is evident that many prior authors have shown significant advancements in healthcare operations. Healthcare firms worldwide use the internet to enhance the accessibility to healthcare services, enabling individuals to get medical assistance online or connect with physicians more conveniently compared to the pre-internet era (Yelton & Schoener, 2020). Enhanced access to advanced computers and upgraded equipment has facilitated the development of more refined results and medical breakthroughs in the field of medicine (Schutte-Rodin, 2020). The following sections discuss key applications transforming healthcare delivery:

Telemedicine is a noteworthy digital breakthrough that is characterised by the use of mobility. The aim is to replace existing communication and information applications to detect, treat, and prevent accidents and illnesses. Telemedicine is a crucial method that offers comprehensive and tailored healthcare, with the ability to provide emergency treatments promptly (Drago et al., 2022). Olatinwo (2019) states that telemedicine has facilitated access to quality healthcare, improving healthcare outcomes in many countries due to technological advancements. It is important to be able to guarantee that every individual in the community has convenient and effective access to healthcare (Olatinwo, 2019).

Electronic Health Records (EHRs) or Electronic Medical Records (EMRs) are changing healthcare all over the world, as they provide a better way to access the complete medical history of patients by any healthcare organisation. EHRs enable access to information such as medical histories, medications, diagnoses, and demographics. EHRs have facilitated the effective tracking of information, resulting in decreased delays and expedited billing processes, among other tasks (Hossain et al., 2019). The invention provides practical and clinical benefits by efficiently storing patient data in cloud computing services. Nevertheless, the use of electronic medical records (EMRs) poses a difficulty in safeguarding patient information due to the ongoing advances in digital application (Bucher et al., 2020).

Artificial Intelligence (AI) has significantly enhanced outcomes at many operational levels. The use of AI in healthcare has been examined for its role in guaranteeing the effective provision of high-quality healthcare (Yu et al., 2018). AI has played a crucial role in ensuring that healthcare processes provide precise results. It has also been shown that deploying computer vision, robots, and smart networks has improved hospital operational efficiency (Reddy et al., 2019). Fogel and Kvedar (2018) put this succinctly, arguing that AI in healthcare will not replace doctors but can augment doctors' capabilities. Given their in-depth clinical experience, doctors can concentrate on those aspects of the profession they are trained in and bring uniquely human but difficult-to-quantify components into focus. Doctors will always need to oversee the deployment of algorithmically optimised diagnoses and care plans. Doctors, in turn, have the unique capacity to perform emotional work, such as conducting empathic interviews to elicit nuanced symptoms from patients and establish trust through interpersonal connections grounded in human understanding.

Robotics deployment in homecare is growing because of the prevalence of ageing in affluent nations. These systems guarantee comprehensive care for the elderly, including regular medication and a focus on food programmes, among other advantages. Robotic surgery has made significant progress in the healthcare sector over recent years. Robots achieve precise surgical procedures by converting the actions of surgeons into mechanical motions using actuators, enabling robots to execute difficult operations that conventional doctors may not be physically capable of executing (Van Velthoven & Cordon, 2019). These developments have resulted in improved patient satisfaction and the resolution of certain healthcare issues.

Blockchain Technology has, in recent years, been integrated into the healthcare sector. Blockchain is a kind of digital integration that involves a shared and unchangeable ledger, which guarantees the capacity to track and manage data. Data within a healthcare system is disseminated across the institution to guarantee that each individual has a copy. Blockchain facilitates the decentralisation of data, preventing the accumulation of data in a single department (Agbo et al., 2019).

Internet of Things (IoT) has enabled the medical industry to make significant progress in carrying out tasks in an intelligent and convenient manner (Yang et al., 2020). The invention of IoT has enhanced both treatment methodologies and the quality of the services provided, consequently enhancing patient satisfaction and securing increased government funding. The IoT enables real-time communication between patients and doctors using various wireless protocols, such as Bluetooth, Wi-Fi, Zigbee, COAP, and MQTT. Emerging ideas such as telemedicine were introduced consequently, enabling patients to be continuously observed (Krishnamoorthy et al., 2021).

2.7. Digital Health Acceptance Drivers

Acceptance drivers in DH refer to the elements that impact an individual's inclination to participate in and use DH treatments. Multiple studies have investigated these catalysts and discovered diverse aspects that lead to the acceptability of DH solutions (El Khatib, 2022; Woolley et al., 2023). This research shows that different elements make DH solutions acceptable. The perceived utility and efficacy of the technology are key factors that influence the acceptability of DH. A study conducted by O'Connor et al. (2016) showed that patients and the public are more inclined to participate in DH treatments when they see them as advantageous and capable of effectively enhancing health outcomes. Similarly, Sifat et al. (2022) discovered that the perceived utility of these platforms impacts the probability of using DH platforms to promote mental health.

Awad et al. (2021) note that the DH revolution occurred with rapid changes in patient care and medical research. Wearable devices enable the quantified self (QS), which allows people to access their clinical measures in real-time. In addition, the IoT supports closed-loop systems, which allow for distant two-way communication.

Bhavnani (2020) asserts that DH provides several avenues for enhancing patient care and results. DH applications facilitate the monitoring of patients from a distance, enhance the availability of healthcare services, increase communication between healthcare providers and patients, and aid in treating diseases. Additionally, DH solutions might decrease the administrative side of healthcare and improve patient care. Managing costs and improving health outcomes can be efficiently addressed with the help of analytics and AI in DH. Generally, it is possible to say that emerging applications in DH open new opportunities for addressing healthcare problems and improving patient outcomes.

The drive for digital transformation in healthcare stems from the need to enhance patient care and safety, optimise operational efficiency and cost-effectiveness, and broaden healthcare accessibility. Digital application has enhanced patient care and safety via mistake reduction, enhanced efficiency, and increased care coordination. Telemedicine and remote patient monitoring (RPM) are DH methods that could lower medical costs and improve healthcare accessibility. Digital application has helped healthcare organisations to solve different issues, including care quality, and data privacy and security (Marques & Ferreira, 2019).

Raimo et al. (2022) noted that the COVID-19 pandemic accelerated the transformation to DH solutions. Research by Raimo et al. (2022) and Woolley et al. (2023) has extensively investigated the shift from non-digital to DH solutions. Those works explored the factors affecting the adoption of digital measures, as well as their integration. The consequences of the digital transformation of healthcare organisations may vary. Hospital size, complexity level, age and teaching status are potential influencing factors. Digital application can save healthcare organisations money while improving patient outcomes. At its core, digital transformation responds to new or existing stakeholders who want higher quality healthcare and decreased costs. Despite being one of the most difficult areas, healthcare digital transformation is a reality.

2.8. Digital Health Acceptance Challenges

The field of DH is rapidly expanding and shows great potential to improve healthcare results. However, the move to DH is hindered by the need for a reliable infrastructure, increased techno-capability and better protocols for sharing data. Moreover, the fast rate of technological progress might pose challenges for healthcare personnel in staying up to date with the newest advances and the most suitable instruments.

DH presents serious problems with accessibility, privacy, security, and ethics. In the health industry, digital applications have given enormous privacy, anonymity, security and informed consent concerns (Favaretto et al., 2020). Privacy and data protection problems affect the reliability of DH systems (Haasteren et al., 2019). The DH ecosystem poses novel ethical dilemmas concerning the choice, examination, integration, and assessment of technology in healthcare (Nebeker et al., 2019). The existing security protection systems need to be enhanced to guarantee the safeguarding of records while upholding privacy, as stated by Archer et al. (2011). The ongoing ethical discourse in the field of DH mostly centres on the issues of privacy and data safeguarding (Mirchev et al., 2020). With the shift of healthcare services to online platforms, the subject of medical ethics increasingly includes information technology experts (Terrasse et al., 2019).

Key ethical considerations for mental health apps using digital phenotyping are ensuring privacy, openness, permission, responsibility and fairness (Martinez-Martin et al., 2021), which need to be addressed in the decision-making process during development. In the

DH area of technology, there are moral and political disagreements about whether or not privacy is a prerequisite (Nyrup 2021). At the application software level in DH, ethical concerns include efficacy, usability, inclusion, and transparency, as well as other functional and direct usage problems (Shaw & Donia, 2021). The level of trust that consumers have in businesses that gather and repurpose personal DH data is contingent upon the proper use of such data (Gupta et al., 2023). The incorporation of ethical principles, the recognition of privacy as intellectual property, and the use of computational trust models may enhance the development of DH information systems that are both morally acceptable and privacy-preserving (Ruotsalainen & Blobel, 2020). The FDA (Food and Drug Administration) encounters difficulties efficiently overseeing expanding DH solutions (Martinez-Martin et al., 2018).

A major obstacle in the healthcare business is the insufficient availability of resources to facilitate the deployment of DH (Hossain et al., 2019; Smits et al., 2022; Kodsi & Bhat, 2022). Implementing DH requires significant financial expenditure and infrastructural support (Labrique et al., 2018; Velthoven et al., 2019; Marwaha et al., 2022). Nevertheless, healthcare organisations, particularly those in countries with limited resources, have challenges in allocating enough resources for the integration and execution of DH applications (Hossain et al., 2019; Kodsi & Bhat, 2022). The limited availability of resources impedes the extensive implementation and incorporation of DH solutions into healthcare (Smits et al., 2022).

Drummond et al. (2015) highlight the difficulty of obtaining financing for healthcare innovations, pointing out that financial factors typically determine the practicality of implementation initiatives (Drummond et al., 2015). Similarly, Magnussen et al. (2004) examined how economic constraints influence healthcare decision-making, emphasising the need to find cost-effective solutions that maintain high-quality standards (Magnussen et al., 2004).

A significant limitation is the scarcity of medical resources, which has been worsened by the COVID-19 pandemic (Rahman et al., 2022). The COVID-19 pandemic highlighted the need for innovative technology and digital services in the healthcare sector to alleviate the burden on the healthcare system (Roth et al., 2021). However, the shortage of medical resources, including hospitals, health commodities, medicines and skilled personnel, has restricted the use of DH solutions (Rahman et al., 2022). In addition, individuals who suffer from financial constraint and nations with a lower standard of living may be too resource-limited to adopt DH models effectively (Kodsi & Bhat, 2022).

The successful execution of DH requires dedication of both organisational resources and technical assistance (Velthoven et al., 2019; Heijsters et al., 2022; Desveaux et al., 2019). The adoption process is determined to some extent by organisational characteristics (i.e., the ability of an organisation to innovate, readiness for DH innovation, and financial access), which influence the acceptance of DH innovations in applied settings (Desveaux et al., 2019). Adoption and adaptation of DH may pose challenges for traditional pharmaceutical companies and many other healthcare organisations that focus on addressing disparities posed by the development of medications and digital solutions (Velthoven et al., 2019).

Furthermore, the paucity of empirical studies that consider organisational aspects linked to technology adoption in healthcare settings has limited understanding of what resources are required for successful implementation (Cresswell & Sheikh 2013). Ultimately, the insufficiency of resources is a substantial obstacle to the execution of DH. This difficulty is exacerbated by a scarcity of medical resources, budgetary limitations, and organisational difficulties. It is essential to tackle these resource limitations to implement and incorporate DH applications into healthcare systems effectively.

Organisational structure and culture often present substantial obstacles to implementing healthcare initiatives. An inflexible hierarchical framework might impede communication and creativity, impacting the implementation of new methods. Goh et al. (2016) examined the hindrance from organisational inertia and resistance to change in relation to implementation efforts, highlighting the need for cultural transformation of flexibility and adaptability (Goh et al., 2016). Tucker and Edmondson (2003) demonstrate that guilt and the absence of psychological safety in healthcare organisations might discourage personnel from participating in innovative projects (Tucker & Edmondson, 2003). Technological obstacles are particularly important since problems with interoperability, usability and compatibility pose substantial difficulties. Holden et al. (2010) stated that the absence of user-friendly interfaces and sufficient training are significant barriers to the successful use of healthcare technology (Holden et al., 2010). Paré et al. (2006) emphasise that the widespread use of EHRs and other DH solutions is hampered by the lack of security, both in terms of data protection and privacy.

Most of the challenges that impede DH integration, such as resistance from healthcare professionals, the inadequacy of skills and knowledge gaps, are caused by human factors. Kotter (2007) examined the significant barrier of staff resistance to change, which is often rooted in the apprehension about the unfamiliar or perceived encroachment on professional independence (Kotter, 1995). Kabene et al. (2006) examined the effects of human resource limitations, such as a lack of competent staff and insufficient chances for professional growth, on the implementation of healthcare initiatives (Kabene et al., 2006).

The deployment of DH is further complicated by problems related to interoperability and integration. Halamka et al. (2005) discuss the challenges involved in successfully integrating new applications into the current healthcare infrastructure. They highlight the need to overcome technical and standardisation concerns. Kellermann and Jones (2013) argue that the lack of standardised protocols and interfaces may also make it difficult to exchange records efficiently among different elements of one healthcare system or between elements of two entirely disparate systems (Kellermann & Jones, 2013).

Another factor that affects the acceptability of DH is the simplicity of the technology and its user-friendliness. According to Rhoon et al. (2022), consumers are more likely to use a digital programme to prevent diabetes if they find it user-friendly and intuitive. In the study by Tan et al. (2023), the impact of mental health platforms for digital workers was assessed and the adoption was influenced by the usability of the platforms.

The trustworthiness and reliability of DH treatments are very important factors that affect their acceptance. According to Ebenso et al. (2021), the adoption and use of DH interventions in rural Nigeria by stakeholders, including providers, are influenced by trust in the technology and reliability of the information shared. Similarly, in the study by Bai and Guo (2022), consumers' willingness to adopt DH information systems was influenced by trust in the technology and information.

Furthermore, acceptability is highly dependent on the degree of DH literacy. Guendelman et al. (2017) pointed out that DH literacy is critical for disadvantaged and expectant mothers when it comes to using DH applications. In the same way, Mackert et al. (2016) observed that there could be a new digital divide due to health literacy, in that those with low health literacy may face challenges when adopting DH solutions.

Both the socio-cultural background and individual traits play a part in influencing DH's acceptability. According to Whitelaw et al. (2020), the adoption of DH applications for cardiovascular care is affected by obstacles and enablers, both of which are informed by socio-cultural variables. In their study of the influence of eHealth technology on motivating health workers in Ghana, Atinga et al. (2020) found that the use of eHealth applications affected the motivation and job satisfaction of health workers.

Organisational culture remains paramount in healthcare implementations as it affects both the willingness and ability of hospital employees to adopt new protocols. Schein (2010) articulates that organisational culture is significant in the willingness and readiness for change. A culture that supports continuous learning and development may greatly boost the adoption of new healthcare practices (Schein, 2010). In addition, Damschroder et al. (2009) provided the Consolidated Framework for Implementation Research (CFIR), which highlights the importance of an organisation's inner context, including its culture, in determining the effectiveness of implementation efforts (Damschroder et al., 2009).

The implementation of the digital hospital consists of a variety of challenges that require proper management. Leadership is one of the key components that contribute to the efficient and successful management of those challenges. Transformational leadership styles are especially useful in this aspect. According to Bass (1985) and Avolio et al. (2009), transformational leaders inspire and motivate their workers to create a work climate that facilitates change and creativity. Such executives express a specific vision for change and gradually link the organisation's objectives with his or her own.

The level of technological preparedness also has a considerable influence on the implementation of DH. Chau and Hu (2002) examined the TAM, demonstrating the impact of perceived utility and simplicity of use on the acceptance of new applications by healthcare professionals (Chau & Hu, 2002). Furthermore, Melas et al. (2011) emphasised the need for sufficient infrastructure and technical assistance to guarantee the effective integration of technology in healthcare environments (Melas et al., 2011).

Financial incentives and resources are crucial catalysts for the adoption of DH. Rosenthal and Frank (2006) examined the impact of financial incentives on hospitals' alignment with healthcare quality improvement initiatives, facilitating the implementation of optimal approaches (Rosenthal & Frank, 2006). Menachemi and Collum (2011) emphasise that resources, such as financing and staff, play a crucial role in facilitating the implementation process. They argue that having sufficient resources may help overcome obstacles to change.

Interprofessional teamwork is crucial for easing the implementation of DH. Reeves et al. (2010) emphasise the significance of collaborative practices in healthcare, asserting that cooperation and shared decision-making may improve the efficiency of DH delivery (Reeves et al., 2010). Zwarenstein et al. (2015) provide evidence that interprofessional cooperation may result in a more comprehensive and patient-focused approach to healthcare.

Ultimately, the adoption of DH practices in hospitals is shaped by a wide range of elements, such as organisational culture, leadership, technical preparedness, financial resources, and interdisciplinary cooperation. It is essential to consider all these factors together to create an environment that supports the effective implementation and long-term viability of healthcare innovations. The barriers to hospital-based health system implementation are similarly multifactorial and interrelated across organisational culture, technology constraints, human factors, financial constraints, and interoperability challenges. This complexity requires a broad-spectrum strategy that includes cultural change, technical enhancement, skill development, financial investments, effective implementation, and standardisation of processes.

2.9. Digital Health in the UAE

The UAE is at the forefront of AI, establishing the first ministry dedicated to AI through the initiative to establish the "Dubai Future Accelerators" programme. Furthermore, Dubai, as one of the emirates of UAE, will house the world's first institution dedicated to research on AI.

The purpose of this AI institution is to promote the widespread integration of AI across all domains of life and enhance efficiency in every sector. Emirati inhabitants and residents may anticipate an enhanced standard of living as AI assumes a crucial function in key sectors, such as education, healthcare, transportation, and commerce (Alhashmi et al., 2019). In a similar vein, the government has made substantial investments in enhancing internet access and facilitating the process of digital transformation.

Additional internet capacity is being allocated to improve accessibility. The network connection is being enhanced by expanding a fibre-optic network throughout the nation, resulting in increased physical density. Integrating public hospitals and nursing homes is anticipated to enhance healthcare services. In addition, AI, especially machine learning algorithms, can change the landscape of the health sector by increasing diagnostic accuracy, improving patient care, and reducing healthcare costs (Al Ali & Badi, 2021). The application of AI in healthcare has been acknowledged as a possible driver that is likely to reduce healthcare costs and improve health outcomes (Väänänen et al., 2020).

EHRs are a digital application that has a transformative impact on healthcare worldwide. EHRs are a collection of standardised applications that provide seamless communication between patients, their families and doctors, allowing easy access to the healthcare system at any time and from any location. EHRs enhance efficiency by providing clinicians with readily accessible information during patient consultations (El Khatib et al., 2022). Consequently, physicians may conduct a greater number of treatments since they do not need to wait for test results, seek advice from experts, or contact pharmacies for medicines.

The healthcare system in the UAE has implemented EHRs to enhance communication between doctors and patients and facilitate the exchange of information across hospitals, specialists, and pharmacies (Zgallai et al., 2022). The nation has used this method to expedite the exchange of medical information and has already significantly reduced the time required. The UAE government has spent more than $6 billion on the worldwide development of EHRs (Zgallai et al., 2022). By 2022, this figure rose by 30% and include more than 6 million individuals. According to data from the Department of Statistics in the government of Dubai, the number of Emiratis and expats with health insurance coverage, including government programmes, was 2.837 million in 2019 and 1.445 million in 2018 (Alshareef et al., 2020).

The Emirates Health Services (EHS) in the UAE recently announced an Innovation Strategy for 2023-2026 aimed at improving the quality and sustainability of healthcare services to strengthen the entire sector (Emirates Health Services, 2023). It builds on global best practices and enhances lifestyle improvements as well as establishing preventative public health policies, including financing social services such as law enforcement and counselling. Additionally, the objective is to enhance collaborations, elevate the standard of services, and attain fiscal effectiveness and worldwide competitiveness. The approach is founded upon six fundamental principles, which include proactive thinking, teamwork, and an emphasis on entrepreneurship. This programme is in line with the UAE's strategic objectives to establish a robust community and make a positive contribution to the National Strategy for Wellbeing 2031 and the 'UAE Centennial 2071' Plan (Emirates News Agency - WAM, 2023).

AD has made significant achievements in the domain of DH, as evidenced by the successful presentation at the Arab Health 2022 Expo (Gulf News, 2022; UK Healthcare Pavilion, 2022). More than 3,500 exhibitors from 60 countries showed the most recent medical innovations to more than 56,000 healthcare professional attendees (Gulf News, 2022). During the event, the AD DoH pointed to a number of healthcare innovations as examples of the emirate’s approach to improving health services and systems. These included two disease registries, a medical education hub, an AI-enabled pandemic manual, a COVID-19 epidemiological forecasting model, a government health platform, digital birth certificates, a vaccine effectiveness dashboard, a long-COVID dashboard, and a virtual care platform (Emirates News Agency, 2022). All these programmes indicated that the department focuses on the opportunities provided by current technological innovations.

Furthermore, DoH presented the Estijaba platform, which was used throughout the COVID-19 pandemic to gather and analyse case data. Malaffi, the first health information exchange (HIE) platform in the area, was identified as a noteworthy initiative, showcasing

AD's leadership in health information management (Emirates News Agency, 2022). Dr Jamal Mohammed Al Kaabi, the Undersecretary of DoH, highlighted the significance of these pioneering initiatives in enhancing AD's ability to combat the COVID-19 pandemic, establishing the emirate as a prominent centre for life sciences at both regional and worldwide levels (Emirates News Agency, 2022).

Establishing global alliances and partnerships and always improving itself is what DoH focuses on to be able to deliver world-class medical services to the community and the international public. DoH officials highlighted the momentum in several addresses, including health transformation and regulation (Emirates News Agency, 2022). As the largest medical exhibition in the Middle East, Arab Health Expo offered DoH an excellent platform to showcase its success and potential future endeavours (Emirates News Agency, 2022).

2.10. Theories of Technology Acceptance and Diffusion

This section is dedicated to the study of theories related to the patterns and dynamics of digital adoption with implications for DH adoption in healthcare settings, including public hospitals in AD. Theories of technology acceptance and diffusion support a systems' view and comprehension of the processes through which hospitals accept new applications. These theories, mainly used in information systems research, can help focus on how organisations adopt new applications, such as telemedicine and EHRs. Some theories analyse how physicians, nurses and others involved in decision-making decide on a new system; others focus on organisations adopting technological innovation in hospitals or the wider healthcare market (Oliveira & Martins , 2011). This study's theoretical approach and model, as indicated in Chapter 1 and explained subsequently in depth in Chapter 3, is grounded in the UTAUT model, which is the outcome of research that combined components from many models, such as Diffusion of Innovation Theory (DOI) (Rogers, 1995), the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), and the Technology Acceptance Model (TAM) (Davis, 1989). Accordingly, given that this research's theoretical model will revolve around the UTAUT, the theories included herein are selected deliberately based on their close relationship to the UTAUT framework, namely the TRA, TAM, and DOI.

The TRA, introduced by Fishbein and Ajzen (1975) dwells on two constructs: attitudes and subjective norms, which serve as foundational blocks for related UTAUT constructs because UTAUT adopts and expands on these constructs in building its social influence and intention constructions. The TAM, developed by Davis (1989), extends TRA by introducing two new constructs: perceived usefulness and perceived ease of use, which are building blocks for UTAUT’s performance expectancy and effort expectancy. The DOI theory by Rogers (2003) focuses on the characteristics of an innovation that influence its adoption, including relative advantage, compatibility, complexity, trialability, and observability. The DOI theory exemplifies an alternative to UTAUT because the two models operate on different analytical levels: UTAUT focuses on predicting user behaviour, whereas DOI provides a framework for understanding the broader social and organisational dynamics of technology adoption. DOI’s inclusion herein provides a basis for appreciating how the UTAUT can be extended by incorporating other complementary theoretical perspectives.

2.10.1. Theory of Reasoned Action (TRA)

The primary objective of the Theory of Reasoned Action (TRA) is to enhance the incorporation of pertinent knowledge about human actions, behaviours, and attitudes. Crucially, the theory serves as a mechanism for forecasting human conduct concerning current attitudes. More precisely, this theory posits that people are driven to act a certain way when contemplating the consequences of their behaviour or actions. Each action has consequences (Nguyen et al., 2018; Orr et al., 2013).

The result of an activity may serve as a source of motivation for an individual to either carry out or refrain from the action. This theory aims to understand the intentional actions of people and examine the underlying factors that drive their conduct. If individuals behave in a certain manner, they need to possess a credible justification for their actions. The hypothesis states that a person's intention to carry out a certain activity is the most significant factor in determining whether they will perform the action, as illustrated in Figure 2.5. Prior to engaging in an activity, it is important to possess the deliberate desire to carry out the action. Failure to have the intention to carry out a task hinders its completion (Nguyen et al., 2018; Orr et al., 2013). According to the theory's proponents, intention is the main factor that leads to an action. Individuals often place more importance on tangible activities than the intention to carry them out. In contrast, TRA is predicated on the intention to carry out or refrain from a certain action or conduct rather than the actual execution of the action or activity. In this context, an intention refers to a deliberate strategy or strong desire to accomplish a certain activity. Nevertheless, executing the specified activity has a foreseeable result that might impact the nearby environment.

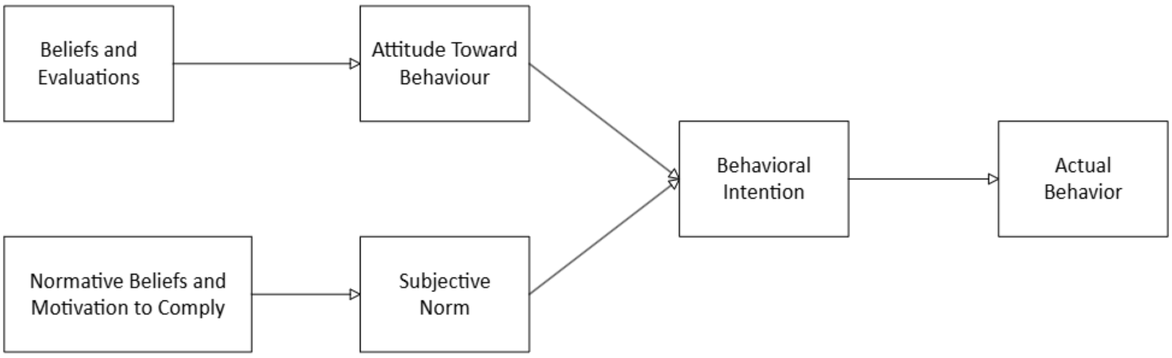

Figure 2.5 **Theory of Reasoned Action (Fishbein & Ajzen, 1975):** This figure illustrates the Theory of Reasoned Action, explaining how attitudes and subjective norms shape behavioural intentions.

People's intents arise from their deeply held beliefs. Furthermore, it is important to acknowledge that the Technology Readiness Assessment (TRA) has a significant correlation with the Technology Acceptance Model (TAM) (Dewberry & Jackson, 2018). There exists a narrow demarcation between the two hypotheses and behavioural purpose is a crucial subject in the Theory of Reasoned Action (TRA). Subjective norms have a significant role in shaping people's attitudes, which are ultimately decided by their behaviours. Crucially, normative ideas influence individuals' intentions. For example, a community that prioritizes progress, advancement, and technology may find it easier to embrace digital applications. Likewise, a society that fails to appreciate the importance of technology may ignore digital applications and their consequences. The TRA argues that having strong intentions increases the chance of behaviour being executed (Nguyen et al., 2018; Orr et al., 2013).

Nevertheless, the TRA model is subject to criticism for lacking some extent of falsifiability, so it might not be empirically testable under certain conditions (Alam et al., 2021). In addition, several researchers have noted that the TRA model misses' aspects outside attitude and subjective standards, limiting its ability to provide a thorough explanation of behavioural intent (Cheng & Yuen, 2022). Furthermore, research that utilises a TRA/TPB strategy has faced criticism for not completely implementing the model, indicating possible constraints in its real-world use (Swanson et al., 2006).

2.10.2. Technology Acceptance Model (TAM)

Davis (1989) developed TAM to explain how users perceive and use technology (Teo, 2012). TAM is founded on Fishbein and Ajzen's (1975) TRA, a sociopsychology-aligned behavioural theory that explains social behaviour and an individual's attitude.

TAM was created to provide an understanding of the cognitive and affective factors identified in prior research and their influence on technology acceptance (Teo, 2012). TAM is the most widely accepted model for describing an individual's behavioural intentions (Granic & Marangunic, 2019; Wong et al., 2013).

During the 1970s, there was a growing reliance on technology but the adoption of technology by organisations did not keep up with demand. Consequently, researchers began to focus primarily on system use (Chuttur, 2009). Davis (1989) found that most studies lacked valid measures to explain system acceptance or rejection. Davis conducted research based on Fishbein and Ajzen's (1975) TRA and enhanced the model to create TAM. As TAM was being developed, Davis added elements and edited other features, while other researchers made similar contributions (Chuttur, 2009).

TAM has been widely implemented in the development of information systems (Venkatesh & Bala, 2008). However, most TAM-related research has been conducted with business representatives (Wong et al., 2013; Wong, 2016). Al-Adwan et al. (2013) state that TAM is one of the most well-known models for determining technology acceptance and use. It has also proven useful for predicting user acceptance.

According to Wong et al. (2013), Davis (1989) introduced TAM to explain the relationship between attitude, intention, and behaviour. TAM has revealed a theoretical framework for technology acceptance that emphasises perceived usefulness and ease of use (Teo, 2011; Wong et al., 2013). The two central views of TAM—perceived use and usefulness of technology—form the basis of user acceptance (Al-Adwan et al., 2013; Teo, Lee, & Chai, 2008; Teo et al., 2012). Davis (1989) states that perceived usefulness and ease of use reflect the extent to which a user believes that technology will improve their job performance, as illustrated by Figure 2.6.

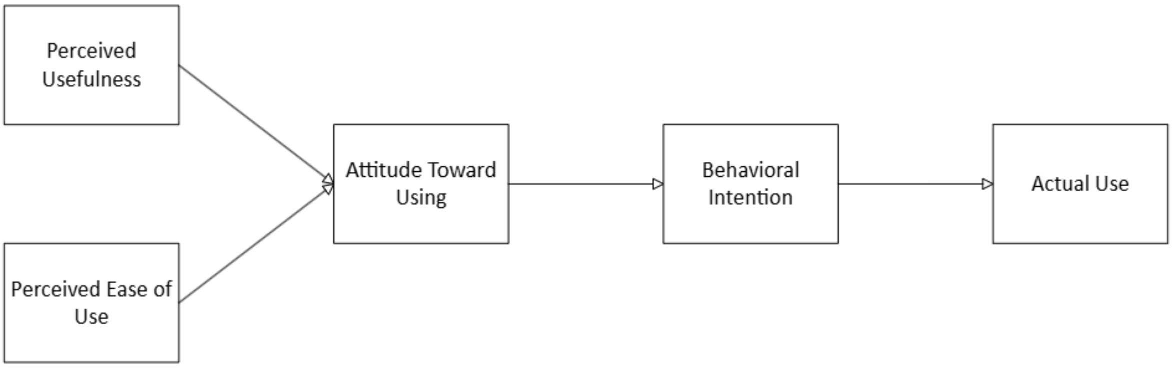

Figure 2.6 **The Technology Acceptance Model (Davis, 1989):** This figure depicts the Technology Acceptance Model, outlining the relationship between perceived usefulness, ease of use, and technology adoption.

TAM, although widely used in research, has been subject to criticism. Ursavas et al. (2019) proposed that TAM be expanded to include multiple cultures and applications. El-Gayar et al. (2011) said that TAM is incapable of directing system design and management practices that influence technology adoption and use. Teo (2011) explained that, despite TAM's claim, it lacks the external validity to explain technology acceptance.

2.10.3. Diffusion of Innovation (DOI)

Rogers (2003), a prominent advocate of the diffusion of innovation (DOI) theory, provided an elucidation for the gradual acceptance and adoption of new ideas, despite their potential advantages. Rogers (2003) defined diffusion as “the transmission of a new idea or innovation within a social group through specific communication channels over a period of time”. Rogers talks about four principal properties of diffusion: innovation, communication channels, time, and social system. As defined by Rogers (2003), innovation is the use of a new idea, method or object. The theory of innovation dissemination by Rogers (2003) asserts that uncertainty and novelty are in inverse relation, such that acceptance reduces as the level of novelty increases. Robinson (2009) observed that, based on Rogers' theory, a limited group of innovators usually initiate the first innovations throughout the adoption phase. Generally, an adoptive population advances through five phases according to the inclination of the person or group involved in the adoption process:

Relative advantage – innovators are more likely to adopt a new technology if they are convinced that the adoption of the technology is superior to the existing choices.

Compatibility – innovators evaluate the extent to which a new technology is consistent with their existing methods and needs only minor modifications before it is embraced.

Complexity – the level of complexity of an invention impacts its acceptance by innovators, who tend to choose straightforward, comprehensible, and user-friendly applications.

Trialability – enables prospective adopters to investigate the innovation, comprehend its functionality, and assess its usefulness and compatibility with their current systems and procedures without committing completely.

Observability – is a critical factor in the adoption of innovation. Innovators are more inclined to embrace innovations with clear and tangible consequences and advantages.

Rogers (2003) emphasised the significance of communication routes in the spread of innovations. There are two distinct categories of channels: mass media, which disseminates messages to broad groups of people; and interpersonal channels, which include the exchange of messages between individuals. Opinion leaders, who are powerful individuals within social groupings and possess greater socio-economic standing, have a significant impact on the acceptance and implementation of new ideas or inventions. Rogers classified people into social groups based on their acceptance of innovation, ranging from late adopters to early adopters. This hypothesis highlights the importance of human interactions in spreading innovation.

Enfield et al. (2011) emphasizes the significance of change agents in influencing the adoption of innovation, specifically in terms of communication channels, opinion leaders, and the link between the change agent and the social group. Ren et al., (2017) emphasizes the significance of social influence and the structure of peer networks in the adoption of innovations in online social networks. These studies provide more understanding of the complex dynamics of how innovation spreads and the significance of interpersonal contact and social impact.

Although the DOI model is useful for understanding the spread of innovations, it has encountered constraints in certain circumstances. The DOI model has been criticised for its limited consideration of socio-economic and cultural elements that might impact the adoption of innovations, suggesting that its reach may be limited (Yu et al., 2022). See table 2.1 below for some details.

Table 2.1 **Technology Acceptance Models and Their Constructs**: This table summarizes key technology acceptance models, their main constructs, and their influence on user adoption.

Model	Constructs	Descriptions
Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975)	Attitude, subjective norm, perceived behavioural control	TRA is a model of human behaviour established to explain how individuals make decisions about their behaviour. It suggests that attitude, subjective norm, and perceived behavioural control are the three main factors influencing an individual's intention to perform a behaviour.
Technology Acceptance Model (TAM) (Davis, 1989)	Perceived usefulness, perceived ease of use	TAM is one of the most widely used models of technology acceptance. It posits that perceived usefulness and ease of use are the two most important factors influencing a user's decision to adopt new technology.
Diffusion of Innovation (DOI) (Rogers, 2003)	Relative advantage, compatibility, complexity, trialability, observability	Explains how new ideas and technologies spread through social systems over time, influenced by communication channels and adopter categories.

2.11. Models in Healthcare Settings

Healthcare settings use models to assess and predict the adoption and usage of different applications and procedures, and an often-used paradigm is UTAUT. Philippi et al. (2021) carried out research to authenticate and enhance UTAUT in the realm of online and mobile-based therapies for somatic and mental health disorders. The researchers discovered that performance expectation had the highest predictive power for acceptance. They suggested a modified UTAUT model that included Internet anxiety as a direct predictor and moderator of SI and effort expectation.

In a working environment, Blut et al. (2022) conducted a meta-analysis and found compatibility, education, personal innovativeness, and expense as significant extensions of UTAUT. Internet anxiety was identified as a major factor that predicts and influences the acceptability and use of Internet and mobile-based treatments. It was incorporated as a direct predictor and moderator in the modified UTAUT model presented by Philippi et al. (2021). TAM is also often used in healthcare settings. Several studies have shown that the perceived utility of TAM is the primary element that influences healthcare professionals' adoption of telemedicine technology. The research by Rouidi et al. (2022) built on TAM by adding different variables. In this case, the perceived relevance of IT use, data privacy, and documentation were used to gain greater insight into factors increasing perceived utility and ease of use.

Rouidi et al. (2022) state that both UTAUT and TAM have greatly enhanced understanding of the elements that impact the acceptability and usage of telemedicine technology by healthcare practitioners. The UTAUT variables, namely PE, EE and FC, along with the additional variable financial incentive, have consistently demonstrated a significant positive impact on the BI of healthcare professionals to use telemedicine technology.
In addition, research undertaken by Alabdullah et al. (2020), Shiferaw et al. (2021), and Kohnke et al. (2014) has confirmed the significance of UTAUT and TAM factors in forecasting the acceptability and intention of healthcare professionals to use telemedicine technology.

These models have been used not just in telemedicine settings but also in several other healthcare scenarios. Akinnuwesi et al. (2022) conducted research on the implementation and use of DH applications to manage COVID-19. The researchers discovered that the UTAUT model is applicable in the field of DH and may provide guidance for investigations. At the same time, they presented numerous issues that impact the behavioural intent of users to adopt and utilise these applications. The scholars stressed the importance of situational awareness, perceived behavioural control, FC, and compatibility in forming the inclination to use digital applications.

Furthermore, alongside UTAUT and TAM, additional models have also been created for specific contexts or concerns. To evaluate healthcare workers' inclination and use of mHealth applications in developing countries, Addotey-Delove et al. (2022) created the Healthcare Workers mHealth Adoption Impact Model (HmAIM). This model considers several elements, including cooperation and money, to comprehend the uptake of mHealth efforts.

In general, models like the UTAUT, TAM, and HmAIM are useful tools for evaluating and forecasting the acceptance and use of technology and therapies in healthcare environments. These insights provide a better understanding of the elements that impact the intent and behaviour of healthcare professionals. This, in turn, helps in the creation and execution of successful healthcare solutions.

2.12. Studies on Digital Health in the UAE

This section aims to synthesise previous studies and research on the present state of DH in the UAE. The aim is to analyse the many factors that impact the level of acceptance of these applications. The study by Abdallah et al. (2021) investigated the acceptance and use of telemedicine among healthcare professionals and patients in the UAE. This research made a valuable contribution to the current body of literature on the use of technology in the healthcare sector. This study applied TAM and DOI to investigate the factors that drive telemedicine technology usage intention and actual usage (AU). The study also discovered a significant positive association between Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), validating the prior studies showing that PU is substantially associated with attitude, although PEOU does not achieve statistical significance. The aforementioned findings suggest that it would be beneficial to combine many models in order to have a comprehensive understanding of technology uptake and use. Moreover, this research has identified crucial factors, such as the individuals' attitudes towards telemedicine, that significantly impact the acceptance and use of this technology. Hence, it is essential for decision-makers to take into account these elements, in addition to other technological attributes, in order to enhance the acceptance rates.

