What explains the older users' continuance intention to use digital healthcare technologies in the UK?

A thesis submitted for the degree of Doctor of Philosophy

By

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Declaration

I hereby declare that the thesis is the result of my own independent and original research. I certify that the work presented contains no material which has been submitted to any other institution of learning in support of attaining any other degree or qualification. All sources have been duly acknowledged in this research.

Masoumeh Jahangiri

Abstract

Research background: As the global population ages, healthcare systems face increasing pressure to manage age-related health conditions. Digital healthcare technologies (DHTs), such as wearable devices, eHealth services, telemedicine platforms, and mHealth apps, offer solutions for promoting healthy ageing and reducing healthcare problems. However, the continued use of these technologies by older adults remains challenging, with many users discontinuing use after initial adoption. Existing research has focused predominantly on adoption, with limited attention on factors influencing post-adoption behaviour and long-term engagement. This study addresses this gap by extending the Expectation Confirmation Model (ECM) to incorporate ageing-specific factors, aiming to understand the determinants of older users' continuance intention to use Digital healthcare technologies.

Aim and Objectives: This research aims to address the significant gaps in the understanding of older users' continued use of digital healthcare technologies, particularly the lack of consideration for ageing-specific characteristics, needs, expectations, capabilities, and limitations in existing models. The study seeks to identify the factors influencing older users' continuance intention to use these technologies by extending the Expectation Confirmation Model (ECM) and developing a theoretical framework. Additionally, it investigates the impact of ageing-specific constructs on the continued use of digital healthcare technologies among older users.

Methodology: An exploratory sequential mixed-methods approach was adopted. The qualitative phase involved semi-structured interviews with older users of wearable technology devices in the UK to explore their experiences, motivations, and perceptions. Thematic analysis, using NVivo software, was employed to identify key themes that informed the subsequent quantitative phase. In the quantitative phase, a survey was conducted with a broader group of older users of digital healthcare technologies in the UK to test the relationships between the identified factors. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to assess the validity and reliability of the proposed theoretical model.

Key Findings: The quantitative phase of this research, using PLS-SEM analysis, confirmed several key relationships. Health consciousness positively influences perceived usefulness, while confirmation of expectation significantly impacts both perceived usefulness and satisfaction. Perceived usefulness also has a strong positive effect on satisfaction. Additionally, satisfaction positively influences both ageing satisfaction and continuance intention to use digital healthcare technologies. Ageing satisfaction significantly predicts continuance intention and mediates the relationship between satisfaction and continuance intention. Lastly, technology anxiety moderates the relationship between satisfaction and continuance intention, weakening the likelihood of continued use for those with higher anxiety.

Contributions: This study offers valuable insights into the factors influencing older users' continued use of digital healthcare technologies, a crucial element for ensuring their long-term success. By incorporating ageing-specific factors into the Expectation Confirmation Model (ECM), this research enhances the theoretical understanding of post-adoption behaviour among older users, refining the model to better capture sustained use in the context of health management. Additionally, the study bridges disciplines, including information systems, gerontology, healthcare, and psychology, providing actionable insights for developers, healthcare providers, policymakers, and brand managers to design and promote age-appropriate technologies that support healthy ageing.

Keywords: Digital Healthcare Technologies (DHTs), Older Users, Expectation Confirmation Model (ECM), Continuance Intention to Use, Post-adoption Behaviour

Dedication

To my husband, for always being there with love and encouragement. Your love and belief in me have made this possible.

To my wonderful parents, for your endless love, support, and belief in me at every step.

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In The name of God, the Most Gracious and the Most Merciful

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My deepest gratitude goes to my family for their love and support. To my husband, thank you for your endless patience, encouragement, and understanding throughout this journey. Your belief in me and your emotional support has been a constant source of strength, making it possible for me to persevere through challenges.

To my mother, your encouraging words and reassurance have always lifted my spirits and motivated me to strive for excellence. To my father, your wisdom, guidance, and belief in my abilities have been invaluable. Your faith in me has been the foundation of my achievements and has driven me to pursue my goals.

I am grateful to my friends. Your friendship, collaboration, and support have made this journey enjoyable and fulfilling.

Last but not least, I extend my sincere thanks to all my participants. Your time and effort in this study have been invaluable. I wish you all healthy, long, and happy lives.

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Chapter 1: Introduction

1.1 Introduction

This chapter introduces the research on factors influencing older users' continuance intention to use digital healthcare technologies (DHTs). It begins by highlighting the global phenomenon of population ageing and its implications for healthcare systems. The chapter then discusses the potential of digital healthcare technologies in addressing healthcare challenges and supporting healthy ageing for older users while acknowledging the barriers to their adoption and continued use. The research problem is presented, highlighting the gap in understanding post-adoption behaviour and the need for an extended Expectation Confirmation Model (ECM) incorporating ageing-specific factors. The chapter outlines the research questions, aim, and objectives, exploring factors influencing continuance intention, investigating the impact of ageing-specific constructs, and examining moderating effects. The research's theoretical and practical contributions are detailed, emphasising its potential impact on digital healthcare technology development and implementation. Finally, the chapter provides an overview of the thesis structure, outlining the contents of each subsequent chapter.

1.2 Research Background

The global population is experiencing a significant shift towards an older demographic (Osareme et al., 2024). Older adults, commonly classified as those aged 65 and above (Orimo et al., 2007), are a rapidly growing segment of the population (Hojnik et al., 2023). As reported by the United Nations (2023), the number of people aged 65 and above is set to more than quadruple, growing from 761 million in 2021 to 1.6 billion by 2050. Furthermore, the United Nations (2024) predicts that the percentage of the global population aged 65 and older will increase from 10% in 2021 to 16% by 2050. In the United Kingdom (UK), this trend is particularly noticeable. In 1976, individuals aged 65 and older made up 14.2% of the population. By 2016, this figure had risen to 18%. Projections suggest that by 2026, 20.5% of the UK population will be 65 and older, increasing to 23.9% by 2036 and around 24.7% by 2046 (Statista, 2024). Figure 1 below illustrates these changes in the UK, highlighting the steady rise in the proportion of adults aged 65 and older over the years.