Abdallah et al. (2021) conducted research to examine the acceptance and attitudes of users in UAE towards telemedicine. The researchers explicitly assessed the impact of the diffusion of innovation as a potential confounding factor. The healthcare professionals' level of knowledge and comprehension of telemedicine influenced their attitudes towards the use of this technology. Research indicates that telemedicine has significant potential for facilitating healthcare services in the UAE for the management of illnesses. However, it emphasizes the need to consider crucial factors, such as the attitudes of participants, to ensure the effective application of telemedicine. To better patient care via the use of telemedicine technology, it is important to develop skills and obtain more knowledge. The study revealed that the implementation of telemedicine is impeded by various barriers, including insufficient training and expertise among healthcare professionals, limited awareness among users, initial financial investments, technical proficiency requirements, and challenges related to the reimbursement of capital costs.

Abdallah et al. (2021) emphasise that healthcare practitioners require a moderate to high level of technical skill to exploit new technological developments. Gaining insight into user perspectives and expertise is vital to efficient execution, as is ensuring that adequate training and resources are provided for successful implementation.

Alrahbi et al. (2021) researched the factors influencing healthcare personnel's willingness to use health information technology (HIT). The findings indicate that individual and organisational motivators are highly important, followed closely by the connection between equipment, processes, and themes. Physicians who prioritise patient-centred treatment are more likely to use HIT, while those without prior experience are less likely to adopt it. HIT has several advantages, including enhanced accuracy in transferring information, prompt transmission, increased productivity, fewer mistakes, and reduced costs associated with keeping physical records. Stakeholder theory provides a conceptual framework for comprehending the implementation of information technology in the healthcare sector. The goal is to analyse and evaluate the factors that impact the acceptance of information technology (IT) across four key groups in the healthcare sector: employees, patients, citizens and residents of the UAE, and experts in future trends. The findings indicate that government aid is the primary factor influencing the outcome, followed by information interchange, infrastructure, environmentally conscious management, efficient management, internal and external circumstances, and social sustainability. Further investigation is necessary to examine the many factors that influence the implementation of Health Information Technology (HIT) in different geographic regions (Alrahbi et al., 2021).

The study conducted by Drissi et al. (2022) examined how various factors impact digital interventions for mental health in the UAE. The UAE is culturally biased, meaning it leans towards family and community values over individualism. This cultural propensity has the capacity to influence patients' willingness to adopt digital mental healthcare therapies. The lack of understanding of mental health concerns is a further obstacle to the acceptance and implementation of mental health programmes. Furthermore, the challenge is intensified by inadequate knowledge and proficiency in reading and computer literacy among certain demographics. To ensure successful implementation, it is essential to address these specific challenges, including concerns around confidentiality, privacy, and security.

In addition, overcoming resistance to change, limited Arabic content, technical challenges, and doubts about digital solutions are major hurdles that must be addressed.

However, there are many advantages to using digital application for mental health in the UAE. Teletherapy offers privacy in treatment delivery and removes financial, physical and social barriers to mental healthcare, compared to traditional therapy methods, and enhances the effectiveness of therapists' work (Drissi et al., 2022).

El Khatib et al. (2022) performed a recent study to examine the challenges associated with incorporating large-scale data in healthcare organisations in the UAE. A significant obstacle is the current infrastructure, which may lack the capacity to manage substantial volumes of data effectively. Furthermore, a shortage of experts might hinder the ability to analyse and determine the facts. The adoption of big data applications may be hindered by concerns about data privacy and security. Smaller healthcare facilities may face significant economic obstacles when attempting to incorporate new systems, equipment, and software. To address these challenges, significant expenditure and encouraging collaboration between healthcare providers and technology enterprises are needed.

Al Badi et al. (2022) found that implementing AI technology in UAE healthcare has various challenges, which centre around workers being reluctant to change and the difficult task of successfully managing all relevant stakeholders. To tackle these challenges, a decision-making framework was used to develop an analytic hierarchy process (AHP) model for prioritising the primary hurdles. This model considers several aspects, with five primary and 25 subordinate criteria. These aspects include precision, bias and unfair treatment, efficiency and originality, moral limitations, confidentiality, and protection. The identification of these aspects was achieved by a comprehensive analysis of current research and discussions with senior executives in healthcare firms. The findings indicate that the enhancement of the healthcare sector via AI is mostly influenced by issues such as accuracy, privacy, and security. Policymakers may use the AHP model to effectively address and navigate the complexities associated with adopting AI, ultimately leading to the deployment of an optimal adoption approach.

A research study was conducted to examine the customers' perceptions of healthcare applications offered by the Dubai Health Authority (DHA) in relation to their utility, user-friendliness, satisfaction, and usability. The research had a cohort of 396 people. The data revealed that a significant majority of users (87.9%) had a positive perception of the utility of the programs, while a substantial proportion (83.6%) regarded them as user-friendly. Furthermore, a substantial percentage (85.9%) expressed contentment with their whole encounter. Nevertheless, the individuals' perspectives varied based on certain demographic variables, such as age and country. This study emphasizes the significance of comprehending the users' viewpoints and demographic disparities in the development of health applications and enhancement of healthcare outcomes (AlSuwaidi & Moonesar, 2021).

Aburayya et al. (2020) conducted a study to investigate the key elements that contribute to the successful implementation of Total Quality Management (TQM) in hospitals in the UAE, specifically focusing on the problems related to DH. The research used a quantitative methodology by distributing questionnaires to senior staff members in two public hospitals in Dubai. It emphasized the need for a strong commitment from the top management and a focus on customer satisfaction. The challenges mentioned were the need for a corporate culture that fosters ongoing improvement and the deliberate use of digital applications in Total Quality Management (TQM) methodologies.

Tortorella et al. (2021) presented a system for prioritizing the incorporation of Industry 4.0 technology in hospitals. This research used Quality Function Deployment to align technology integration with healthcare value chain issues by conducting case studies at a major public hospital in Brazil and a private hospital in India. It emphasized the widespread usefulness of their approach in facilitating the organized implementation of digital application in hospitals, independent of their ownership structure.

In their study, Andreadis et al. (2022) investigated the capacity of 3D printing applications to transform the field of medication manufacture. The research conducted a thorough examination that emphasized the potential of customized medicine enabled by 3D printing. It specifically addressed the obstacles related to regulations, quality assurance, and acceptability that need to be overcome to utilize this technology in healthcare. The results indicate a change in the way treatment choices are approached, focusing more on customization and tailoring them to individual patients.

In their study, Schober et al. (2023) examined the obstacles that hinder the implementation of DH. The research conducted a study using a questionnaire among hospitals that serve patients with allergies. The study found that the restricted reimbursement and underutilization of DH apps are important barriers. This research emphasizes the need to tackle financial and adoption obstacles to improve the deployment of DH.

These studies jointly demonstrate the complex and diverse aspects involved in adopting DH in hospitals, including technical, managerial, regulatory, and financial elements. The results emphasize the need for all-encompassing strategies that include effective leadership, patient-centred methods, regulatory frameworks, and financial incentives to overcome obstacles and use the advantages of DH technology.

Tan (2022) critically examines the integration of DH advancements within the pandemic and suggests a comprehensive framework for assessing and adopting them. Although the problems of incorporating applications such as IoT, AI, and big data into healthcare systems are relevant to hospitals in the UAE, it is important to emphasize the need for strategic planning and the careful consideration of practical consequences.

Supriadi et al. (2023) discusses the execution of infection prevention and control, emphasizing difficulties such as modifying behaviour and the insufficient capacity of microbiology laboratories. Despite being conducted in Indonesia, the research addresses issues that are applicable to the adoption of DH in the UAE, such as the significance of infrastructure and personnel training.

Okegbile et al. (2023) examined the idea of human digital twins in the field of healthcare. The article emphasizes the difficulties in modelling intricate physiological changes and assuring the precision of medical data. These factors are of utmost importance for UAE institutions that want to adopt tailored DH solutions. See table 2.2 below for a summary.

Table 2.2 **DH Studies in UAE**: summarizes research on DH adoption, highlighting key factors, barriers, and strategies, including privacy concerns, infrastructure, stakeholder resistance, and policy support in the UAE.

Study	Authors	Key Findings
User Acceptance Level of and Attitudes towards Telemedicine in the United Arab Emirates	Abdallah et al. (2021)	• Used TAM and DOI theories; found that PU significantly influenced attitudes towards telemedicine, while PEOU was not statistically significant. • Barriers include a lack of training, awareness, and financial investment.
Exploring the motivators of technology adoption in healthcare	Alrahbi et al. (2021)	• HIT adoption depends on individual and organisational motivators.

		• Key barriers are government support and information exchange infrastructure. • The study emphasises stakeholder theory for analysing IT acceptance across different groups.
A Conceptual Framework to Design Connected Mental Health Solutions in the United Arab Emirates: Questionnaire Study	Drissi et al. (2022)	• Cultural factors and lack of awareness of mental health issues hinder adoption. • Privacy concerns and limited Arabic resources also act as barriers, although digital mental health can provide accessible care through teletherapy.
Digital Disruption and Big Data in Healthcare - Opportunities and Challenges	El Khatib et al. (2022)	• The main challenges to big data implementation include infrastructure limitations, data privacy, and economic obstacles in smaller healthcare facilities. • Collaboration with technology enterprises is recommended for improvement.
Challenges of AI Adoption in the UAE Healthcare	Al Badi et al. (2022)	• Identified challenges in AI integration, including resistance to change and managing different stakeholders. • The AHP model was developed to prioritise accuracy, bias, and privacy concerns.
UAE Resident Users' Perceptions of Healthcare	AlSuwaidi &	• A survey of 396 people showed high satisfaction (85.9%) with DHA healthcare applications, with

Applications from Dubai Health Authority: Preliminary Insights	Moonesar (2021)	utility and user-friendliness rated highly. • Perceptions varied based on demographic factors like age and nationality.
Critical Success Factors Affecting the Implementation of TQM in Public Hospitals: A Case Study in UAE Hospitals	Aburayya et al. (2020)	• Top management commitment and a customer-focused culture are key to successful TQM and DH integration in UAE hospitals. • Barriers include the need for continuous improvement culture and digital application incorporation.
DH Innovations and Implementation Considerations Under the COVID-19 Pandemic	Tan (2024)	• Suggests a comprehensive framework for integrating DH applications like IoT and AI during pandemics • Emphasising strategic planning and practical implementation in healthcare systems.
Economic transformation of Indonesia in the era of Digital 5.0: challenges and opportunities	Supriadi et al. (2023)	• Examines infection control strategies and highlights the need for behaviour change and improved laboratory capacity, • Findings are also relevant to DH in the UAE, particularly infrastructure and training needs.
Differentially Private Federated Multi-Task Learning Framework for Enhancing Human-to-Virtual Connectivity in Human Digital Twin	Okegbile et al. (2023)	• Discusses the difficulties of modelling physiological changes and the accuracy of medical data in digital twin applications, which are crucial for tailored DH solutions in the UAE.

2.13. Challenges in DH Theoretical Research

Although the adoption of DH technologies has gained significant scholarly attention and consensus, key conflicts persist in current research. For instance, while studies such as Abdallah et al. (2021) demonstrate that perceived usefulness is a critical driver of DH adoption, others, like El Khatib et al. (2022), argue that infrastructure readiness and economic constraints are far more decisive and influential factors that precede and, in fact, define the construction of this perceived usefulness. This discrepancy suggests that existing research struggles to balance individual behavioural factors with broader systemic and organisational challenges and how their interaction impacts DH adoption. Furthermore, while Abdallah et al. (2021) endorse TAM and DOI as predictive frameworks in the context of modelling DH adoption and its determinants, the limitations of these theoretical frameworks and perspectives in addressing interoperability and cultural barriers are evident. TAM primarily focuses on perceived usefulness and ease of use but does not address organisational or infrastructural challenges like interoperability regulatory clarity, emphasized by Jain (2023) as a critical precipitant of DH adoption. Similarly, DOI emphasises innovative attributes such as relative advantage and compatibility but does not account for cultural barriers, such as those highlighted in Abdallah et al. (2021), where healthcare professionals in the UAE faced resistance due to cultural norms and limited technological alignment across systems.

Another area of contention in the extant research involves the role of healthcare professionals as primary adopters. Studies such as Alrahbi et al. (2021) emphasize individual motivators, including training and patient-centred attitudes, as pivotal to adoption. However, Drissi et al. (2022) highlight cultural resistance, particularly in regions like the UAE, where familial and community values often complicate the individual-centric focus of existing DH models.

The theoretical frameworks used in DH research are also associated with several areas of ambiguity and conflict among diverse scholarly perspectives. While TAM and TPB effectively address usability and behavioural intentions as determinants and drivers of DH adoption, noted in numerous studies including UAE-specific research such as Alabdullah et al. (2020), they often fall short in capturing ethical concerns like privacy and trust, which are increasingly critical in digital healthcare (Haasteren et al., 2019). Similarly, DOI's focus on innovative characteristics (Rogers, 2003) often overlooks the complex socio-political factors that influence technology diffusion, especially in public health systems like those in AD (Al Badi et al., 2022). These omissions create a fragmented understanding of DH adoption, necessitating more comprehensive frameworks that address both technical and non-technical dimensions.

Moreover, conflicting findings about patient engagement further complicate DH adoption research. While Silven et al. (2022) demonstrate the effectiveness of patient-facing technologies like wearables and telemedicine, Schober et al. (2023) highlight low utilisation rates due to trust and usability issues. There is also limited consensus on the long-term impacts of DH adoption on healthcare outcomes, whereby studies like Olu et al. (2023) argue that DH technologies enhance operational efficiency and patient satisfaction, while others like Alrahbi et al. (2021) caution against over-reliance on technology due to potential job displacement and reduced interpersonal care. These conflicting perspectives reveal a pressing need for longitudinal studies to evaluate the sustained effectiveness of DH initiatives beyond DH adoption, including investigating whether the route to and experience of adoption influences the nature of these long-term outcomes. Addressing these conflicts requires integrating behavioural, organisational, and cultural factors into a unified framework while simultaneously considering policy, ethical, and infrastructural dimensions. As the theoretical framework for this study demonstrates subsequently in Chapter 3, the UTAUT model, customised to the AD context, offers a promising avenue for resolving some of these tensions by incorporating its core traditional dimensions and accommodating evidence-based extensions based on the current empirical research.

2.14. Research Gap

Previous studies in the field of DH have examined its implementation from various perspectives, primarily focusing on the general aspects of technology adoption, patient outcomes, and specific applications. However, this research distinguishes itself by concentrating on the broader scope of DH within AD's public hospitals, based on the Unified Theory of Acceptance and Use of Technology (UTAUT). The primary emphasis is on matters pertaining to one's career rather than any other consideration.

Despite a growing body of literature on DH, several research gaps persist, particularly in the context of AD's public hospitals. Most research has been conducted in Western contexts, with limited studies focusing on the Middle East and even fewer on AD. This geographical gap means that the unique cultural, organizational, and regulatory environments of AD's public hospitals are underrepresented in the literature. Understanding these local nuances is critical for developing effective strategies tailored to the specific needs of a region.

While some studies have dealt with healthcare professionals' points of view, comprehensive research is still needed on their experiences, attitudes, perceived barriers and facilitators. Theoretical explanatory paradigms in the current literature aggregate data from patients, managers and policies, which can often cover narratives from frontline actors. Previous research has not focused on the clinical considerations of healthcare professionals in AD, and this study set out to address this gap.

Although the UTAUT framework has been widely utilized to study technology acceptance, its application must be expanded and adapted specifically to the DH context in AD. This study aimed to address this gap by customizing the UTAUT model to include factors such as MLI, SE, and DH experience, which are particularly relevant in the AD context. By doing so, this research will offer a more tailored and effective model for understanding technology acceptance in this unique setting.

Additionally, empirical data on the actual usage and acceptance levels of DH applications among healthcare professionals in AD is scarce. Existing studies have often relied on qualitative methods and small sample sizes, which limits the generalizability of their findings. This study aims to address this gap by providing robust quantitative data through extensive surveys, offering a more reliable basis for policy and decision-making.

Additionally, empirical data on the usage and acceptance levels of DH applications among healthcare professionals in AD is limited. These studies have primarily utilised qualitative methods with relatively small sample sizes, and thus, their findings may not generalise well. The qualitative and experiential component of this research was to be enriched in due course, but this study fills a vacuum by providing substantive quantitative data through widespread surveys, leading to more robust findings and a firmer ground for policymaking.

The current literature has limited elucidation of the barriers and enablers responsible for the adoption of DH in AD public hospitals. This study addresses these elements by looking at technology infrastructure, training and education, managerial support, and cultural attitudes to technology. Upon identifying such factors, this research can guide actions concerning how these obstacles are avoided or how facilitators can be improved.

To the best of the researchers' knowledge, this thesis is among the first to comprehensively investigate both drivers and barriers to DH adoption in public hospitals specifically, and not from employer-based views but from the healthcare professionals' perspectives.

The main strength of this study lies in filling a gap in the extant literature, describing the current state of the art concerning eHealth/HIT implementation and allowing the transfer of findings to other contexts. Building on the UTAUT model and using empirical data, this study adds to knowledge about the region's DH adoption theory.

2.15. Summary

This chapter extensively analyses the variables affecting the organisational acceptance of DH among professionals working at AD public hospitals. This section introduces the healthcare system in AD, including the progress made and how the government promotes DH. The literature review discusses DH, explaining how DH is beneficial for patient care, efficiency, and accessibility. This chapter traces global growth in DH applications like telemedicine, robotics, and AI, which promise to dramatically improve access to care. It also analyses the facilitators of DH adoption regarding PU, ease of use, and organisational culture against barriers such as service externalities, ethical implications, data security, and resource constraints.

In addition, the chapter reviews different technology acceptance theories, i.e., TRA, TAM, and UTAUT, to underpin the understanding of DH adoption. The chapter concludes by identifying the research gap related to DH adoption in AD public hospitals, which sets a platform for the proposed model to include factors in addition to those in UTAUT.

3. Theoretical Framework

The theoretical framework of this research uses UTAUT as its guiding model to examine the factors that impact the effective deployment of DH applications. This model outlines four basic drivers, namely PE, EE, SI, and FC that influence healthcare workers' desire to apply and actually use healthcare technology. The discussion herein explains the model as the theoretical framework's foundation, considers its critiques and limitations, and proposes a modified and extended UTAUT framework addressing the observed limitations and applied by this thesis as the research model.

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

In the late 1980s, many technological acceptance models were put forward (Teo & Van Schaik, 2009), including the seminal TAM, TPB, and DOI theoretical models discussed throughout the literature review in Chapter 2. The UTAUT model is an integration of these diverse theoretical perspectives incorporating eight pragmatic theoretical frameworks (Mtebe & Raisamo, 2014). Mtebe and Raisamo (2014) identified eight combined models, which include: (a) the Technology Acceptance Model (TAM); (b) Innovation Diffusion Theory (IDT); (c) the Theory of Reasoned Action (TRA); (d) the Motivation Model; (e) the Theory of Planned Behavior (TPB); (f) PC Usage Model; (g) Social Cognitive Theory; and (h) the Motivational Model. Mtebe and Raisamo (2014) and Thomas et al. (2014) identified four components of UTAUT: (a) effort expectancy, (b) social influence, (c) conducive circumstances, and (d) performance expectancy. In a subsequent study, Thomas et al. (2014) included user behaviour and behavioural intent in their research. The following Table 3.1 summarizes the origin of UTAUT's core constructs.

Table 3.1 **Origin of UTAUT Core Constructs:** This table summarizes the core constructs of the UTAUT model, outlining their original sources and theoretical background. Adapted from Zalah (2018)

Core Constructs	Definitions	Constructs and Theories	References
Performance Expectancy	"The degree to which an individual believes that using the system will help him or her attain gains in job performance." Venkatesh et al. (2003)	Perceived usefulness (TAM/TAM2 and CTAM-TPB)	Davis (1989)
		Extrinsic motivation (MM)	Davis, Bagozzi, & Warsaw (1992)
		Job-fit (MPCU)	Thompson, Higgins, & Howell (1991)
		Relative advantage (IDT)	Moore & Benbasat (1991)
		Outcome Expectations (SCT)	Compeau & Higgins (1995)
Effort Expectancy	"The degree of ease associated with the use of the system" Venkatesh et al. (2003)	Perceived ease of use (TAM)	Davis (1989)
		Complexity (MPCU)	Thompson et al. (1991)
		Ease of use (IDT)	Moore & Benbasat (1991)
Social Influence	"The degree to which an individual perceives that important others believe he or she should use the new system." Venkatesh et al. (2003)	Subjective norm (TRA, TAM/TAM2, TPB and CTAM-TPB)	Ajzen (1991), Davis (1989), Fishbein & Ajzen (1975), Taylor & Todd (1995)
		Social factors (MPCU)	Thompson et al. (1991)
		Image (IDT)	Moore & Benbasat (1991)

Facilitating Conditions	"The degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system." Venkatesh et al. (2003)	Perceived behavioural control (TPB and CTAM-TPB)	Ajzen (1991), Taylor & Todd (1995).
		Facilitating conditions (MPCU)	Thompson et al., 1991
		Compatibility (IDT)	Moore & Benbasat (1991)

Wong et al. (2013) state that the focus of UTAUT is on behaviour. Nistor et al. (2014) examined this perspective. They determined that Venkatesh et al. (2003) formulated the UTAUT with the goal of use while also considering the impact of PE, EE, and SI on the variable. Thomas et al. (2014) discovered a reciprocal link between age and gender, as well as performance expectation and social determinants, which is a crucial aspect of the UTAUT model. The core of UTAUT (Venkatesh et al., 2003) is the connection between the voluntary nature of usage and the social factors influencing BI. UTAUT did not explicitly evaluate the individual's attitude towards technology usage, which was a crucial element in TAM (Thomas, Singh, & Gaffar, 2013). Nevertheless, Venkatesh et al. (2003) argued that attitude has little impact on an individual's inclination to utilise technology and is only significant when PE and EE are not included in the model. Teo and Noyes (2014) found that the evaluators' choice to adopt technology is influenced by the simplicity of use and the predicted amount of work. The UTAUT model emerged from these considerations with PE, EE, SI and FC as the core concepts in the original formulation or configuration as defined and explained below:

Performance Expectancy (PE) refers to the level of conviction a person has in using a technology or system to enhance their work performance (Teo & Noyes, 2014). According to a study by Venkatesh et al. (2003), PE is the most accurate indicator of the desire to adopt information technology. This view is consistent with the main idea of UTAUT, which claims that better performance expectations increase task performance by directly affecting the use behaviour.

Effort Expectancy (EE) refers to the ease with which individuals can use information systems. People may be reluctant to embrace new applications when introduced because they fear potential technical failures (Khechine et al., 2014). Over time, as users become more familiar, the importance of perceived usability increases. Effort expectancy is particularly evident in the first phases of the desire to utilise technology, as stated by Khechine et al. (2014).

Social Influence (SI) refers to the extent to which an individual places importance on how others view their utilisation of innovation (Venkatesh et al., 2003; Yueh et al., 2016). The validity of this proposition has been shown in both the UTAUT model and previous models, and it is linked to a favourable inclination to use technology (Khechine et al., 2014).

Facilitating Conditions (FC) is where individuals possess knowledge of the organisational and technological frameworks implemented to facilitate their use of a system. This phenomenon is referred to as a facilitating situation (Khechine et al., 2014). Attuquayefio, Addo, and Attuquayefio (2014) argue that the extent to which a person uses something is influenced by the presence or absence of consistent assistance. According to Martin and Herrero (2012) and Teo and Noyes (2014), FC can be described as the impact of the environment on the perceived difficulty of using technology. The availability of training is a potentially important factor in determining technology use. Venkatesh et al. (2003) argue that enabling factors, such as infrastructure support, are included under the effort expectation variable. This variable determines the degree of difficulty experienced when using technology.

The discussion above demonstrates that the UTAUT model is useful in conceptualizing DH adoption but there are some noteworthy limitations when the framework is applied to explaining the adoption of DH in AD's public hospitals. First, while UTAUT incorporates the PE, EE, SI, and FC constructs, it does not necessarily integrate due and comprehensive consideration of how individual attitudes and orientations towards use of technology influence the DH adoption process in healthcare organizations significantly (Davis, 1989).

Thomas et al. (2013) identify that, although UTAUT contains these constructs, it lacks an explicit elaboration into individual perceived attitudes, which are empirically demonstrated as having a critical impact on BI and technology usage. This is especially important in relation to healthcare professionals' characteristics where awareness of technology usefulness and ease are the key drivers to adoption. Thomas et al (2014) and Mtebe and Raisamo (2014) have established that incorporating attitudes as a construct can explain these professionals' DH adoption behaviour more effectively.

A second shortcoming of UTAUT is its approach to and treatment of the variables associated with technology users' demographic characteristics. The UTAUT treats factors like gender, and education as moderators of the connections among its basic constructs rather than as influential determinants of DH adoption (Venkatesh et al., 2003) in contrast with more recent scholarly works revealing that each of these demographic variables can cause a direct effect on the use of DH technologies in hospitals. For instance, eHealth use, according to research, is higher among young professionals most inclined towards the adoption of new technologies (Gordon & Hornbrook, 2018). Woolley et al. (2023) also demonstrated that demographic characteristics are predictors of the perceived usefulness (PU) and perceived ease of use (PEOU) of DH tools and, therefore, should be viewed as ultimate variables in the perfect version of an improved UTAUT model.

Additionally, the UTAUT framework in its original configuration does not address the organizational dynamics that have a large effect on technology adoption in healthcare. Healthcare management and leadership or the contribution of management and leadership to support and advocate the use of technology is an essential precipitant of DH adoption as demonstrated by empirical research focusing on the UAE (Alsyouf & Ishak, 2022, Al-Marzouqi et al., 2022). Thus, failing to address this variable in the UTAUT is a critical gap because, among other reasons, leadership support is essential to surmount the barriers to technology adoption. UTAUT includes only the FC construct, which to some degree addresses the availability of resources and support for using technology but lacks comprehensive coverage of how organizational leadership impacts adoption decisions in various dimensions. Studies by Alsyouf and Ishak (2022) and Al-Marzouqi et al. (2022) expose the significance of this limitation by providing empirical evidence of how leadership engagement can positively affect DH technologies adoption in healthcare settings.

Thus, it can be argued, as demonstrated in the explanations of relevant theory in Chapter 2, that alternative models like the TPB, TRA, and DOI, by specifically focusing on the areas of UTAUT's limitations, offer more effective conceptualizations of the DH adoption dynamics. However, when compared to TAM, TPB, and DOI, UTAUT still presents a more holistic framework for explaining technology adoption in healthcare. While TAM’s focus on PU and PEOU provides valuable insights into individual perceptions and attitudes and their influence on DH adoption, it overlooks external influences, such as SI and FC, which the UTAUT addresses more fully in connection to the individual factors, even though it treats the latter implicitly and secondarily rather than explicitly (Davis, 1989). UTAUT’s inclusion of these external constructs makes it more suitable for healthcare environments where both individual attitudes and external support play a role in the adoption of DH technologies.

Similarly, TPB can offer a more comprehensive perspective by including subjective norms and PBC (perceived behavioural control), which address external influences on adoption but it does not provide the same level of focus on the organizational factors that UTAUT addresses through the FC and SI constructs, which are crucial in healthcare settings (Ajzen, 1991). In the same line, DOI, while valuable in its emphasis on the attributes of DH technology and innovation itself, does not fully consider the organizational and social factors that influence adoption decisions in healthcare (Rogers, 1995). UTAUT's broader scope, including the SI and FC constructs, makes it more effective in capturing the complex, multifactorial nature of technology adoption in healthcare environments. The implication, therefore, is that despite its limitations, UTAUT remains the most suitable model for this study. Yet, the significant limitations raised above demand a systematic approach to remedy the gaps, hence the decision in this thesis to extend UTAUT by incorporating additional constructs such as demographic factors and management and leadership as proposed below for a more holistic approach to addressing the specific dynamics of DH adoption in AD's public hospitals.

The UTAUT model (shown in Figure 3.1) is the researcher-favoured choice since it integrates essential components from earlier theories on the adoption of innovation. The UTAUT model seeks to elucidate the impact of new technology on an individual's BI. The UTAUT model also includes personal and demographic variables that make it applicable for researching B2C (business-to-consumer) products or services. The UTAUT paradigm has also been used in different areas, such as e-commerce, services, e-learning, and electronic payment systems, demonstrating its versatility and appropriateness.

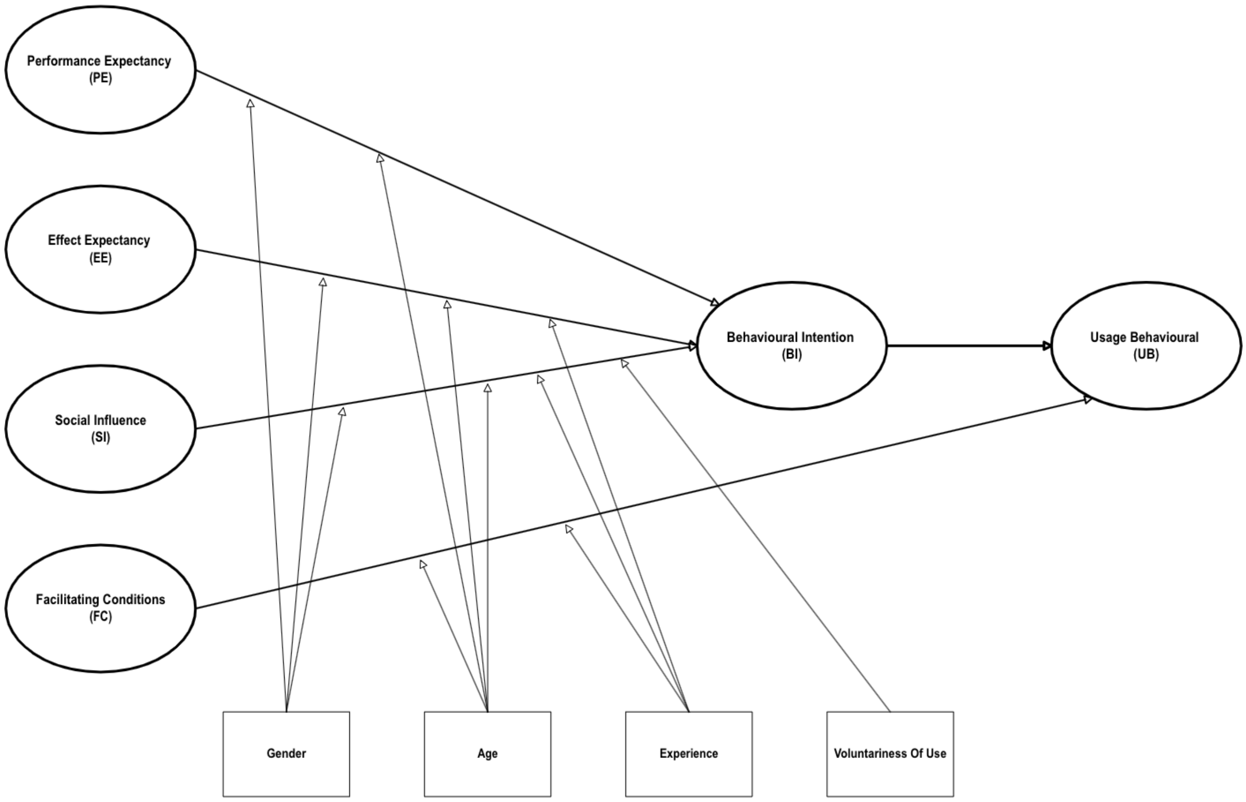

Figure 3.1 **Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)** *:* This figure presents the UTAUT framework, which forms the theoretical basis for the study's investigation into digital health adoption.

3.2. Suggested Elements for the Proposed Revised UTAUT

The UTAUT model in its original configuration may not fully capture factors influencing digital adoption in healthcare, particularly in the AD context. This observation necessitates the addition of other instructive variables, starting with personal and demographic factors, such as gender, age, education, position and work experience, which are considered in this study as factors directly impacting usage behaviour rather than as moderators as originally proposed in UTAUT. Through extensive literature, it has been observed that personal and demographic factors significantly impact DH technology usage behaviour, with the studies reviewed indicating that these variables can influence the perceived usefulness and ease of adoption of DH tools. In addition, the original model has been enhanced herein to include elements specifically relevant to the field of DH, such as the user DH experience, training, IT skills, SI and MLI. This comprehensive approach provides a robust theoretical and conceptual foundation to understand the adoption and utilisation of DH applications in AD public hospitals. The literature also shows that including elements relevant to DH enhances the applicability of models. Crucial factors in this regard, include user experience of DH, training received, IT skills, and management involvement, all influencing the adoption of such applications (Jokisch et al., 2022; Tetri & Juujärvi, 2022). Work experience and training improve readiness and competence (Konttila et al., 2019; Tegegne et al., 2023). Higher IT skills are related to greater adoption (Woolley et al., 2023). SE impacts the usage of applications, and leadership involvement promotes a supportive culture for technology (Alsyouf & Ishak, 2022; Al-Marzouqi et al., 2022). This comprehensive approach provides a strong foundation for understanding DH adoption in AD public hospitals.

Thus, the UTAUT model has been revised to include a series of bespoke components that cater for the specific needs of healthcare settings. The result of influencing people's willingness to adopt DH applications is related to the factors of gender, age, education, position, IT skills, DH experience, training, SE, and MLI. These findings have been reported by Gordon and Hornbrook (2018), Woolley et al. (2023), Ben-Gal (2023), and Xie et al. (2021). Multiple studies have investigated the correlation between these variables and the implementation of DH applications using the UTAUT paradigm (Cassidy, 2021; Woolley et al., 2023). As a result, this updated model aims to provide a comprehensive framework that better predicts and enhances the adoption of DH applications. These elements have been carefully chosen to reflect the complexities of the healthcare industry, ensuring that the study's theoretical model aligns more closely with the practical and dynamic environment of health service delivery as explained in these subsequent sections.

3.2.1. Gender

Gender has not consistently been identified as a key determinant of the desire to adopt DH tools. Several research studies have shown no statistically significant variations between the genders in their views towards DH applications (Cassidy, 2021). However, it is important to note that the effect of gender should be tested based on the specific conditions and populations being studied.

3.2.2. Age

Age is a crucial factor that determines the adoption of DH solutions. Older adults have been shown to report less confidence in, and use of eHealth for patient education or self-care than younger adults (Gordon & Hornbrook, 2018). Older adults experience similar differences in their adoption and use of various digital applications, such as health applications and patient portals (Gordon & Hornbrook, 2018). Finally, research about perceptions of DH applications found an adverse association with age and use of DH applications (Cassidy, 2021).

The UTAUT model has undergone extensive empirical testing in practical settings, such as healthcare, to examine the determinants of adoption and acceptability of eHealth in certain geographical areas (Puspitasari & Firdauzy, 2019). This implies that although age may not have a direct effect on the acceptance of technology, other factors within the UTAUT model, such as PE, EE, SI, and FC may have a stronger impact on healthcare professionals' acceptance of DH applications.

The research conducted by Alhajri et al. (2022) revealed that a minimum of 20% of middle-aged patients in AD showed a willingness to embrace telemedicine, suggesting that age alone may not be the only determinant of technological adoption. The adoption of telemedicine may be attributed to its ease, safety, efficiency, and cost-effectiveness. This suggests that for some people, the perceived advantages of DH technology may surpass any concerns connected to age.

In addition, the research conducted by Barchielli et al. (2021) highlights the significance of customized management approaches in promoting the willingness of nurses to adopt and use new applications in healthcare settings that heavily rely on technology. This emphasizes the need to take into account the unique qualities and job-related attributes of healthcare workers when studying their acceptance of technology. It further reinforces the idea that age alone may not be the only determining factor in whether they embrace technology or not.

3.2.3. Education

Education level has been found to impact the adoption of DH applications significantly. Woolley et al. (2023) found a positive association between higher education levels and the more extensive use of DH applications. According to Van Velthoven and Cordón 2019, the level of education is found to be a significant driver of the use of DH applications. Their research shows that the more educated you are, the more likely you will adopt and use DH solutions. The strength of this association implies that education is crucial in improving the capacity and confidence to engage with and understand DH applications. Thus, the argument is that people with higher education levels are more capable of understanding and adoption of DH apps as well due to being digitally literate in general. As a result, the creation of DH applications that are suitable for any level of education can improve usability and accessibility, which in turn facilitates more equal adoption across diverse user groups. A recent study on the use of FinTech payment services revealed that the effort expectation factor, an attribute of perceived technology usability, greatly affected trust and adoption among newly employed college graduates (Kurniasari et al., 2022).

3.2.4. Position

Position and expertise have been recognised as key elements that might affect the inclination to embrace DH applications. According to Magal et al. (2021), who explored the attitudes of mental healthcare professionals towards the adoption of telepsychiatry. They found that Attitudes were related to hierarchical position, organizational affiliation, perceived benefits and barriers associated with telepsychiatry, and personal experiences with telepsychiatry. This signals a potential role for the attitudes and beliefs of healthcare professionals, or individuals within specific specialties or roles, in acceptance of DH applications

Research conducted by Ben-Gal in 2023 examined the acceptability of AI-based technology in primary care. The study indicated that variables such as patient health knowledge, empathy, and sociodemographic characteristics like age and education level did not have a significant impact on the preparedness to employ AI-based technology. This implies that there are elements beyond position and expertise that play a more significant role in the acceptance and use of DH applications in some circumstances.

The study by Konttila et al. (2019) suggests that the digital literacy of healthcare workers is influenced by various elements, of which employment position is one. The research determined that employment status has a statistically significant impact on healthcare practitioners' opinions of the advantages of EHRs. Physicians in particular were more inclined than nurses and midwives to believe that EHRs reduce the need for paper-based documentation. This implies that an individual’s rank or level within the healthcare system might influence their attitudes and beliefs regarding digital application (Konttila et al., 2019).

3.2.5. Work Experience

To understand the impact of work experience on the use of DH in hospitals, it is important to consider healthcare professionals' perspectives and factors influencing their intention to use DH platforms. According to Alharbi's (2021) research, the great potential that healthcare consumers have in adopting DH platforms during and in the post-COVID-19 pandemic indicates a favourable trend towards DH, possibly influenced by the exposure and sympathies of healthcare professionals.

According to Shiferaw et al. (2021), There is also some evidence that DH usage is not influenced by work experience. That means lots of work experience does not necessarily correlate to being more skilled or comfortable with digital technology. It indicates that more experienced healthcare professionals might be less able to operate DH systems, maybe considering a familiarity with conventional ways of practicing healthcare. Therefore, Shiferaw et al. 's study builds a case that work experience is not only medically air, but also far from an in-stand DH competence or usage and leads to consider targeted digital training for physicians no matter how many years they have been working.