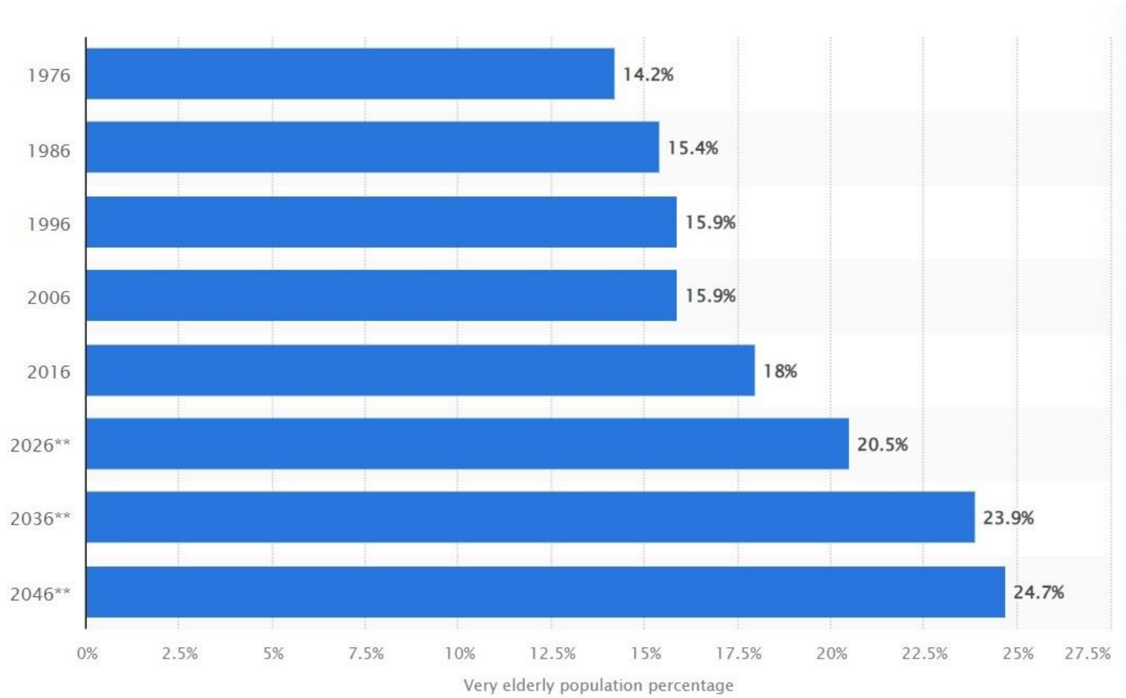

Figure 1: Proportion of Population Aged 65 and Over in the UK from 1976 to 2046 (Statista, 2024)

The ageing process brings various physical, mental, and cognitive changes, significantly impacting individuals' overall health (Menassa et al., 2023). As people age, they often require more frequent healthcare services, including regular hospital visits and continuous monitoring of physiological signs (Feng et al., 2020). However, several barriers, such as transportation challenges, high healthcare costs, and declining physical abilities, complicate access to necessary care for older adults (Mohd Rosnu et al., 2022). These barriers suggest that traditional healthcare approaches may no longer be sufficient for addressing the healthcare needs of this growing population (Kekade et al., 2018). Although increased life expectancy represents a public health success, it has simultaneously increased the prevalence of age-related diseases such as heart disease, cancer, and dementia, which impose significant financial and resource burdens on healthcare systems (Noto, 2023; World Health Organization, 2020). As populations age, these diseases drive up healthcare costs, mainly because older adults often suffer from multimorbidity and two or more chronic conditions (Calderón-Larrañaga et al., 2017; Porter et al., 2020). This condition leads to increased healthcare expenditures and worse health outcomes, further complicating the provision of care (Prados-Torres et al., 2015; Zhang et al., 2023). The healthcare system's ability to manage multimorbidity effectively is limited by its dependence on frequent, in-person interactions, which are becoming increasingly unfeasible given the rising demand for long-term care (Moffat and Mercer, 2015; Zhou et al., 2023). According to the World Health Organization (2022), the ageing population worsens staffing shortages in the healthcare sector, particularly in geriatrics and long-term care. This shortage impacts the quality of care and the ability to meet healthcare demands, as the number of professionals specialised in elderly care is insufficient to cope with the growing need (Teixeira et al., 2020).

One promising avenue for addressing these challenges is the adoption of Digital Healthcare Technologies (DHTs) (Meskó et al., 2017; Nikou et al., 2020). These technologies offer potential solutions for managing health more efficiently, particularly by reducing reliance on in-person care and enabling remote monitoring of health conditions (Gopal et al., 2019; Shaw et al., 2017). These technologies include a wide range of applications designed to support various aspects of healthcare management and healthy ageing. Key examples include electronic health (eHealth), wearable technology, telemedicine platforms, and mobile health (mHealth) apps (Hoque and Sorwar, 2017; Kasoju et al., 2023; Kim et al., 2022). Wearable devices, including fitness trackers, smartwatches, and medical wearables, have become crucial instruments for health monitoring in daily routines. These devices are capable of tracking various health metrics such as vital signs, physical activity levels, and sleep patterns, as well as playing a pivotal role in supporting adherence to prescribed medications (Cheung et al., 2018; Liao et al., 2019; Nasir et al., 2023; Poongodi et al., 2020). Medical wearables, including devices that monitor blood pressure, glucose levels, and heart rate, provide real-time monitoring and enable timely interventions, contributing to better management of chronic diseases. The data collected is often sent to healthcare providers or personal health apps for continuous monitoring and analysis, making these technologies particularly effective in promoting improved health outcomes (Haghi et al., 2017). In addition to real-time tracking through wearables, electronic health (eHealth) services, such as online health portals, electronic health records (EHRs), and remote diagnostic systems, have transformed healthcare by enhancing patient accessibility and engagement (Oh et al., 2005; Xie et al., 2022). These platforms enable patients to access their medical information, communicate with healthcare professionals, and receive diagnostic services from the comfort of their homes (Wernhart et al., 2019). By streamlining healthcare processes and improving communication between patients and providers, eHealth services facilitate timely interventions and foster better health management (Wager et al., 2021). Telemedicine platforms utilise Internet of Things (IoT) devices to improve remote consultations by providing real-time health data during virtual visits. This real-time data integration enhances the quality of remote care and ensures timely interventions (Haleem et al., 2021). In addition, mobile health (mHealth) applications integrate with various IoT devices to offer a comprehensive view of an individual's health, promoting self-care and enabling informed healthcare decisions (Ammar et al., 2021).

While adopting digital healthcare technologies offers potential solutions for managing health more efficiently, the key challenge is ensuring that older adults continue to use these technologies over time (Ahmad et al., 2020). Factors such as unfamiliarity with technology, physical limitations, and cognitive decline can hinder sustained engagement. The success of digital healthcare technologies in promoting healthy ageing depends not just on their initial adoption but also on continued use and regular engagement. However, despite their promise to alleviate healthcare burdens, integrating digital healthcare technologies into existing systems to effectively support older adults remains a challenge that requires further exploration (Bertolazzi et al., 2024). Although these challenges exist, digital healthcare technologies have the potential to play a critical role in supporting healthy ageing by identifying health trends, detecting abnormal activities, and enabling early interventions to prevent adverse health outcomes (Alessa et al., 2021; Lee et al., 2021). They empower individuals to access health information from anywhere at any time, enhancing self-management and independence (Kim and Shin, 2015; Niknejad et al., 2020; Perera and Vasilakos, 2016). By facilitating ageing in place, reducing the demand for hospital and institutional resources, and supporting early detection of changes in health status through advanced infrastructure for remote care, monitoring, and therapy, digital healthcare technologies address many challenges associated with global ageing (Patel et al., 2022; Wang et al., 2022). However, the design of many digital healthcare technologies often overlooks the specific needs, preferences, and capabilities of older users, resulting in unsatisfactory user experiences and decreased engagement and usage (Wildenbos et al., 2018). To promote the sustained use of digital healthcare technologies among older individuals, it is essential to address these barriers and develop user-centred solutions tailored to this population's unique requirements and preferences, ensuring long-term engagement and better health outcomes (Oderanti et al., 2021).