The research conducted by Shinners et al. (2020) points out that the emergence of digital hospitals means that healthcare staff need to have digital skills to find their way around significant changes within the health system, especially with the integration of other applications for data capture. The odds of wanting to use DH might be an effect of an older staff member who has so much more work experience and will likely have more skills and knowledge on how to integrate these resources being used in DH.

The study conducted by Masum et al. (2016) is pertinent as it underscores the significance of examining factors such as job satisfaction and turnover among nursing professionals with a view to improving hospital care quality. The implementation of DH platforms by hospitals could have a large-scale impact on work satisfaction, turnover intention, and adoption intentions among healthcare professionals.

3.2.6. Digital Health Experience

It is important to note that there is a difference between “work experience” and the “experience of actually using DH applications”, which is discussed later in this chapter. This distinction is critical for understanding the dynamics of DH adoption among healthcare professionals. The actual use of the applications might have a significant effect on the integration of new healthcare technology in the future. Bhavnani et al. (2016) emphasise the growing interest in patient care due to the progress in mobile technology and the digitalisation of healthcare. This implies that healthcare practitioners with expertise in DH applications will likely be more receptive to embracing and customising new technology.

Konttila et al. (2019) performed a comprehensive analysis of the proficiency of healthcare workers in the process of digitalisation. It was shown that healthcare workers need the drive and readiness to gain expertise in digitalisation within their professional settings. These findings indicate that healthcare workers are more likely to adopt DH if they have favourable experiences and are skilled in using digital technology.

Shinners et al. (2020) performed a comprehensive analysis of healthcare workers' comprehension and encounters with the use of AI technology in healthcare provision. The research revealed that healthcare workers who lacked comprehension of the underlying principles of digital technology or were sceptical about its potential to enhance the interaction with patients or the quality of care provided, were less inclined to embrace its adoption. These findings suggest that the views and comprehension of healthcare professionals on digital application might impact their willingness to use DH treatments.

Alghamdi et al. (2021) examined the enhancement of DH applications platforms (DHTPs) via knowledge translation and past experience in the field of DH applications. These findings indicate that healthcare practitioners with expertise in DH applications may make valuable contributions to the development and enhancement of future healthcare technology. Jarva et al. (2022) engaged in qualitative descriptive research to investigate the opinions of healthcare workers on their proficiency in DH. They indicated that healthcare professionals' acceptability and adoption of DH are influenced by their skills, experience, and competence. These findings indicate that healthcare professionals' adoption and implementation of DH treatments might be influenced by their personal experiences with such initiatives.

Moreau et al. (2018) performed a comprehensive analysis of the use of digital storytelling in education for health professionals. The research revealed that digital storytelling has a beneficial effect on health professionals' learning. This suggests that healthcare workers are more likely to embrace and use DH solutions when they have favourable experiences with engaging instructional techniques. The acceptability of DH among health workers depends largely on their experiences with digitalisation, literacy in digital technology, skills and attitudes, as well as training. Good experiences, competence and understanding of DH interventions could increase their acceptability and use by healthcare professionals. It is important to consider these elements when introducing DH treatments in order to achieve successful uptake and implementation into healthcare practice.

3.2.7. IT Skills

Proficiency in IT, which encompasses digital literacy and abilities, has continuously been identified as a crucial determinant in the acceptance and utilisation of DH solutions. Research has shown that people with advanced IT abilities are more inclined to embrace and use DH solutions (Woolley et al., 2023). Xie et al. (2021) found that PE and EE were significant in perceiving an individual value. This also indirectly influenced adoption intention.

The study by Kuo et al. (2013) claimed that the adoption of mobile EMR systems by nurses may be influenced more by certain technological personalities, such as openness to new technology, willingness to experiment and adaptability rather than their actual IT skills or knowledge. This result reveals that the predisposition for and integration of technology in general are more important than technical skill when it comes to using DH tools.

According to Perski and Short (2021), who performed a thorough narrative review of theoretical and empirical papers that are available in this area, acceptability is multifaceted when it comes to DH interventions. Their study indicated that more than IT skills and knowledge, user motivation, perceptions of how relevant the intervention is to the user, and overall experience were highly influential for adoption and continued use of DH applications. In combination, these studies highlight the importance of individual attitudes, beliefs and psychological preparedness in the uptake of DH applications, indicating that simply being technologically competent may not be sufficient for diffusion.

3.2.8. Training

Training is essential for professionals to embrace and implement DH applications. Multiple studies have highlighted that training improves attitudes, knowledge and skills for working with DH applications (Tegegne et al., 2023; Mendes-Santos et al., 2022; Eeg-Olofsson et al., 2020; Esposito et al., 2023). Training programmes equip professionals with the necessary education and skills to effectively use DH applications in their work, to help experts understand the incentives and opportunities of these technological tools, facilitate solving problems or remove barriers, and improve confidence in implementation (Eeg-Olofsson et al., 2020; Esposito et al., 2023). An important element of improving the digital literacy required to work with DH applications competently, is training (Tegegne et al., 2023). Research has demonstrated that training in DH tools makes individuals more likely to have high levels of digital literacy and competency (Tegegne et al., 2023).

Research has shown that those trained in DH applications are more inclined to possess elevated digital literacy and proficiency (Tegegne et al., 2023). Training programmes can enhance professionals' comprehension of the functionalities and characteristics of DH applications, improving their proficiency in navigating and using these applications, and boosting their confidence in integrating them into their practice (Tegegne et al., 2023; Mendes-Santos et al., 2022).

Furthermore, there is potential for training programmes to greatly influence the professional attitude to DH applications in a positive way. Research conducted by Tegegne et al. (2023) shows that people with a positive attitude toward these applications are more likely to accept and use them. Training develops professionals' ability to recognise the value and potential benefits of DH applications, increasing openness and willingness to adopt these applications (Mendes-Santos et al., 2022; Safi et al., 2018).

Training programmes contribute to knowledge and skills and reflect specific problems or difficulties professionals may have with DH applications. Training might address concerns about privacy and security, usability, and integration of digital solutions into existing workflows (Mendes-Santos et al., 2022; Safi et al., 2018). It may be beneficial for professionals to undergo training to address these issues, improving the acceptance and use of DH applications.

DH applications require the training of professionals to strengthen their knowledge, skillsets, and strategies, and resolve any fears or problems they have. Providing effective and tailor-made training programmes can help organisations support professionals in taking up and using DH applications in their work.

3.2.9. Self-Efficacy (SE)

SE is the belief in one's ability to perform in a specific situation and has been revealed as an important contributor to DH technology acceptance and use among professionals (Jokisch et al., 2022; Tetri & Juujärvi, 2022). Research has shown that higher SE positively correlates with greater use of these tools (Jokisch et al., 2022). SE is hypothesised to help people make more confident use of DH applications and thus be predisposed and prepared to use them (Tetri & Juujärvi, 2022; Jokisch et al., 2022).

PU, a key variable in TAM, has been found to mediate the relationship between SE and technology acceptance. SE beliefs shape individuals' beliefs that they can adequately use DH applications to perform or accomplish their goals, i.e., perception of the usefulness of DH applications. These beliefs eventually construct positive attitudes and intentions to use these applications (Davis,1989; Tetri & Juujärvi, 2022).

Moreover, the research conducted by Jokisch et al. (2022) demonstrated that SE is an important predictor for the likelihood of older adults to use DH services. According to Jokisch et al. (2022), those who have a greater belief in their ability to utilise DH applications are more likely to intend to use these services. Conversely, those with less confidence in their abilities are less likely to have the intent to use them.

SE significantly influences the extent to which professionals adopt and use DH applications. Increased degrees of SE are linked to higher levels of acceptance, positive attitudes, and plans to use these applications. Improving self-confidence via training, education and support may encourage professionals to accept and use DH technology.

3.2.10. Management and Leadership Involvement (MLI)

Management and leadership involvement (MLI) denotes the proactive and dedicated involvement, commitment, and active participation of managers and leaders at different hierarchical levels within the healthcare organisation in embracing, endorsing, and advocating DH projects. This participation is crucial in determining the strategic course, culture, and operational efficiency of an organisation's digital transformation endeavours.

Management and leadership engagement is pivotal in determining the acceptability and implementation of healthcare innovations (Alsyouf & Ishak, 2022). The endorsement of top-level executives might favour the inclination to use technology and expedite its execution (Alsyouf & Ishak, 2022). Conversely, a lack of support from management can hinder the acceptance and usage of technology (Alsyouf & Ishak, 2022).

Till et al. (2020) emphasise the need for leadership development within the medical school curriculum and the vital role of experienced faculty members in effective developmental discussions. Alqudah et al. (2021) and Joniaková et al. (2021) highlight the favourable influence of robust leadership on deploying healthcare technology. The study conducted by Joniaková et al. (2021) emphasises the favourable influence of leadership quality on team performance in the healthcare sector. Idoga et al. (2019) investigated the determinants of healthcare workers' willingness to adopt cloud-based health centres. They found that performance expectations and social Influence (SI) have a substantial impact on adoption. These references show that the involvement of managers and leaders in health is critical to professionals accepting and successfully using healthcare applications, reinforcing the need for leadership development, clear communication, and an engaging organisational culture.

As AlQudah and Shaalan (2021) and Al-Marzouqi et al. (2022) noted, management engagement may impact trust in technology and organisation. Professional confidence in the technology deployed and trust in the organisation's ability to implement and support it may influence their adoption and use of healthcare applications (Al-Marzouqi et al., 2022).

The active participation of management and leadership is essential for the successful adoption and integration of healthcare technology among professionals (Dadheech et al., 2022). According to Dadheech et al., (2022), managing the complexities of healthcare IT adoption efficiently calls for effective leadership and management. Consequently, leaders should present competencies for digesting diverse data, testing novel strategies, and making judicious decisions (Dadheech et al., 2022). Despite this, healthcare leaders may not appreciate all of their duties in HIT implementation, emphasising support and enforcement to improve leadership understanding of HIT implementation (Laukka et al., 2022). The changing landscape and the introduction of recent healthcare applications also broadened the duties of healthcare executives (Laukka et al., 2022). Thus, understanding the aspects of HIT implementation (Laukka et al., 2022) that healthcare executives must deal with is essential. Ineffective leadership is associated with unsuccessful HIT deployment; thus, a leadership role in HIT implementation is indicated (Laukka et al., 2022).

The way leaders lead and the strategies they utilize have a direct effect on the level of dedication, drive, contentment, and productivity of employees. These factors, in turn, have an impact on the provision of healthcare services and their overall quality (Mulenga et al., 2018). Improved healthcare service delivery results are linked to effective leadership (Mulenga et al., 2018). According to Joniaková et al. (2021), possessing leadership competency, which encompasses understanding of the organization, alignment with objectives, and effective decision-making abilities, has a beneficial influence on team performance in the healthcare sector. The caliber of leadership is intricately linked to the caliber of the healthcare services and is regarded as the foundation of well-organized and unified healthcare providers (Joniaková et al., 2021). The efficacy of healthcare leadership may be enhanced via the cultivation of emotional intelligence and empowerment among managers (Teame et al., 2022).

Leadership based on these techniques could improve the quality of community health education, also affecting the acceptance and implementation of technological improvements in healthcare (Kalalo et al., 2023). Leadership styles, transformational and transactional, affect healthcare providers as well as service delivery (Mulenga et al., 2018). The proficiency of leadership abilities within healthcare teams has a direct influence on the performance and decision-making process in emergencies (Joniaková et al., 2021).

Proficient management and active leadership participation are crucial for successfully adopting and implementing healthcare technology, leading to enhanced service delivery and attaining favourable healthcare results. Ultimately, management's active participation greatly influences the acceptance of healthcare technology among experts. Key components of management involvement that influence uptake and implementation among professionals are management support, trust-building, resource allocation, training, and removal of barriers to the use of healthcare technology. By openly embracing and supporting healthcare workers, management can create an environment that is welcoming of technology and capable of implementing, for instance, healthcare innovations in an effective manner.

Table 3.2 below outlines additional elements in the extended UTAUT model.

Table 3.2 **Proposed Elements**: This table presents the additional elements proposed in the extended UTAUT model, which account for contextual and demographic factors influencing DH adoption in AD.

Element	Description and findings	Resources
Gender	While gender is not a consistent determinant in DH adoption, understanding its potential influence in certain contexts can ensure more inclusive DH strategies.	Cassidy (2021)
Age	Age affects DH adoption, with older adults being less engaged. Incorporating age-related considerations can help tailor DH solutions, making them more accessible across age groups.	Gordon & Hornbrook (2018); Puspitasari & Firdauzy (2019)
Education	Higher education correlates with increased DH adoption. Recognising this can aid in designing educational interventions that improve DH acceptance.	Woolley et al. (2023); Kurniasari et al. (2022)
Position	Job position influences attitudes toward DH applications, with higher-ranking professionals often more receptive. Acknowledging this can improve DH integration strategies across different roles.	Ben-Gal (2023); Konttila et al. (2019)
Work Experience	Experienced professionals are more likely to adopt DH, suggesting the need to leverage their expertise in promoting DH technology usage.	Alharbi (2021); Shinners et al., (2020)
DH Experience	Familiarity with DH tools enhances adoption, emphasising the importance of	Bhavnani et al. (2016); Konttila et al. (2019); Shinners et al. (2020);

	integrating DH experience into training programmes.	Alghamdi et al. (2021); Jarva et al. (2022); Moreau et al. (2018)
IT Skills	Advanced IT skills facilitate DH adoption, highlighting the need for skill development initiatives to boost confidence in using digital applications.	Woolley et al. (2023); Xie et al. (2021)
Training	Effective training fosters positive attitudes toward DH, supporting the inclusion of comprehensive training programmes to enhance technology adoption.	Tegegne et al. (2023); Mendes-Santos et al. (2022); Eeg-Olofsson et al. (2020); Esposito et al. (2023); Safi et al. (2018)
Self-Efficacy	Confidence in using DH tools drives adoption, suggesting a focus on building self-efficacy through support and education.	Jokisch et al. (2022); Tetri & Juujärvi (2022); Davis (1989)
Management and Leadership Involvement	Active leadership support is crucial for DH adoption, indicating the need for leadership engagement in promoting and implementing DH applications.	Alsyouf & Ishak (2022); Alqudah et al. (2021); Joniaková et al. (2021); Idoga et al. (2019); Mulenga et al. (2018); Teame et al. (2022); Laukka et al. (2022); Dadheech et al. (2022)

In summary, the study proposes a model with additional elements to enhance the UTAUT model in the context of AD public hospitals. The original UTAUT constructs—PE, EE, SI, and FC—are supplemented with new elements specifically tailored for this research, namely SE, MLI, and personal and demographic factors, including gender, age, education, position, work experience, DH experience, IT skills, and training. By incorporating these additional constructs, the revised model aims to address the unique challenges and opportunities within AD's healthcare environment.

3.3. Proposed Model

Figure 3.2 illustrates the proposed theoretical framework for this research, integrating both the original constructs from the UTAUT and additional variables tailored to the specific context of DH adoption in AD's public hospitals.

The grey-coloured elements in the figure—Management and Leadership Involvement (MLI), Self-Efficacy (SE), Digital Healthcare (DH) Experience, IT Skills, and Training—represent newly proposed variables. These factors have been identified as key determinants influencing the adoption and utilization of DH applications. The proposed variables are expected to exert a direct impact on the core UTAUT constructs, ultimately shaping healthcare professionals' behavioural intentions and actual usage of DH

Opposite to these proposed elements, references from prior studies provide theoretical justification and empirical evidence supporting this extended model. These references reinforce the academic rigor and practical relevance of the framework, ensuring that it aligns with established literature while addressing the unique contextual challenges of AD's healthcare sector.

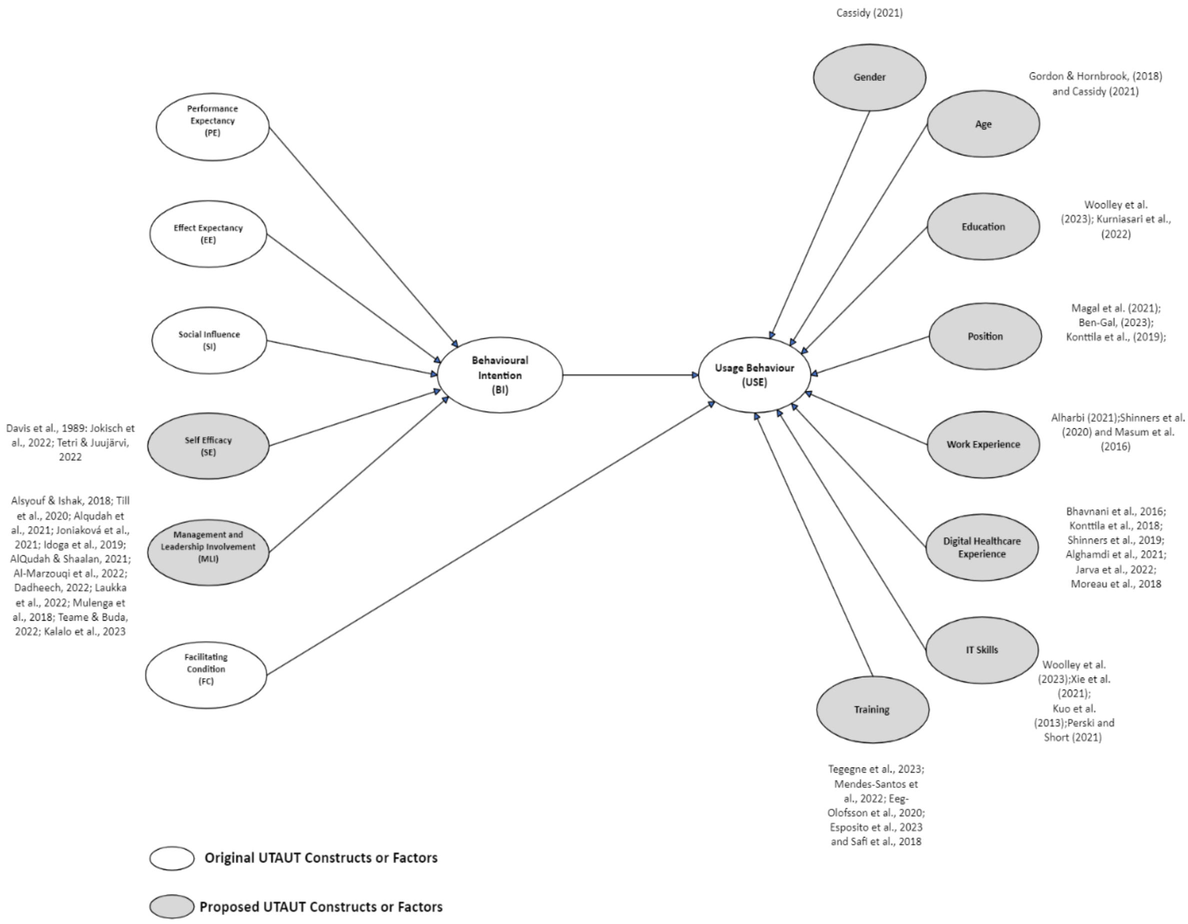

Figure 3.2 **Revised Model with Suggested Elements and their References**.

This extended framework provides a structured approach to understanding DH adoption in public hospitals. It enables researchers and practitioners to examine how traditional UTAUT constructs interact with newly introduced factors within a healthcare setting. Furthermore, it offers insights into the specific barriers and facilitators influencing the integration of digital technologies in AD's public hospitals.

By offering a comprehensive theoretical foundation, this model serves as a valuable tool for policymakers, healthcare administrators, and technology developers seeking to enhance the successful implementation of DH solutions.

3.4. Hypothesis

This subsection presents the hypotheses developed to test the relationships outlined in the revised theoretical framework. These hypotheses are derived from the integration of the original UTAUT model constructs, including PE, EE, SI, and FC, with additional constructs such as SE, MLI), and various demographic factors. The relationships among these constructs are depicted in Figure 3.3, which illustrates the proposed theoretical model for DH adoption in AD's public healthcare sector.

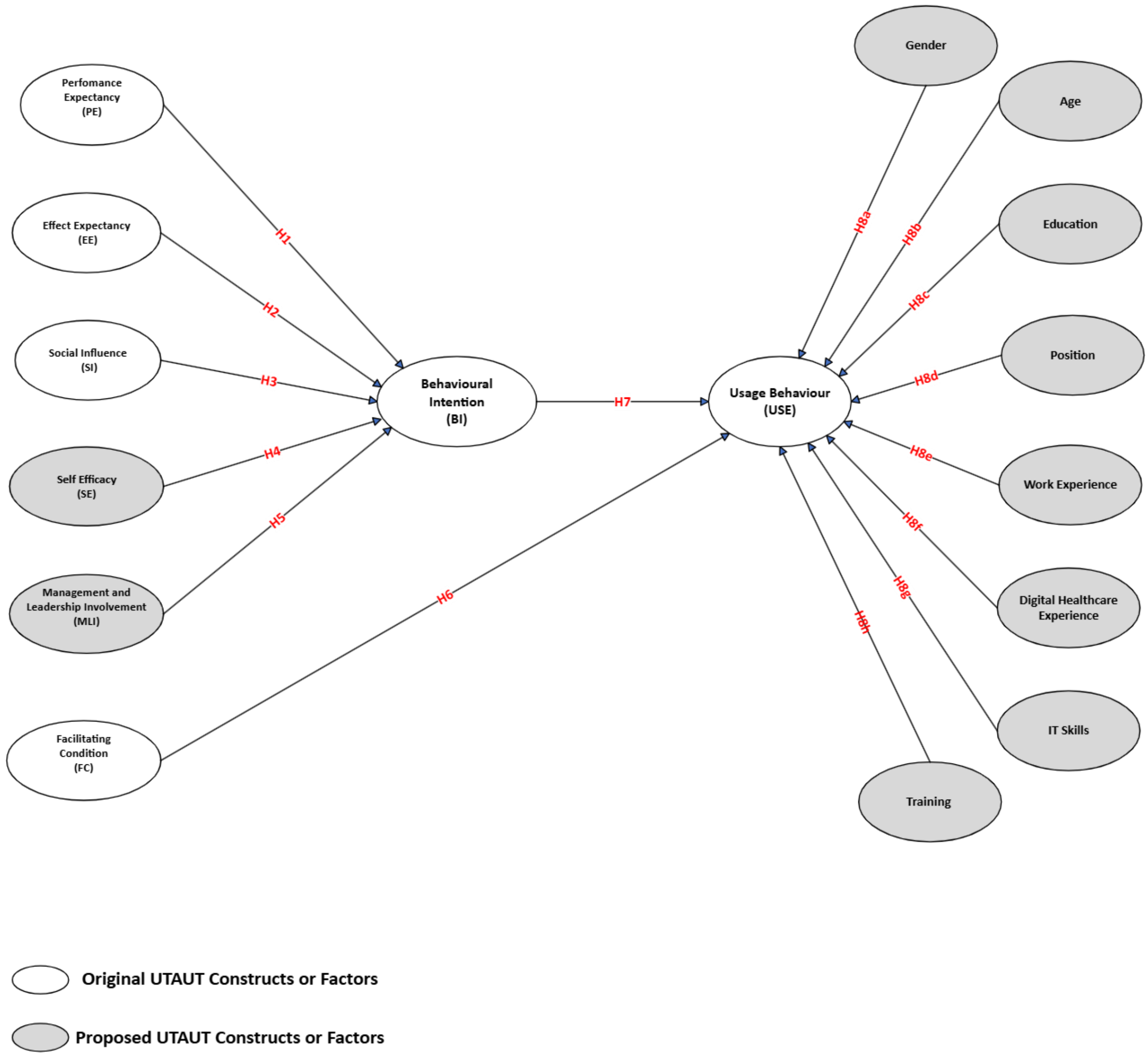

Figure 3.3 **Proposed Theoretical Framework**: This figure illustrates the proposed theoretical framework. White ovals represent original UTAUT constructs, while grey ovals indicate proposed elements. Arrows depict relationships, with red labels (H#) marking tested hypotheses.

Accordingly, the following hypotheses derive from the proposed study's research model illustrated above:

- **H1**: There is a significant positive relationship between PE and the BI to use DH.
- **H2**: There is a significant positive relationship between EE and the BI to use DH.
- **H3**: There is a significant positive relationship between SI and the BI to use DH.
- **H4**: There is a significant positive relationship between SE and the BI to use DH.

- **H5**: There is a significant positive relationship between MLI and BI to use DH.
- **H6**: There is a significant positive relationship between FC and the use of DH (USE).
- **H7**: There is a significant positive relationship between BI and the use of DH (USE).
- **H8**: There is a significant positive relationship between demographic factors (gender, age, education, position, work experience) and the use of DH.

Sub-hypotheses

- **H8a**: Gender significantly influences the use of DH.
- **H8b**: Age significantly influences the use of DH.
- **H8c**: Education significantly influences the use of DH.
- **H8d**: Position significantly influences the use of DH.
- **H8e**: Work experience significantly influences the use of DH.
- **H8f**: DH experience significantly influences the use of DH.
- **H8g**: IT skills significantly influence the use of DH.
- **H8h**: Training significantly influences the use of DH.

3.5. Summary

This research utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical framework to investigate the adoption of DH in public hospitals in AD. The UTAUT model identifies four primary constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), which serve as predictors of Behavioural Intention (BI) and technology utilization. The model's limitations, including its insufficient consideration of demographic and organizational factors, require an expanded framework specifically designed for the AD healthcare context.

The proposed framework enhances UTAUT by integrating supplementary constructs, such as demographic factors (e.g., age, gender, education), self-efficacy (SE), and management and leadership involvement (MLI). The enhancements target significant deficiencies, acknowledging the impact of personal attitudes, organizational backing, and previous experience on the adoption of digital health (DH). Training, IT skills, and digital health experience contribute to improved readiness and capability, thereby decreasing resistance and promoting acceptance among healthcare professionals.

This comprehensive framework incorporates internal and external factors to enhance the understanding of DH adoption. The revised UTAUT model, tailored to AD’s specific cultural, organizational, and regulatory contexts, provides significant insights for enhancing the adoption and implementation of DH applications, thereby establishing a solid theoretical and practical foundation for this study.

4. Methodology

4.1. Introduction

The role of a methodology chapter is very important because it defines the method of research, and the tools used to reach the results or goals set by the research work. This chapter focuses on the methodology adopted in this study and elaborates on how it was conceptualised to establish the findings credibility, appropriateness, and reliability.

To facilitate the study, an application of the research onion model put forward by Saunders et al. (2023) is adopted. The model consists of six levels that are instrumental in understanding, distinguishing, and building the investigation according to its needs. Throughout this chapter, the layers will be elaborated upon. This model comprises six layers, as shown in Figure 4.1 below.

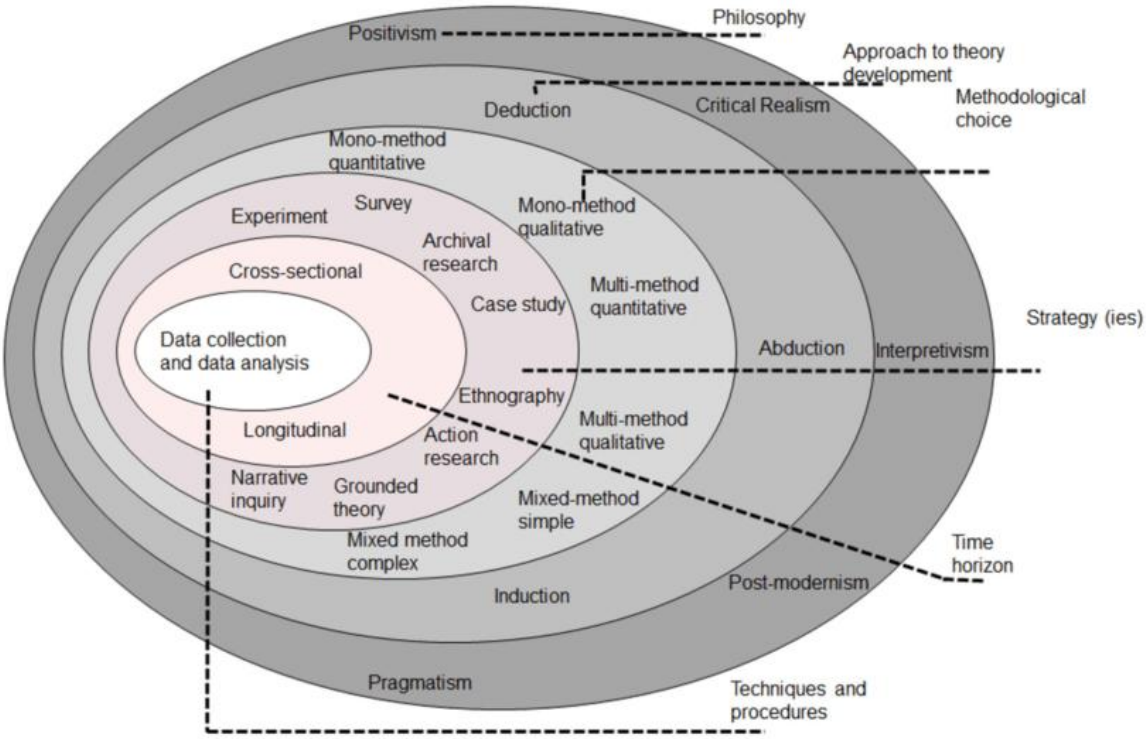

Figure 4.1 **The Saunders et al. (2023) Research Onion Model**: This figure shows the Saunders research onion, explaining the layers of research methodology selection.

This chapter describes in detail the approach used in this research, consisting of methods for data collection, tools for analysing collected information and justification behind the selected strategy. With this description of the approach, the thesis performs an interpretable and reproducible methodological process in the data collection and analysis.

4.2. *The Study Philosophy*

This thesis' philosophy centres on ideas about the generation and understanding of knowledge, as well as the attributes of the knowledge produced (Saunders & Tosey, 2015). The research design aims to solve a particular issue or offer a comprehensive solution to the inquiry posed by the research problem (Saunders & Bezzina, 2015). These investigations often start by generating data, which is then gathered in line with the study's needs, demands, and the nature of the project or issue. In addition, they highlight the specific data that will be necessary during the entirety of the research procedure (Saunders et al., 2019).

Ponterotto (2005) contends that scholars should avoid adhering exclusively to a single philosophical standpoint and its corresponding attributes. Ponterotto (2005) highlights the need to be receptive to many philosophical viewpoints, acknowledging the dynamic character of scientific investigation.

Although Saunders is a well-known expert in research philosophy, it is crucial to expand the current viewpoint by acknowledging the contributions of other researchers on the subject. Easterby-Smith et al. (2021) explore the importance of philosophical factors in design and methods of research and the significance of comprehending epistemological, ontological and axiological assumptions informing research methodologies. Yin (2018) suggests guidance on how to pick which research methodologies are right for your specific study goals and objectives. Easterby-Smith, Thorpe Jackson, and Yin made the research philosophy discussion more multifaceted.

Easterby-Smith et al. (2021) argue that recognising the significance of philosophical issues is essential when conducting research, and they provide at least three arguments to support this assertion, with the main function being to assist in developing research designs. A thorough understanding of philosophy allows the researcher to distinguish and choose the appropriate design for execution. The research philosophy is grounded on three fundamental assumptions: epistemology, ontology, and axiology, as shown in Table 4.1 below.

Table 4.1 **Assumptions of research philosophy (Easterby-Smith et al., 2021):** This table summarizes the fundamental assumptions underlying different research philosophies, guiding the study's methodological choices.

Assumption	Description
Epistemology (How?)	General set of assumptions about acquiring and accepting knowledge about the world
Ontology (What?)	Assumptions made about the nature of reality
Axiology (Why?)	Assumptions about the nature of values and the foundation of value judgements

4.2.1. Epistemology

This consists of two primary components: positivism and social constructionism (interpretivism). Positivists assert that the world has an independent existence and advocate a more objective rather than subjective approach to measuring its features. The text explores a deductive approach and a perspective of the scientific method that highlights the notion that only information based on observations in the real world can be deemed legitimate (Easterby-Smith et al., 2021). According to Travers (2001), positivists argue that sociology should be treated as a scientific discipline and use quantitative techniques to demonstrate logical relationships between variables, following the principles of natural science.

Epistemology relies on numerical data to depict and demonstrate occurrences. The triumph of rationality and science in the late nineteenth century laid the foundation for the emergence of positivism. It includes interpretations based on observable data and the methodical and clear use of tools for collecting and analysing data (Patton, 2002). The positivist paradigm exerts its strength through an orderly and rationally oriented focus on observation. However, the problem of positivism is that it is associated with abstract concepts when clarity and objectivity can be tangible, particularly with complex social and behavioural manifestations.

Interpretivists, also known as social constructionists, believe that reality is not an objective and external entity. Instead, they argue that reality is socially created, with people assigning meanings to it (Easterby-Smith et al., 2021). This study employs a qualitative research approach to elucidate how people comprehend and actualise their own behaviours (Travers, 2001). Interpretivists, in contrast to positivists, reject the notion that knowledge is based on concrete and objective elements. Instead, they aim to comprehend social reality by considering the viewpoints of the individuals under scrutiny. Furthermore, the interpretative paradigm and qualitative research rely on the notion that social reality is shaped and maintained by the subjective experiences of those engaged in communication. Hence, the interpretative approach acknowledges that reality is shaped and influenced by humans rather than dictated by objective external causes.

4.2.2. Ontology

Ontology is the field of study that examines the nature of existence and reality. The study discusses the factors that contribute to a comprehension of the research process and evaluates the potential impact of the study on the social environment. Analysts investigate methods of obtaining insights in an unexpected manner. According to Sexton (2003), philosophy primarily concerns itself with authenticity and optimism. He establishes a relationship between objectivism and subjectivism, with parallels to astronomy and epistemology. In contrast, Saunders et al. (2019) assert that two specific aspects of philosophy are likely to be seen as offering reliable and accurate knowledge by a significant number of scientists. The essential perspective is that objectivism focuses on the existence of social phenomena in the external world and their impact on social actors. The second perspective is subjectivism, which posits that social phenomena are shaped by the consciousness and behaviours of the social actors who have been affected (Saunders et al., 2019). Given the objective of this study, which was to examine the degree of agreement in the acceptance of DH, this research project adopted an objective philosophical stance.

The objectivist stance posits that social phenomena, such as healthcare professionals' acceptance of DH technologies, exist independently of individual perceptions (Saunders et al., 2023). This approach rejects subjectivism and reinforces that DH adoption determinants, such as organizational readiness and perceived usefulness, are external realities measurable through empirical methods (Saunders et al., 2019). Objectivism enables the identification of causative factors influencing DH adoption rates without relying on subjective interpretation, thus ensuring unbiased generalizations.

4.2.3. Axiology

Axiology is a branch of philosophy that examines the individual ideals and prejudices of each person. According to Saunders et al. (2023), scientists possess "axiological expertise" when discussing their own characteristics as a basis for evaluating their study. Saunders et al. (2023) said that researchers demonstrate axiological competence when they can articulate their beliefs and use them to guide the decision-making process about their study and methodology. Heron (1996) defines axiology as the opportunity to articulate one's personal values toward a particular subject of contemplation. Axiology primarily relies on fundamental concepts and is sometimes seen as the foundation of the philosophy discipline (Topi, 2010). Additionally, there are two "axiological positions". Axiologically, this research embraces value-neutrality, aiming to minimize bias in data collection and interpretation, which are aspects that are entirely consistent with the selected objective and positivist paradigms. This neutrality is achieved by employing structured questionnaires, standardized Likert scales, and statistical analysis techniques to further eliminate the inconsistencies attributable to subjectivity in the scientific method (Patton, 2002). By adopting this approach, the study ensures that findings reflect objective phenomena rather than subjective influences and biases.

Furthermore, the thesis applied the positivism paradigm in this research. This paradigm aims to improve understanding of the determinants of diffusion and adoption of DH by healthcare professionals, through quantifiable factors. This study utilised positivism in line with its intent to use empirical facts and objective measurement to understand the phenomenon. Positivist studies use quantitative factors to analyse phenomena. This method is essential for testing hypotheses about phenomena using data from a representative population sample. Positivists emphasise scientific truths and ideas that are logically consistent, falsifiable, and explainable, supported by empirical evidence over time (Easterby-Smith et al., 2008). This study takes a positivist approach since it uses a quantitative approach to examine health professionals' DH acceptance. This paradigm uses quantifiable variables to improve comprehension, corresponding with the study's goal of employing scientific facts and objective measurement to explain phenomena.

Positivism methods allow for the collection of representative sample data and the generalisation to a larger population. This rigorous strategy ensures research transparency and reliability. Positivism and quantitative methods enable a full and objective study of DH adoption criteria. Thus, epistemologically, this study aligns with positivism's emphasis on empirical observation and deduction (Creswell & Creswell, 2017). Using quantitative methods, this research systematically tests hypotheses derived from established models, focally the UTAUT, with observations concentrating on identifying relationships between measurable constructs, including perceived ease of use, behavioural intention, and technological competence. The reliance on observable, replicable data ensures that knowledge generation adheres to the principles of validity and reliability, which are foundational to positivist inquiry (Easterby-Smith et al., 2021).

In examining DH adoption in AD's public hospitals, this study draws on the Paradigm Matrix proposed by Johnson and Duberley (2000) to align its methodological choices with both the ontological and axiological dimensions of healthcare professionals' experiences. The Paradigm Matrix facilitates a structured exploration of how foundational beliefs, values, and subjective experiences influence the interpretation and application of DH technologies. By acknowledging both objective (quantifiable adoption behaviours) and subjective (healthcare professionals' perceptions and values) aspects, this approach ensures that the study's methodology is both theoretically robust and practically relevant. This dual consideration aligns with the UTAUT, which incorporates both technological and human factors in adoption models. Furthermore, embedding ontological and axiological considerations enhances the study's ability to generate ethically grounded, contextually relevant insights into DH implementation in AD's public healthcare sector.

In conclusion, the positivist paradigm ensures a methodical, objective, and replicable approach to studying DH adoption variables, which fits the study's quantitative methodology and objectives.

4.3. Research Approach

To accomplish this study's aims and objectives, it was essential to carefully choose a research approach. The two primary methodological techniques are inductive and deductive. These techniques vary in their fundamental reasoning and method of generating knowledge. The deductive approach is a method that begins with a theory or hypothesis and proceeds to gather facts to examine and validate or disprove the theory (Locke, 2007). This method is grounded in the positivist paradigm, which prioritises using objective and quantifiable facts to elucidate social processes (Kuhn, 2012). The deductive research method involves starting with a broad theory or hypothesis and then formulating particular predictions or hypotheses that may be empirically evaluated via observation (Shaher & Radwan, 2022). The researcher gathers evidence that has the potential to either corroborate or refute the original idea or hypothesis (Locke, 2007). This methodology is often used in quantitative research to examine causal correlations between the variables (Abood & Alalwany, 2021).

In contrast, the inductive approach is a method that begins with actual data and then formulates ideas or generalizations based on those facts (Azungah, 2018). This method is linked to the interpretivist paradigm, which highlights the subjective and contextual characteristics of social processes (Kuhn, 2012). The inductive technique involves researchers starting their investigation by examining particular findings or patterns in the data and then formulating hypotheses or ideas to explain these observations (Azungah, 2018). The researcher gathers data and analyses it to identify any discernible patterns, themes, or categories that arise from the data (Azungah, 2018). Subsequently, these patterns or themes are used to build hypotheses or conceptions that might explain the observed facts (Azungah, 2018). Qualitative research often employs this methodology, whereby researchers seek to comprehend the significance and understanding of social phenomena as seen by the participants (Azungah, 2018).

Both deductive and inductive procedures include their own advantages and drawbacks. The deductive methodology enables researchers to empirically examine and validate pre-existing ideas or hypotheses. It offers a methodical and organized framework for gathering and analysing data (Woiceshyn & Daellenbach, 2018). Researchers find it especially beneficial when they want to determine cause-and-effect linkages between the variables (Woiceshyn & Daellenbach, 2018). Nevertheless, the deductive technique may restrict the investigation of novel ideas or concepts that do not align with the current theoretical framework (Woiceshyn & Daellenbach, 2018).

In contrast, the inductive technique enables researchers to investigate the novel ideas, concepts, or hypotheses that arise from the data (Azungah, 2018). Azungah (2018) states that it offers adaptability and receptiveness to novel perspectives and understandings. The inductive technique is very advantageous when researchers want to comprehend intricate social phenomena inside their authentic setting (Azungah, 2018). Nevertheless, the inductive technique may suffer from a lack of generalizability, since the conclusions drawn from it are often particular to the environment in which they were obtained and may not be relevant to other contexts or populations (Azungah, 2018).

Researchers often use a hybrid strategy called the abductive approach, which combines deductive and inductive methods (Tashakkori & Creswell, 2007). The abductive technique is characterized by a series of recurrent cycles in which researchers gather evidence, analyse it, and construct theories. During this process, researchers alternate between deductive reasoning, which includes drawing conclusions from general principles, and inductive reasoning, which involves drawing conclusions from specific observations (Tashakkori & Creswell, 2007). This methodology enables researchers to expand upon established hypotheses while being receptive to the novel insights and interpretations that arise from the collected data (Tashakkori & Creswell, 2007).

Ultimately, the deductive and inductive techniques are two prevalent research methodologies used in social research. The deductive technique starts by formulating a theory or hypothesis and then verifies it using empirical observation. Conversely, the inductive approach commences by gathering actual data and thereafter formulates hypotheses or generalizations based on these findings. Both deductive and inductive procedures have their own advantages and disadvantages, and researchers often use a blend of both methods to get a thorough comprehension of social phenomena.

The researcher in this study adopted a deductive strategy, assessing established theories on the acceptance of technology in the context of public hospitals in AD. This approach is consistent with the goal of confirming established connections between variables such as demographic characteristics, technological proficiency, and the acceptance of DH innovations.

4.4. Research Strategies

Saunders et al. (2019) classified research strategies into seven distinct categories and underlined that each method had its own set of benefits and drawbacks and that no one strategy is better or incompatible with another. Several methodologies that may be used include action research, ethnography, grounded theory, content analysis, surveys, experiments, and case studies. The following techniques are outlined below:

4.4.1. Action Research

Gummesson (2001) argues that an action research project emphasises the intricate character of the projects examined and refrains from taking a broad approach, instead focusing on gaining a comprehensive grasp of the present context. In addition, it may use both quantitative and qualitative methodologies (such as interviews, observation, and surveys) to facilitate the development of a full comprehension of the project and provide the required enhancements. On the other hand, action research enables the researcher to engage actively in the planning of the process, to strive to execute change, and then to evaluate the result. The extent of any alterations, whether intentional or unintentional, may be regulated based on the degree of engagement. Consequently, a crucial element of this technique is the researcher's involvement in action research. Hales and Chakravorty (2006) state that action research has two primary benefits:

- It provides a substantial reason for the occurrence of the event, which provides challenges for statistical models to explain.
- Action research initiatives, in contrast to lab tests, examine the problem in real-world situations, avoiding the time-consuming, costly, and impractical nature of the latter.

4.4.2. Ethnography

Ethnographic research involves spending a long period with a particular group or organisation to learn how the culture works and be able to document it (Gilbert et al., 2015). Researchers spend extensive time with a particular group (questioning, interviewing, observing behaviour, interpreting and critiquing employee discourse) (Bryman et al., 2008). Hence, it is evident that an ethnography is a study approach that relies on the involvement of proficient people capable of conducting extensive investigations.

4.4.3. Grounded Theory

This technique lacks any theoretical framework, since the data collecting procedure is carried out without incorporating such a framework (Partington, 2000). Consequently, hypotheses are formulated based on the collected data and then evaluated before being subjected to testing. Grounded theory, action research, and ethnographies vary in their foundations in social science and the researcher's ability to interact actively with the study topic (Berg, 2004). Applying grounded theory to enterprises is difficult due to the limited access to data compared to the more flexible availability of data in health systems. Consequently, grounded theory is more extensively developed inside such systems (Easterby-Smith et al., 2021).

Grounded theory employs many methods, such as documents, observations, interviews, historical records, videotapes, and other suitable techniques to address the research gap (Bryman et al., 2008). As previously stated, this method must be used consistently and for an extended duration in a professional setting.

4.4.4. Content Analysis

Holsi (1969) defines content analysis as a systematic and objective approach to detecting certain qualities of messages to derive conclusions. Moreover, implementing rules objectively necessitates a clear method and minimising human biases, whereas implementing rules systematically entails doing so consistently. The Bureau of Justice Assistance (2006) provides an alternative definition of content analysis as "a series of methods used to collect and arrange unstructured information into a consistent format, enabling the deduction of insights about the attributes and significance of written or recorded material". Content analysis may be used to analyse both qualitative and quantitative data. Visual and written data, such as field notes, interview transcripts, newspapers, and media material, may be subjected to analysis (Krippendorff, 2004).

4.4.5. Surveys

This approach helps extract data that is important when it is to understand patterns or trends in the target population. Surveys have proven foundational instruments in delivering valuable data on people's experiences, behaviours, beliefs, and attitudes. Questionnaire design is a critical aspect of research because of the potential for false findings if the study is improperly performed (Babbie, 1990). To address this issue, it is essential to establish a well-thought-out set of questions after conducting a comprehensive assessment of the existing literature. In addition, questions must provide dependable information that can be used to conduct a suitable analysis. To enhance the quality of the questions, preliminary research was carried out on the first version of the questionnaire with healthcare experts with extensive work experience and project managers specialising in information technology.

In healthcare research, for instance, surveys can be most useful in revealing the views of healthcare professionals on DH implementation, providing critical insights into policy and decision-making. Survey research is derived from the survey method; it provides a relatively cost-effective and quick way to obtain a large amount of information about the population, discovering patterns in the data collected and generalising results to larger profiles (Saunders et al., 2019).

According to Oppenheim (2001), questionnaires mainly take two forms: structured and unstructured. Structured questionnaires enhance data management by simplifying the process and ensuring more consistent responses. Instructional Assessment Resources (2007) categorised survey questions into five primary types: open-ended, closed-ended, partial-open-ended, scaled, and ranking. Given the scope of this study, closed-ended and scaled questions were used. Consequently, the questionnaire was structured.

4.4.6. Experiment

A study is conducted by selecting a subset of the population and investigating if there exists a cause-and-effect link between the variables being studied (Fellow & Liu, 2015). Typically, experiments are conducted in a controlled setting, such as a laboratory, where the conditions and outcomes are distinct (Yin, 2014). In an experiment, the relationship between two variables can be established because the independent variable depends on the dependent variable.

4.4.7. Case Study

This research method aims to provide new insights into real-world contexts through in-depth analysis of an individual case. It is adopted when the researcher intends to gain an in-depth understanding of a particular case, and this case requires looking into multiple indicators and experiences. They are not generalisable, and case studies are commonly used when the phenomenon is multifaceted (Yin, 2018). Case studies rely on various methods, such as observation, interviews, focus groups, documents, and records, to undertake an in-depth investigation or validation of a research issue (Yin, 2003). The objective of the case study is to explore deeply the phenomena and uncover the intrinsic reasons, mechanisms and dynamics.

As discussed by Gerring et al. (2007) and Yin (2014), case study research has several advantages compared to other research methodologies. Nevertheless, the methodology often faces criticism due to its inherent bias, lack of rigour, reliance on incomplete information, and high costs and time requirements (Yin, 2014).

This research adopted a survey method as the research strategy. Surveys are a good way to effectively collect data from a wider population, allowing for the representation of different views. It offers standardised, structured data through questionnaires designed for reliability and comparability. Moreover, surveys are well-suited to studies producing huge samples by eliminating interviewer bias and being highly cost-effective. The design adopted is most appropriate for exploring the elements on which DH adoption by healthcare professionals at public hospitals conducting AD practices, depends.

This research used a survey to ascertain professionals' attitudes about the acceptability of DH applications. The questionnaire was developed utilizing research resources, specifically focusing on the literature on the adoption of information technology as indicated in the literature review chapter.

On the other hand, methodologies like action or ethnographic research seem inadequate for this study, as they do not fit in 'in the field' studies and might not allow us to grasp social relevance relevant to this investigation accurately.

4.5. Research Choices

4.5.1. Mono-method Versus Multiple-method

Saunders et al. (2019) classified research choices into two basic categories: mono-method and multiple-method. A mono-method means only one method is used for data collection, and all the methods and activities are carried out in parallel with field data to postprocess it. On the other hand, the multiple ways mean that there is utilisation of more than one style for data collection and analysis processes needed to answer a study research question(s).

In addition, mixed-method and multi-method studies are derived from using different research methodologies. Using qualitative and quantitative data-gathering methods and the corresponding analytic techniques within a single study design, is referred to as using a mixed-method approach. To overcome the limitations of individual methods and to obtain a deeper understanding of the phenomenon under investigation, researchers use a mixed-approach strategy (Shukshina et al., 2022).

4.5.2. Quantitative Versus Qualitative Methods

When both qualitative and quantitative data-gathering methods and analytic techniques are used within the same study design, this is described as a mixed-method approach. Quantitative and qualitative research methodologies are separate and unique business and social research approaches. These strategies provide distinct viewpoints and possess their own merits and drawbacks. Researchers must thoroughly comprehend the distinct attributes and disparities between quantitative and qualitative research to choose the most suitable approach for their topic.

Quantitative research is a methodical and unbiased strategy that centres on gathering and examining numerical data, as stated by Strijker et al. (2020). It involves the application of structured surveys, questionnaires and statistical methodologies in gathering data from a sizeable sample population (Mayombe, 2020). One of the main advantages of quantitative research is its ability to produce true and measurable data that can be subjected to statistical analysis and generalised for a wider population (Seitakhmetova et al., 2022). This approach is especially valuable for examining extensive social phenomena or when the research seeks to discern patterns, trends, and correlations among the variables (Daflizar & Petraki, 2022). Nevertheless, quantitative research tends to oversimplify intricate phenomena and disregard contextual elements that are not readily quantifiable (Gani et al., 2022).

In contrast, qualitative research relies on subjective interpretation and aims to comprehend the significance and personal experiences of the sampled persons (Amin et al., 2021). Qualitative research includes the gathering of non-numerical data using techniques including interviews, observations, and document analysis. This approach is especially beneficial when investigating delicate or intimate subjects and when the research seeks to reveal new thoughts or theories (Dimyati et al., 2022). Nevertheless, qualitative research may lack generalizability and require significant time and resources (Shara et al., 2020).

This research favoured a quantitative approach over a qualitative approach to investigate the acceptance and integration of DH applications among professionals. A quantitative approach is ideal for this subject since it allows for the systematic examination of phenomena using statistical, mathematical, or computer tools. It enables the precise quantification and examination of the data, identifying patterns and correlations between the variables (Creswell & Creswell, 2017).

This methodology can be used effectively in a research study in which the goal is to quantify both the size and nature of a phenomenon being studied and thus helps project broad conclusions and projections. Quantitative studies, such as that of Mertens (2014), have been said to contribute a more comprehensive conceptualisation and, hence, nuance interventions and policies constructed upon their findings. Furthermore, Saleh and Bista (2017) point out that because of the systematic and rigorous data collection and analysis process in quantitative research, high replicability and dependability can be guaranteed as important components for empirical research. Thus, a quantitative methodology in this research delves deeply into the factors that positively promote or preclude the effective adoption of DH in public hospitals in AD and confirms the robustness and generalizability of these results to other contexts.

4.6. Time Horizons

When performing this kind of study, researchers have the option to utilize either cross-sectional or longitudinal time frames. Cross-sectional research, as defined by Saunders and Tosey (2015), aims to address a specific subject or problem at a particular point in time. Instead of claiming to include every aspect of the issue over a specific timeframe, this kind of research functions as a "snapshot," capturing a particular moment in time. The use of research methodologies such as surveys and case studies are often the most advantageous for cross-sectional investigations.

Longitudinal research is performed when the task demands the collection of information on a particular topic or problem over a long-time horizon. Types of research in this paradigm include experimentation, grounded theory and archival research. These disparities are a manifestation of the project's driving research concerns over different timescales. This research is an in-depth study of a particular sample at a given time and is not a full-scale examination of a particular subject or phenomenon.

A cross-sectional design was used in this study to collect the opinions of public hospital healthcare workers regarding DH deployment, which reflects their views on this technology at a specific time. The result is a cross-sectional snapshot of DH usage using an online survey to provide data on current views and experiences. Because the study focused on understanding proximal barriers and facilitators in a particular context, examining factors influencing health at the exposure level was more practical than over time. In survey-based studies, cross-sectional research can more easily gather large volumes of data, mitigating recent time and resource limitations.

4.7. Data Collection

Survey data was collected using structured questionnaires to obtain meaningful conclusions from the sample and generalise them to the population. As Babbie (1995) and Creswell et al. (2004) noted, this method is effective in gathering quantitative data. According to Fellows and Liu (2022), surveys employ statistical sampling techniques to select a representative sample from the larger population, ensuring that the findings apply to the broader context.

4.7.1. Questionnaire

Questionnaires used for data collection in surveys have both benefits and drawbacks. Despite the anonymity of the questionnaire and its ability to mitigate interviewer bias, the researcher lacks control over the conditions in which it is completed (Neuman, 2007). Despite its limitations, such as low response rates, this study provides an opportunity to investigate a variety of difficulties, including some that were expected. A questionnaire is a compilation of inquiries administered to individuals to acquire data (Saunders et al., 2019). A questionnaire is an efficient instrument for collecting substantial volumes of data with little effort or cost. While the questionnaire offers a notable advantage, it lacks data about changes in emotions, behaviours, or reactions.

Therefore, the questionnaire is the best way to gather accurate data in this particular research. Questionnaires allow further reach and greater numbers, which help collect the expansive statistical research required for this study. One of the important methodological decisions in this study was to limit the data collection tool to a questionnaire, which emphasised consistency across all sites and allowed for rapid information capture from diverse groups of healthcare providers in multiple locations. The research sample is a questionnaire-based survey of healthcare professionals in public hospitals in AD. They know the work of DH practitioners and are generally people employed in the healthcare system, so they will give thoughtful responses. In addition, the structured questions format of the survey means that all respondents answer the same questions, enabling comparison of information and minimising data variation (Bryman & Bell, 2015).

This study has chosen to use questionnaires. The choice to use questionnaires for data collecting is driven by the study questions and goals since they may be effectively addressed via the systematic and extensive data-gathering capabilities offered by questionnaires.

The questionnaire was designed to be user-friendly and included unambiguous, succinct, and elaborate guidelines. Each respondent received a cover letter informing them about the study's nature and objective. Closed-ended questions using Likert scales were included to optimise the ease of completing the questionnaire.

Participants were asked to complete the questionnaire in English and select an option that most closely presents their opinion. The subjects also received confidentiality (privacy) assurances and were asked not to use names that would identify anyone personally.

The main instrument used in the questionnaire was a five-point Likert scale. The questionnaire featured closed-format questions and was organised into parts to gather data from a demographic background standpoint.

4.7.2. Questionnaire Design

The questionnaire was developed under the UTAUT model, which was established by Venkatesh et al. (2003), to investigate the adoption of technology in this study. A review of numerous surveys from technology acceptability research was also conducted during the development of the questionnaire (Jokisch et al., 2022; Tetri & Juujärvi, 2022).

Many of the questions in the final draft of the questionnaire have already been tested and validated in other studies, providing a robust foundation for the research. Some questions were adapted specifically for the context of AD public hospitals, while others were developed from scratch to address unique aspects of the local healthcare environment. These newly developed questions aimed to capture the unique aspects of DH technology acceptance in AD public hospitals. Specifically, they focused on elements such as user DH experience, training, IT skills SE, and MLI (Jokisch et al., 2022; Tetri & Juujärvi, 2022).

This research used a cross-sectional survey, which means it focused on present behaviours and opinions were not tracked over time. Although cross-sectional research is more efficient, saving time and costs compared to a longitudinal study, it cannot show changes over time unless the comparisons are repeated at some later point (Janssen & Creswell, 2005).

Several factors guided the creation of the questionnaire, including a goal to prevent leading questions and to avoid writing complex or technical jargon that could be challenging for participants. In both inquiries and assertions, this was expressed through avoiding double negatives and carefully using open-ended questions.

The sequence of the questions was crucial, and they followed a logical progression (Cohen et al., 2007). The formulation of questions considered both insights gained from previously conducted work in the field and the specific requirements of this study's context. The types of questions used in the actual survey questionnaire are discussed in detail in Appendix 1. In addition to the constructs in the previous table, this study also collected personal and demographic data, such as gender, age, education, position, work experience, DH experience, IT skills, and training. The original and proposed UTAUT factors examined in the questionnaire are presented in Table 4.2.

Table 4.2 **Summary of UTAUT Constructs and Corresponding Statements** : This table gives details about the measured constructs, corresponding survey statements for their operationalization, and the sources from which these constructs were adapted.

UTAUT Construct	Statement	Source
Performance Expectancy(PE)	I find DH Applications useful in my work	Venkatesh et al. (2003)
	Using DH applications enables me to accomplish tasks more quickly	Venkatesh et al. (2003)

	Using DH applications makes it easier to treat patients	Venkatesh et al. (2003)
	Using DH applications increases my productivity	Venkatesh et al. (2003)
Effort Expectancy (EE)	I find DH Applications easy to use	Venkatesh et al. (2003)
	I have the skills I need to use the DH applications in my hospital	Venkatesh et al. (2003)
	Learning to operate and use a new DH technology is easy for me	Venkatesh et al. (2003)
Social Influence (SI)	Supervisors think that I should use DH technology	Venkatesh et al. (2003)
	My colleagues have helped me to use DH technology	Venkatesh et al. (2003)
	Most staff in my hospital think DH is important	Venkatesh et al. (2003)
Facilitating Conditions (FC)	I have access to devices used for DH easily	Venkatesh et al. (2003)
	I have the resources necessary to use DH applications in hospital	Venkatesh et al. (2003)
	A team is available for assistance with DH applications	Venkatesh et al. (2003)
Self-Efficacy (SE)	I can do a job or task using DH applications if no one is around to tell me what to do	Jokisch et al. (2022); Tetri & Juujärvi, (2022)

	I can complete a job or task using DH applications if I can call someone for help if I get stuck	Jokisch et al. (2022)
	I can complete a job or task using DH applications if I have just the built-in help facility for assistance	Jokisch et al. (2022)
Management and Leadership Involvement (MLI)	I believe if the administration involves me in the process of implementing new DH technology, that will help to adapt easily	Self-developed
	If management shares with us the future plans for Digital Health, that will help to accept the technology quicker	Self-developed
	The administration encourages me to use DH	Self-developed
Behavioural Intention (BI)	I intend to use DH applications in the future	Venkatesh et al. (2003)
	I predict I will use DH applications in the future	Venkatesh et al. (2003)
	I intend to attend a training programme on using DH applications in the future	Venkatesh et al. (2003)

4.7.3. Online Questionnaires

The online questionnaire is convenient when it comes to collecting data related to those who are located a distance from the researcher. Post may not be reliable in other postal systems or areas, and email can be used instead of real letter writing. Contrary to conventional survey techniques, which may be expensive, the expenses associated with conducting online questions are very modest. The probability of errors is reduced due to the data's electronic handling and database storage. Users may have enhanced ease of navigation while using an online questionnaire that employs an automated system to guide them to the subsequent question. This feature can potentially minimise mistakes and perhaps boost the response rate. Additionally, it reduces the time consumption as the researcher is relieved of manually inputting the data (Sincero, 2012).

Although there are advantages to adopting online surveys, there are also disadvantages. For instance, they are unsuitable for a target demographic, including many individuals without internet connectivity. Given that this survey was tailored to healthcare professionals, it was presumed that most of the population have internet connectivity at home, in the workplace, or both. An important drawback of online surveys is survey fraud, which refers to individuals completing the questionnaire to obtain a reward (Sincero, 2012). This drawback is irrelevant in this situation since no incentive was offered. Nevertheless, there is the noteworthy occurrence of a low response rate (Harris, 1997), making it crucial to emphasise the significance of the respondent's contribution in the cover letter. Given the immediate relevance of the issue to healthcare professionals, it is likely that their desire to reply was heightened, leading to a high response rate.

The researcher used the web platform SurveyMonkey to disseminate the survey. This platform is the first in the world used for collecting and analysing data. The advantages of using this survey tool are that the researcher gets instant access to the findings and that the participants may use it effortlessly. SurveyMonkey has a comprehensive analytical tool that allows users to analyse the data collected from their surveys. The platform provides summaries and visualisation of statistics and other essential metrics to assist customers in discovering relevant trends in their data faster. Because of compatibility, surveys are written through SurveyMonkey and can be viewed and answered on any mobile device. The idea is that the wider audience contributes to more accurate data collection.

4.7.4. Study Population and Sampling

A target population refers to individuals who exhibit the specified qualities that interest the researcher. Discrepancies may exist between the whole target population and the sample. However, sampling becomes necessary due to the impracticality and costliness of individually studying every person in the complete population. A population encompasses all entities, occurrences, and individuals that the researcher intends to examine. It encompasses all relevant instances that form a portion of the acknowledged whole (Yount, 2006). As defined by Landreneau (2005), a sample is a smaller group of individuals selected by the researcher to participate in a research project. The purpose of the sample is to reflect the larger target population accurately.

The researcher used a convenience sample technique as a result of the practical limitations imposed by time, money, and accessibility. This method included disseminating surveys to a specific cohort of hospitals that were within reach and familiar to me. The researcher depended on intermediaries inside these institutions to help distribute the surveys among healthcare workers. Although this strategy facilitated rapid and practical data collection, it is acknowledged that the sample may not accurately reflect the whole population of healthcare professionals owing to its dependence on particular locations and the networks of the mediators participating.

Although convenience sampling is widely used in several research domains (Weigold & Weigold, 2021), it is important to note that this approach has limits in terms of obtaining a representative sample and may introduce possible biases, as numerous studies have pointed out. The constraints mentioned may undermine the capacity to apply the study findings to a larger population and question the accuracy of the results, especially when trying to make wider inferences based on a convenience sample (Schwarcz et al., 2007).

Many strategic measures can be used to reduce bias in the research. To obtain responses from different types of healthcare professionals with different job tasks and backgrounds, the questionnaires were carefully planned to be distributed as widely as possible. This approach also helped reduce the bias that might exist in one or other professional networks. Mediators and participants alike received clear and uniform instructions to homogenise the supportive offerings being made and cut down on misinterpretation. The data was used with awareness of both the limitations of a convenience sample and differences from face-to-face communication that might characterise the general population, to qualify those abstract speculations. The conclusions were also matched with the previous study findings and subordinate data, which enabled authentication to reinforce the survey results.

Lastly, the research demonstrated transparency in reporting with a detailed explanation of how the sampling approach could have influenced the results and what steps were taken to mitigate it. Thus, these procedures were employed with the aim of ensuring that the research was reliable and valid and that derived knowledge about the adoption of DH in the AD context was accurate.

To ensure the representativeness of the sample, the researcher selected two major public hospitals and one minor public medical facility in AD as the sources for this research sample. Table 4.3 outlines the main characteristics of the three hospitals, specifying their classification, number of staff, bed capacity, and specialised services.

Table 4.3 **Summary of the Selected Hospitals:** This table provides an overview of the hospitals included in the study

Hospital	Type	Number of Staff	Beds	Specialties
A	Tertiary (providing advanced medical services and specialised treatments)	1228	365	A broad range of specialities, including ICU, burn ICU, cardiac care, and psychiatric services
B	Secondary (offering essential medical services and supporting the main facility in Abu Dhabi)	490	260	Focuses on ophthalmology and complex surgeries with advanced applications
C	Primary (Family Medicine Centre)	272	NA	Family Medicine and Emergency Department

The researcher selected these three public hospitals in AD as they are at different stages of DH implementation. The first hospital (A) had been implementing EMRs as an example of DH applications for over 10 years, the second hospital (B) had been doing so for between five years to 10 years, and the third (C) had been doing so for less than 5 years. This allowed insights around the experiences and challenges.

This approach was supported by similar methodologies reported in the literature, particularly in studies involving healthcare settings where convenience sampling methods are commonly used. For example, in the study by Golzar et al. (2022), convenience sampling was used to recruit nurses from multiple hospitals, effectively targeting institutions at different stages of technology adoption to gather in-depth insights. Another study by Martins et al. (2019) used convenience sampling across various educational institutions and patient associations to collect data, demonstrating the validity and effectiveness of focusing on specific organisations to yield significant results.

Focusing on hospitals at different stages allows for a deeper understanding of the contextual factors and aligns with the research on organisational behaviour, where structured equation modelling (SEM) is used with small, targeted samples to yield robust insights (Podsakoff et al., 2003).

The convenience sampling strategy enhanced the validity and reliability of the thesis findings, making it a robust approach despite the limited number of hospitals involved. Due to the online nature of the survey and the fact that most healthcare practitioners do not need to be personally contacted for the distribution or collection of the questionnaire, a random systematic sample was deemed suitable (Saunders et al., 2019). Pilot study participants were purposefully selected and contacted based on their potential to provide helpful insights to improve the questionnaire. Their insights were often indispensable to keep survey questions as clear and relevant as possible.

The researcher determined the appropriate sample size by using data from pre-existing healthcare databases. The AD DoH reported that the entire healthcare staff at public hospitals in AD in 2021 was around 14,370 (AD Department of Health, 2021).

The researcher followed a 'small sample approach' as per the US National Education Association's research in educational and psychological assessment. It was used to determine the sample size of the survey. This formula has been internally tested for empirical research, as described by Krejcie and Morgan (1970). For further details, refer to Appendix 2.

Given that the entire workforce target population in AD public hospitals is 14,370, the survey sample size suggested was 375, which is appropriate for a population of 15,000. Due to the expectation of a response rate of less than 100%, the total number of healthcare professionals contacted had to exceed 375. A total of 450 links to the online survey were issued. The researcher anticipated a substantial response rate due to the target population's inherent interest in the survey's subject matter. Additionally, the cover letter effectively highlighted the study's significance in enhancing conditions for healthcare professionals' adoption of DH.

The survey was sent to 450 participants, and 364 responses were received, which is an 81% response rate. This is much higher than the typical response to academic surveys (generally 20 to 30% for online surveys), with anything over 50% typically being considered quite good in most research contexts (Ericson et al., 2023; Smith et al., 2019). A total of 361 questionnaires were completed, and three were removed because of missing data, making the loss minimal. This further validated the reliability and representativeness of the results due to the high response rate along with minimal data loss.

Lavrakas (2008) contends that it is essential to preserve a maximum number of responses while ensuring the integrity of data in order to enhance the dependability of statistical studies. However, Groves and Lyberg (2010) stress that the representativeness of a sample is crucial in ensuring that survey results may be applied to the larger population.

Retaining the complete sample count of 364, even with some data exclusions, is in accordance with survey research best practices that strive to achieve a balance between data quality and representativeness (Fowler, 2014). The rationale for this method is supported by the significant rate of response and the insignificant loss of data, which collectively improve the dependability and accuracy of the study's results (Lavrakas, 2008; Groves & Lyberg, 2010; Fowler, 2014). To conduct a thorough analysis and preserve the reliability of the study's results, the researcher utilised a sample size of 364.

4.7.5. Pilot Study

A pilot study is a preliminary data-gathering method conducted on a select group of participants before the main research (Saunders et al., 2019). The pilot research was carried out subsequent to the completion of the final version of the questionnaire, which was prepared based on the analysis of the existing literature. The pilot work included a diverse group of people from multiple hospital departments. The pilot study participants included five healthcare professionals (three from Hospital A and Hospital B) and two managers (one from both hospitals); all of whom were very knowledgeable in the area with a good understanding of DH concepts, applications, and their own practical applications. The background knowledge informed their feedback, so it was credible and enabled us to refine the survey.

Each participant was asked to articulate their opinions on many subjects presented by Bryman and Bill (2015), including the comprehensibility of the instructions, the comprehensibility of the questions, additional inquiries, potential modifications to the questions, and the duration necessary to finish the questionnaire. The feedback indicated that all aspects of the questionnaire were satisfactory, and no modifications were necessary. Consequently, the first questionnaire remained unchanged, as it was deemed effective in its original form.

4.7.6. Survey Analysis

The data analysis techniques used were chosen based on their relevance to the research inquiries and the nature of the data to be examined (Pallant, 2020). The efficacy of the data analysis process relies not only on the choice of suitable software for the analysis but also on the fundamental tasks that need to be accomplished from the beginning. The research used descriptive statistics to condense a substantial volume of data into the numerical and graphical formats necessary for the study. Additionally, the inferential statistics used included

SEM, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), binary logistic regression, and discriminant validity assessment methods to make inferences about the target demographic of healthcare professionals in public hospitals in AD.

The data analysis approach included both the selection of suitable statistical analysis tools and the first stages of handling the data, such as coding the replies and refining the raw data (Pallant, 2011). Due to the use of an online questionnaire, the researcher was able to establish clear definitions for all variables at the initial design stage. This facilitated the seamless transfer of data to statistical tools.

In the second phase of the analysis, a thorough search for any missing data is needed; this is a common problem in research. Missing data may occur as a result of a respondent's unfamiliarity with a particular item, a mistake made during data input, or the respondent's reluctance to answer certain questions (Creswell, 2015).

Ultimately, the data needed to undergo scrutiny for outliers and distribution normality using multiple regression tests, assuming the absence of any outliers and adherence to normal distribution. Prior to doing the study, the researcher thoroughly analysed the standardised scores of the key variables, as well as the kurtosis values and skewness of the data distribution (Pallant, 2011).

4.7.7. Validity and Reliability

Validity and dependability are crucial to research development as they ensure the study's requisite quality. The perception of validity and reliability is necessary throughout the data collecting and processing phases. Validity refers to the degree to which the results are accurate and true, while reliability refers to the consistency and dependability of the data (Saunders & Tosey, 2015; Bryman & Bill, 2015). Questionnaires were used in this study to enhance the research study's validity and reliability.

Construct validity, internal validity, external validity, and reliability are the four commonly used assessments for evaluating the quality of empirical social research. The following evaluations were conducted in this investigation:

Construct validity refers to the process of accurately determining the appropriate measures for the concepts under investigation (Yin, 2016). In this research, construct validity was enhanced by reviewing the questionnaire with key informants to ensure that the measures accurately reflected the concepts being studied.

Internal validity refers to the degree to which the study methodology and data enable the researcher to draw reliable conclusions about cause-and-effect and other connections within the data (Neuman, 2007). Although internal validity is typically used in explanatory investigations (Yin, 2016), it was considered during the formulation of the research design to ensure that the relationships identified were not influenced by unique conceptual characteristics specific to each data set.

External validity pertains to a study's capacity to apply its results to a broader context and is contingent upon the study's selected environment and scope (Yin, 2016; Neuman, 2007). This research used a carefully selected sample and considered replication logic to enhance the external validity, ensuring that the findings could be generalised beyond the specific context of the study.

Reliability was ensured by consistently applying the same research procedures and maintaining a transparent chain of evidence throughout the investigation, ensuring that the results can be replicated in future studies (Saunders & Bezzina, 2015; Bryman & Bill, 2007).

To ensure the depth and trustworthiness of the views of healthcare workers at AD public hospitals on DH applications, several steps were taken to minimise bias in this research. First, the thesis adopted a robust quantitative method employing UTAUT as an established and validated theoretical model. This approach also helped to minimise subjectivist bias by grounding it within a well-studied framework. In addition, a sample of 364 healthcare workers was carefully recruited to represent different types of personnel (six professions), based on experience and education. The inclusion of multiple perspectives across the healthcare industry in this sample helped to reduce any bias and ensure that the results reflected a broad range of opinions.

4.8. Data Analysis

To achieve the aims of this study, various statistical techniques were employed during the data analysis process. These are detailed below and can be found in the respective sections:

Descriptive Statistics: Descriptive statistics were applied to determine the frequency of the participants' participation in terms of gender, age, and IT skills. The frequencies included the means, frequencies, and standard deviations (see Section 5.5)

Cronbach's Alpha: this was used to evaluate the internal consistency of scales measuring each of the respondents' construct (see Section 5.7.5).

Correlation Analysis: applied to measure the relationship between variables, this technique allows the researcher to obtain a single numerical value, indicating the strength and direction of the relation (see Table 5.6).

Binary Logistic Regression Analysis This assessed the impact of various predictors such as gender, age, education, training, profession, professional experience, DH experience, computer knowledge and skills, behavioural intention, and facilitating conditions on Usage Behaviour, showing significant predictive capability. (See Section 5.8).

Exploratory Factor Analysis (EFA): Conducted to determine the underlying variables and ensure the constructs' validation, supporting the factor structure (see Section 5.7.1).

Confirmatory Factor Analysis (CFA): This validated the measurement model to ensure the constructs used in this study were reliable and valid, confirming the structural validity of the measurement model (see Section 5.7.2).

Hypotheses Testing: This assessed the relationship of distinct theoretical constructs on BI and usage behaviour (see Section 5.7.8 and 5.8).

Model Fit Statistics: These were used to evaluate how well the proposed model fits the collected data (see Section 5.7.7).

This structured approach ensures that each statistical technique is appropriately applied to support the research objectives and hypotheses, providing a comprehensive analysis of the data.

The detailed process for each statistical technique, including tables and results, can be found in the respective sections of the analysis chapter. This thorough methodology enables a robust understanding of the factors influencing the adoption and utilisation of DH applications in AD public hospitals.

This study employs Structural Equation Modelling (SEM) and logistic regression as complementary analytical techniques to examine the adoption of DH technologies in AD's public hospitals. SEM was selected due to its superior ability to analyse complex interrelationships between observed and latent constructs, while accounting for measurement error. Unlike traditional regression methods, SEM enables the simultaneous modelling of multiple dependent and independent variables, making it ideal for investigating digital healthcare adoption among healthcare professionals (Kline, 2016). This capability is particularly crucial for operationalizing constructs such as perceived ease of use, organizational readiness, and technological competence, which are not directly observable but significantly impact DH adoption (Creswell & Creswell, 2017).

One of the key advantages of SEM is its ability to assess both direct and indirect effects, making it essential for analysing mediating relationships. In this study, SEM is used to determine how organizational support indirectly influences DH adoption through technological competence, a latent mediating factor. This analytical approach provides deeper insights into interdependencies, which conventional regression methods struggle to capture. Furthermore, SEM facilitates model fit assessment using indices such as the Comparative Fit Index (CFI) and the Root Mean Square Error of Approximation (RMSEA), ensuring that the theoretical model accurately represents the data and enhances the validity of the study's conclusions (Kline, 2016).

Despite its strengths in structural modelling, SEM has limitations when handling categorical dependent variables, particularly binary outcomes such as whether healthcare professionals adopt DH technologies (Yes/No). To address this, logistic regression is employed as a complementary method. Logistic regression is particularly well-suited for predicting adoption behaviours based on independent factors such as organizational readiness, digital literacy, and perceived usefulness (Dünnebeil et al., 2012). By focusing on predictive analysis, logistic regression enables this study to quantify adoption likelihood and examine the probability of occurrence for categorical outcomes.

Several studies have successfully combined SEM and logistic regression to analyse technology adoption in healthcare and related fields. For instance, Osman (2024) investigated digital transformation acceptance among employees in online distance learning environments. The study utilized SEM to analyse theoretical constructs related to technology acceptance while applying logistic regression to predict categorical adoption behaviours. This methodological approach closely aligns with the current study, as it enables the examination of both latent factors influencing DH adoption and the likelihood of actual adoption among healthcare professionals.

Similarly, Rusu (2023) explored DH adoption across various organizational settings, integrating SEM to assess structural relationships between latent variables and logistic regression to determine adoption probability based on binary outcomes. The study highlighted how factors such as organizational readiness and perceived usefulness significantly influence healthcare professionals' decisions to adopt DH technologies. By combining theoretical validation with predictive modelling, this research approach strengthens the justification for applying SEM and logistic regression in analysing technology acceptance in AD's public hospitals.

Additionally, Ming et al. (2023) examined the feasibility of implementing mobile digital personal health records in primary care settings. The researchers employed SEM to explore interdependencies among key constructs and used logistic regression to assess the likelihood of technology adoption among healthcare professionals. This study demonstrates how SEM enables a comprehensive understanding of adoption determinants, while logistic regression provides practical insights into real-world adoption behaviours. The integration of both methods ensures a robust and well-rounded analysis, similar to the approach adopted in this research.

These examples reinforce the validity of combining SEM and logistic regression in digital healthcare adoption research. They demonstrate that this hybrid approach effectively captures theoretical insights through SEM while providing practical, predictive capabilities through logistic regression. Moreover, segmentation analysis has been used alongside SEM and logistic regression to explore how different workforce groups respond to DH initiatives, ensuring a more tailored understanding of adoption behaviours (Osman, 2024).

In conclusion, the integration of SEM and logistic regression enhances the analytical depth of this study, allowing for both structural modelling and predictive analysis. SEM provides a sophisticated method for examining latent constructs and interdependencies, while logistic regression ensures clarity in predicting real-world adoption behaviours. This hybrid methodological approach is particularly well-suited for examining DH adoption in AD’s public hospitals, capturing both theoretical insights and practical implementation factors. The application of a numerical technique encompassing survey-oriented investigations and partial least squares structural equation modelling (PLS-SEM) is substantiated by prior studies on the acceptance of HIT. Comparable methodologies have been used to assess the factors impacting the acceptance of technology among healthcare practitioners. For instance, Kijsanayotin et al. (2009) conducted a nationwide inquiry in Thailand to explore HIT acceptance in community health facilities using the UTAUT framework and PLS path modelling. Their discoveries on elements such as performance anticipation, effort anticipation, social impact, and facilitating circumstances showed that they considerably influenced HIT acceptance and use.