1.3 Research Problem

Although digital healthcare technologies have the potential to meet the healthcare needs of older users, their adoption and continuous usage within this demographic are hindered by numerous barriers (Bertolazzi et al., 2024; Frishammar et al., 2023; Yusif et al., 2016). Global ageing trends and the growing demand for healthcare services place immense strain on healthcare systems (Hajizadeh et al., 2024), making the role of digital healthcare technologies (DHTs) increasingly critical. To fully leverage digital healthcare technologies in supporting healthy ageing, overcoming these obstacles and ensuring that older individuals possess the necessary skills, support, and confidence to effectively utilise these technologies is essential (Tandon et al., 2024; Wilson et al., 2021). While the initial adoption of digital healthcare technologies by older users is vital, their sustained and continuous usage is even more crucial for realising the long-term health benefits these technologies offer (Curtis and Price, 2017). The ageing process involves a complex interplay of physical, cognitive, and psychological changes, making it imperative for older individuals to maintain consistent health monitoring to effectively detect and manage age-related health conditions (Jimenez et al., 2023). Alarmingly, high abandonment rates among older users undermine these benefits, leading to missed opportunities for early intervention, poorer health outcomes, and increased disparities in health equity. As the population ages, the rise in age-related chronic conditions is putting significant pressure on healthcare systems already under strain (Daniels, K. and Bonnechère, 2024). In the UK, conditions like cardiovascular diseases, diabetes, and arthritis are major reasons for healthcare visits among older adults (Age UK, 2024), highlighting the need for technology-based solutions. The cost of managing these conditions is expected to grow, with spending on older adults likely to dominate healthcare budgets in many developed countries by 2030 (WHO, 2022).

Continuous engagement with digital healthcare technologies ensures their full integration into daily life, providing ongoing insights into health trends, detecting early signs of deterioration, and facilitating timely interventions (Alruwaili et al., 2023). Wearable devices and mHealth apps, for example, offer significant health benefits when used regularly (Majumder et al., 2017), while irregular use can lead to missed opportunities for early intervention and poorer health outcomes (Greenhalgh et al., 2017). The lack of familiarity or perceived ease of use among older users often exacerbates these challenges, further reducing the effectiveness of these technologies (Fowe and Boot, 2022). Abandonment rates remain alarmingly high, with research suggesting that usability issues, lack of perceived relevance, and anxiety around technology are some of the key contributors (Catania et al., 2024; Yu et al., 2023). The failure to ensure sustained usage of digital healthcare technologies results in underutilised resources, increased reliance on traditional healthcare services, and delays in early interventions, which further contribute to worsening health inequities and avoidable health crises (Balcombe and De Leo, 2021; Yao et al., 2022). Continuity in digital healthcare technology usage is about sustained engagement and embedding these technologies into daily routines to enable older users to age independently and with a higher quality of life (Gutman and Shade, 2020). This highlights an urgent need to investigate the specific factors that influence continuance intention and to address the barriers leading to discontinuation. Accordingly, this study's focus on the post-adoption phase of digital healthcare technology usage among older users is crucial for unlocking the full potential of these technologies in supporting healthy ageing (Mace et al., 2022).

Existing research primarily focuses on the early stages of technology adoption, with limited exploration of what drives long-term engagement. While theories such as the Innovation Diffusion Theory (Min et al., 2019; Putteeraj et al., 2022), Technology Acceptance Model (TAM) (Kim and Shin, 2015; Li et al., 2021), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Philippi et al., 2021; Reyes-Mercado, 2018; Yuan et al., 2015) provide insights into initial acceptance behaviours, they fail to address the post-adoption phase. Moreover, these models inadequately capture the unique challenges faced by older adults, such as cognitive decline, physical limitations, and psychological barriers like technology anxiety (Dehghani, 2018; Elnadi et al., 2024). Understanding the post-adoption phase is especially critical because the abandonment of digital healthcare technologies by older adults directly undermines their ability to manage age-related conditions and live independently.

1.4 Research Gap

Continuance intention refers to the decision by users to persist in utilising an Information System (IS) they have already adopted (Cheng, 2021). This concept is a significant focus in IS research (Lee, 2010; Oghuma et al., 2016). It is distinct from initial adoption behaviour and is influenced by different factors (Veeramootoo et al., 2018). To thoroughly understand the motivations behind continued technology use, a theoretical framework is required (Stone and Baker-Eveleth, 2013). While previous research has extensively examined the initial adoption of digital healthcare technologies, there is limited understanding of the factors influencing their sustained use among older adults. This is particularly critical because the abandonment of these technologies undermines their potential to improve health outcomes, reduce healthcare costs, and support healthy ageing (Bölen, 2020; Talukder et al., 2021; Yang et al., 2018).

Despite the need for further research on the continuance of digital healthcare technologies, there remains a scarcity of studies addressing this issue (Cho, 2016). To comprehensively understand individuals' use of technology, it is essential to examine their initial adoption and ongoing intention to continue using it (Cho, 2016; Yan et al., 2021). Recognising the critical role of sustained use in the long-term success of information systems, this study takes a post-adoption perspective to explore how the ongoing use of digital healthcare technologies by older users relates to different cognitive beliefs. A detailed research model, grounded in the expectation confirmation model proposed by Bhattacherjee (2001), is developed and empirically tested using a sample of current users of digital healthcare technologies. Bhattacherjee's work serves as a foundational framework for understanding continuance intention and addressing the limitations of earlier adoption-focused models like the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003).

Previous research using the ECM has primarily focused on technology constructs (e.g., perceived usefulness and satisfaction) while overlooking other important determinants, such as socio-emotional and ageing-specific factors (Kim and Han, 2021; Obeid et al., 2024; Wu et al., 2022). Furthermore, while there has been significant exploration of the adoption of digital healthcare technologies by older users, their perceptions and continued use have received limited attention (Begde et al., 2024; Meng et al., 2022; Talukder et al., 2020).

Although the Expectation Confirmation Model (ECM) is a robust framework for understanding post-adoption behaviour, it has been criticised for not considering factors that vary across different contexts (Ghazali et al., 2024; Tam et al., 2020; Venkatesh et al., 2011). Also, it has not accounted for the ageing-specific characteristics, needs, expectations, capabilities, and limitations of older users (Meng et al., 2022). Accordingly, since older users have distinct characteristics compared to younger users, and ageing-specific factors significantly influence the adoption and use of digital healthcare technologies, it is crucial to consider the impact of ageing on various aspects of life (Lee and Coughlin, 2015; Van Acker et al., 2023). These aspects include physical abilities, functionality, mental well-being, and social interactions (Hargittai et al., 2019; Kalu et al., 2022; Saadeh et al., 2020).

This research builds upon these foundational studies by addressing the unique needs and characteristics of older adults. It extends the ECM to incorporate ageing-specific factors, providing a more nuanced understanding of older users' post-adoption behaviours. By explicitly linking seminal works on continuance intention in IS research (e.g., Bhattacherjee, 2001) with critical studies on ageing and technology use (e.g., Lee and Coughlin, 2015; Meng et al., 2022), this study seeks to close the gap in existing literature. An extended expectation confirmation model that integrates ageing-specific factors will provide deeper insights into the continued usage intention of digital healthcare technologies among older users, ultimately supporting their sustained engagement and improving health outcomes.