Dünnebeil et al. (2012) used PLS-SEM to study the adoption behaviour of physicians in using eHealth applications in outpatient healthcare settings, highlighting the capability of the technique to handle complex models. Similarly, Kim et al. (2021) used an investigation based on surveys and PLS-SEM to gain insights into healthcare professionals' acceptance of DH applications, showing the importance of this methodology in a complete picture of technology acceptance and usage.

These findings support the thesis’ proposed approach, aligning with the first literature review findings and reinforcing the view that survey-related questions using PLS-SEM could be a suitable method to explore DH integration motivation and barriers in AD public hospitals. The uniformity of the results obtained in different settings reflects the importance and reliability of this methodological tool for assessing DH adoption by healthcare professionals.

4.9. Analytical Process

The proposed framework in Figure 4.2 includes key constructs PE, EE, SI, SE, FC, and MLI. Each construct was measured with specific items (e.g., PE1, EE1, SI1) and associated with a hypothesis indicating the expected effect on the BI and intention to use (USE). It should be noted that the squares in the figure are the specific items of these constructs obtained from questionnaires.

The framework also assesses at a high level, several control variables related to USE and how differences in the control variables, including personal and demographic factors (gender, age, education, and position) and experiential factors (DH experience, IT skills, and training) affect the direct relationship with BI. These variables allowed us to understand the sociodemographic and professional characteristics of healthcare professionals who shape the adoption and use of DH applications.

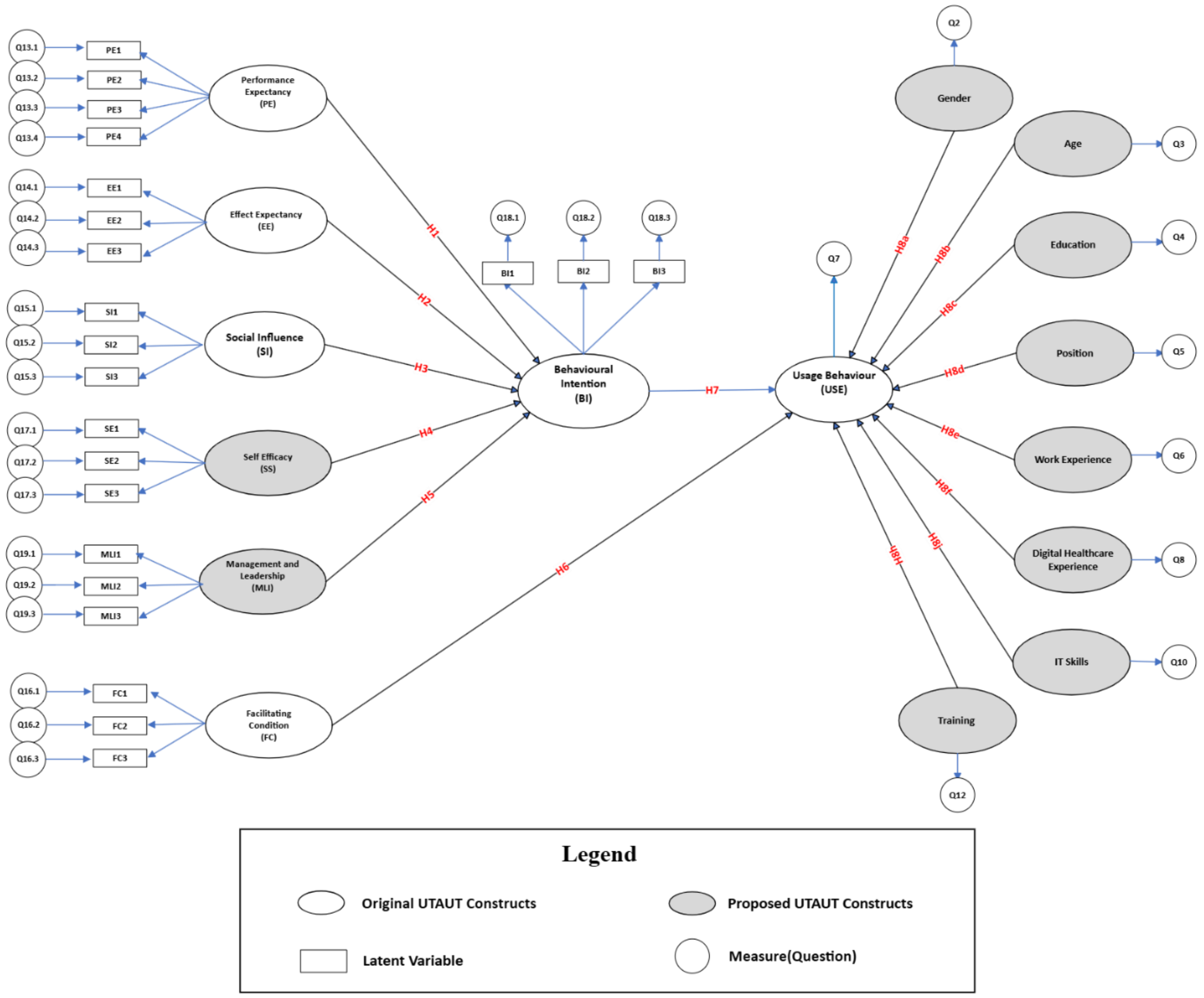

Figure 4.2 **Proposed Framework in details:** This figure provides a detailed view of the proposed research framework, illustrating variable interactions.

The researcher chose to split the proposed model into two different parts. Each segment uses different tools to explore the outcomes, resulting in a more focused and comprehensive review by referring back to the conceptual model discussed earlier. Dividing the model led to a refined approach, where each segment observed key drivers and used appropriate data for better results.

Segmentation is a term frequently used in economics and social research contexts, and it allows researchers to handle complexity with more clarity. Hair et al. (2010) showed that dividing complex models into smaller workable units makes it easier for researchers to develop them further, allowing more targeted analytical techniques that could enhance the reliability and accuracy of results. Furthermore, Saunders et al. (2019) showed that segmentation can be applied to various tools and methodologies developed for individual components of a model, as discussed in Borkar (2016), facilitating a fine-grained verification approach.

Figure 4.3 below shows how the steps in the analysis of the process are followed from data collection until reaching the conclusion. The figure presents different steps in the analysis, i.e. sequentially and in parallel, that guide research from one stage to the next, ensuring that the process is performed as efficiently and thoroughly as possible.

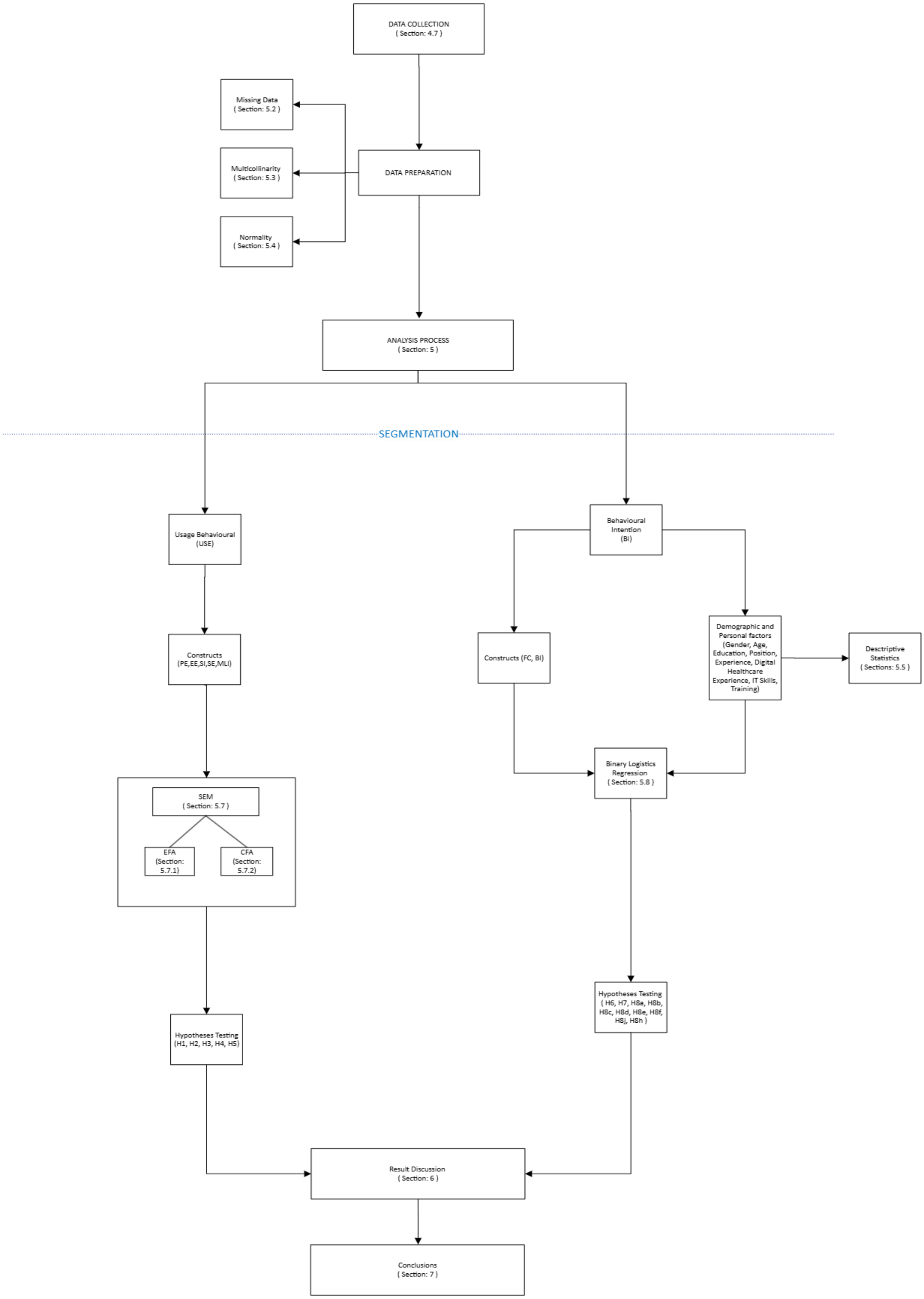

Figure 4.3 **Analysis Process Steps**: This figure outlines the step-by-step process used in analysing survey data.

The first segment illustrated in Figure 4.4 comprises PE, EE, SI, SE and MLI as common constructs. As shown in the figure, each of these constructs is measured by some of the items in the questionnaire (e.g., Q13 for PE, Q14 for EE).

Initially, EFA was performed to determine the underlying structure of the data. This step is important, as it sets the stage for determining how many factors there are, and which items load onto each factor to give an initial sense of the constructs. Factor analysis with varimax and principal component methods was used to conduct EFA. This procedure allows each factor to explain as much variance as possible, leading to a clearer interpretation of the factor structure. The study suggested that the observed constructs formed unique factors based on the results of factor analysis confirming BE, EE, SI, SE and MLI as theorised constructs, thus aligned with known dimensions PE, EE, SI, SE, MLI and BI. EFA results demonstrated that each item has a solid load on its respective factor, further validating the initial factor structure.

Following the EFA, CFA was executed to verify the factor structure that emerged. The thesis examined the hypothesised relationships between the observed variables (measurement items) and their underlying latent constructs in the CFA. This step is crucial to establish whether data will fit the measurement model proposed and to validate compounds to be used for the study (Byrne, 2010; Hair et al., 2014). The CFA was performed using SEM with maximum likelihood estimation. Fit indices of the CFI (comparative fit index), TLI (Tucker-Lewis index), RMSEA (root mean square error of approximation), and SRMR (standardised root mean square residual) were applied to assess model fit. This step resulted in the excellent fit of each construct, indicating their validity and reliability. The convergent validity of the constructs was upheld, as factor loadings for all items were significant and above the recommended cut-off point. Moreover, CFA also established composite reliability and average variance extracted (AVE) to test for convergent and discriminant validity of the constructs.

By conducting both EFA and CFA, the study ensured a robust and comprehensive examination of the measurement model, providing confidence in the validity and reliability of the constructs used to explore the factors influencing the acceptance and use of DH applications in AD public hospitals. The segment, shown in the figure 4.4 below, represents a crucial part of the proposed model. This segment specifically deals with the factors impacting BI for DH applications. (Hair et al., 2014).

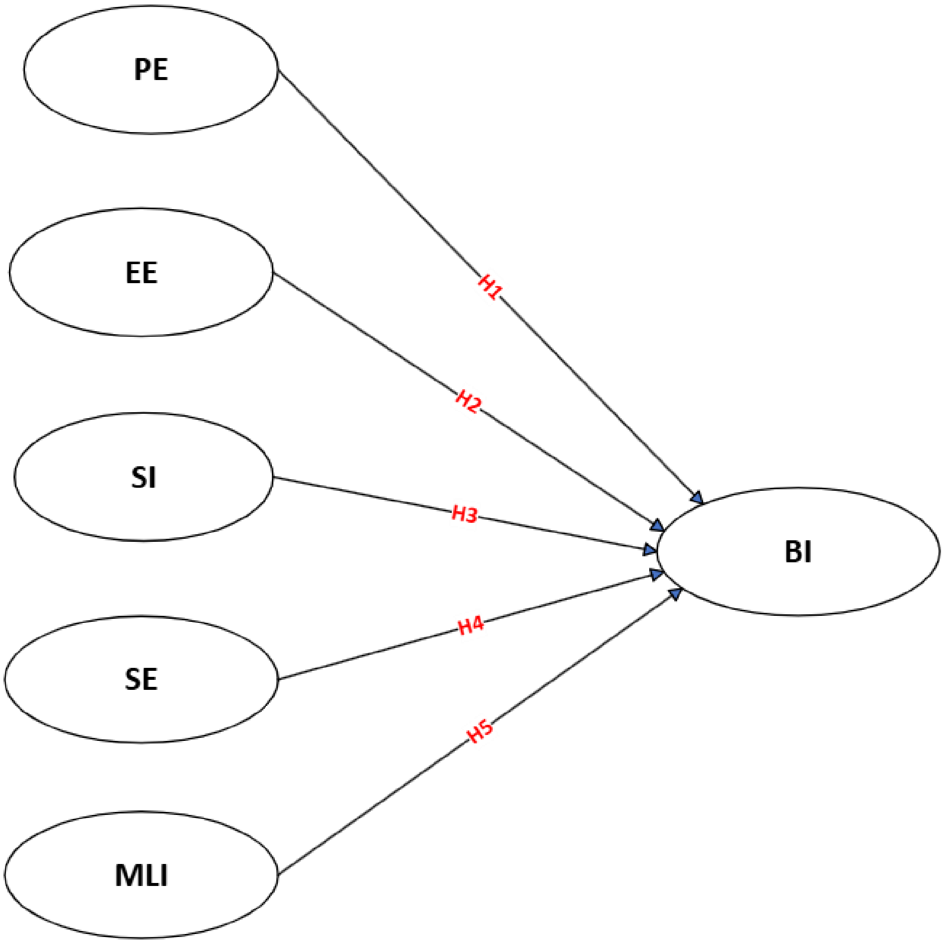

Figure 4.4 **Constructs Impacting BI**: This figure presents the proposed framework, showing PE, EE, SI, SE, and MLI as predictors of BI, with hypotheses (H1–H5) representing their relationships.

Figure 4.5 shows the key constructs BI and FC, measured by specific items from the questionnaire (e.g., Q18 for BI, Q19 for FC). BI reflects the likelihood that healthcare providers will use digital applications, and the FC include mechanisms to help them, once they use these new tools. These constructs are proposed to affect USE and are represented by Q7 in the questionnaire. The diagram presents the hypothesised paths from BI and FC to USE, which implies that higher behavioural intention and facilitating conditions are expected to impact the AU of DH applications directly.

Moreover, the diagram includes personal and demographic characteristics that were measured by specific items in the questionnaire: gender (Q2), age (Q3), education (Q4), position (Q5), work experience (Q6), DH experience (Q8), IT skills (Q10), and training (Q12).

These factors are assumed to directly influence USE, reflecting the degree to which distinctive individual characteristics and experiences of healthcare professionals' matter in terms of adoption and usage, as reflected in Hypotheses H8a to H8h.

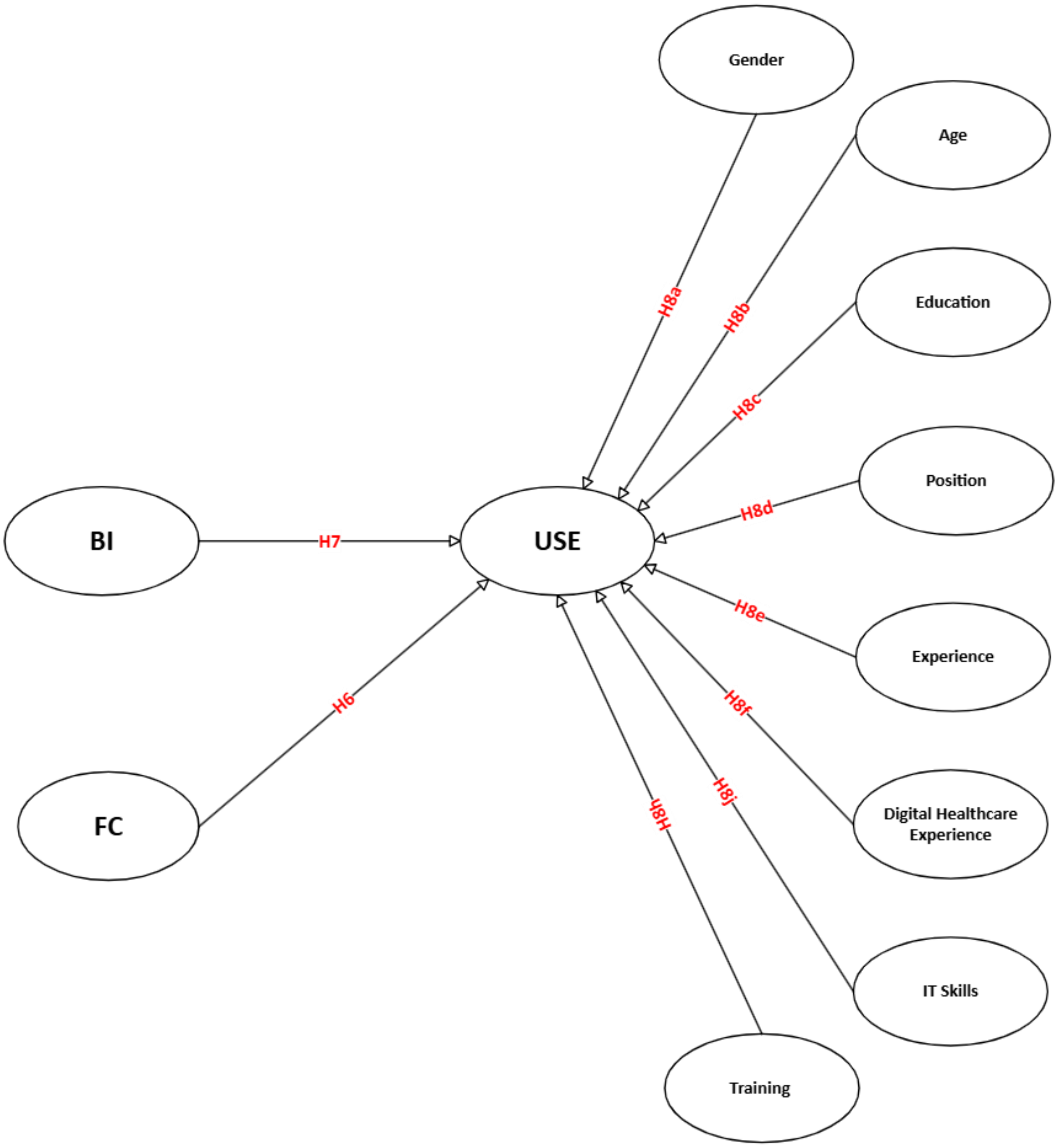

Figure 4.5 **Constructs and Factors Impacting USE**: This model shows BI and FC as predictors of USE, with demographic factors influencing adoption. Hypotheses (H6–H8) represent these relationships.

The second segment of the model was examined using binary logistic regression. Logistic regression is an effective way of modelling a binary outcome response of a variable based on information that would indicate its potential association with the dependent variables. The binary dependent variable in this study is narrow and is USE, which shows whether or not health professionals use DH applications. The independent variables BI, FC, and personal and demographic factors were analysed.

Binary logistic regression analysis helped determine the predictors for using DH applications, significant factors that can predict the likelihood of using DH applications. For example, the analysis was performed to investigate how gender (Q2), age (Q3), education level (Q4) and other such variables can singly and jointly explain USE. This analysis helps identify the key drivers and barriers for DH technology adoption among healthcare professionals in AD public hospitals.

In summary, by segmenting the proposed model and employing binary logistic regression, the study comprehensively examines the impact of both attitudinal constructs (such as BI and FC) and personal and demographic factors on the intention to use USE) of DH applications.

4.10. Ethical Concerns

Data collection leads to many ethical issues, mostly pertaining to the rights of anyone associated with the data being gathered. Ethical concerns often focus on participants' voluntary, informed consent, protecting their confidentiality/anonymity and any risks associated with participating in research.

The questionnaire had a cover letter (See appendix 3), and participants were provided with a comprehensive introduction to the study subject and the objectives of the data-gathering elements (questionnaires) and provided their informed consent (see copy in Appendix 4). All research questions were directly relevant to the subject matter, with no inquiries of a personal or unconventional kind. Participants were informed that they were not obligated to provide any information voluntarily throughout the data-gathering process, eliminating any pressure to participate.

The participants were given the choice to continue with the data collection components (questionnaire) or withdraw from the study at any point. Consequently, the researcher gave the respondents absolute autonomy to either engage in the questionnaire or opt-out without being obligated to provide an answer. The participants had the option to evaluate the research results to mitigate any future risks. The researcher remained unaware of the identity of the individuals during the questionnaire phase.

Before the data collection stage, an ethical permission form was submitted to the ethics committee at Sheffield Hallam University for approval. This form addressed previously identified ethical concerns and sought authorisation to proceed with the research after thoroughly reviewing the questionnaire. For more information, see Appendix 5.

Further, the researcher provided the necessary documents and a concise overview of the study proposal to the management of the selected hospitals to get ethical permission. This phase was essential for obtaining authorisation to carry out the study and get funding from the hospital.

4.11. Summary

The research onion model, as studied by Saunders et al. (2023), was adapted for the approach taken in this study. This model consists of six layers, which help in classifying and generating research. The thesis employed a mono-methodology (i.e., a quantitative research method) to gain a holistic overview of the unit under study.

This strategy was selected based on its capacity to provide unbiased and quantifiable information, which is necessary for a systematic and structured evaluation of the introduction of DH in AD public hospitals. Through significant emphasis on quantitative data, the research tried to determine patterns or correlations and establish cause-and-effect relationships — aspects that might not be easily recognisable via qualitative analysis.

A study using this methodology, recommended by Creswell (2015), collects data from a larger sample. This helps in strong and statistically significant results promoting the validity and reliability of study findings. This study employed descriptive statistics to condense a substantial volume of data into the numerical, tabular, and graphical formats necessary for the report. Additionally, inferential statistics were utilised to make inferences about the target population of healthcare professionals in AD public hospitals.

5. Analysis

5.1. Introduction

This chapter reveals various findings from the data analysis collected via survey questionnaire. This study aimed to contribute knowledge of the adoption and use of DH applications in AD public hospitals using the quantitative data collected. The chapter starts with a discussion of missing data, followed by how the study handled or imputed the missing values for a complete and clean dataset. The process then includes checking multicollinearity among the variables by methods including variance inflation factor (VIF) to identify and manage multicollinearity, thus ensuring robust results from regression.

Next, the chapter sets out descriptive statistics related to respondents' gender, age, years of education, professional position and work experience. The demographic overview summarises the sample population; this is important because it provides the framework for interpreting the results of subsequent analyses.

Following the demographic presentation, the chapter delves into the current usage patterns of DH applications and IT skills among healthcare professionals in AD, examining the types of DH applications being used, the frequency of use, and the extent of DH experience and training among the respondents.

The analysis then proceeds with structural equation modelling (SEM), first determining the data's latent factor structure with respect to EFA. CFA is then employed to test the hypothesised relationships between observed variables and their latent constructs based on a previously identified factor structure from EFA. This chapter explains the factor loadings output from the CFA, which measures links between observed variables and their corresponding factors. Model fit statistics are analysed to determine how well the proposed model fits the collected data, with indices such as CFI, TLI, RMSEA, and SRMR, as discussed earlier.

To ensure the consistency and reliability of the data, reliability analysis was conducted, calculating Cronbach's Alpha, composite reliability, and average variance extracted (AVE) for the various scales used in the survey, including PE, EE, SI, FC, SE, BI, and MLI.

Then, the structural model analysis is performed to investigate the structural relationship among constructs in the model and test the hypothesised paths and their significance. Finally, binary logistic regression is employed to evaluate the impact of various predictors on USE, examining factors such as gender, age, education, training, position, work experience, DH experience, and IT skills.

The study used various statistical techniques to test the hypotheses to understand whether the data collected supported the proposed hypothesis and what it reveals about predictors of adoption by healthcare professionals in DH. It provides a systematic way of developing an in-depth understanding of the elements that may be driving the acceptance and adoption of DH applications in AD public hospitals.

5.2. Missing Data

Most of the variables in the sample of 364 individuals had complete data, with no missing data for gender, education, age, position, work experience, current use of DH applications, and experience with DH.

In this research, data was collected using measures related to DH applications. The variables measured included aspects of PE, EE, SI, FC, SE, BI, and MLI. Upon examination of the dataset, it was found that there were instances of missing responses, varying across different variables, with a maximum of six responses missing for any given variable.

In the context of this study, the approach of retaining all responses, including those with missing data, is supported by established research principles regarding the handling of incomplete datasets. According to Bennett (2001), the impact of missing data on the broader analysis is usually negligible when it comprises a small proportion of the dataset, generally defined as less than 5%. In this study, the maximum missing data for any question was approximately 1.65% (6 out of 364 responses), well below this threshold. This would imply that excluding these responses would not substantially affect the study's outcomes.

Furthermore, Dong and Peng (2013) emphasized that the challenges posed by missing data can be effectively mitigated in studies with large samples. They highlight that the assumption of robustness in the presence of missing data holds particularly true in scenarios where the sample size is substantial, and the rate of missing data is low. Given that this study has a considerable sample size of 364 respondents, and the rate of missing data does not exceed 1.65% for any variable, these conditions are met, indicating a high level of data completeness and reliability (Ericson et al., 2023; Smith et al., 2019). Therefore, the decision to include all responses, despite some missing data, stands on solid methodological and statistical grounds. This approach ensures the integrity and comprehensiveness of the analysis, leading to more reliable and representative findings from the study.

By including all data, the research acknowledges the value of each participant's contribution, however incomplete it may be. This type of inclusivity is consistent with the larger ethical commitment to approach the data such that every voice in the sample has an opportunity to be heard, ensuring that the dataset includes a representative slice of the diversity and variance among those targeted.

The inclusion of cases with missing data necessitates a cautious interpretation of the study's findings. Statistical analyses were conducted with an understanding of this aspect, ensuring that all conclusions and inferences account for the presence of incomplete data. This approach enhances the authenticity and reliability of the research outcomes.

For future research, it is recommended that alternative methodologies and imputation techniques be explored to help account for the sensitivity of response to missing data. Moreover, improving survey design and engagement strategies could reduce the occurrence of missing data.

5.3. Multicollinearity

According to Pallant (2020), multicollinearity occurs when two or more variables are highly correlated. Different scholars have suggested different satisfactory values. For instance, correlations around 0.8 or 0.9 are considered highly problematic according to Tabachnick and Fidell (2007), while a value of 0.7 or higher is considered a reason for concern according to Pallant (2010).

The presence of multicollinearity is determined by two values: tolerance and VIF (Pallant, 2010). If the tolerance value is greater than 0.10 and the VIF value is less than 3.0, there is no multicollinearity. All the independent constructs had a VIF value of less than 3.0 and a tolerance value above 0.10 (see Table 5.1), suggesting the absence of multicollinearity in this study. Therefore, the regression results were relatively stable, and the analysis was conducted confidently.

Table 5.1 **Construct Tolerance and VIF**: This table presents Variance Inflation Factor (VIF) and Tolerance values, used to assess multicollinearity in the regression analysis.

	Tolerance	**VIF**
PE	.441	2.270
EE	.353	2.834
SI	.341	2.935

SE	.439	2.275
MLI	.364	2.745
FC	.363	2.754

5.4. Normality

In statistical analysis, especially multivariate analyses, the concept of normality is pivotal. Normality is the assumption that sample data follows a normal distribution (Gaussian). Hair et al. (2014) point out that many of the parametric tests that are applied in multivariable analyses rely on normality as an assumption. This assumption is critical because the validity of conclusions drawn from these analyses largely depends on the normality of the data involved.

Two main measures are used to determine normality: skewness and kurtosis. Skewness reflects the asymmetry of the distribution, while kurtosis indicates the peakedness or flatness of the distribution relative to a normal distribution. In an ideal scenario, both skewness and kurtosis values should be zero, indicating a perfectly normal distribution. A perfect normal distribution would have skewness and kurtosis of zero. As Pallant (2020) pointed out in the same example, this is a rare phenomenon in social science research because of the complexities and variances in human behaviour and response.

According to Curran, West, and Finch (1996) and Hair et al. (2014), data is considered to be normally distributed when skewness lies between -2 to +2 and kurtosis sits within the range of -7 to +7. The researchers can decide, based on this range, how many different values of normality they can accept in their datasets. It is important to note that while deviations from these ranges suggest non-normality, they do not necessarily invalidate the use of parametric analyses, especially in large sample sizes.

The significance of the normality assumption diminishes with an increase in sample size. Ghasemi and Zahediasl (2012) and Pallant (2020) suggest that when the sample size is greater than 30 participants, non-normality has a negligible effect on the results of the statistical analysis. Since larger sample sizes tend to result in sampling distributions that approximate normality, thereby reducing the risk of significant errors in inference. Elliott and Woodward (2007) also affirm that parametric analyses can still be validly performed with non-normally distributed data in the context of large sample sizes.

In the context of this research, where the sample comprises 364 participants from public hospitals in AD, normality should be theoretically assumed. Given the large sample size, any deviations from the normality assumption are unlikely to have a significant effect on the analysis. In this study, skewness and kurtosis values in the test to validate normality do not go beyond minimal limits, as shown in the table 5.2 below.

Table 5.2 **Skewness and Kurtosis**: This table presents the results of the normality test for survey data distribution, using skewness and kurtosis values.

	BI	PE	EE	SE	FC	SI	MLI
Skewness	1.408	1.303	1.066	.872	1.265	.854	1.178
Kurtosis	.399	.380	.314	.689	.218	.672	.158

5.5. Descriptive Statistical Analysis

This section provides a descriptive statistical analysis of survey questions on demographics.

What is your Gender (Q2)

Regarding gender, 23.7% (n = 119) of the participants identified as male, while 67.3% (n = 245) identified as female.

What is your Age (Q3)

Regarding age distribution, 29 individuals, only 8.0% of the sample, fell within the 21–30-year range. The majority of participants, 45.3% (n = 165), were between 31 and 40 years old. In addition, 31.9% (n = 116) of the sample fell within the 41–50-year range, while 12.4% (n = 45) were aged between 51 and 60. Further, a small fraction of the sample, 2.5% (n = 9), were over 60.

What is your Education (Q4)

For education, a total of 31 respondents, only 8.5% of the sample, reported holding a high school diploma. Most participants, 242 individuals or 66.5% of the sample, indicated obtaining a bachelor's degree. In addition, 58 respondents, constituting 15.9% of the sample, reported holding a master's degree. Further, 33 individuals, representing 9.1% of the sample, reported possessing a PhD.

I am a (What is your Profession) (Q5)

Regarding their profession, most participants, specifically 58.2% (n = 212), identified themselves as nurses. A smaller proportion, 6.6%, revealed that they were pharmacists, while 12.1% identified that they were doctors. The remaining 23.1% of respondents chose to classify their occupation as "Other".

Work Experience (Q6)

Regarding years of work experience, 1.6% (n = 6) of respondents said they had less than one year of experience, 6.3% (n = 23) had between one and five years, 17.0% (n = 62) had between six and ten years, and the majority 75.0% (n = 273) had more than ten years.
Table 5.3 Summarise the demographic statistics:

Table 5.3 **Participant Profiles (n=364):** This table summarizes the demographic characteristics of study participants, including gender, age, education, profession, and years of experience

	Demographic Statistics	Frequency	Percentage
Gender	Male	119	32.7%
	Female	245	67.3%
	Total	364	100%
Age	21-30 years	29	8%
	31-40 years	165	45.3%
	41-50 years	116	31.9%
	51-60 years	45	12.4%
	Over 60	9	2.5%
	Total	364	100%
Education	Diploma	31	8.5%
	Bachelor’s	242	66.5%
	Master’s	58	15.9%
	Doctorate	33	9.1%
	Total	364	100%
Position	Physician	44	12.1%
	Nurse	212	58.2%

	Pharmacist	24	6.6%
	Other	84	23.1%
	Total	364	100%
Work Experience	< 1	6	1.6%
	1 – 5	23	6.3%
	6 – 10	62	17%
	> 10	273	75%
	Total	364	100%

5.6. DH Usage and IT Skills Statistics

Descriptive statistics of DH usage and IT skills addressed by the survey questions are presented in this section.

Do you currently use any DH (DH) application(s)? (Q7)

When asked whether they used DH applications, such as wearable technology, telehealth, and telemedicine, 81.6% (n = 297) of respondents said they did, while 18.4% (n = 67) said they did not. These applications include (mHealth) applications, EMRs, and EHRs.

DH Experience (Q8)

For DH experience, 64 respondents, accounting for 17.6% of the sample, indicated having less than one year of experience. Also, 130 respondents, representing 35.7% of the sample, reported having between one and five years of experience. Additionally, 112 respondents, constituting 30.8% of the sample, stated they had between six and ten years of experience. Further, 58 respondents, making up 15.9% of the sample, claimed more than ten years of experience as summarized in the following table 5.4 below:

Table 5.4 **DH Usage Statistics**: This table presents DH application usage patterns among study participants, detailing frequency and types of use.

	Demographic Statistics	Frequency	Percentage
Usage of DH	Yes	297	81.6%
	No	67	18.4 %
	Total	364	100%
Experience in DH	< 1	64	17.6%
	1 – 5	130	35.7%
	6 – 10	112	30.8%
	> 10	58	15.9%
	Total	364	100%
Course taken	Yes	192	52.9%
	No	171	47.1%
	Total	363	100%
Usage patterns for DH technology	Not at all	36	9.9%
	Rarely	31	8.5%
	Sometimes	59	16.2%
	Often	78	21.4%
	Always	160	44%
	Total	364	100%
Computer knowledge and skills	Very Poor	2	0.6%
	Poor	4	1.1%
	Average	70	19.3%
	Good	166	45.9%
	Very Good	120	33.1%
	Total	362	100%

How frequently do you use DH technology? (Q9)

The analysis reveals an insight into the participants' usage patterns of DH applications. Of the 364 respondents, 9.9% (n = 36) revealed that they do not use DH applications at all. Also, 8.5% of respondents (n = 31) use it infrequently. A little more than 16.2% of respondents (n = 59) indicated they occasionally use such technology, while 21.4% of respondents (n = 78) claimed they frequently do so. 44.0% of respondents (n = 160) said they always utilise DH technology.

How do you rate your computer knowledge and skills? (Q10)

The participants' self-rated computer knowledge and skills were evaluated in the dataset. Here, 362 respondents—out of 364—provided their ratings. 1.1% (n = 4) of respondents (n = 2) gave their talents a "Poor" rating, while 0.6% (n = 2) gave "Very poor." Also, 19.3% (n = 70) of the participants revealed that they are "Average". A considerable 45.9% (n = 166) of respondents revealed they had "Good" computer skills, while 33.1% (n = 120) revealed they had "Very good" skills. Notably, only two responses were missing, making up about 0.5% of the entire sample.

What are the applications of DH you use most? (Q11)

The data revealed clear patterns between the respondents and their usage of DH applications in the realm of DH technology usage. EHRs and EMRs are particularly popular, with 12.67% (n = 46) always using them. On the other end of the spectrum, wearable devices are less prevalent, with 37.57% (n = 133) of respondents not using them at all (for more details, see Figure 5.1 below).

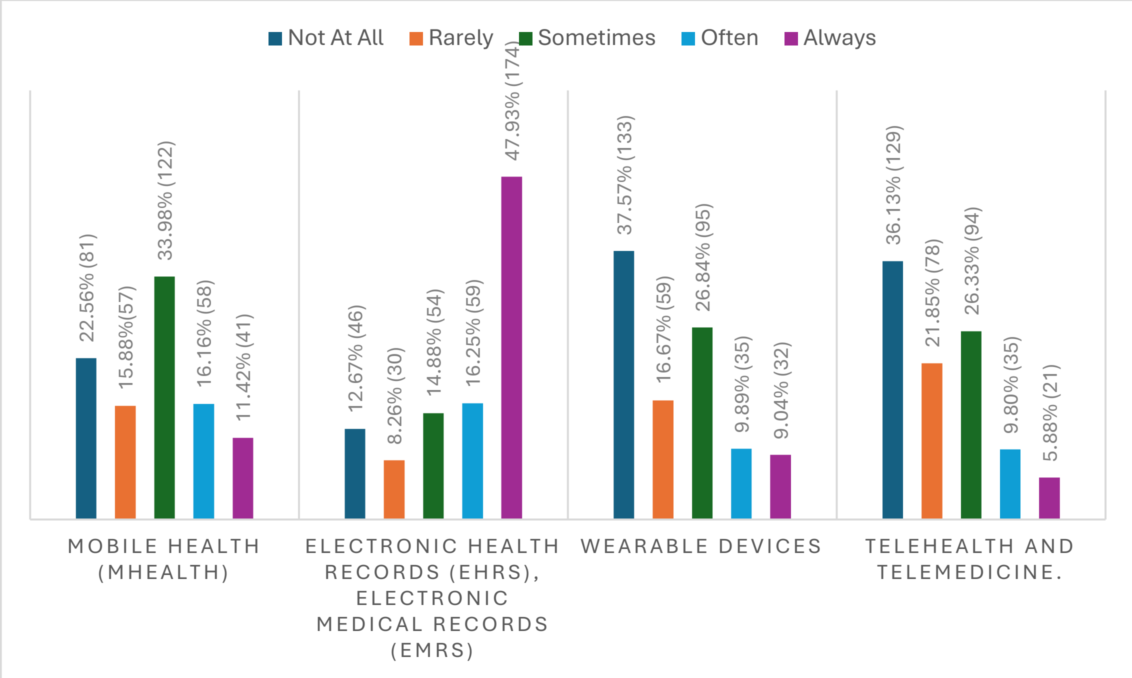

Figure 5.1 **DH Applications Usage**: The figure shows a breakdown of how healthcare professionals in AD's public hospitals use DH applications.