1.5 Research Aim, Objectives, and Questions

This research aims to address significant gaps in the existing body of knowledge, particularly the lack of consideration for ageing-specific characteristics, needs, expectations, capabilities, and limitations in the expectation confirmation model. By exploring the factors influencing older users' continuance intention to use digital healthcare technologies as essential tools for managing their health, the study seeks to promote the long-term use of these technologies, ultimately supporting healthy ageing and enhancing the quality of life for older adults. To achieve this aim, the research extends the expectation confirmation model by incorporating ageing-specific constructs, including health motivation, health consciousness, health anxiety, and technology anxiety. It further examines the effect of these constructs on the continuance intention to use digital healthcare technologies among older users. Additionally, the moderating effects of health anxiety and technology anxiety on the relationship between satisfaction and continuance intention are explored.

Based on this aim, the objectives of the study are as follows:

- To identify the factors influencing older users' continuance intention to use digital healthcare technologies by extending the Expectation Confirmation Model (ECM) with ageing-specific constructs and developing a theoretical model based on this extension.
- To investigate the impact of ageing-specific constructs on the continued use of digital healthcare technologies among older users.
- To explore the effect of moderators on the relationship between satisfaction and continuance intention to use digital healthcare technologies in the context of older users.

This research highlights the key factors influencing older users' decision to continue using digital healthcare technologies. By understanding these factors, the study contributes to facilitating the long-term adoption of these technologies, enabling older adults with complex health needs to manage their health better, maintain independence, and improve their overall quality of life. Specifically, the study investigates how health motivation, health consciousness, and confirmation of expectations influence perceived usefulness and how perceived usefulness and confirmation of expectations impact satisfaction. Additionally, it examines the effects of satisfaction on continuance intention. Furthermore, the study explores how health and technology anxiety moderate the relationship between satisfaction and continuance intention among older users.

To address the study's objectives, the following Research Questions (RQs) have been formulated. These questions reflect the core aspects of the investigation and are aligned with the gaps identified in the literature:

- RQ1: What factors influence older users' continuance intention to use digital healthcare technologies?
- RQ2: How do ageing-specific constructs impact the continued use of digital healthcare technologies?
- RQ3: How do moderators affect the relationship between satisfaction and continuance intention to use digital healthcare technologies?

1.6 Research Contribution

This study provides valuable insights into the continuance intention to use digital healthcare technologies among older adults, a critical factor in ensuring these technologies' long-term success and effectiveness. By examining how ageing-specific factors influence the ongoing use of digital healthcare technologies, the study offers a comprehensive understanding of post-adoption behaviour, particularly within the ageing population. Additionally, this research expands upon the originally validated post-acceptance theoretical framework, known as the Expectation Confirmation Model (ECM) (Bhattacherjee, 2001; Wu et al., 2022), by incorporating constructs relevant to the ageing population. The integration of ageing-specific constructs enhances the theoretical understanding of how older adults engage with digital healthcare technologies over time. By doing so, the study deepens the knowledge of long-term digital healthcare technology usage. It provides a refined framework that is better suited to explain sustained use in the context of older adults' health management.

This research also bridges the gap between multiple disciplines, including information systems, gerontology, healthcare, and psychology. Adopting an interdisciplinary approach can inspire further research at the intersection of these fields, leading to a more holistic understanding of the complex issues surrounding older users' interactions with technology for health management

(Blandford et al., 2018; Lepore et al., 2023; Schulz et al., 2015). Furthermore, the study significantly contributes to the broader field of ageing and technology studies, offering an in-depth analysis of the continuous use of digital healthcare technologies by older users. This focus on continuance intention, rather than just initial adoption, addresses a critical aspect of technology use in later life, thereby aiding in the development of sustainable technological interventions for healthy ageing (Forsman et al., 2017; Morato et al., 2021; Peine and Neven, 2019). This study enhances our understanding of the most effective strategies for leveraging digital healthcare technologies to promote the independence and well-being of older adults in an increasingly digital society (Gell et al., 2015; Hill et al., 2015; Ienca et al., 2021). This focus aligns with the broader objectives of creating age-friendly environments and promoting active ageing through technology (Bernardo et al., 2022; Liddle et al., 2020).

In addition to advancing theoretical understanding, this research provides actionable insights that can be applied by various stakeholders involved in the development, implementation, and promotion of digital healthcare technologies for older users. Understanding the factors that influence older users' continued use of digital healthcare technologies is critical for these stakeholders, as it enhances their ability to design and promote technologies that meet the needs of this population. For digital healthcare technologies developers, the findings offer guidance on creating more user-centric and age-appropriate digital healthcare technologies. By recognising the distinct needs and preferences of older users, developers are able to customise digital healthcare technologies, improving usability and encouraging sustained engagement over time (Nascimento et al., 2018; Wildenbos et al., 2018). For healthcare providers and brand managers, the study offers insights into developing effective user retention strategies and improving service delivery. Strategies include tailored feedback and efforts to emphasise the perceived usefulness and benefits of digital healthcare technologies, offering personalised user support to address older users' specific concerns, implementing continuous improvement processes based on user feedback, and developing targeted training programs to enhance older users' intention to use digital healthcare technologies (Ji and Kim, 2022; Zhao et al., 2023). Additionally, this research can assist policymakers in creating guidelines, programs, and policies that encourage older users to adopt and continue using digital healthcare technologies. Achieving this may involve establishing national digital health literacy programs for older users, implementing reimbursement policies that promote the prescription and use of practical digital health tools, creating guidelines for the design and evaluation of digital health tools for older users, and allocating resources for the development and implementation of age-friendly digital health tools (Jimenez et al., 2023; Kante and Ndayizigamiye, 2021).

1.8 Overview of Thesis Structure

This thesis consists of six chapters, the contents of which are summarised below:

Chapter 1 – Introduction: This chapter introduces the research by outlining the study's background, research problem, aim, objectives, and questions. It highlights the study's contributions, particularly the integration of ageing-specific constructs into the Expectation Confirmation Model (ECM). The chapter concludes with an overview of the thesis structure.

Chapter 2 – Literature review: This chapter reviews digital healthcare technologies (DHTs), focusing on their definitions, impacts, classifications, and theoretical foundations, particularly for older users. It examines key frameworks like the Expectation Confirmation Model (ECM) and its role in shaping continuance intention. The chapter also identifies gaps in the literature and presents a working conceptual model for this study.

Chapter 3 – Methodology: This chapter details the mixed-methods approach used to study factors influencing older users' continuance intention to use digital healthcare technologies. It covers the pragmatic research philosophy, the abductive approach in the qualitative phase, and the quantitative phase, which tested key relationships through a survey. Data collection and analysis methods are also outlined.

Chapter 4 – Qualitative Findings: This chapter presents the qualitative analysis of semi-structured interviews, detailing the thematic analysis process using an abductive approach and NVivo software. Key themes identified include Health Motivation, Health Consciousness, Confirmation of Expectation, Perceived Usefulness, Satisfaction, Ageing Satisfaction, Health Anxiety, Technology Anxiety, Self-efficacy, and Continuance Intention to Use. These findings refine the conceptual framework, which informs the hypotheses developed for testing in the quantitative phase. The chapter concludes with a proposed conceptual model outlining the relationships between constructs.