Have you attended any training programmes in how to use DH technology? (Q12)

The participants were asked if they had taken any courses about how to use DH applications (Q12), 52.7% of respondents answered "Yes" (n = 192) and 47.0% "No" (n = 171), with one missing data point (about 0.3% of the total).

5.7. Structural Equation Modelling (SEM)

This section examines the relationship between the factors in the revised UTAUT model. SEM allows the testing of complex models that include multiple dependent and independent variables, thus capturing a comprehensive view of the interaction between and among those constructs.

5.7.1. Exploratory Factor Analysis (EFA)

Similar variables in the factor analysis are grouped together into dimensions, a process referred to as the identification of latent variables. This process does not need the user to distinguish between the dependent or independent variables because it is an exploratory analysis that reduces the observation dimensions to simplify the data. In the factor analysis below, the abbreviations are as follows:

PE: Performance Expectancy

EE: Effort Expectancy

SI: Social Influence

FC: Facilitating Conditions

SE: Self-Efficacy

MLI: Management and Leadership Involvement

BI: Behaviour Intention

Despite the exclusion of USE from the SEM model due to its measurement by a single item, understanding the factors influencing USE remained necessary. To address this question, logistic regression was employed to predict USE. Logistic regression is appropriate for this purpose because it can effectively handle dependent variables measured with single items and does not require the latent construct modelling that SEM does. Further, the USE in this study was likely dichotomous (use vs. non-use), and logistic regression was specifically designed for binary outcome variables. Hosmer et al. (2013) demonstrate the suitability of logistic regression in analysing binary outcomes and producing reliable estimates of how predictors relate to the outcome variable.

Menard (2001) supports the use of logistic regression in social science research for predicting binary outcomes, emphasising its flexibility and effectiveness in such contexts. Therefore, logistic regression was employed as a complementary analysis to maintain the robustness of the study while allowing for an exploration of the factors influencing USE, providing a comprehensive understanding supported by the literature.

Various statistical methods aim to define the structure underpinning the structure of the variables, and factor analysis was used to investigate the correlations among the variables. This allowed the researcher to establish the structure's separate dimensions and then describe the extent to which each of the dimensions explained each variable (Straub, 1989; Hair et al., 2010). To establish that a group of items is indeed measuring their underlying constructs, it is important to evaluate the validity of the constructs and combine the evaluation results into the final research model so that a good level of fit with the data acquired from the measurement model can be demonstrated. This should ideally be done before any validation or analysis procedures are carried out (Hair et al., 2010).

The questionnaire used for this study was refined using EFA, such that the factorial validity of the items that the questionnaire was composed of was assessed, and a check was made on how well they measured the same concepts or variables. In social science, this technique is widely used (Costello & Osborne, 2005). Traditionally, EFA has been a method for exploring the factor structure that possibly underlies a group of observed variables without imposing a preconceived structure on the outcome.

When the underlying structures of a model's variables are to be defined, EFA is commonly used, especially when the researcher is not certain about the relationship between the constructs (unobserved variables) and the items (observed variables) (Byrne, 2010). Although EFA is usually considered unnecessary when the theory is already established, and UTAUT is one such theory, it was considered precautionary to confirm the validity of the constructs used in the revised UTAUT proposed for this study. It was felt to be important to make sure that the survey items really measured the underlying variables. Version 22.0 of the Statistical Package for Social Science (SPSS) was used for this EFA (Pallant, 2015).

EFA allowed the researcher to evaluate both convergent and discriminant validity by checking that items loaded cleanly onto only those factors that they had been expected to load onto (convergent validity), while not cross-loading onto other factors (discriminant validity) (Straub et al., 2004).

The descriptive statistics (see table 5.5 below) show that each construct in the factor analysis of seven constructs related to management practices and attitudes, had a mean value above 3.9 on a Likert scale of 1–5, with BI having the highest mean (4.2442) and SI having the lowest (3.9829). The standard deviations were all below 0.8, indicating mild variances.

Table 5.5 **Construct Descriptive Statistics**: This table provides mean and standard deviation values for key research constructs.

	Mean	***Std. Deviation***	***Analysis N***
PE	*4.1884*	*0.71844*	*361*
EE	*4.0766*	*0.6903*	*361*
SI	*3.9829*	*0.65388*	*361*
FC	*3.9954*	*0.75296*	*361*
SE	*4.0125*	*0.66961*	*361*
BI	*4.2442*	*0.69842*	*361*
MLI	*4.1514*	*0.673*	*361*

The correlation matrix table 5.6 below illustrates the relationships between the various constructs. It is noteworthy that MLI and BI show a substantial positive correlation of 0.729, indicating that as one construct increases, the other is likely to do so as well.

Table 5.6 **Correlation Matrix**: This table displays Pearson correlation coefficients between research constructs, showing their relationships.

	PE	**EE**	**SI**	**FC**	**SE**	**BI**	**MLI**
PE	1						
EE	.711	1					
SI	.642	.669	1				
FC	.585	.659	.733	1			
SE	.528	.642	.623	.651	1		
BI	.574	.603	.663	.609	.656	1	
MLI	.588	.667	.705	.693	.684	.729	1

The sample is suitable for factor analysis according to the Kaiser-Meyer-Olkin (KMO) (see Table 5.7) measure of sampling adequacy, which has a value of 0.919, which is near to 1. The data's suitability for this kind of analysis was further supported by Bartlett's Test of Sphericity, which had a significant Chi-square value of 1780.882 (p = .000s) for 21 degrees of freedom. In conclusion, the constructs showed strong correlations, and the data set was determined to be suitable for factor analysis, suggesting the presence of significant factor structures.

Table 5.7 **KMO and Barlett's Test**: This table presents the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test for sphericity, assessing factor analysis suitability.

KMO and Bartlett's Test		
KMO Measure of Sampling Adequacy		.919
Bartlett's Test of Sphericity	Approx. Chi-Square	1780.882
	Df	21
	Sig.	.000

5.7.2. *Confirmatory Factor Analysis (CFA) and Model Measurement*

CFA is an effective tool for determining whether the measures used to assess a construct in a theoretical model align with the underlying latent construct (Hair et al., 1999). The present study utilised CFA as a suitable method for evaluating construct validity, following the approach of previous studies that employed pre-validated instruments or measures (Belanche et al., 2012; Dhagarra et al., 2020; Slade et al., 2015). CFA is a statistical method used to assess the extent to which a theoretical model accurately represents the observed data (Byrne, 2016). CFA is frequently used to examine the associations between multiple indicators or measured variables and underlying constructs. In addition, CFA evaluates the degree to which a hypothesised model, based on theory, aligns with a model created using the research data that has been collected (Marsh et al., 1988).

To conduct CFA as an appropriate preliminary step in research analysis, it is crucial to ensure the validity of the research model constructs, particularly focusing on convergent and discriminant validity (Henseler et al., 2015). Discriminant validity is necessary to ensure that a construct measure is distinct and captures distinctive phenomena not covered by other measures in a structural equation model (Henseler et al., 2015).

The CFA method was used to test the factor structure of a set of observed variables. The proposed equation model that explains the drivers and barriers to the use of DH systems was constructed using seven latent variables, namely PE, EE, SI, FC, SE, and MLI, which were examined, as well as BI, and each was operationalised through multiple indicators derived from the survey responses.

The analysis revealed that all factor loadings were significant ($p < 0.05$), indicating that the survey items reliably measured their respective constructs. The range of standardised loadings supported the constructs' reliability, contributing to the overall structural validity of the measurement model.

In general, the CFA supported the structural validity of the measurement model used in this study. This validation is necessary as it supports the subsequent structural equation modelling, which will explore the relationships between these constructs. The results provide a strong foundation for further analysis, aimed at uncovering the factors that influence the adoption of DH applications among healthcare professionals in the region. This step is essential in ensuring that the theoretical framework is robust and applicable to the specific context of Abu Dhabi's public healthcare sector.

5.7.3. Factor Loading

As part of the measurement analysis, the first step is to assist the factor loading. Factor loading is the correlation between the item and the factor, indicating that each observed variable significantly contributes to its associated latent construct. Strong factor loadings ensure that the constructs are measured accurately. Factor loading is a crucial component of factor analysis, representing the strength of the relationship between the items and factors.

According to Goni et al. (2020) a factor loading higher than 0.30 generally reflects a moderate relationship, while they suggest a higher threshold of over 0.70 for robust relationships. In the study's results presented in Table 4.8, all items show factor loadings greater than 0.70, except for SE1 and SI2, which had loadings of 0.697 and 0.692, respectively. However, these two items slightly fall below the recommended threshold, however, since most of the items are over this benchmark, the overall factor loading can still be considered acceptable.

This finding is in line with the work of Goni et al. (2020) and Karuniawati et al. (2021), who state that factor loadings above 0.3 indicate a close relationship between the factors and items. Additionally, Karuniawati et al. (2021) imply an important relationship between factors and the items; the cumulative contribution should exceed 40%, with each item loading higher than 0.4, which also indicates that this factor loading was found to be acceptable in this study.

In conclusion, despite SE1 and SI2 having factor loadings slightly below the recommended threshold, the majority of items exceed 0.70, indicating a strong relationship between the items and factors, supporting the conclusion that the factor loading in this study can be considered acceptable. The results (see table 5.8 below) reveal that all items have a factor loading over 0.70 except for SE1 and SI2, with loadings of 0.697 and 0.692, respectively. Hence, the factor loading can be referred to as acceptable.

Table 5.8 **Factor Loading**: This table lists the factor loadings of questionnaire items, showing their association with theoretical constructs.

	PE	EE	SI	FC	SE	BI	MLI
PE1	0.78						
PE2	0.875						
PE3	0.859						
PE4	0.806						
EE1		0.858					
EE2		0.89					
EE3		0.842					
SI1			0.779				
SI2			0.692				
SI3			0.798				
FC1				0.884			
FC2				0.949			
FC3				0.862			
SE1					0.697		
SE2					0.883		
SE3					0.855		
BI1						0.91	
BI2						0.883	
BI3						0.807	
MLI1							0.918
MLI2							0.921
MLI3							0.751

5.7.4. Model Fit Statistics

CFA was conducted using PLS to evaluate the measurement models. The model fit measures were used to assess the model's overall goodness of fit (CMIN/df, GFI, CFI, TLI, SRMR, and RMSEA) and all values were within their respective common acceptance levels (Ullman, 2001; Hu & Bentler, 1998; Bentler, 1990). The six-factor model (PE, EE, SI, SE, MLI, and BI) yielded a good fit (see table 5.9 below) for the data: CMIN/df=2.793, GFI=0.954, CFI=0.954, TLI=0.936, RMSEA=0.070 and SRMR= 0.055) (See table 5.9 below for details). Although the p-value is significant (Bagozzi & Yi, 1991), it was disregarded due to the sample size. Overall, the model aligns well with the data, yielding a good fit across all indices.

Table 5.9 **Model Fit Statistics:** This table provides key fit indices (e.g., CFI, RMSEA) assessing the structural equation model's goodness-of-fit.

Fit Indices	Recommended Value	Sources (s)	Obtained Value
P	Insignificant	Bagozzi & Yi (1988)	.000 (Due to the sample size, was insignificant, and ignored)
CMIN /df	3-5	Less than 2 (Ullman, 2001) to 5 (Schumacker & Lomax, 2004)	2.786
GFI	>.90	Hair et al. (2010)	0.954
CFI	>.90	Bentler (1990)	0.954
TLI	>.90	Bentler (1990)	0.936
RMSEA	<.08	Hu & Bentler (1998)	0.070
SRMR	<.08	Hu & Bentler (1998)	0.055

5.7.5. Reliability and Validity

When conducting research that involves collecting data through surveys, confirming the reliability and validity of the constructs is a necessary step in order to maintain strict standards for correlational analysis with surveys. This will help to properly reflect the intended measures. Construct reliability refers to the extent that measuring a latent variable yields similar results using different items; it measures how well a certain set of items actually tracks the intended variable it aims to measure (Straub & Gefen, 2004). Cronbach's alpha and composite reliability are methods used to evaluate the internal consistency of measurement scales (Thorndike, 1995).

Meanwhile, construct validity assesses how well the measurement scales actually represent the underlying theoretical constructs. Convergent validity guarantees that multiple items designed to assess the same concept are closely aligned, while discriminant validity ensures that theoretically distinct constructs do not overlap (Gefen, Straub, & Boudreau, 2000). The criterion developed by Fornell and Larcker in 1981 and the Heterotrait-Monotrait ratio proposed by Henseler et al. in 2015, are commonly employed techniques for verifying discriminant validity. Ensuring a high level of reliability and validity is essential because it enhances the credibility of the research findings and allows for more precise conclusions about the relationships between different concepts.

Construct Reliability

Construct reliability refers to the degree of consistency when measuring a latent variable, indicating that a set of items consistently captures the intended variable it is meant to measure (Straub & Gefen, 2004). Construct reliability for each construct was evaluated using Cronbach's Alpha and composite reliability. The Cronbach's Alpha values exceeded the minimum threshold of 0.70 (Thorndike, 1995), while the composite reliability values ranged between 0.926 and 0.795 (as shown in Table 5.10), surpassing the 0.70 benchmark (Hair et al., 2010). Hence, construct reliability was established. This assessment ensures that the variables consistently measure the intended constructs (Straub & Gefen, 2004).

Table 5.10 **Cronbach's Alpha and Composite Reliability:** This table presents reliability metrics for the constructs, including Cronbach's alpha and composite reliability values.

	Cronbach's alpha (standardised)	**Composite reliability (rho_c)**
PE	0.897	0.899
`1EE	0.899	0.899
SI	0.802	0.795
FC	0.924	0.926
SE	0.844	0.851
BI	0.899	0.901
MLI	0.889	0.893

Convergent Validity

Convergent validity refers to the extent to which different measures of a theoretically related construct align, providing evidence that they consistently measure the same underlying concept (Gefen, Straub, & Boudreau, 2000), ensuring that this alignment establishes uni-dimensionality in multi-item constructs disregarding any unreliable indicators (Bollen, 1989).

The convergent validity of the measures was examined using AVE as suggested by Fornell and Larcker (1981). The AVE indicates the proportion of the variance in the indicators that is explained by the unobserved latent variable. The scales in this study obtained AVE values above the threshold of 0.50 (Fornell & Larcker, 1981), signifying that the latent variables account for more than half of the variance in the corresponding indicators (see Table 5.11 below). Such values represent empirical evidence of strong convergent validity (Bagozzi & Yi, 1988).

Table 5.11 **Average Variance Extracted (AVE):** This table provides AVE values to assess convergent validity of constructs.

	Average variance extracted (AVE)
PE	0.69
EE	0.746
SI	0.574
FC	0.808
SE	0.665
BI	0.753
MLI	0.752

5.7.6. Analysis of the Structural Model

On construct reliability, convergent validity, and discriminant validity for the sample were established, the subsequent course of action was to examine the associations between the exogenous and endogenous latent variables. This was accomplished in the structural model phase (Arbuckle, 2009; Hair et al., 2010). In contrast to CFA, differentiation between dependent and independent variables is required. SEM operates under the assumption of covariance among the independent variables, denoted by a pair of headed arrows, while a single-headed arrow signifies the causal relationship between an independent variable and a dependent variable. This was achieved by specifying the relationship between the constructs subsequent to the transition from the measurement model to the structural model as illustrated in Figure 5.2. The findings derived from the structural model analysis have been elaborated upon in distinct subsections.

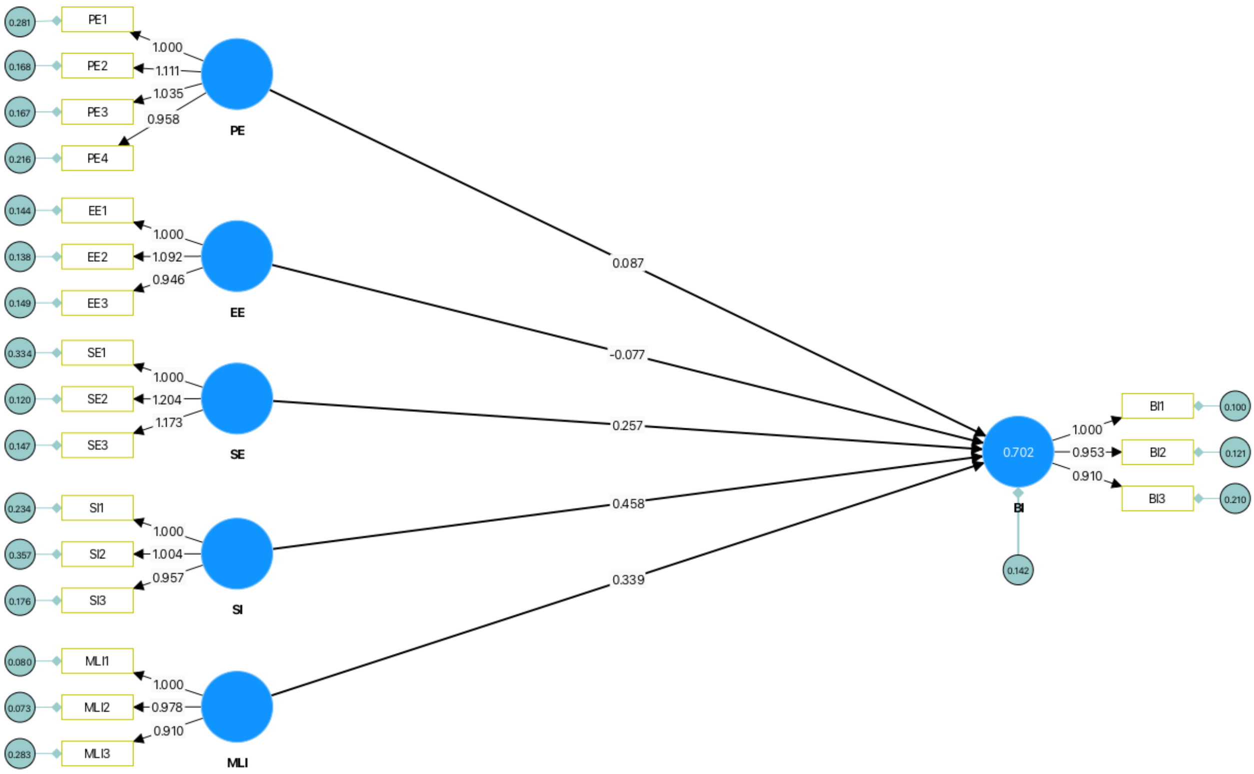

Figure 5.2 **Structural Equation Model (SEM):** This figure demonstrates the structural equation (SEM) model applied to test the theoretical framework.

5.7.7. Model Fit Statistics

Based on the same criteria used for the measurement model to measure the goodness of fit for the proposed model, the model fit measures were used to assess the model's overall goodness of fit (CMIN/df, GFI, CFI, TLI, SRMR, and RMSEA) and all values were within their respective common acceptance levels (Ullman, 2001; Hu & Bentler, 1998; Bentler, 1990). The six-factor model (PE, EE, SI, SE, MLI, and BI) demonstrated a good fit to the data, as indicated by the following values: CMIN/df = 2.828, GFI = 0.897, CFI = 0.954, TLI = 0.942, RMSEA = 0.071, and SRMR = 0.051 (as shown in Table 5.12 below).

Table 5.12 **Model Fit:** This table reports additional model fit indices used in confirmatory factor analysis (CFA).

Fit Indices	Recommended Value	Sources (s)	Obtained Value
P	Insignificant	Bagozzi & Yi (1988)	.000 (Due to the sample size, it is insignificant, so ignored
CMIN /DF	3-5	Less than 2 (Ullman, 2001) to 5 (Schumacker & Lomax, 2004)	2.828
GFI	>.90	Hair et al. (2010)	0.897
CFI	>.90	Bentler (1990)	0.954
TLI	>.90	Bentler (1990)	0.942
RMSEA	<.08	Hu & Bentler (1998)	0.071
SRR	<.08	Hu & Bentler (1998)	0.051

5.7.8. Hypotheses Testing

This section evaluates the proposed relationships within the model:

H1: There is a significant positive relationship between PE and the BI to use DH.

The results indicate that the effect of PE on BI is insignificant (Path Coefficient = .087, T = 1.118, p = .264). Thus, the study does not support H1. This result suggests that while perceived usefulness is necessary, it may not be sufficient on its own to drive adoption. Other factors, such as user training and organisational support, may need to be in place (Davis, 1989).

H2: There is a significant positive relationship between EE and the BI to use DH.

The results indicated that the effect of EE on BI is insignificant (Path Coefficient = -0.077, T = .797, p = .426). Hence, the study does not support H2.

This result aligns with previous studies suggesting that ease of use may become less critical in environments where users are already familiar with technology or where ease of use is taken for granted (Venkatesh et al., 2003).

H3: There is a significant positive relationship between SI and the BI to use DH

The results indicated that the effect of SI on BI is significant (Path Coefficient = .458, T = 3.458, p < .001). Hence, the study support H3.

SI significantly impacts BI, suggesting that peer pressure and the expectations of colleagues and supervisors play a crucial role in shaping technology adoption behaviours. This finding aligns with other research that underscores the role of social context in technology adoption (Venkatesh et al., 2003).

H4: There is a significant positive relationship between SE and the BI to use DH

The results indicated that the effect of SE on BI is significant (Path Coefficient = .257, T = 2.945, p < .01). Hence, the study support H4.

SE significantly influences BI, underscoring the importance of ensuring that healthcare professionals feel capable of using new applications. Training programmes and hands-on experience can enhance SE, leading to higher adoption rates (Bandura, 1986).

H5: There is a significant positive relationship between MLI and the BI to use DH.

The results indicated that the effect of MLI on BI is significant (Path Coefficient = .339, T = 4.592, p < .001). Hence, the study support H5. The significant positive impact of MLI on BI highlights the critical role that management and leadership play in fostering the adoption of DH applications. Effective leadership can create a supportive environment and motivate staff to embrace new applications, consistent with the literature emphasising a higher level of leadership support in successful technology implementation (Avolio et al., 2009). Table 5.13 shows the results of the hypothesis testing, and Table 5.14 summarises the results.

Table 5.13 **Hypotheses Relationships:** This table outlines the hypothesized relationships among constructs in the structural model.

	Parameter estimates	Standard errors	T values	P values
PE -> BI	0.087	0.078	1.118	0.264
EE -> BI	-0.077	0.096	0.797	0.426
SI -> BI	0.458	0.129	3.544	< .0
SE -> BI	0.257	0.087	2.945	0.003
MLI -> BI	0.339	0.074	4.592	< .0

Table 5.14 **Hypothesis Results Summary:** This table summarizes hypothesis testing results, indicating supported and rejected hypotheses.

Hypothesis	Proposed Relationship	Path Coefficient	Study Results
H1	PE → BI	0.264	Rejected
H2	EE → BI	0.429	Rejected
H3	SI → BI	< .0	Supported
H4	SE → BI	0.003	Supported
H5	MLI → BI	< .0	Supported

5.7.9. Explanatory Power (R2)

The explanatory power, or R^2, is a statistical measure representing the variance proportion of the dependent variable that can be explained by independent variables in the model. In other words, it indicates how well the data fits the statistical model. An R^2 value ranges from 0 to 1, where higher values imply a better explanatory power. According to Cohen et al. (2002), an R^2 value closer to 1.0 signifies that the model accounts for most of the variability found in the outcome variable, while values near 0 mean that the model explains very little of the variance. Thus, R^2 provides an important indication of a model's predictive accuracy and explanatory strength.

The structural equation model (SEM) (Figure 4.3) shows that the latent variable BI has an R^2 of 0.702. It suggests that the joint influence of PE, EE, SE, SI and MLI can account for 70.2% of the variance in BI. An R^2 value such as this reveals that the model has good explanatory power, and the predictors were able to effectively account for the variation in BI. The rest of the 29.8% contribution is attributed to other unconsidered or unmeasurable factors, and randomness.

5.8. Binary Logistic Regression

Binary logistic regression analysis was performed to assess the impact of gender, age, education, position, work experience, DH experience, IT skills, training, BI and FC on USE. USE was measured where the binary outcome variables with 0 signified NO, while 1 represented usage behaviour.

5.8.1. Logistic Regression Analysis

The omnibus test of the model coefficients (shown in the table 5.15 below), specifically the significance test, showed that $P<.001$ indicating a significant improvement in model fit compared to the null model. This suggests that the predictors included in the model are informative of its predictive ability. According to Hosmer and Lemeshow (2000), the omnibus test is essential when evaluating how significant the model can predict and if it added any information on top of using a model without predictors. Furthermore, Field (2013) states that the omnibus test is important in logistic regression to assess whether the model benefits from adding predictors.

Table 5.15 **Omnibus Tests of Model Coefficients:** This table reports results from omnibus tests, assessing overall model significance in logistic regression analysis.

		Chi-square	df	Sig.
Step 1	Step	155.874	10	.000
	Block	155.874	10	.000
	Model	155.874	10	.000

For the next model summary (see Table 5.16 below), the pseudo-R^2 was determined to be an approximate variation explained in the criterion variable (USE) in this study. This meant that a 57.3% change in the USE was explained by the predictors in this study.

Table 5.16 **Model Summary:** This table provides R^2 values and other key statistics summarizing the logistic regression model's performance.

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	186.329[a]	.353	.573

a. Estimation terminated at iteration number 7 because parameter estimates changed by less than .001.

The classified table (shown in Table 5.17) presents how well the model predicted the correct category. The model correctly classified 90.8% of cases.

Table 5.17 **Classification Table:** This table presents the classification accuracy of the logistic regression model in predicting DH usage.

			Predicted		
			USE		Percentage Correct
	Observed		No	Yes	
Step 1	USE	No	46	20	69.7
		Yes	13	279	95.5
	Overall Percentage				90.8

a. The cut value is .500

5.9. *Hypothesis Testing*

Each of the predictors and their impact on USE are presented next, as detailed in Table 5.18 below.

Table 5.18 **Predictors' Impact on USE:** This table details the impact of independent variables on actual DH usage (USE) as assessed via logistic regression.

	B	SE.	Wald	df	Sig.	Exp(B)
Gender	0.538	0.417	1.665	1	0.197	1.713
Age	-0.595	0.261	5.208	1	0.022	0.552

Education	0.779	0.324	5.770	1	0.016	2.178
Position	-0.076	0.151	0.253	1	0.615	0.927
Work Experience	0.229	0.324	0.500	1	0.479	1.257
DH Experience	2.452	0.349	49.242	1	0.000	11.613
IT Skills	0.268	0.238	1.264	1	0.261	1.307
Training	0.722	0.440	2.693	1	0.101	2.059
BI	0.377	0.313	1.456	1	0.228	1.458
FC	0.132	0.287	0.210	1	0.647	1.141

5.9.1. Gender

The Wald statistic for gender was calculated as 1.665, corresponding to a p-value of .197, indicating no difference in the likelihood of using DH applications between male and female respondents (B=.538, P=.197). In practical terms, this means that within the scope of this research, being of one gender does not significantly increase or decrease the odds of using DH applications compared to being of another gender.

Furthermore, the Exp(B) value/ODDS RATIO associated with gender is 1.713. An odds ratio of 1.713 implies that the odds of using DH applications are 1.173 times higher for one gender compared to the other. Nevertheless, as there were no significant differences ($p > .05$), this result should be viewed with caution. It suggests that while there might be a difference in the odds of using DH applications between genders, this difference is not statistically significant in the context of this study. Therefore, the present analysis would suggest that gender does not lead to significant differences concerning the use of DH applications among participants.

This finding aligned with Cassidy's (2021) study, which reported non-significant gender differences in attitudes towards DH technology.

5.9.2. Age

The Wald statistic for age was calculated as 5.208, corresponding to a p-value of .022, indicating a statistically significant difference in the likelihood of using DH applications based on age (B = -.595, P = .022). Practically, this means that the odds of using DH applications decrease as age increases. The odds ratio (Exp(B)) associated with age is 0.552, implying that for every unit increase in age, the odds of using DH applications are 0.552 times or approximately 45% less, assuming all other variables are constant. Therefore, age plays a significant role in the usage of DH applications among the study's participants, with younger individuals being more likely to use these applications.

This result is consistent with previous research in the healthcare context which has identified age as a significant factor that influences the behavioural intention to use DH applications. Previous research has indicated that older individuals exhibit reduced levels of preparedness and involvement with eHealth resources for patient education and self-care compared to their younger counterparts (Gordon & Hornbrook, 2018). The elderly population encounters digital disparity in terms of their ability to access and utilize different digital applications, such as health-related applications and patient portals (Gordon & Hornbrook, 2018). Additionally, a study on people's opinions of DH technology discovered a link between age and favourable opinions of technology (Cassidy 2021).

The significant influence of age on the adoption of DH technology requires a targeted strategy to reduce inequalities and ensure fair access. Addressing these disparities is not just a measure to promote inclusivity, but a fundamental aspect of guaranteeing that DH resources are accessible and advantageous for individuals of all age groups. Prioritizing the design and implementation of DH solutions that are suitable for different age groups and that take into account the users' abilities and preferences is crucial. This will help create an inclusive DH system.

5.9.3. Education

The Wald statistic for education is 5.770, with a p-value of .016, suggesting a statistically significant association ($B = .779$, $P = .016$). This result reveals that people with a high educational level are more expected to use DH apps. The Exp(B) value, or odds ratio, for education is 2.178, suggesting that the odds of using DH applications are over two times higher for individuals with higher educational qualifications compared to those with lower educational qualifications. Therefore, education is a strong predictor of DH application usage in this study.

This is supported by Woolley et al. (2023), who found that education level significantly affects DH technology adoption, and higher DH usage has been linked with higher levels of education.

5.9.4. Position

The analysis revealed a Wald statistic of 0.253 for position, corresponding to a non-significant p-value of 0.615. This result indicates that the role of healthcare professionals—whether nurses, pharmacists, physicians, or others—does not significantly impact their likelihood of using DH applications within the context of this research.

The analysis also revealed a position-based odds ratio, Exp(B) 0.927. An odds ratio of less than 1 indicates a small decrease in the odds of using these apps for respondents based on professional roles. Nevertheless, the statistical insignificance of this finding implies that the specific healthcare role participants fill is not a pivotal factor in their adoption of DH applications in this study.

This finding does not agree with Magal et al. (2021), who explored the attitudes of mental healthcare professionals towards the adoption of telepsychiatry. They found that attitudes were related to hierarchical position, organisational affiliation, perceived benefits and barriers associated with telepsychiatry, and personal experiences with telepsychiatry. This signals a potential role for the attitudes and beliefs of healthcare professionals, or individuals within specific specialities or roles, in acceptance of DH applications.

5.9.5. Work Experience

In the analysis concerning years of work experience, the Wald statistic is reported as 0.500 with a corresponding p-value of .479. This result indicates no significant effect due to work experience on the probability of utilising DH applications within the confines of this study. Furthermore, the calculated odds ratio (Exp(B)) is 1.257, suggesting only a marginal tendency towards the use of DH applications increasing with the amount of work experience; however, this difference proved non-significant.

The findings aligned with the findings from Shinners et al. (2020) and Masum et al. (2016) who suggest that experience significantly impacts the usage of DH applications, as more experienced healthcare professionals tend to have greater digital literacy and are more likely to adopt DH if it enhances job satisfaction and work quality.

5.9.6. Digital Health Experience

DH experience was revealed to be a strong factor in the logistic regression analysis, indicated by a Wald statistic of 49.242 and a p-value of (< .01). With an odds ratio (Exp(B)) of 11.613, it is more likely that those already familiar with DH will be the ones to participate in applying them; the odds for using DH apps amongst them exceed twelve times more than those without this background.

This strong correlation ($p < .05$) highlights a significant link between DH Experience and participants application usage, suggesting that ease with DH applications is a critical driver of its uptake. The evidence from this analysis emphasises the critical role that previous exposure plays in influencing DH application usage among the participants in this study. Shinners et al. (2020), Alghamdi et al. (2021), and Wang et al. (2021) collectively emphasise the significant role of experience with DH applications in the adaptation and acceptance of new healthcare applications, including AI and DH applications platforms.

Additionally, Moreau et al. (2018) claimed that positive experiences with a DH intervention have been shown to result in greater healthcare professionals' acceptance and adoption of these interventions. Additionally, Konttila et al. (2019) painted that positive experiences and competence in using digital applications can meaningfully enhance the acceptance of DH. Therefore, it can be concluded that positive experiences with DH interventions play an essential role in influencing the acceptance of DH among healthcare professionals (Moreau et al., 2018; Konttila et al., 2019).

5.9.7. IT Skills

The analysis conducted did not reveal a statistically significant relationship between the participants' IT skills and their utilisation of DH applications, as evidenced by a Wald statistic of 1.264 and a corresponding p-value of .261, which exceeds the standard significance threshold of .05. The calculated odds ratio of 1.307 intimates that individuals with higher IT skills have a somewhat increased likelihood of engaging with DH applications. However, this is not statistically substantial.

These results imply that while there might be a marginal positive correlation perceived between IT skills and the usage of DH applications, such an association is not supported by the data within this research framework.

These results contradict Woolley et al. (2023) and Xie et al. (2021) who found that advanced IT skills positively influence the use of DH (DH) applications, but Kuo et al. (2013) and Perski and Short (2021) emphasize that factors such as openness to technology, motivation, and psychological readiness are equally important for DH adoption and sustained usage.

5.9.8. Training

The analysis results on the influence of training on the utilisation of DH applications are as follows. The calculated Wald statistic for training was 2.693, corresponding to a p-value of .101. This result, marginally above the standard alpha level of .05, indicates a potential link between participation in training programmes and the usage of DH applications. The odds ratio, at 2.059, suggests that individuals who have received training are more than twice as likely as those who do not interact with DH applications. However, since the p-value slightly exceeds .05, this conclusion needs to be treated with caution. The results imply a possible positive correlation between training participation and the use of DH applications, but the evidence is not robust enough to confirm a definitive effect within the parameters of this study.

This aligned with Eeg-Olofsson et al. (2020) and Esposito et al. (2023) who emphasize that training is importance to enhance DH (DH) adoption as it provides healthcare workers with the needed capabilities and trust to effectively execute those tools. Similarly, Tegegne et al. (2023) who highlighted that training improves digital literacy. Together, these studies demonstrate that training also positively influences attitudes toward DH adoption by showcasing its value and benefits, making it essential for increased acceptance.

5.9.9. Behavioural Intention (BI)

The Wald statistic for BI was determined to be 1.456, which yields a p-value of .228. This suggests that the intention to use DH applications does not significantly predict actual usage (USE) (B=.377, P=.228). Moreover, the odds ratio associated with BI is 1.458. An odds ratio of 1.458 indicates that for each unit increase in the intention to use DH applications, the odds of using them increase by 1.458. However, due to the p-value being greater than .05, this effect is not statistically significant.

Research on the impact of BI on the usage behaviour (USE) of DH has yielded mixed results. Ofori's (2021) and Prayoga's (2016) studies suggest that while BI is important, it may not be the sole determinant of usage behaviour in the context of DH. Additionally, there is a gap between healthcare professionals' understanding of DH advantages and effective use due to system complexities, workflow integration challenges, and data privacy concerns (Keen, 2014; Limna, 2023).

5.9.10. *Facilitating Conditions (FC)*

An investigation into the role of FC in the use of DH applications revealed a Wald statistic of .210, correlating to a p-value of .647. This implies no statistically significant predictive value due to FC on the actual use of DH applications (B=.132, P=.647). The Exp(B) value, or odds ratio, for FC is 1.141. This ratio suggests that an enhancement FC could potentially increase the odds of using DH applications by 1.141 times. Nonetheless, given how the p-value exceeds the .05 threshold for statistical significance, this effect is not considered statistically robust within the confines of this study.

The impact of FC on the USE of DH is complex and multifaceted. While some studies have found a positive association between FC and USE (Mahmood et al., 2019), others have found the persistence of existing inequalities in the digital realm (Müller, 2020). This suggests that while FC may play a role in DH USE, they are not the sole determinant, and other factors such as personal and demographic characteristics and health literacy also need to be considered.

5.10. *Binary Regression Summary*

In sum, the analysis demonstrates that among the variables considered, age, education, and DH experience are significant predictors of DH application usage, with DH experience being the most powerful predictor among them. Gender, position, work experience, self-assessed computer skills, training attendance, FC and BI did not show a statistically significant effect on the likelihood of using DH applications in the context of this research.

The following model (figure 5.3) shows the outcome:

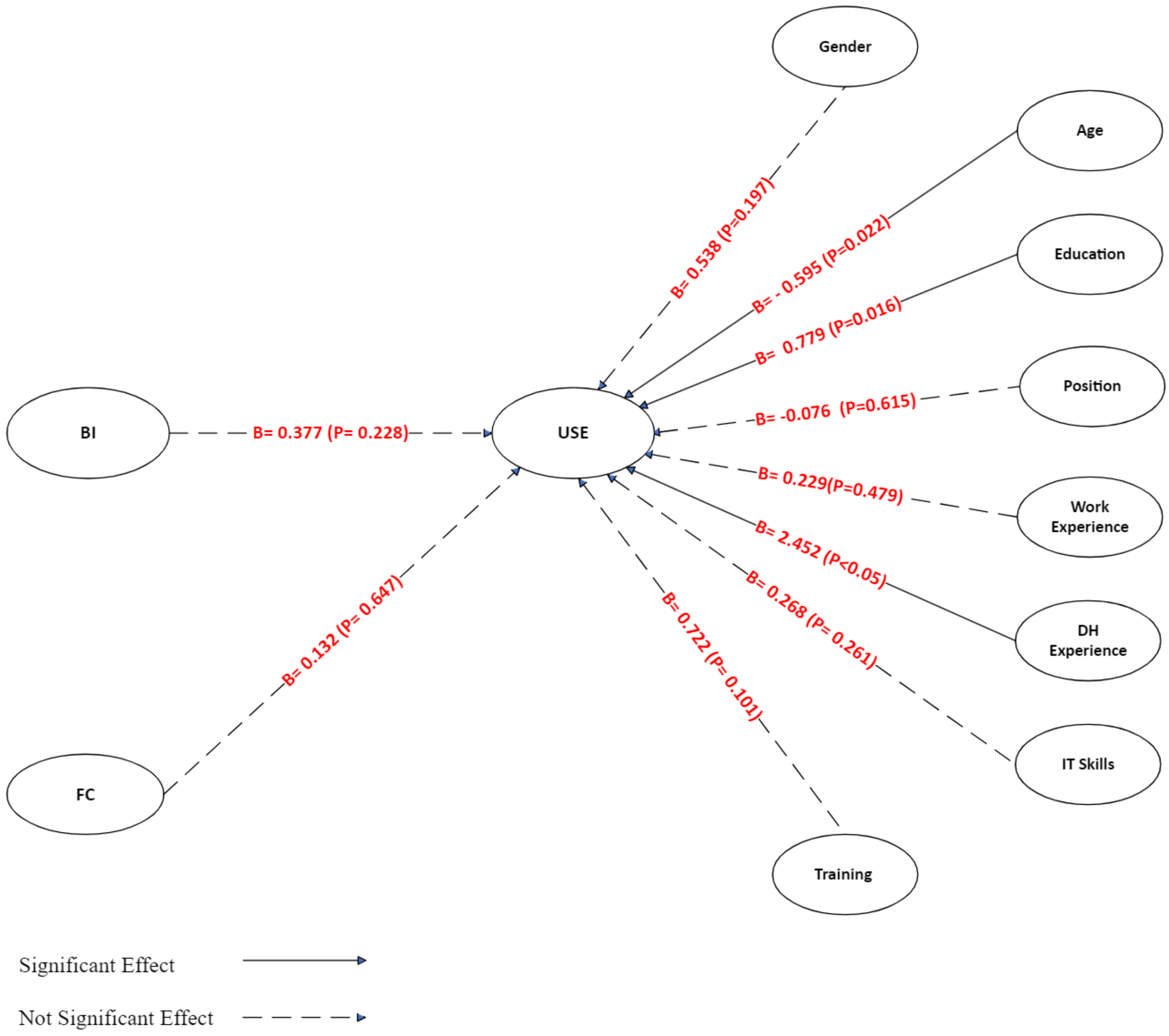

Figure 5.3 **Binary Regression Outcome**: This figure presents regression results for USE, showing effects of BI, FC, and demographics. Age, education, and DH experience significantly impact USE, while other factors are non-significant.

Table 5.19 below presents a summary of the binary regression hypothesis testing results.

Table 5.19 **Hypotheses Summary:** This table consolidates the results of hypothesis testing across all theoretical constructs.

Hypothesis	Proposed Relationship	Path Coefficient	Study Results
H6	FC → USE	0.228	Rejected
H7	BI → USE	0.123	Rejected
H8a	Gender → USE	0.197	Rejected
H8b	Age → USE	0.022	Supported
H8c	Position → USE	0.615	Rejected
H8d	Education → USE	0.016	Supported
H8e	Experience → USE	0.479	Rejected
H8f	DH Experience → USE	< .0	Supported
H8g	IT Skills → USE	0.261	Rejected
H8h	Training → USE	0.101	Rejected

5.11. Summary

A comprehensive overview of the research hypotheses tested in this study and their corresponding results are presented in Table 5.21. Each hypothesis examines a specific factor's impact on either the BI to use DH applications or the actual usage of these applications (USE) within the context of Abu Dhabi's public hospitals.

The hypotheses (H1 to H5) focus on various constructs derived from the UTAUT model, PE, EE, SI, SE, and MLI. These constructs were assessed to determine their influence on healthcare professionals' intentions to adopt DH applications.

The following hypotheses (H6 to H8) examine the impact of FC, BI, and various personal and demographic factors on the actual use of DH applications. These personal and demographic factors are further broken down into sub-hypotheses (H8a to H8h) to explore the effects of gender, age, education, position, work experience, DH experience, IT skills, and training.

The study results column in the table 5.20 below shows whether each hypothesis is supported or rejected based on the statistical analysis. The supported hypotheses indicate that there is no significant impact due to the factor being evaluated, while the rejected hypotheses suggest a significant impact, thereby influencing the adoption and usage of DH applications.

Table 5.20 **Research Hypotheses Results:** This table includes research hypotheses, study results (supported/rejected), statistical methods used, and corresponding thesis sections.

Research Hypotheses	Study Results	Method(s) Used	Section(s)
H1: There is a significant positive relationship between PE and the BI to use DH.	Rejected	EFA, CFA, Regression Analysis	5.7.1, 5.7.2, 5.7.6
H2: There is a significant positive relationship between EE and the BI to use DH.	Rejected	EFA, CFA, Regression Analysis	5.7.1, 5.7.2, 5.7.6
H3: There is a significant positive relationship between SI and the BI to use DH.	Supported	EFA, CFA, Regression Analysis	5.7.1, 5.7.2, 5.7.6
H4: There is a significant positive relationship between SE and the BI to use DH.	Supported	EFA, CFA, Regression Analysis	5.7.1, 5.7.2, 5.7.6
H5: There is a significant positive relationship between MLI and BI to use DH.	Supported	EFA, CFA, Regression Analysis	5.7.1, 5.7.2, 5.7.6
H6: There is a significant positive relationship between FC and the use of DH.	Rejected	Binary Logistic Regression	5.8
H7: There is a significant positive relationship between BI and the use of DH.	Rejected	Binary Logistic Regression	5.8
H8: There is a significant positive relationship between demographic factors (gender, age, education, position, work experience) and the use of DH.			

H8a: Gender significantly influences the use of DH.	Rejected	Binary Logistic Regression	5.8
H8b: Age significantly influences the use of DH.	Supported	Binary Logistic Regression	5.8
H8c: Education significantly influences the use of DH.	Supported	Binary Logistic Regression	5.8
H8d: Position significantly influences the use of DH.	Rejected	Binary Logistic Regression	5.8
H8e: Work experience significantly influences the use of DH.	Rejected	Binary Logistic Regression	5.8
H8f: DH experience significantly influences the use of DH.	Supported	Binary Logistic Regression	5.8
H8g: IT skills significantly influence the use of DH.	Rejected	Binary Logistic Regression	5.8
H8h: Training significantly influences the use of DH.	Rejected	Binary Logistic Regression	5.8

6. Discussion

This chapter discusses the results obtained from the present study, specifically focusing on their significance when addressing the research questions. This study investigated the current state of DH utilisation in public hospitals in AD, followed by an evaluation of each factor in the proposed revised theoretical model. The model utilised in this study is based on the UTAUT model by Venkatesh et al. in 2003. The additional factors that have been found to affect the adoption and use of DH applications among professionals have been given much attention. These constructs included SE, MLI, DH experience, IT skills, and training, as well as other factors such as age, gender, education level, job position, and work experience. The constructs of the revised UTAUT model were evaluated for their ability to explain professionals' acceptance of technology in AD public hospitals.

Sections 5.1, 5.2, 5.3 and 5.4 answer the major research questions, which represent the primary focus of the data collection in this study. This was accomplished through an investigation of the following aspects:

1. To what extent and why do personal and demographic factors explain the variances in the actual usage of DH applications in AD public hospitals?
2. To what extent and why do personal and demographic factors explain the variances in the intention to use DH applications in AD public hospitals?
3. To what extent and why do FC and BI explain the variances in the intention to use DH (USE) applications in AD public hospitals?
4. To what extent and why do PE, EE and SI explain the variances in the BI to use DH applications in AD public hospitals?
5. To what extent and why do SE and MLI impact the BI to use DH applications?

Section 5.5 explores further question regarding the implications of this study for the original UTAUT model.

How can the UTAUT model be used to better understand what healthcare professionals in AD public hospitals perceive they need to effectively adopt DH applications?

6.1. Current DH (DH) Technology Usage in AD Public Hospitals

The results of this study's data analysis showed interesting findings regarding the usage patterns of DH applications among the participants. Among 364 respondents, 9.9% did not use any DH applications at all; another 8.5% reported using them rarely. Meanwhile, 16.2% said they sometimes use DH applications, and 21.4% claimed frequent usage.
Some 44.0% of respondents reported always using DH applications. In addition, the data revealed that the participants had varying usage patterns for different DH applications. EHRs and EMRs were the most commonly used, followed by mHealth, and a relatively lower prevalence of wearable devices and telehealth/telemedicine applications. Thus, these findings can be informative in understanding the adoption and use of DH applications among those surveyed.

Abdallah et al. (2021), Alrahbi et al. (2021), and Ancarani et al. (2016) reported findings that are consistent with this study regarding the adoption of DH applications in the UAE healthcare sector. These authors observed that using applications such as telemedicine, HIT, and EMRs enhances acceptance rates and operational efficiency. Alrahbi et al. (2021) also noted that the UAE had demonstrated its commitment to enhancing healthcare delivery and patient participation by actively implementing DH initiatives, including mobile applications, data analytics, and the digitisation of EMRs.

However, it is important to note that the study identified the limited and basic usage of advanced DH applications in AD. Despite progress, more recent applications available worldwide, such as AI in diagnostics, wearable devices for remote patient monitoring, and blockchain for secure health data exchange, are not widely used. Based on this research, adopting advanced DH applications could provide significant advantages to patients.

The findings of this study indicate that while basic DH solutions have been implemented in public hospitals in AD, there remains a gap in the adoption of more advanced applications. A significant proportion of professionals regularly interact with those basic DH applications, demonstrating a notable degree of acceptance and seamless integration into their daily practices. This is an encouraging indication that suggests that the healthcare sector is well-prepared for more advanced digital transformation.

However, the study also revealed considerable variability in the adoption rates among healthcare professionals, ranging from infrequent to regular use. This variation highlights the need to delve deeper into the factors that drive or hinder the consistent use of these applications. Understanding the motivations, barriers, and facilitators influencing these behaviours is essential for devising targeted strategies to promote uniform adoption across the board.

A particular point of interest is the dominance of EHRs and EMRs in current usage patterns. Although this preference indicates a certain level of ease with digital systems that are essential to healthcare information technology, it also implies a possible lack of interest in embracing more advanced applications. The potential of mHealth, wearables, and telehealth to bring about significant changes seems not fully realised, suggesting the need for more investigation and investment in these domains.

Given the current level of technology integration, it is important to highlight the potential for more advanced DH solutions to be integrated. The next step in healthcare is characterised by advancements such as AI in diagnostics, wearable devices for patient monitoring, and blockchain for secure data exchange. The successful deployment of these applications will change healthcare in AD, offering tremendous benefits to patients and improving operational efficiency.

Based on the data collected, it is important to understand the specific challenges and needs that healthcare professionals face, to enhance the successful integration of such applications.

Finally, this study highlights the need to understand the unique challenges and requirements that healthcare workers face in order to support successful technology integration. Thus, this research adds to scholarly discussions and provides valuable guidance for healthcare policymakers. By utilising these valuable insights, AD can establish a course of action towards a healthcare ecosystem that is more interconnected, streamlined, and focused on the needs of patients. This can be achieved through the careful implementation of DH applications.

6.2. Personal and Demographic Factors Impact

The impact of personal and demographic factors on the adoption of DH solutions is of great importance. These factors, which include gender, age, education, position, work experience and IT skills, play a pivotal role in determining how healthcare applications are adopted and utilised by professionals (Gordon & Hornbrook, 2018; Woolley et al., 2023; Ben-Gal, 2023; Xie et al., 2021; Cassidy, 2021; Kurniasari et al., 2022). Several studies have examined the relationship between these factors and the adoption of DH applications using the UTAUT model. Each factor will be examined in detail to understand its specific role and influence on adopting DH applications.

6.2.1. Gender

The analysis results revealed no significant influence of gender on the usage of DH applications. The logistic regression analysis showed a Wald statistic of 1.665, a p-value of .197, and a B value of 0.538. The odds ratio (Exp(B)) was calculated as 1.713, suggesting that the odds of using DH applications are approximately 71.3% higher for one gender compared to the other. However, as the p-value exceeds the threshold for significance ($p > .05$), this finding indicates that gender does not play a meaningful role in predicting the likelihood of DH application usage when holding other factors constant. Our findings supported the existing research indicating non-significant gender differences in attitudes towards DH applications. Cassidy (2021) identified the absence of statistically significant gender disparities in attitudes toward DH applications. Regardless, it is worth noting that the impact of gender can be different depending on the conditions studied and the population.

In the context of the AD public hospitals, it is observed that the adoption and usage of DH is not significantly influenced by gender. This can be described as both genders having equal access to technology and training, supportive institutional policies, a cultural emphasis on equality, and professional motivation. Collectively, these factors create an environment that allows both male and female healthcare professionals to embrace and benefit from DH advances equally.

6.2.2. Age

The analysis results revealed a strong influence due to age on the usage of DH applications. It revealed a negative correlation, with a Wald statistic of 5.208, a p-value of .022, and a B value of -0.595. The odds ratio (Exp(B)) is 0.552, suggesting that a one-unit increase in age would decrease the probability of using DH applications by around 45% when holding the other factors constant. With increasing age, the likelihood of adopting these applications decreases, indicating a greater inclination towards DH usage among younger individuals.

This result is consistent with previous research in the healthcare context, which has identified age as a significant factor that influences the BI to use DH applications. Research has shown that ageing adults are less ready to engage with eHealth resources for patient education and self-care than younger people, making e-Learning courses essential for the older group (Gordon & Hornbrook, 2018). The elderly population encounters digital disparity in terms of their ability to access and utilise different digital applications, such as health-related applications and patient portals (Gordon & Hornbrook, 2018). A study on people's opinions of DH applications also discovered a link between age and favourable opinions of the technology (Cassidy, 2021).

The significant influence of age on the adoption of DH applications requires a targeted strategy to reduce inequalities and ensure fair access. Addressing these disparities is not just a measure to promote inclusivity, but a fundamental aspect of guaranteeing that DH resources are accessible and advantageous for individuals of all age groups. Prioritising the design and implementation of DH solutions suitable for different age groups and considering the users' abilities and preferences is crucial. This will help create an inclusive DH system.

6.2.3. Education

The analysis results revealed a significant influence of education on the usage of DH applications. The logistic regression analysis showed a Wald statistic of 5.770, a p-value of .016, and a B value of 0.779. This indicates a statistically significant association between education and DH application usage, with higher educational levels positively influencing adoption. The odds ratio (Exp(B)) was calculated as 2.178, suggesting that individuals with higher levels of education are more than twice as likely to use DH applications compared to those with lower education levels, when holding other factors constant. These findings underscore the critical role of educational attainment in predicting and enhancing DH application usage.

The results of this study are in line with the findings from the literature, where education level is a primary factor for the use of DH applications. The use of DH applications has been associated with higher levels of education (Woolley et al., 2023). Additionally, Velthoven and Cordón, 2019 emphasise that education level has been identified as a significant determinant of the adoption of DH applications.

The results highlight the importance of designing user-friendly applications, especially for those with lower levels of education to facilitate the use and accessibility of DH solutions. These findings carry implications beyond the field of healthcare and suggest that educational initiatives may be able to effect significant progress in utilising and integrating emerging applications across industries. Comprehending and utilising the factors that influence the adoption of technology in education will aid in creating comprehensive health interventions and guarantee fair access to healthcare advancements as DH progresses.

6.2.4. Position (Job)

The analysis results revealed no significant influence of position on the usage of DH applications. The logistic regression analysis showed a Wald statistic of 0.253, a p-value of 0.615, and a B value of -0.076. The odds ratio (Exp(B)) was calculated as 0.927, suggesting that a change in position slightly decreases the odds of using DH applications by approximately 7.3%. However, as the p-value exceeds the threshold for significance ($p > .05$), this result indicates that position does not play a meaningful role in predicting the likelihood of DH application usage when holding other factors constant.

The acceptance of DH applications among healthcare professionals appears to be broadly consistent across different work positions, as supported by Shinners et al. (2020). Their study focused on healthcare professionals' understanding and experiences with AI technology in healthcare delivery, highlighting that work position does not significantly influence DH acceptance. Additionally, Vehko et al. (2019) discuss the widespread digitalisation of healthcare, suggesting that acceptance of DH solutions is not isolated to certain professional roles but is a general trend across the sector.

In contrast, the literature acknowledges the importance of individual position in adopting DH applications. For instance, Ben-Gal (2023) investigates how AI-based applications are perceived in primary care settings, indicating that professional roles play a critical role in the adoption process. The picture is further complicated by the findings from the current study, which show that factors like patients' health awareness, empathy needs, and sociodemographic characteristics, such as age and education level, are not significant predictors of readiness to adopt AI-based technology. This suggests that acceptance of DH applications can be influenced by factors beyond just professional position, indicating a more complex interplay of influences at work.

The lack of a significant impact due to professional position on the usage of DH applications indicates that effective implementation can be achieved across all roles in the healthcare sector. This can be attributed to the increasing presence of digital applications and pre-structured learning modules that technology companies are providing to make sure professionals are equipped with the requisite skills to use these applications. The tools are also intended for everybody, whether in healthcare or not. That means that the organisation recognises the digital skills of all employees.

6.2.5. Work Experience

Work experience in the healthcare sector consists of all the clinical and healthcare applied knowledge or skills gathered by an individual. It encompasses a range of competencies, from patient care and clinical decision-making to administrative and operational tasks. This kind of experience plays an important role in shaping the overall clinical understanding of a professional in relation to healthcare processes and patient management.

The analysis results revealed no significant influence of work experience on the usage of DH applications. The logistic regression analysis showed a Wald statistic of 0.500, a p-value of 0.479, and a B value of 0.229. The odds ratio (Exp(B)) was calculated as 1.257, suggesting that each additional unit of work experience increases the odds of using DH applications by approximately 25.7%. However, as the p-value exceeds the threshold for significance ($p > .05$), this result indicates that work experience does not play a meaningful role in predicting the likelihood of DH application usage when holding other factors constant. This suggests only a marginal tendency for DH application usage to increase with the accumulation of work experience. The implications of these findings are substantial, challenging the assumption that more work experience will significantly boost the usage of DH applications.

The view that work experience has no impact on DH usage is supported by a study by Shiferaw et al. (2021), which indicated that longer years of experience were associated with lower digital competency, further supporting the idea that work experience does not necessarily enhance DH experience.

Because of the difference in the utilisation of technology between generations, professionals with greater work experience stick to older ways of doing things because they do not know how to use digital applications. Healthcare practices are often set in stone, which makes it hard to use new digital applications that could change everything. If these applications do not improve clinical outcomes, professionals, especially those with greater work experience, might wonder if they are useful. This complicated situation shows how important it is to have well-thought-out digital adoption plans that consider the specific problems that experienced healthcare professionals face. Also, it is crucial to identify training and support needs for healthcare professionals at various stages of their careers, ensuring a smooth transition and effective implementation of DH practices.

6.2.6. Digital Health Experience

The analysis results revealed a highly significant influence of DH experience on the usage of DH applications. The logistic regression analysis showed a Wald statistic of 49.242, a p-value < .001, and a B value of 2.452, indicating a strong and statistically significant association. The odds ratio (Exp(B)) was calculated as 11.613, suggesting that individuals with digital health experience are over 11 times more likely to use DH applications compared to those without such experience, when holding other factors constant. This means that individuals familiar with DH are over twelve times more likely to use the applications compared to those without such experience, emphasising the crucial role of prior exposure and familiarity in driving the adoption and utilisation of DH applications.

This finding is critical in understanding the dynamics of DH adoption and stresses the importance of practical exposure and familiarity with DH applications in fostering user engagement and consistent application use. The correlation between DH experience and application usage not only highlights user proficiency but also suggests that continued interactions with DH systems may develop user trust and confidence in these applications for healthcare management.

These findings are supported by work of Mohammed et al. (2022) on the influence of DH systems on the future of healthcare, who emphasise that implementing digital systems can support users while also making health information more accessible and actionable. This good experience with DH systems may lead to a more positive attitude towards future applications. Moreover, the study highlighted the impact of mobile health and medical applications on clinical practice in gastroenterology, emphasising that the effects of digital transformation will impact patients and healthcare professionals in the near future (Kernebeck et al., 2020). For this reason, healthcare professionals' experiences with DH applications in specific medical domains might influence their readiness to adopt more applications in the future, especially as they witness the transformative effects of such applications in their practice in treating their patients.

Overall, the findings of the present study suggest that various factors in the healthcare system affect healthcare professionals' use of DH applications. Healthcare environments are complex and changing rapidly (Newton-Lewis & Nanda, 2021), but organisational culture and support systems are crucial to technology adoption (Meskó et al., 2017). The adoption of technology depends on its perceived relevance and immediate usefulness for specific clinical practices (Alkhaldi, 2016). The development and assessment of digital interventions to change health behaviour requires better methods and considerations (Michie et al., 2017). The rapid pace of technological advancement and the complexity of health issues makes DH technology adoption challenging (Patrick et al., 2016). Digital medicine dispensers in home healthcare demonstrate the need to balance efficiency and patient empowerment, making this challenge harder (Nakrem et al., 2018). These factors are the facilitating condition that need to be considered in healthcare technology adoption (Topacan et al., 2010).

6.2.7. IT Skills

The exploration of IT skills in relation to the use of DH applications reveals no significant influence of IT skills on the usage of digital health (DH) applications. The logistic regression analysis showed a Wald statistic of 1.264, a p-value of 0.261, and a B value of 0.268, indicating a lack of statistical significance. The odds ratio (Exp(B)) was calculated as 1.307, suggesting that individuals with higher IT skills are approximately 30.7% more likely to use DH applications compared to those with lower IT skills. However, as the p-value exceeds the threshold for significance ($p > .05$), this finding suggests that IT skills do not play a substantial role in predicting the likelihood of DH application usage within the scope of this research.

Although the logistic regression analysis showed that the self-assessed skill in using computers was not significantly associated with the actual use of DH applications (Wald statistic of 1.264 and p-value of .261), these findings imply that though IT skills might shape the probability use of DH, they are not the sole markers of this study.

This view is supported by the study by Konttila et al. (2019), which emphasises that the successful implementation of new technology requires organisational and collegial support, suggesting that acceptance may not solely depend on IT skills and knowledge. In addition, the study by Kuo et al. (2013) points out that the adoption of mobile EMR systems might be affected by nurses' technological personality rather than their IT skills and knowledge. Furthermore, the study by Perski and Short (2021) involved a narrative review of theoretical and empirical examples from the literature, indicating that DH interventions' acceptability is a complex phenomenon that may not be solely influenced by IT skills and knowledge.

However, these results are consistent with the literature, which shows that IT skills, including digital literacy and proficiency, are key factors in the adoption of DH applications.

According to Woolley et al. (2023), DH applications are more likely to be adopted and used by people with higher IT skills.

Within the complicated healthcare system, it is becoming clearer that IT expertise and knowledge are a prerequisite but not a standalone key factor for the wider use of DH. This realisation arises from the observed disparity between an individual's self-assessed computer proficiency and their actual ability to effectively use DH applications. Considering the complex and varied nature of healthcare practice, which is influenced by factors such as user-centric design, interoperability, and institutional support, it is risky to focus solely on IT proficiency and overlook the other important aspects of digital adoption. Healthcare professionals with a high degree of self-rated computer mastery face difficulty in adopting these digital applications when the processes from their own operational routines are not working to be integrated into the system, or when they see a lack of benefits in terms of clinical returns.

In summary, personal and demographic profile factors, such as age and education, can impact the usage behaviour of using DH applications. These factors should be considered when designing and implementing DH interventions to ensure equitable access and adoption.

6.2.8. Training

The analysis results revealed no statistically significant influence of training on the usage of digital health (DH) applications. The logistic regression analysis showed a Wald statistic of 2.693, a p-value of 0.101, and a B value of 0.722, indicating a non-significant association. The odds ratio (Exp(B)) was calculated as 2.059, suggesting that individuals who have received training are approximately twice as likely to use DH applications compared to those without training. However, as the p-value exceeds the threshold for significance ($p > .05$), this result indicates that training does not have a substantial or statistically significant impact on the likelihood of DH application usage in this study.

This finding is aligned with Müller (2020) and Scott et al. (2016), both of whom suggest that attending training by itself may not be sufficient to drive USE. Additionally, Thapa et al. (2021) stress the role of attitude and SE in willingness to use DH tools, further supporting the idea that training alone may not be sufficient.

Based on this research, the influence of training on the acceptance and usage of DH applications (USE) is complex and subtle. While training programmes are helpful, they may not be enough on their own to ensure extensive use among healthcare professionals. Other factors, such as organisational culture, system compatibility, and ongoing support, also play significant roles (Pathipati and Ko, 2016). The acceptance of DH applications is influenced by various factors such as PU, ease of use, SI, and privacy concerns (Jokisch et al., 2022; Liu et al., 2022). Furthermore, the presence of appropriate infrastructure and continuing technical support are both necessary for the successful adoption of DH initiatives (Labrique et al., 2018; Ebenso et al., 2021).

However, traditional models of technology acceptance and diffusion of innovation have not been able to accurately predict behaviour in the complex domain of health (Ward, 2013). Overall, the acceptance and usage of DH applications are influenced by a multitude of factors, and a comprehensive understanding of these factors is essential for the successful implementation and utilisation of DH initiatives.

Therefore, while training is important, it should be complemented by other factors, such as workflow integration and peer support, to ensure effective technology usage.

6.3. UTAUT Main Constructs Impact

The main constructs of the UTAUT model are PE, EE, SI and FC (Davis, 1989; Venkatesh & Davis, 2000; Alshahrani et al., 2022; Kurniasari et al., 2022; Broetje et al., 2022). The next sections examine how these constructs affect AD public hospitals' DH implementation, using the healthcare professionals' viewpoints.

6.3.1. Performance Expectancy (PE)

PE, as explained previously, is the belief that using technology will lead to gains in job performance. Therefore, when DH applications are considered beneficial and useful in improving work performance, healthcare professionals are more likely to engage with these tools. The analysis revealed a positive relationship between PE and the use of DH applications (USE). The logistic regression output showed a coefficient ($B = 0.087$, $p = 0.264$), although it was not statistically significant. The odds ratio ($Exp(B) = 1.118$) indicates that individuals with higher PE are somewhat more likely to engage with these applications than their peers with lower expectations of performance, but again, this relationship does not reach statistical significance.

This finding supports research such as the work by Zhou et al. (2019), which shows that in certain contexts, like nursing, EE or ease of use may be more effective than PE. Additionally, Xiao et al. (2022) point out that variables beyond PE, like SI and FC, can significantly impact technology usage intentions (USE).

This view contradicts the traditional notion that PE is the dominant factor in technology acceptance, underscoring the need for a broader perspective that considers a combination of influencing factors within the UTAUT framework. Understanding this complex interplay is essential for developing effective strategies to promote the acceptance and use of DH applications.

The discussion on PE should emphasise its crucial role as both a predictor of usage and a component that can be utilised through training and development efforts. Institutions can create a more favourable environment for the widespread adoption and effective use of DH applications by raising healthcare professionals' expectations regarding their performance.

6.3.2. Effort Expectancy (EE)

EE refers to the degree to which a person thinks that using particular technology would be easy for them and takes less effort. It is influenced by factors such as PEOU, cognitive instrumental processes, and perceived interactivity (Venkatesh et al., 2003; Li et al., 2023). Research has found that higher levels of EE are positively associated with acceptance and the use of DH applications (Li et al., 2023).

The analysis revealed a negative relationship between EE and the use DH applications (USE), though this relationship was not statistically significant ($B = -0.077$, $p = 0.426$). The odds ratio of 0.797 suggests that individuals with a higher EE, or a belief that using the technology requires more effort, are slightly less likely to engage with DH applications compared to those with a lower effort expectancy. However, the lack of statistical significance indicates that EE may not be a strong predictor of BI in this context.

While the literature has often highlighted the importance of ease of use, in this instance, the study's findings do not support a significant relationship between the two. This could imply that other factors may be more influential in shaping the behavioural intentions towards DH technology adoption among healthcare professionals.

Holtz and Krein (2011) similarly found that EE did not significantly affect the intention to use (BI) the EMR system among nurses. Similarly, Indah and Agustin (2019) found that EE had a negative effect on the behavioural intention to use Go-Pay, a digital payment application. These findings suggest that in specific contexts, such as DH applications and digital payment systems, the relationship between EE and BI may not align with the UTAUT framework.

In this study, the researcher discovered that 81.6% of respondents adopted DH applications, 82.4% used them for over a year, and 52.9% took appropriate training courses. The users' high self-rated IT skills may explain this result. Comfort with digital applications may reduce the impact of EE on their decision to use them. This suggests that the familiarity and proficiency of users with digital applications diminishes the importance of EE in their decision to adopt and use DH applications. Instead, as users become more skilled and comfortable with the technology, factors like perceived expectancy (PE) and social influence (SI) play a more significant role in influencing their intentions and behaviours. This shift explains why EE is not a strong predictor of technology adoption in this study.

6.3.3. Social Influence (SI)

SI refers to the degree to which individuals perceive that important other, such as colleagues or supervisors, believe that they should use a particular technology (Venkatesh & Davis, 2000; Alshahrani et al., 2022). Recent studies indicate that SI plays a significant role in shaping the acceptance and use of DH applications by professionals (Alshahrani et al., 2022; Janssen et al., 2022).

The analysis highlighted a statistically significant positive relationship between SI and the intentional behaviour (BI) ($B = 0.458$, $p < 0.001$). The odds ratio of 3.544 underscores that individuals who perceive a higher SI are significantly more likely to use DH applications compared to those with a lower perceived SI. This finding suggests that social factors, such as the influence of peers and colleagues, play a crucial role in the adoption and utilisation of DH applications.

This finding aligns with Venkatesh et al.'s (2003) assertion in TAM that social factors can heavily influence an individual's acceptance and use of new technology. Thus, social determinants are a crucial driver of DH system exaptation and utilisation in healthcare environments. The implications of the findings related to SI also notably reveal that DH adoption in AD’s public hospitals is deeply influenced by the emirate’s cultural context, where collectivist ethos plays a pivotal role in shaping perceptions of DH adoption. Thus, the results corroborate and offer important interpretations of related aspects discussed in the extant literature, including resistance to telehealth and mHealth applications, particularly for sensitive services such as mental health, underling that overcoming these issues requires culturally-informed strategies and approaches (Drissi et al., 2022). For instance, the lack of culturally relevant Arabic-language content has been identified as a significant barrier to adoption. Thus, the practical implications of these observations point to the feasibility of recommendations regarding It suggests strategies to enhance DH adoption that should include fostering a supportive environment where influential peers and thought leaders advocate for and demonstrate the benefits of DH solutions and the development of localized DH applications that address linguistic and cultural complexities, thereby fostering greater acceptance among both healthcare professionals and patients.

6.3.4. Facilitating Conditions (FC)

FC refers to the degree to which individuals believe that necessary resources and support are available to use a particular technology. It is affected by other factors such as technical support, information and communication technology infrastructure, and the availability of qualified human resources (Alshahrani et al., 2022; Kurniasari et al., 2022). Research has demonstrated that higher levels of facilitating conditions are associated with a greater acceptance and use of DH applications (Kurniasari et al., 2022; Janssen et al., 2022).

The regression analysis herein has shown that FC do not have a statistically significant impact on the use of DH applications. The Wald statistic for FC resulted in a p-value of .647, suggesting that while there may be a slight positive trend, it is not strong enough to confirm that improvements in FC lead to the increased usage of DH applications within the context of this study. This finding suggests that other factors beyond the immediate environment and support systems may play a more critical role in influencing the adoption and usage of DH by professionals.

This finding is aligned with the study of Vanneste et al. (2013), who found that constructs related to FC influenced BI in healthcare settings, indicating that it may not significantly impact DH acceptance. Additionally, the study by Holtz and Krein (2011) applied the UTAUT model to understand how hospital nurses perceived the implementation of a new EMR system, suggesting that the impact of FC on DH acceptance may not be decisive.

The presence of a sophisticated technological infrastructure in AD public hospitals may have contributed to the finding that FCs did not significantly predict the usage behaviour of DH applications. When users operate within an already advanced IT environment with accessible tools and systems, the relative influence of additional support structures may not be distinct enough to further drive usage behaviour. Moreover, the high self-reported digital literacy among healthcare professionals suggests a level of SE that diminishes the necessity for external FCs, as individuals are confident in their ability to use DH applications without additional support.

At a broader level, these findings also relate to the significant influence that organizational and economic context factors have in shaping DH adoption in AD public hospitals. They indicate empirically that in terms of the organizational context in which AD public hospitals operate, the centralized governance of AD’s healthcare system creates both opportunities and challenges for DH adoption. While larger public hospitals benefit from economies of scale and strong leadership support, smaller facilities face significant resource constraints that impact DH adoption as also discussed by El Khatib et al. (2022). Moreover, economically, the high cost of DH infrastructure remains a critical challenge for smaller hospitals in AD despite government support for healthcare innovation, given that disparities in resource allocation have created an uneven landscape for DH adoption. El Khatib et al. (2022) also noted that financial incentives are essential for promoting equitable adoption across healthcare facilities. Thus, the study highlights the need for a phased implementation approach when considering promising DH solutions in AD public hospitals, wherein foundational technologies such as EHRs are prioritized in resource-constrained settings before scaling to advanced applications like AI and blockchain. Additionally, policymakers must, therefore, explore funding models that incentivize DH implementation in under-resourced hospitals, such as public-private partnerships or performance-based grants.

6.3.5. Behavioural Intention (BI)

In this study on DH adoption in AD public hospitals, The regression analysis indicates that Behavioural Intention (BI) does not have a statistically significant impact on the usage of DH applications. The Wald statistic for BI was 0.210, with a p-value of .647, suggesting that while there may be a slight positive association, it is not strong enough to conclude that variations in BI lead to increased usage of DH applications within the context of this study.

According to Ajzen (1991), the theory of planned behaviour (TPB) simply suggests that intention does not always translate directly into behaviour, especially in complex environments like healthcare, where external barriers such as infrastructural limits or organisational inertia may impede actual usage (USE). In addition, Kim and Park (2013) illustrated the impact of the socio-cultural context within healthcare organisations, which can either facilitate or restrict technology adoption. Holden and Karsh (2010) also suggest that technology-specific characteristics like perceived ease of use (PEOU) are important mediators of the intention-usage relationship.

Gagnon et al. (2016) further illuminate the intrinsic complexities of the healthcare sector, such as sudden situations and fluctuating priorities, which can disrupt intended usage

patterns. These findings suggest that the simple models assuming a direct influence of BI on USE may not fully capture the nuanced reality of technology adoption in healthcare.
Thus, addressing these challenges requires more than just acknowledging the intention to use applications, but necessitates comprehensive strategies that embrace a broader set of facilitating and hindering determinants. Enhancing infrastructure, providing adequate training, and fostering an organisational culture conducive to innovation are crucial in bridging the gap between intention and usage.

In conclusion, this study underlines the need for a multifaceted approach to understand and enhance DH adoption, compelling a comprehensive assessment of the ecosystem influencing technology use in healthcare settings. This includes individual capabilities, organisational culture, infrastructural readiness, and the broader socio-cultural context.

6.4. Proposed Constructs

6.4.1. Self-Efficacy (SE)

SE is an individual's belief in their own ability to perform successfully a particular task or behaviour (Jokisch et al., 2022). This confidence in one's own abilities enables healthcare professionals to overcome any perceived difficulties or barriers when using technology. This increases their confidence in navigating and effectively using DH tools, resulting in greater adoption. Thus, SE makes a positive contribution to the implementation of healthcare technology, allowing professionals to accept and apply technological advancement in their practice.

The analysis indicates a significant and positive association between self-efficacy (SE) and behavioural intention (BI) to use digital health (DH) applications. The results revealed a path coefficient of 0.257, a T-value of 2.945, and a p-value less than .01, underscoring that healthcare professionals' confidence in their ability to use DH applications effectively is a crucial determinant of their behavioural intention to adopt these technologies. This finding is consistent with Bandura's (1977) theory of SE, emphasising the role of self-confidence in performing tasks.

The findings are supported by the literature, which states that SE influences professional acceptance and the use of DH applications (Jokisch et al., 2022; Tetri & Juujärvi, 2022). Higher levels of SE have been linked to a stronger desire to use these applications (Jokisch et al., 2022). The relationship between SE and technology acceptance is mediated by PU (Davis et al. 1989; Tetri & Juujärvi 2022). SE is a significant predictor of older adults' intention to use DH services (Jokisch et al. 2022).

In conclusion, this finding points to the need for training and educational programmes aimed at enhancing the technical skills and self-assurance of healthcare professionals, fostering a more proficient and widespread adoption of DH systems.

6.4.2. Management and Leadership Involvement (MLI)

MLI is distinct from FC in healthcare technology adoption. Unlike the practical focus of FC, which ensures that healthcare professionals have the necessary tools and support for the daily operation of DH applications, MLI takes a strategic stance. It involves senior staff and administrators actively supporting and guiding DH usage, establishing policies, and fostering a culture that prioritises technological advancement. This strategic approach ensures that any DH initiatives are in line with the organisation's broad goals and gain support across all levels.

The analysis indicates a significant and positive association between management and leadership involvement (MLI) and behavioural intention (BI) to use digital health (DH) applications. The results revealed a path coefficient of 0.339, a T-value of 4.592, and a p-value less than .001. This highlights the critical role of effective leadership and management support in fostering the adoption of DH systems. Convincing leadership not only drives the integration of technological solutions but also creates a conducive environment that encourages acceptance and optimal use of these innovations in healthcare settings.

The findings in this study show that MLI significantly affects DH application usage. This study emphasises the importance of understanding professional needs and preferences when using DH applications. A statistically significant correlation exists between DH application use and professional healthcare function. The findings indicate that effective management and leadership are crucial for the adoption and use of DH applications.

These findings are aligned with the literature, which declares that management involvement plays a decisive role in the acceptance of healthcare applications by professionals (AlQudah & Shaalan, 2021; AlQudah et al., 2021; Cobelli & Blasioli, 2021; Al-Marzouqi et al., 2022; Ljubicic et al., 2022). Top management support positively influences technology acceptance and facilitates implementation, whereas a lack of management support hinders adoption (Alsyouf & Ishak, 2018). Trust in technology and the organisation is also influenced by management involvement, impacting acceptance (AlQudah & Shaalan, 2021; Al-Marzouqi et al., 2022). Management involvement addresses difficulties by providing resources, training, and support and enhancing digital literacy skills (Alsyouf & Ishak, 2018). It also contributes to creating a positive organisational culture that promotes technology acceptance (Al-Marzouqi et al., 2022). Clearly, MLI is critical for fostering a positive environment for technology acceptance and the successful implementation of healthcare applications among professionals.

It is also important to note that effective leadership and management is also contingent on the regulatory context in which healthcare operates in the AD. Thus, in the context of the wider literature as addressed in research such as Jain (2023), these results indicate that AD's unique regulatory context can also influence DH adoption by public hospitals. Unfortunately, these effects, mediated through the clarity of measures to guide MLI in their support of DH adoption efforts are a source of barriers in the UAE context. Jain's (2023) empirical research identifies barriers to DHI adoption that work by minimizing MLI effectiveness, including the absence of explicit telehealth legislation and concerns over digital consent in healthcare data use and management, which were found to limit trust among healthcare professionals and patients. Therefore, these findings point to the much-needed direction towards a comprehensive regulatory framework that aligns with international best practices while accounting for AD's unique context, which can promote DH adoption by addressing extant concerns with regulations as well as providing the clarity needed to reinforce MLI.