Chapter 5 – Quantitative Findings: This chapter presents the quantitative analysis and survey results to test the hypothesised conceptual model. It includes preliminary data analysis, respondent demographics, and descriptive statistics. Using PLS-SEM, the study confirms the validity and reliability of the measurement and structural models. Key findings reveal significant effects of confirmation of expectation, perceived usefulness, and satisfaction on continuance intention, with technology anxiety showing a notable moderating impact. A mediation analysis using SPSS highlights that ageing satisfaction mediates the relationship between satisfaction and continuance intention.

Chapter 6 – Discussion and conclusion: This chapter discusses the key findings, highlighting the roles of health consciousness, confirmation of expectations, perceived usefulness, satisfaction, ageing satisfaction, and technology anxiety in older users' continuance intention to use digital healthcare technologies. It outlines theoretical and practical contributions, offering implications for stakeholders such as healthcare providers, policymakers, developers, and brand managers. The chapter concludes with the study's limitations and suggestions for future research to improve support for older users.

Chapter 2: Literature Review

2.1 Introduction

The literature review chapter explores the broad domain of Digital Healthcare Technologies (DHTs), exploring their definitions, impacts, classifications, theoretical underpinnings, and use among older users. It begins by defining digital healthcare technologies and presenting various authoritative definitions, highlighting the consensus and diversity in understanding digital healthcare technologies across the field. The impact of digital healthcare technologies is discussed, highlighting their role in transforming healthcare through data-driven decision-making, personalised treatment plans, and improved access to care. The chapter then deeply explores various classifications of digital healthcare technologies, focusing on eHealth services, wearable technology devices, telemedicine platforms, and mobile health (mHealth) apps. Theoretical frameworks underpinning the use and adoption of digital healthcare technologies are discussed, focusing on Continuance Theory, which emphasises the importance of continued use over initial adoption for long-term success, and the Expectation Confirmation Model (ECM), which explains users' continued use based on their satisfaction with and perceived usefulness of the technology. The application of ECM in contexts of digital healthcare technologies is examined, providing insights into factors driving continued use. The chapter concludes by reviewing research on factors influencing older users' continuance intention to use digital healthcare technologies.

2.2 Digital Healthcare Technologies (DHTs)

2.2.1 Definitions of Digital Healthcare Technologies

Digital Healthcare Technologies (DHTs) leverage digital tools, resources, and systems to enhance healthcare delivery, manage health information, and support health-related decision-making. This interdisciplinary field, merging healthcare with digital technology, has gained significant global attention over the past decade (Fatehi et al., 2020). Digital healthcare technologies encompass software and hardware components, enabling efficient, personalised, and accessible healthcare solutions (Gopal et al., 2021). The concept of digital healthcare technologies has been defined in numerous ways by various organisations, researchers, and regulatory bodies. To provide a thorough understanding of digital healthcare technologies across the field, Table 1 presents a collection of definitions from various authoritative sources.

NO.	Digital Healthcare Technologies Definition	Reference
1	Digital health technologies encompass a range of platforms and solutions leveraging data and connectivity systems to meet healthcare needs.	Bhavnani et al. (2016)
2	Digital healthcare technology represents the fusion of digital innovations with healthcare and societal needs. It promises to transform healthcare delivery by optimising operations, enhancing patient outcomes, and reducing healthcare expenses.	Mitchell and Kan (2019)
3	Digital health means using digital technology for medical, healthcare support, and nursing care. This includes big data from health records and genomics, artificial intelligence (AI), and extended reality (XR).	Nomura (2023)
4	"The field of knowledge and practice associated with the development and use of digital technologies. Digital health expands the concept of eHealth to include digital consumers with a wider range of smart and connected devices. It also encompasses other uses of digital technologies for health such as the Internet of Things, advanced computing, big data analytics, artificial intelligence including machine learning, and robotics."	World Health Organization (2021)
5	"Digital health technologies comprise a wide range of products including apps, software and online platforms that are intended to benefit people or the wider health and care system."	Unsworth et al. (2021)
6	"Digital healthcare technology is a system that uses computing platforms, connectivity, software, and sensors for healthcare and related uses."	US Food and Drug Administration (2021)
7	"Digital healthcare technologies are applications, programmes, and software used in the health and care system. They may be individual or combined with other products such as medical devices or diagnostic tests."	National Institute for Health and Care Excellence (2019)
8	"Digital health connects and empowers people and populations to manage health and wellness, augmented by accessible and supportive provider teams working within flexible, integrated, interoperable, and digitally enabled care environments that strategically leverage digital tools, technologies and services to transform care delivery."	Healthcare Information and Management Systems Society (2020)
9	"Digital health describes using digital information, data, and communication technologies to collect, share, and analyse health information for purposes of improving patient health and health care delivery."	Sharma et al. (2018)

Table 1: The Definition of Digital Healthcare Technologies
(Developed by the author)

As highlighted by these definitions, digital healthcare technologies encompass a wide array of digital and electronic devices, applications, and systems aimed at improving patient outcomes, streamlining healthcare processes, and enhancing health management at both individual and population levels (Kataria and Ravindran, 2018; Lowery, 2020). They have become essential tools for addressing the healthcare needs of older users, especially given the challenges posed by an ageing population to healthcare systems worldwide (Jimenez et al., 2023; Wang et al., 2022). These technologies include mobile health (mHealth) applications, telemedicine, eHealth services, and wearable technology devices, each offering opportunities to expand access to healthcare, support disease management, and encourage self-care for older users (Majumder et al., 2017; Nasir et al., 2023; Shaw et al., 2017; Stavropoulos et al., 2021).

Building on the existing definitions in Table 1, this thesis focuses on digital healthcare technologies in the context of continuance intention to use by older users. Synthesising common themes and elements from the various definitions in the literature, this study defines digital healthcare technologies as a range of digital tools and systems, including wearable technology devices, telemedicine platforms, eHealth services, and mobile health (mHealth) apps (Bhavnani et al., 2016; National Institute for Health and Care Excellence, 2019; Unsworth et al., 2021), that are specifically designed to support the ongoing management of health and well-being for older adults (Mitchell and Kan, 2019; Sharma et al., 2018; World Health Organization, 2021). These technologies are crucial in enabling continuous engagement with healthcare resources (Healthcare Information and Management Systems Society, 2020), allowing older users to maintain and improve their physical and mental health, promote healthy ageing, and enhance their quality of life through accessible, personalised, and user-friendly solutions (Mitchell and Kan, 2019; Nomura, 2023; US Food and Drug Administration, 2021).