6.5. Implications on the UTAUT Model (Revised UTAUT Model)

This section explores the implications of this study on the original UTAUT model and further aspects of Research Question 4. The thesis makes significant theoretical contribution by advancing the understanding of DH adoption through the extension of the UTAUT model in a manner successfully addressing critical gaps in the literature concerning the unique factors that influence technology adoption in AD. Unlike prior research, which primarily examined DH adoption through the original UTAUT constructs (Venkatesh et al., 2003), this study contextualizes these constructs to AD’s public hospital setting, thereby providing locally adapted and relevant framework that fits the more nuanced context of the research focus (Alrahbi et al., 2021).

The revised and final UTAUT model extending the unified theory and use of technology was developed through an iterative process, combining theoretical argument with empirical evidence. Originally, the core UTAUT constructs of PE, EE, SI and FC were used as the foundational elements to assess DH adoption among healthcare professionals in AD public hospitals. While the research was progressing, it became evident that additional factors played an important role in behavioural intention to adopt DH applications. SE and MLI were incorporated into the model as both were shown to substantially affect an individual's willingness to try these new solutions. Confirmatory and exploratory factor analyses confirmed that these elements accurately captured the determinants of intention in this medical environment. Empirically assessing the framework revealed that SI, SE, and MLI were robust indicators of BI, which in turn shapes whether applications are actually utilised.

However, when PE and EE were evaluated on their own, they did not appear to sway intention in this particular context. Instead, it was revealed that FC and personal and demographic factors for healthcare professionals, including age, education, DH experience and training, directly influence the independent variables. Considering these factors enabled prediction of whether healthcare professionals would or would not engage with DH tools depending on infrastructure support, technical assistance, and their experience. As a result, the final model comprises SI, SE, and MLI as key drivers of BI, while FC and demographic factors were validated as significant predictors of USE. All results in the final model that reflect the relationships between the factors explored in the study were proven to have an impact on BI and USE (see Figure 6.1 for the revised model).

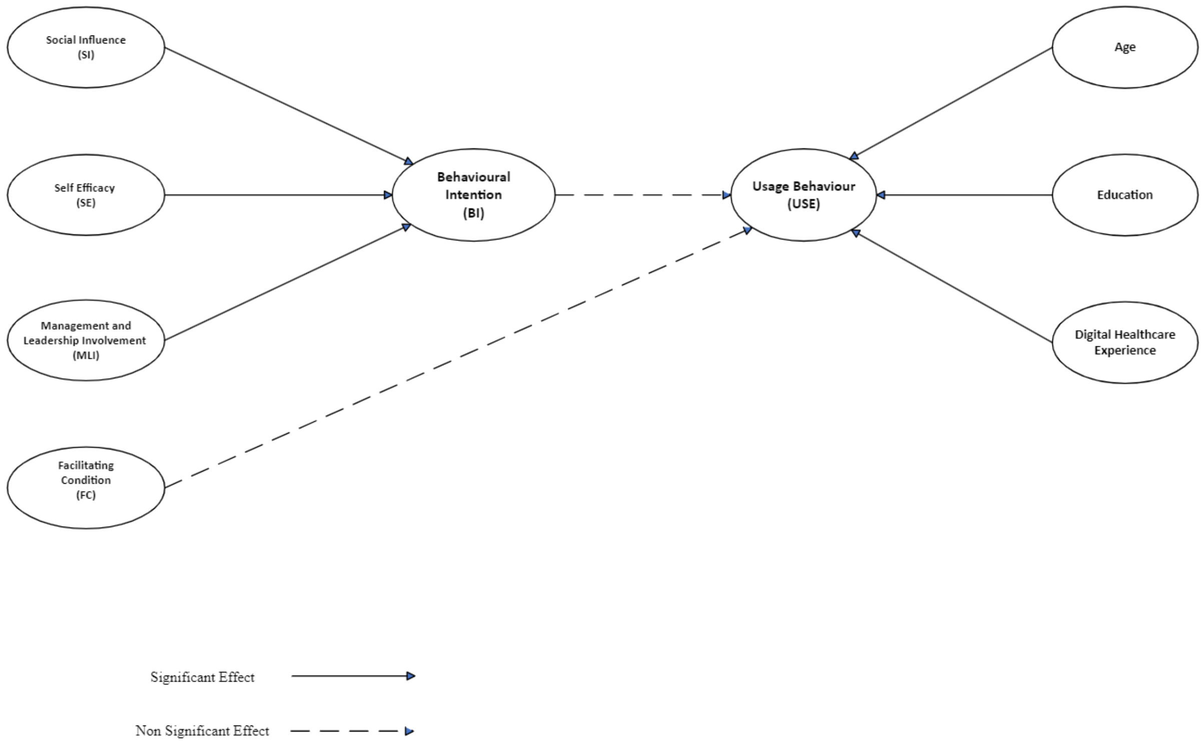

Figure 6.1 **Revised UTAUT model**: This figure shows the final modified UTAUT model, reflecting empirical findings from the study.

The study's results offer significant implications for the usage of the UTAUT model to understand the application of DH to AD public hospitals. SI, SE, and MLI were the most effective predictors of BI, showing the importance of the social and organisational factors in healthcare technology use. The model, initially proposed by Venkatesh et al. (2003), is centred on the four main contributing factors, PE, EE, SI, and FC. However, SI turned out to be the overwhelmingly predominate factor in this study, meaning that the involvement and support from peers, colleagues, and leadership was the decisive factor in the adoption of DH applications at the AD public hospitals. The applicability of SI as a major predictor was supported by the multiple earlier studies showing that social influence is of critical importance in shaping healthcare professionals' intention to implement new applications. SE was not directly connected to the UTAUT model, which explains why the analysis proved it to be less predictive, yet not inconsequential.

The concept of SE, which refers to the user's confidence in their own skills when fulfilling required tasks, has been successfully applied by many earlier technology acceptance models, especially in the context of healthcare. This result shows that healthcare professionals will only tend to adopt DH applications if their SE levels are high enough.

MLI is also a major driver for DH adoption. The inclusion of SE is one of this thesis' most important contributions in expanding the current knowledge in the research area because it highlights how healthcare professionals' confidence in navigating DH systems directly influences their BI, corroborating existing literature on technology acceptance, which emphasizes the importance of user readiness and training in driving DH adoption (Abdallah et al., 2021). The importance of managerial help to guide, support and facilitate the uptake of DH applications was underscored in this study. It is leadership that instils a culture of innovation and use of DH applications. This finding is consistent with other research, which stresses the importance of management support to create an encouraging environment for technology adoption.

In contrast, FC, which include access to technical support and necessary resources, had a less significant impact on BI. This finding contrasts to that in other studies where FC were found to be important but is consistent with research conducted in environments with advanced infrastructure. In AD, FC are considered less relevant because public hospitals are well-equipped, and healthcare professionals already have access to advanced technological support; therefore, organisational and social factors seem to be more important.

Personal and demographic factors also performed as important predictors of USE. Age, education level, experience with DH and training were significant predictive factors emerging from the analysis; all of which correspond to results reported in previous studies that confirm the vital role played by training and DH experience in technology adoption. However, unlike other studies, gender, position, and IT skills were not significant predictors of USE in this context. This difference from the existing literature suggests that in AD, where digital literacy is relatively high, these personal and demographic factors may play a less significant role in impacting DH adoption.

The findings imply that when the UTAUT model is adapted in a healthcare context, variables like SE and MLI should be considered as direct determinants of BI. Thus, in well-resourced environments like AD, SI and MLI are more important than FC in predicting DH technology use. The findings provide a roadmap for scaling DH adoption beyond AD to the wider Middle East region and even globally based on the thesis' empirical demonstration of the feasibility of extending the UTAUT framework to incorporate context-specific variables. Through this successful extension, the study sets a precedent for applying similar adaptations in other culturally and economically diverse regions by offering a proposed framework that can serve as a blueprint for addressing the challenges of DH adoption in non-Western healthcare settings, thereby contributing to global scholarship on technology acceptance.

Future research should test these associations more rigorously in other healthcare contexts, and especially in less-developed settings where infrastructure could be more of a barrier to technology adoption.

From a practical perspective, the theoretical advancement and innovation this study presents offers actionable recommendations for under DH adoption and addressing adoption barriers in AD's public hospitals. This research also bridges the gap between theory and practice by identifying key success factors for DH implementation. For instance, the analysis of significant predictors such as SE and MLI offers valuable insights for hospital administrators and policymakers seeking to foster a culture of innovation. These findings emphasize the need for a user-centric approach to DH deployment, which prioritizes the needs and preferences of healthcare professionals while ensuring robust infrastructure and leadership support. The practical, evidence-based interventions that the research supports include the development of targeted training programs to build digital literacy among professionals, particularly those with limited IT skills, as well as the introduction of multilingual support systems to cater to the diverse expatriate workforce in AD. Additionally, it is clear from the implications of implementing the revised theory in action that policymakers should prioritize the establishment of clear regulatory frameworks for better DH adoption outcomes.

6.6. Summary

This chapter explores the interpretation of the findings in connection with the initial research questions presented in Chapter One. The study is concluded in the following chapter, where the findings are reframed in terms of their contribution to the current understanding of the factors influencing the adoption of DH in AD Public hospitals and offer some suggestions for improving the adoption process better going forward.

7. Conclusion

This chapter summarises the main findings and contributions of this research, followed by the practical implications of aiding technology adoption by enhancing DH acceptance in public hospitals in AD, as well as limitations of this study. Some ideas for further research are also provided. Before turning to the contributions of this research, it is necessary to recall the research objectives and summarise how they were achieved. This research aimed to investigate the factors impacting the acceptance and use of DH applications among healthcare professionals in AD public hospitals, utilising the UTAUT model as the guiding framework. The specific research objectives were:

- To what extent and why do personal and demographic factors explain the variances in the actual usage of DH applications in AD public hospitals? These questions were answered through statistical analyses, confirming that age, education, and DH experience had a significant impact on USE. Conversely, the factors gender, position, IT skills, work experience and training were found to have no significant influence, leading to their exclusion from the final model.
- To what extent and why do PE, EE, SI, and FC explain the variances in behavioural intention (BI) and actual usage of DH applications in AD public hospitals? The analysis demonstrated that SI strongly impacted BI, while FC directly influenced USE. However, PE and EE were found not to significantly impact BI in this context.
- To what extent and why do SE and MLI impact the BI to use DH applications? The study confirmed that both SE and MLI were significant predictors of BI, emphasising the need for personal confidence and strong leadership to drive adoption.
- How can the UTAUT model be used to understand better what healthcare professionals in AD public hospitals perceive they need in order to adopt DH applications effectively? Based on the empirical findings, several recommendations were developed, aimed at addressing the barriers identified and leveraging the drivers of DH adoption to improve the overall acceptance and usage of these applications.

Through addressing these questions, the study successfully completed its aim of providing a comprehensive understanding of the adoption of DH applications in AD public hospitals. These findings have important implications for policy, management, and healthcare practice, contributing to the growing body of knowledge on DH adoption.

7.1. Contribution to Knowledge

This research expands significantly on existing models of technology adoption, specifically enhancing the UTAUT model through the inclusion of SE and MLI. While the UTAUT framework has been widely utilized in various settings, its application to DH adoption, particularly in AD's healthcare system, introduces crucial insights. Studies like Venkatesh et al. (2003) and Davis (1989) laid the groundwork by examining general technology acceptance; however, this study adapts these models to account for the unique cultural, economic, and organizational characteristics present in AD. It is clear based on the results generated by this thesis that classical theoretical approaches to exploring technology acceptance may be limited in unique contexts because they are not effectively tailored to address these sociocultural, economic and organizational factors that are specific to non-Western contexts, such as AD public hospitals. In fact, the study's results challenge prior assumptions in classical UTAUT models, where PE and EE were often regarded as strong predictors of adoption. However, in AD's public hospitals, these constructs had limited significance in predicting BI to use DH applications. This discrepancy suggests that in non-Western healthcare systems, where organizational culture and professional experience may shape perceptions of technology, SI and MLI may play a larger role than perceived usefulness or ease of use. In this regard, this study's extension and modification of the UTAUT model provides a stable framework using which the more complex nature of DH adoption determinants in non-Western contexts can be better understood.

The specific findings that this study's application of the extended UTAUT model generates also provided novel findings that expand the current literature and body of knowledge. SE emerged as a powerful predictor of healthcare professionals' BI and USE) of DH applications, supporting Bandura's (1997) theoretical stance that individuals' beliefs in their capabilities directly impact their actions. This was particularly significant in AD, where healthcare professionals' confidence in their ability to use DH systems is crucial for successful DH adoption. In this study, SE is shown to directly contribute to higher adoption rates, echoing the need for pertinent interventions for enhanced SE.

Furthermore, MLI proved to be a critical factor in driving DH adoption in AD's public hospitals. MLI is essential in creating a supportive organizational culture that encourages technological change. This study uniquely demonstrates how hospital leaders' active participation in the planning and execution of DH projects can increase acceptance rates among healthcare professionals, a critical finding that should be leveraged in AD's healthcare reforms. Thus, the thesis positions at the centre of the DH adoption discourse the proposition that leadership-driven initiatives mitigate resistance to technology adoption to promotion adoption outcomes in sociocultural unique healthcare contexts. Overall, this thesis' primary contribution is that it produces a new theoretical framework and pertinent findings unique to the AD public hospital context that future research can find useful as a foundation for further research to evaluate the replicability of these findings in wider contexts across the UAE, in the Middle Eastern region, and globally.

7.2. Practical Recommendations

7.2.1. Measures and Interventions

Based on the findings of this study, the following practical, evidence-based recommendations are indicated:

1. Improving IT Training and Education

Implementing DH requires a well-planned, comprehensive education and training framework to ensure that healthcare professionals in AD are capable of adopting and utilising the latest applications. The intention of healthcare professionals is influenced by their DH experience in daily practice as well as the level of training they have as regards DH applications. That is why it is wise to organise regular obligatory training sessions concerning IT competencies and dexterity (including digital competencies). Further, healthcare professionals would also be more confident about the technical requirements of DH with sessions to educate personnel at all levels about system functionality, data security, and patient privacy.

In addition, the use of experiential learning approaches, like simulations and role-playing, enables staff to practice using digital applications within a safe setting, reducing anxiety and increasing levels of comfort before transferring the digital applications into real-world settings. The results underscore that it is imperative to provide continuous learning opportunities (e.g., workshops, seminars, e-learning platforms, certification courses) in order to support the use of digital applications, as professionals need to be current with evolving technological capabilities. These training techniques are also important to develop DH skills in healthcare providers, thus improving patient care and system-wide adoption.

Main recommendation components:

Curriculum Development: Design and evolve an extensive curriculum with a focus on DH applications (e.g., EHRs, telemedicine, mobile health apps).

Specialised training for healthcare professionals: Incorporation of the specialised modules of health technology in nursing and other healthcare field education, so that these professionals are trained well in DH techniques.

Practical experience and simulation: Hands-on experiences are integrated, both in terms of training and performing some experiences and using DH applications.

Lifelong learning for healthcare workforce: Create continuous education programmes to update digital skills and knowledge of in-service personnel as technology evolves.

Partner with tech companies and universities: Ensure that the curriculum remains up to date.

This approach can be applied to increase the digital readiness of the healthcare workforce in AD public hospitals.

2. Promoting Management and Leadership Involvement

The involvement of hospital management and leadership in DH applications is a known determinant of attaining success. The results showed leadership involvement to be a strong determinant of behavioural intention among healthcare professionals to incorporate digital applications into their practice on a regular basis. Consequently, hospital leaders should actively establish or participate in the planning and implementation of DH projects.

Study participants emphasised the importance of involving healthcare professionals in the early stages of planning. This involvement ensures that the technology can be adapted to meaningful needs instead of requests from doctors, resulting in better usability and acceptance.

Additionally, hospitals should establish incentive programs that recognize and reward healthcare staff who show exceptional skill or innovation in utilizing DH applications. Celebrating these successes not only boosts morale but also motivates others to engage with digital innovations, thereby fostering an organizational culture that values and encourages digital innovation. This recognition is a crucial motivator for continuous personal development and collective advancement towards superior healthcare provision.

3. Establishing a Collaborative Regulatory Framework

A national committee should be formed, consisting of representatives of the MoH, DoH, other regulators, healthcare professionals, and technology experts in the UAE to unify policies on implementing DH. The committee's role would be to:

- Create comprehensive regulations, including data privacy, security, interoperability, and user interfaces, that meet the needs and specificities of healthcare professionals.
- Approve and implement training courses to enhance DH literacy and SE as a required aspect identified in this study, and value creation training to familiarise healthcare professionals with several DH tools and value creation.
- Motivate and reward healthcare professionals and institutions for integrating DH across the hospital spectrum, with recognition or funding.
- Initiate periodic audits followed by reports every two years to achieve compliance with the created regulations and to identify the need for further consultations and guidance.
- Provide regular reports to the MoH along with updated and revised regulations reflecting healthcare technological advances.

The proposed solution agrees with relevant studies previously discussed in the literature review, on management participation, training, and continued support.

4. Continuous Technical Support

Continuous support for healthcare professionals using DH applications is a multifaceted endeavour that ensures not only the resolution of immediate technical challenges but also the sustained adoption and optimization of these tools. Selecting digital solutions that align with an organization's specific needs is crucial, as is partnering with vendors known for exceptional ongoing support. Effective support services empower healthcare workers to utilize digital applications more efficiently, ensuring their consistent performance over time.

To facilitate this, healthcare organizations should establish a dedicated IT support team that is available 24/7 to address any technical concerns. Providing healthcare staff with accessible resources such as quick reference guides, frequently asked questions (FAQs), and troubleshooting manuals can proactively resolve common issues. Additionally, offering individual support sessions for staff who require extra assistance ensures that each team member can competently navigate the digital landscape. This comprehensive support framework is critical for creating a seamless DH experience that benefits both providers and patients.

5. Boosting Self-Efficacy

The improvement of SE among healthcare professionals is a key driver in the successful adoption of DH applications. This study found powerful evidence that more significant levels of SE were positively associated with greater odds in favour of digital application adoption. As such, it is necessary for healthcare organisations to increase SE with interventions and long-term technical support.

Increasing the usage of digital systems in day-to-day practice will help build confidence in healthcare professionals to use these systems efficiently. Professionals who are confident in their ability to use DH applications have been found to be more likely to accept innovation, which could potentially lead to better quality of healthcare. Healthcare organisations can increase the overall adoption of digital applications by creating a supportive environment for staff to grow their competencies.

7.2.2. Stakeholders' Actionable Roadmap

Based on the results and recommendations of this study, AD's policymakers should adopt a phased and strategic approach to achieve successful adoption of DH tools within public healthcare institutions. The first part of this actionable roadmap is to create a collaborative regulatory framework. This thesis suggests the formation of a national committee, comprising stakeholders from government ministries and agencies involved in the nation's healthcare policies and services, healthcare professionals, and healthcare technology experts. The intent of this committee will be to propose standardized regulations, in pertinent areas, such as data privacy, security, and interoperability to promote the integration of DH solutions within healthcare institutions. Policymakers will then prioritize the development of comprehensive regulations that will provide enough clarity for healthcare providers and technology developers so that trust and consistency are developed within this ecosystem. They should also oversee the development, implementation, and standardization of the training of healthcare professionals for digital literacy and self-efficacy in relation to using DH tools.

This regulatory foundation should then be followed by interventions to enhance leadership involvement in addressing DH resistance as the next priority action. The planning and implementation of DH projects must be overseen not only by hospital leadership but also entail healthcare professionals' and public support. The management of hospitals should make sure that DH goals are embedded within other organizational strategies and that these initiatives strictly fit with other clinical needs and priorities. The leadership must also promote and cultivate an innovative culture through evidence-based measures like incentive programs developed to reward healthcare professionals who excel in utilizing DH applications in practice of their daily work to strengthen patient and overall healthcare outcomes. Policymakers at the organizational level can drive leadership driven initiatives with an atmosphere of rewarding of digital innovation that will lead to more buy-in from healthcare professionals and less resistance to DH tools.

At the same time, policymakers need to provide healthcare professionals with continuous training in IT and improve IT training as the third priority. Part of this recommended effort covers the development of a comprehensive training framework involving hands on learning, simulation exercises, and e-learning modules. This effort presents a major opportunity for DH training programs to grow and evolve alongside technical advancements, making sure that ongoing or continuous education programs can keep healthcare staff informed about the most pressing and cutting-edge developments in DH. This will help keep the workforce adaptive and comfortable using digital health tools. Efforts should also be implemented to ensure that training curriculums remain relevant and current, as lifelong learning across the healthcare sector is simultaneously supported by partnerships with tech companies and universities. With these actions, AD will build a digitally competent workforce that can realize efficient patient care through the use of innovative DH solutions.

The figure 7.1 below highlights a roadmap for adopting DH tools in AD, prioritizing immediate regulatory frameworks for data privacy and interoperability. Long-term goals include leadership involvement to drive innovation, IT training for healthcare professionals, and sustained workforce adaptability through continuous learning and collaboration.

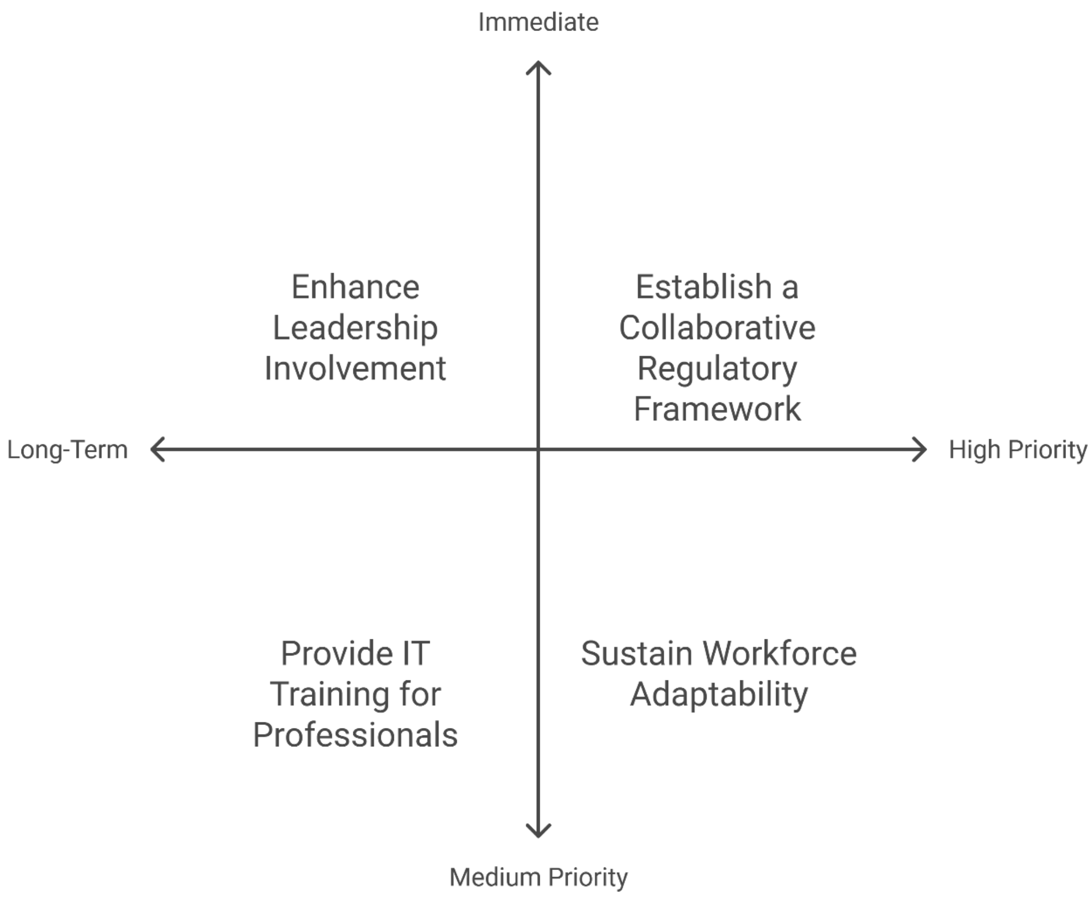

Figure 7.1 **Prioritized Roadmap for Digital Health Adoption**: This figure maps key priorities based on urgency and importance

7.3. Limitations of the Study

Conducting research relying only on survey affects the study's quality in terms of validity and reliability. Surveys can gather different perspectives and also collect quantitative data for statistical analysis. However, subjective interpretations by the participants make self-reported measures prone to bias or inaccuracy. The participants' answers reflect a range of experiences, and responses are constrained by the researcher's available resolution. In this research, not all of the participants responded to the surveys; this can produce a non-response bias. In addition, researchers should be cautious about generalising results from a survey to larger populations, given the self-selection that occurs with surveys. For example, one of the issues encountered by the researcher was that some of the participants did not return completed questionnaires. This was likely an artefact from how the questionnaire was designed (participants were not required to fully complete the questionnaires before submission). Consequently, in some cases, not all the questions were answered by participants, leading to data loss. This limitation may reduce the quality and reliability of a study as missing data can introduce bias that could threaten the validity of the findings. Future research should include checks to ensure that participants complete the questionnaire in full.

This research was carried out with healthcare professionals from AD public hospitals, and the results cannot be generalised to other regions (countries), or to different care contexts. This study targeted professionals in AD only, and it is unique as the context of this region and its characteristics might influence the acceptance and utilisation of DH applications differently than other regions. The cultural aspects, healthcare infrastructure and organisational policies in AD public hospitals might have influenced the thesis results, which were limited to only a single geographic region. Consequently, care should also be taken when trying to generalise these results to other geographic areas and health systems. It would also be important to undertake more studies in multiple settings to replicate and extend the findings of this study in order to develop a more complete picture of DH acceptance across different national circumstances.

This research was limited by the exclusive involvement of healthcare professionals in the DH acceptance assessment, and implications need to be carefully considered due to the lack of inclusion of managers or leaders. Thus, the results may lack generalisability to all of the AD healthcare professionals in DH, reinforcing a need for caution concerning the interpretation of results.

A noticeable problem faced when researching for this thesis was the scarcity of targeted literature or studies about using DH in UAE, and in particular, hospitals in AD. As a result, it was hard to get a clear perspective of the DH status on the subject. A limited number of UAE-based resources led to the use of Middle Eastern or global studies, due to availability and feasibility. While these overarching themes are useful, they may not account for the nuances and challenges or opportunities of DH practices in the UAE health sector. This means that although the study is a sound starting point to identify what areas of health are being researched in and around this country, it highlights the need for more comprehensive studies when examining DH in the UAE, especially within AD's healthcare ecosystem.

Another limitation of this study is that data collection was conducted using only one method, an online questionnaire. This was largely because of the goal of the study and the limitations of available resources. As such, the researcher spent a considerable amount of time collecting and analysing data; the goal had been to recruit as many moderators as possible so that it would be a representative sample within this population. There were some issues faced when performing the statistical analyses, which are harder to perform, and it is obvious that the researcher was a professional with no experience in using these methods. This meant that the statistical analysis in this study was very complex, and, as a result, an official Chartered Statistician was needed to provide guidance.

7.4. Recommendations for Future Research

Subsequent research on the acceptance of DH in AD public hospitals may need to be more focused on what is available and indeed used, with a view to exploring and analysing this further. To the best of the researcher's knowledge, no specific evidence is available to further comprehend why these applications are accepted and used by AD public hospitals; future studies can explore these applications (e.g., telemedicine, EHRs, and remote patient monitoring tools) in such a context-based mode.

The study population was restricted to people linked with public hospitals in AD; hence, private sector participants were exempted from inclusion. While this study provides important information in the public health field, little insight into DH practices in private settings is still a notable limitation. More research should be done in this unexplored area to provide a more complete picture of the healthcare system for AD health professionals.

Policies and regulations have a central role that evidence more in-depth investigation. The AD healthcare system functions within a regulatory framework just like many others worldwide, and insights into how this may affect DH can be useful. Future studies could investigate how these policies and guidelines serve as either barriers or enablers to integrating DH tools, potentially uncovering areas in need of refinement or enhancement for streamlining the delivery of care.

The study of the uptake and use of DH in practice shows that physicians and other healthcare practitioners are concerned about security and privacy. They want good digital applications, but they also need to be cautious about patient information. However, the more they believe that digital applications respect the secrecy of data, they will be more likely to use them and will persuade those around them. Hence, it may be more productive to research what these professionals fear regarding safe use, and how DH tools can address these concerns. This might then be able to make those tools more accepted and used in hospitals. Although the present study may offer unique and useful views into the realm of DH, the door is open for a qualitative approach to better understand DH. Qualitative interviews with a purposeful sample of decision-makers and hospital managers could provide further insights into the strategic relevance attributed to DH. Recommendations for future research are to explore through a qualitative lens what motivates, challenges and drives key stakeholders to advocate or mainstream DH tools. This is an approach that would provide us with more knowledge and, at the same time, carry possible regulatory guidance to increase the odds of a successful enthusiasm for DH across various healthcare institutions.

Research should be conducted on DH in different domains and emirates to explore the insight of healthcare professionals throughout the country with respect to the perception and adoption of DH applications. This undertaking should enable synergies between different healthcare stakeholders in the country, thus lending coherence to nationwide efforts that address challenges and obstacles to scaling the implantation of health technology. These entities can all contribute to making better use of DH, and where one falls short, another(s) should prevail. This combined strength has the capability to elevate healthcare standards and save time and resources from being wasted, ultimately serving the nation.

7.5. Summary

This chapter highlights the primary findings and contributions of this study, discusses the limitations encountered, and proposes suggestions for future research and practical recommendations. The research fills a research gap, as it is the first study, to the researcher’s knowledge, which suggests and validates an explanatory model for acceptance of DH applications in AD public healthcare. These findings offer insights into the factors influencing technology acceptance and can help policymakers and hospital managers formulate strategies for seamless integration. The limitations include incomplete questionnaires and potential bias in self-reported measures. Additionally, the study's focus on AD public hospitals may limit its generalizability to other regions or healthcare settings. Recommendations for future research include exploring the acceptance and utilization of specific DH applications, considering private sector perspectives, examining the impact of policies and regulations, and incorporating qualitative perspectives through interviews with decision makers. It is crucial to conduct research in various areas to gain a comprehensive understanding of DH adoption nationwide. This collaborative effort can lead to improvements in healthcare services and resource utilization.

8. References

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Appendix 1: Questionnaire

Questionnaire

Q1. By selecting the "Yes" option, you consent to participate in this survey.

- o Yes (Please Complete the following form)
- o No

Q2. What is your Gender:

- o Male
- o Female

Q3. What is your age:

- o 21-30 Years
- o 31-40 Years
- o 41-50 Years
- o 51-60 years
- o > 60 Years

Q4. What is your Education?

- o Diploma
- o Bachelors
- o Masters
- o Doctorate

Q5. I am a

- o Physician
- o Nurse
- o Pharmacist
- o Other ....

Q6. Years of Experience:

- o < 1 year

- 1 - 10 years
- > 10 years

Q7. Do you currently use any DH application(s)?

(DH consists of mobile health (mHealth) applications, electronic health records (EHRs), electronic medical records (EMRs), wearable devices, telehealth and telemedicine.)

- Yes
- No

Q8. DH Experience:

- < 1 year
- 1 - 5 years
- > 5 years

Q9. How frequently do you use DH technology?

- Not at all
- Rarely
- Sometimes
- Often
- Always

Q10. How do you rate your computer knowledge and skills?

- Very Poor
- Poor
- Average
- Good
- Very good

Q11. What are the applications of DH you use most ?

		Not at all	Rarely	Sometimes	Often	Always
11.1	Mobile health (mHealth)					

11.2	Electronic health records (EHRs), electronic medical records (EMRs)					
11.3	Wearable devices					
11.4	Telehealth and telemedicine.					
11.5	Other ……………………….					

Q12. Have you attending any training programmes in how to use DH technology?

- o Yes
- o No

Q13. Performance expectancy (These questions seek to determine the extent to which you believe DH applications currently facilitate your job performance)

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
13.1	PE1	I find DH Applications useful in my work					
13.2	PE2	Using DH applications enable me to accomplish tasks more quickly					
13.3	PE3	Using DH applications make it easier to treat patients					
13.4	PE4	Using DH applications					

		increase my productivity					

Q14. **Effort Expectancy** (with these questions, we want to know how easy it is for you to use DH applications right now.)

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
14.1	EE1	I find DH Applications easy to use					
14.2	EE2	I have the skills I need to use the DH applications in my hospital					
14.3	EE3	Learning to operate and use a new DH technology is easy for me					

Q15. **Social Influence** (The purpose of these questions is to find out what you think other people think about how you use DH applications.)

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
15.1	SI1	Supervisors think that I should use DH technology					
15.2	SI2	My colleagues have helped me					

		to use DH technology					
15.3	SI3	Most staff in my hospital think DH is important					

Q16. Facilitating conditions (The purpose of these questions is to determine your opinion of the current facilities that support your use of DH applications.)

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
16.1	FC1	I have access to devices used for DH easily					
16.2	FC2	I have the resources necessary to use DH applications in hospital					
16.3	FC3	A team is available for assistance with DH applications					

Q17. Self-Efficacy (SE)

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
17.1	SE1	I can do a job or task using					

		DH applications if no one is around to tell me what to do.					
17.2	SE2	I can complete a job or task using DH applications if I can call someone for help if I get stuck.					
17.3	SE3	I can complete a job or task using DH applications if I have just the built-in help facility for assistance.					

Q18. Behavioral Intention

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
18.1	BI1	I intend to use DH applications in the future					
18.2	BI2	I predict I would use DH applications in the future					

18.3	BI3	I intend to attend a training programme on using DH applications in the future					

Q19. Management and leadership involvement

Q	Code	Statement	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
19.1	MLI1	I believe if administration involve me in the process of implementing new DH technology that will help to adapt easily					
19.2	MLI2	If management share with us the future plans for DH that will help to accept the technology quicker					
19.3	MLI3	Administration encourages me to use DH					

Appendix 2 *Krejcie and Morgan (1970) Sampling Ratio Research Instrument*

N	S	N	S	N	S	N	S	N	S
10	10	100	80	280	162	800	260	2800	338
15	14	110	86	290	165	850	265	3000	341
20	19	120	92	300	169	900	269	3500	346
25	24	130	97	320	175	950	274	4000	351
30	28	140	103	340	181	1000	278	4500	354
35	32	150	108	360	186	1100	285	5000	357
40	36	160	113	380	191	1200	291	6000	361
45	40	170	118	400	196	1300	297	7000	364
50	44	180	123	420	201	1400	302	8000	367
55	48	190	127	440	205	1500	306	9000	368
60	52	200	132	460	210	1600	310	10000	370
65	56	210	136	480	214	1700	313	15000	375
70	59	220	140	500	217	1800	317	20000	377
75	63	230	144	550	226	1900	320	30000	379
80	66	240	148	600	234	2000	322	40000	380
85	70	250	152	650	242	2200	327	50000	381
90	73	260	155	700	248	2400	331	75000	382
95	76	270	159	750	254	2600	335	1000000	384

Appendix 3 *Cover* letter

Questionnaire Cover letter

Greetings, Sir/Madame

My name is Khalfan Alnuaimi, and I am a DBA student at Sheffield Hallam University in the United Kingdom. I am conducting research to determine the extent to which healthcare-providing organizations have the necessary technical and technological skills to service their potential patients using disruptive technology. The study will explore the different digital healthcare systems across Abu Dhabi, evaluate the successful applications, identify resisting factors, and propose the best possible framework to accomplish the digitalization of healthcare in Abu Dhabi. This research will investigate the reasons why some Abu Dhabi hospitals are more progressive than others when it comes to adopting digital healthcare, even though they all use the same vendors and solutions. Moreover, this study will help policymakers and healthcare-providing organizations/ professionals to understand the facilitating and hindering factors for healthcare digitalization in the country. Thus, paving the way for seamless adoption of such technologies across the public hospitals in Abu Dhabi.

Please, I respectfully ask you to complete the questionnaire and be assured that the data collected will be kept confidential and no firm, organization or individual will be identified in the thesis or in any report or publication based on this research. I would also like to assure you that this study has been reviewed and received ethics clearances through the office of research ethics at Sheffield Hallam University.

Thanks in advance for your co-operation.

Appendix 4 Consent Form

SAMPLE PARTICIPANT CONSENT FORM

TITLE OF RESEARCH STUDY:

Please answer the following questions by ticking the response that applies

	YES	**NO**
1. I have read the Information Sheet for this study and have had details of the study explained to me.	☐	☐
2. My questions about the study have been answered to my satisfaction and I understand that I may ask further questions at any point.	☐	☐
3. I understand that I am free to withdraw from the study within the time limits outlined in the Information Sheet, without giving a reason for my withdrawal or to decline to answer any particular questions in the study without any consequences to my future treatment by the researcher.	☐	☐
4. I agree to provide information to the researchers under the conditions of confidentiality set out in the Information Sheet.	☐	☐
5. I wish to participate in the study under the conditions set out in the Information Sheet.	☐	☐
6. I consent to the information collected for the purposes of this research study, once anonymised (so that I cannot be identified), to be used for any other research purposes.	☐	☐

Participant's Signature: ____ **Date:** ___________

Participant's Name (Printed): ___________________________________

Contact details: ____

____

Researcher's Name (Printed): __________________________________

Researcher's Signature: ______________________________________

Researcher's contact details:

(Name, address, contact number of investigator)

Please keep your copy of the consent form and the information sheet together.

Appendix 5 Ethics Approval

Advancing Healthcare Digitalization in UAE Hospitals: Professionals and Decision Makers' perspective

Ethics Review ID: ER48672045

Workflow Status: Application Approved

Type of Ethics Review Template: Very low risk human participants studies

Primary Researcher / Principal Investigator

Khalfan Alnuaimi
(Sheffield Business School)

Converis Project Application:

Q1. Is this project ii) Doctoral research

Director of Studies

Malihe Shahidan
(Sheffield Business School)

Supervisory Team

Alireza Pakgohar
(Department of Finance, Accounting and Business Systems)

Q4. Proposed Start Date of Data Collection: 02/01/2023

Q5. Proposed End Date of Data Collection : 15/03/2023

Q6. Will the research involve any of the following

i) Participants under 5 years old: No
ii) Pregnant women: No
iii) 5000 or more participants: No
iv) Research being conducted in an overseas country: Yes
v) Research involving aircraft and offshore oil rigs: No
vi) Nuclear research: No
vii) Any trials/medical research into Covid19: No
Q7. If overseas, specify the location: UAE

Q8. Is the research externally funded?: No
Q9. Will the research be conducted with partners and subcontractors?: No

Q10. Does the research involve one or more of the following?

i. Patients recruited because of their past or present use of the NHS or Social Care: No
ii. Relatives/carers of patients recruited because of their past or present use of the NHS or Social Care: No
iii. Access to data, organs, or other bodily material of past or present NHS patients: No
iv. Foetal material and IVF involving NHS patients: No
v. The recently dead in NHS premises: No