2.2.2 Impact of Digital Healthcare Technologies

Digital healthcare technologies have significantly transformed the landscape of healthcare delivery, offering numerous advantages for patients and healthcare providers (Mitchell and Kan, 2019). This section explores how digital healthcare technologies impact healthcare systems, patient care, and overall health outcomes. A crucial feature of digital healthcare technologies is their capacity to gather, analyse, and use extensive health-related data. This data-centric approach allows healthcare providers to make better-informed decisions, anticipate health trends, and tailor treatment plans to individual needs. For example, remote monitoring technologies facilitate the real-time tracking of various physiological parameters in older users, transmitting this data to healthcare providers for analysis and timely intervention (Lee et al., 2021). The growing reliance on these technologies was especially evident during the COVID-19 pandemic, which considerably increased the use of digital healthcare technologies. These technologies have proven vital in keeping healthcare services running during such a crisis (Golinelli et al., 2020). Telemedicine, in particular, experienced significant growth. They enabled patients to receive medical care remotely, reducing the virus transmission risk (Whitelaw et al., 2020). Integrating digital healthcare technologies into medical practice has brought about remarkable improvements in patient care, leading to more efficient, precise, and personalised medical services (Meskó et al., 2017). These tools allow patients to monitor their health, access medical information, and actively participate in their care. Digital healthcare technologies extend beyond hospitals and clinics, integrating into daily life and home settings. This widespread use can revolutionise preventive care, chronic disease management, and health promotion. Through continuous health monitoring and timely interventions, digital healthcare technologies enable early detection of health problems, reduce hospital readmissions, and improve health outcomes, specifically for older users with chronic conditions (Bhavnani et al., 2016; Samal et al., 2021; Singh et al., 2021).

The rapid adoption of digital healthcare technologies is primarily driven by their potential to enhance healthcare quality while reducing costs. These technologies make healthcare systems more efficient by automating routine tasks, streamlining workflows, and supporting remote care (Ibrahim et al., 2022). For instance, electronic health records (EHRs) have significantly changed patient information management by revolutionising how data is stored, accessed, and shared among healthcare professionals. This advancement has resulted in better care coordination and a reduction in medical errors (Kruse et al., 2017). Additionally, telemedicine is helpful for older users in remote or rural areas with limited healthcare access. Research by Batsis et al. (2019) demonstrates that telemedicine can effectively deliver geriatric care to these populations, thereby improving access to specialised services and reducing the necessity for travel. This not only enhances the quality of care but also contributes to cost savings by minimising unnecessary travel and hospitalisations. In addition to enhancing efficiency, digital healthcare technologies leverage advanced tools such as big data and artificial intelligence to help doctors create treatments tailored to each patient. This means considering everything from a person's genes to their daily habits and environment (Corridon et al., 2022). This personalised approach makes treatments more effective and reduces the chance of adverse side effects, leading to better patient health outcomes (Mathur and Sutton, 2017).

Additionally, digital healthcare technologies support the mental health and well-being of older users (Andrews et al., 2019; LaMonica et al., 2021). Social isolation and loneliness, common issues among older adults, can negatively impact their mental and physical health (Armitage and Nellums, 2020). Digital technologies can help maintain social connections and alleviate feelings of loneliness (Chen and Schulz, 2016). mHealth, which provides remote access to mental health professionals, has also proven effective in addressing the mental health needs of older users (Belanger and Winsberg, 2022). The ability of digital healthcare technologies to improve both physical and mental health is particularly relevant in the context of healthy ageing. These technologies have shown significant potential in supporting healthy ageing, enabling older users to sustain their independence, manage chronic illnesses, and improve their overall quality of life (Ollevier et al., 2020). These technologies are notably effective in promoting physical activity and enhancing functional capacity among older users (De Santis et al., 2022). According to Stockwell et al. (2019), digital behaviour change interventions can boost physical activity levels and decrease inactive behaviour in older adults. Such interventions often utilise mHealth applications and wearable devices to offer personalised exercise programs, activity tracking, and motivational support (Muellmann et al., 2018). By encouraging regular physical activity, digital healthcare technologies are vital in the healthy ageing process, aiding older users in preserving their mobility, strength, and overall health (Alruwaili et al., 2023; Ienca et al., 2021).

2.3 Classifications of Digital Healthcare Technologies

This research focuses on wearable technology devices, mHealth, telemedicine, and eHealth services while excluding other forms of digital healthcare technologies. These selected technologies are particularly relevant to older users, especially for managing chronic conditions and monitoring health (Chandrasekaran et al., 2021; Christiansen et al., 2020; Mace et al., 2022).

Research highlights that these digital healthcare technologies are among the most commonly adopted by older users, with significant uptake in those designed for chronic disease management. For example, wearable devices and mHealth applications support older users in maintaining physical activity and managing chronic diseases despite challenges like privacy concerns and device usability (Aslam et al., 2020; Nebeker and Zlatar, 2021). This study focuses on these technologies due to their demonstrated impact on the health outcomes and quality of life of older users, ensuring practical relevance and generalisability of the research findings (Fox and Connolly, 2018; Talukder et al., 2020).

The integration of these technologies into modern healthcare systems is another crucial factor in their selection. Wearable devices, mHealth, telemedicine, and eHealth services are being increasingly incorporated into healthcare practices for monitoring, communication, and patient management, making them essential for understanding healthcare trends and continuance intentions among older users (del Río-Lanza et al., 2020; Grau-Corral et al., 2020; Lee and Lee, 2020). These technologies also have a demonstrated impact on health outcomes, particularly in managing chronic diseases, improving access to care, and promoting healthy behaviours. For instance, mHealth has been shown to effectively support cardiovascular rehabilitation among older users despite some barriers to adoption (Bostrom et al., 2020). Moreover, the selected digital healthcare technologies are known for their relative accessibility and ease of use compared to more complex technologies. For example, wearable devices and mHealth apps are perceived as user-friendly by older users, which increases their likelihood of adoption and consistent use (Kononova et al., 2019; Wang et al., 2019). They have broad applicability across various healthcare settings. This means that insights gained from this research can be extended to other emerging technologies as they become more relevant and accessible to older users (Chandrasekaran et al., 2021). The following sections will provide a detailed exploration of each technology.

2.3.1 Electronic Health (eHealth) Services

eHealth services refer to using digital tools and technologies to deliver healthcare services and manage health information (Blaya et al., 2010). It covers a wide range of digital tools and services aimed at improving healthcare. It includes electronic health records (EHRs), online health portals, and remote diagnostic systems (Da Fonseca et al., 2021; Goldzweig et al., 2013; Papa et al., 2020). These technologies are instrumental in improving the efficiency of healthcare delivery and ensuring that healthcare providers and patients have seamless access to essential health information (Blaya et al., 2010).

For older users, eHealth services offer several significant benefits. Electronic health records (EHRs) allow for comprehensive and accessible management of health data, enabling healthcare providers to coordinate care more effectively, which is especially critical for older users managing multiple chronic conditions (Xie, 2011). Online health portals allow older users to access test results, arrange appointments, and connect with healthcare providers remotely, enhancing patient engagement and promoting self-management (Sakaguchi-Tang et al., 2017; Taha et al., 2009). Additionally, remote diagnostic systems provide older users with access to healthcare diagnostics without the need for frequent in-person visits, particularly benefiting those with mobility issues (Muellmann et al., 2018). These eHealth services empower older users by giving them more control over their healthcare and facilitating better communication between multiple healthcare providers, which is essential for coordinated care (Fang et al., 2018). Furthermore, these systems enhance caregiver involvement by allowing caregivers to access important health information and provide more informed support for older users (Tremblay et al., 2019).

Despite these benefits, the adoption of eHealth services among older users faces challenges. Digital literacy remains a significant barrier, with many older individuals struggling to navigate complex online platforms (Ware et al., 2017). Additionally, concerns about the privacy and security of personal health information must be addressed to ensure the broader adoption of these technologies (Schomakers et al., 2019). Nevertheless, eHealth services have the potential to transform healthcare for older users by providing accessible, continuous, and coordinated care. As these technologies evolve and become more user-friendly, they are likely to play an increasingly significant role in improving health management and outcomes for the ageing population (Buyl et al., 2020).

2.3.2 Wearable Devices

Wearable devices are digital tools worn on the body that provide continuous health monitoring and real-time data collection. These devices encompass a wide range of applications, from general health and fitness to more specialised medical tracking. Examples include smartwatches, fitness trackers, and more advanced wearable medical devices like continuous glucose monitors (CGMs), wearable electrocardiograms (ECGs), hearing aids, and wearable blood pressure monitors (Patel et al., 2015; Stavropoulos et al., 2021; Yang et al., 2022). They have gained popularity across various age groups, including older users, due to their potential to enhance the quality of life and improve health outcomes (Jang et al., 2018; Kyytsönen et al., 2023).

They monitor vital signs, physical activity, and sleep patterns and can even detect falls, providing valuable data to healthcare providers and caregivers (Majumder et al., 2017). Using digital healthcare technologies for continuous monitoring helps detect health issues early and ensures timely interventions. This approach is essential for managing chronic conditions that are common in older populations (Lin et al., 2020). These devices also have advanced beyond simple fitness tracking to encompass sophisticated health monitoring systems, such as continuous glucose monitors for diabetes, continuous electrocardiograms (ECGs) monitors for detecting heart irregularities, insulin pumps, and continuous wearable blood pressure monitors for hypertension (Mizuno et al., 2021; Schwartz et al., 2018; Qiao et al., 2023). These more specialised devices deliver essential health data to both patients and healthcare professionals, facilitating ongoing health monitoring and prompt medical interventions (Duncker et al., 2021). In addition to health monitoring, these devices encourage active ageing by promoting physical activity and providing feedback on health goals. They remind users to take medications, stay hydrated, or exercise, which helps manage health conditions (Fioranzato et al., 2021; Mercer et al., 2016). Additionally, they support older users' independence by offering emergency alert systems and GPS tracking, giving peace of mind to users and their families (Stavropoulos et al., 2021).

Integrating wearable devices with other technologies, such as smartphone apps and electronic health records, creates a comprehensive health monitoring system. This integration allows for more personalised care plans and improved communication between older users and healthcare providers (Bhavnani et al., 2016). By providing continuous health data, wearable devices enable healthcare professionals to make more informed decisions and personalise actions to each individual's needs, leading to improved health outcomes for older users (Jang et al., 2018; Kekade et al., 2018). However, the adoption and long-term use of wearable devices among older users can be challenging. Issues such as device complexity, privacy concerns, and data security must be addressed to ensure widespread acceptance and use (Lee et al., 2021). Despite these challenges, wearable technology devices hold significant potential to support healthy ageing and improve healthcare delivery for older users (Chandrasekaran et al., 2021). As these technologies evolve and become more user-friendly, their role in geriatric care will likely expand, offering new opportunities for proactive health management and improved quality of life for older populations. The ability of wearable devices to provide real-time health data, encourage preventive health behaviours, and facilitate timely medical interventions makes them a promising tool for addressing the healthcare needs of an ageing population (Armstrong et al., 2017; Li et al., 2019).

2.3.3 Telemedicine Platforms

Telemedicine refers to using digital communication tools, such as video conferencing systems, secure messaging, and remote monitoring platforms, to provide healthcare services remotely (Sood et al., 2007). This technology enables healthcare providers to deliver medical care to patients at a distance, thereby overcoming geographical barriers and making healthcare more accessible (Haleem et al., 2021; Heřman et al., 2022). It has revolutionised healthcare delivery, particularly for older users, by enabling remote consultations and healthcare services through digital communication tools (Jnr, 2020). Given the mobility limitations and chronic health issues common among older populations, telemedicine offers critical access to care that might otherwise be challenging to obtain. Telemedicine enables older users to access healthcare services directly from their homes, minimising the necessity for in-person appointments and supporting consistent, ongoing care (Stronge et al., 2007; Şahin et al., 2024).

The benefits of telemedicine are especially notable for older users who may have mobility limitations or live far from healthcare facilities (Batsis et al., 2019). Studies have shown that telemedicine interventions for older users significantly reduce healthcare costs, enhance care access, and increase satisfaction. Furthermore, telemedicine has proven effective in managing chronic conditions such as diabetes, high blood pressure, and heart failure in this population (Şahin et al., 2024), thereby improving patient outcomes (Chalfont et al., 2021; Guo and Albright, 2018). Beyond chronic disease management, telemedicine also offers solutions for mental health care, particularly through telepsychiatry. This approach has been shown to be as effective as in-person care for treating depression and anxiety in older users, making mental health services more accessible to those who may face barriers to traditional care due to stigma or geographical isolation (Egede et al., 2015). Despite the numerous benefits, there are challenges associated with the adoption of telemedicine among older users. Digital literacy, particularly among older users, remains a significant barrier, with many older users struggling to navigate new technologies (Sieck et al., 2021; Wilson et al., 2021). Additionally, concerns about data privacy and security in telemedicine platforms require ongoing attention and robust regulatory frameworks (Mishkin et al., 2023).

2.3.4 Mobile Health (mHealth) Apps

Mobile health apps (mHealth) are digital platforms designed to support wellness through mobile devices like smartphones and tablets (Iyengar, 2020). These apps provide various features, from tracking physical activity and monitoring chronic conditions to providing medication reminders and connecting users with healthcare providers (Kao and Liebovitz, 2017; Okolo et al., 2024). The widespread availability of smartphones and high-speed internet has made mHealth apps easily accessible, promoting more personalised and convenient healthcare management (Lee, 2016; Sharma et al., 2022). Research has demonstrated that mHealth apps significantly enhance patient engagement, support adherence to treatment plans, and improve overall health outcomes (Alessa et al., 2021; Meskó et al., 2017). For older users, in particular, these apps have become increasingly valuable in managing health-related behaviours, improving medication adherence, and enhancing access to health information (Bhuyan et al., 2016; Kampmeijer et al., 2016). Additionally, mHealth apps enable older users to self-monitor their health and stay connected with healthcare professionals through remote consultations, making healthcare more accessible and patient-centred (Bodnar et al., 2017; Jaana and Paré, 2020; Parker et al., 2013).

One of the primary benefits of mHealth apps for older users is the ability to manage medications more effectively (Russell et al., 2018). Many older users take multiple medications daily, and mHealth apps can provide reminders and alerts to ensure timely administration, reducing the risk of missed doses or drug interactions (Stuck et al., 2017). Research has shown that mHealth apps can significantly improve medication adherence among older users, leading to better health outcomes (Russell et al., 2018). In addition to medication management, mHealth apps enable older users to access important health information and stay connected with their healthcare providers (Lefler et al., 2018). These applications allow users to track their health data, receive personalised health recommendations, and connect with healthcare providers remotely. This is especially advantageous for older users with mobility challenges or those residing in distant locations, as it lessens the necessity for regular in-person appointments (Sproul et al., 2023).

2.4 Theoretical Underpinning

2.4.1 Continuance Theory

The literature on information systems (IS) has extensively explored the factors influencing technology acceptance and usage (Davis, 1989; Venkatesh et al., 2003). However, researchers have argued that the success of information systems is largely dependent on ongoing user engagement rather than initial adoption (Bhattacherjee, 2001; Nascimento et al., 2018; Zhang et al., 2018). Moreover, retaining users is crucial for companies, as it is significantly more cost-effective than acquiring new ones, costing five times less (Alkitbi et al., 2020; Juwaini et al., 2022). Studies show that while attracting new users and encouraging initial engagement are essential, companies must prioritise the retention of existing users and foster their continued usage (Gao et al., 2015; Zhao and Bacao, 2020). However, a significant limitation in prior research is its tendency to focus on the predictors of adoption, neglecting the cognitive and emotional factors critical to sustained engagement, especially in critical contexts like healthcare technologies (Azam et al., 2023; Talukder et al., 2020). This gap highlights the need for theoretical frameworks that specifically address post-adoption behaviours, such as continuance intention.

Research has explored this through various technologies, such as social networking (Liao et al., 2019), e-learning (Lou et al., 2019), internet banking (Yuan et al., 2019), and personal technology devices (Li and Li, 2020). Bhattacherjee (2001) notes that while initial acceptance is vital, the long-term success of IS primarily relies on sustained usage. Although frameworks like Rogers' (2003) Diffusion of Innovations (DOI) theory have considered continuance intention, they rely heavily on pre-adoption variables, failing to account for post-adoption factors like satisfaction and evolving expectations. This study addresses this gap by exploring continuance intention in the context of digital healthcare technologies, focusing on factors that go beyond initial adoption and examining sustained user engagement.

2.4.2 Post-Adoption Theories

Post-adoption theories aim to explain user behaviour after the initial adoption of technology, focusing on the factors that influence continued engagement over time. These theories extend beyond the acceptance phase, addressing the complexities of technology use as it becomes integrated into daily life. While frameworks like Appropriation Theory (DeSanctis and Poole, 1994), Adaptive Structuration Theory (AST) (Poole and DeSanctis, 1990), and Technology Domestication Theory (Silverstone and Haddon, 1996) provide valuable insights, their fragmented focus limits their applicability to digital healthcare technologies and older users.

Appropriation Theory emphasises how users adapt and integrate technology into their lives by modifying its use to suit personal and contextual needs (DeSanctis and Poole, 1994). This view highlights how people adapt and reuse technology in creative ways, influenced by social and cultural factors (Alberts, 2013). For example, a wearable fitness tracker may be utilised not only for health monitoring but also as a social tool for sharing achievements within a community. However, this theory does not account for the cognitive and emotional processes that are critical for understanding continuance intention in health-related contexts, such as satisfaction with achieving health goals or alignment with health-specific expectations. Its focus on creative adaptation makes it more suited for examining collective and social dynamics rather than individual behaviours (Bar et al., 2007). In the context of this research, this limitation makes it less applicable for explaining the sustained usage of digital healthcare technologies.

Building on the interaction between users and technology, Adaptive Structuration Theory (AST) examines how the structures embedded within technology influence user behaviour over time

(Poole and DeSanctis, 1990). AST highlights the duality of structure and agency, showing how organisational or societal norms shape technology use and how users, in turn, reshape these norms through their actions (Poole and DeSanctis, 1990). For example, institutional rules influence how users and healthcare providers interact on telemedicine platforms. However, AST does not consider how individual users, especially older adults, think and feel about these technologies when deciding whether to keep using them, which is key to understanding. While AST helps explain how technology use changes in organisations, it does not focus on individual thoughts and feelings, such as usefulness, satisfaction, and confirmation, which influence long-term use (Poole and DeSanctis, 1990). In DHTs, these factors are crucial for older adults, who decide to keep using the technology based on their trust in its ability to meet their health needs (Cao et al., 2022; Nie et al., 2023).

In contrast, the Technology Domestication Theory explores how technology becomes integrated into everyday life, emphasising its normalisation and personalisation (Silverstone and Haddon, 1996). This theory is particularly relevant in contexts where technology transitions from being novel to becoming a routine part of daily activities (Nimrod and Edan, 2022), such as older adults incorporating digital healthcare technologies into their health management practices. However, this theory falls short in addressing the specific drivers of continued use, such as the alignment of users' expectations with perceived outcomes or the emotional satisfaction derived from managing health effectively (Nikou et al., 2020). Its emphasis on social integration offers a broad narrative but lacks a structured approach to examining the individual-level factors that influence long-term continuance intention for DHTs (Sovacool and Hess, 2017).

These theories provide a multidimensional understanding of post-adoption behaviour. Appropriation Theory sheds light on the dynamic and creative adaptation of technology (DeSanctis and Poole, 1994), AST examines the interplay between structural constraints and user agency (Poole and DeSanctis, 1990), and Domestication Theory captures the normalisation of technology in daily life (Silverstone and Haddon, 1996). Despite their contributions, these theories do not sufficiently address the socio-emotional (e.g., satisfaction, ageing satisfaction), cognitive (e.g., perceived usefulness, confirmation of expectations), and contextual (e.g., technology anxiety) factors that are central to understanding continuance intention to use DHTs among older users. The focus of these theories highlights the need for a more comprehensive framework that integrates these dimensions, such as the ECM (Bhattacherjee, 2001).

2.4.3 Expectation Confirmation Theory and Expectation Confirmation Model

Expectation Confirmation Theory (ECT), also called expectation-disconfirmation theory (EDT), is grounded in marketing principles and serves as a model for examining consumers' repurchase intentions, primarily through the lens of satisfaction. According to ECT, consumers decide to repurchase based on a specific process. First, they come into a purchase with particular expectations about a product or service, which are shaped by their past experiences and what they already know (Oliver, 1980; Zeithaml et al., 1990). This information comes from media, marketing, customer reviews, and discussions with friends. These pre-purchase expectations vary depending on prior knowledge and perceived value (Rahi and Ghani, 2019; Rogers, 2003). Post-purchase, consumers evaluate the product or service, forming perceptions of its performance. This evaluation involves comparing the perceived performance to the initial expectations, resulting in confirmation or disconfirmation of those expectations. When a product's performance aligns with or surpasses consumer expectations, confirmation takes place. Conversely, if the performance does not meet expectations, disconfirmation occurs (Oliver, 1980; Boulding et al., 1994). Disconfirmation may be positive if the performance goes beyond expectations or negative if it fails to meet them. This difference between expectations and actual performance subsequently impacts the consumer's satisfaction level (Oliver, 1993; Bhattacherjee, 2001).

Although traditional Expectation Confirmation Theory (ECT) provides useful insights, it has certain limitations when it comes to explaining how expectations for information systems (IS) are established (Mamun et al., 2020). For example, consumers might choose a product even without clear pre-existing expectations, and new or unique information systems features can create diverse expectations across user groups. ECT generally emphasises attitudes and beliefs concerning a product's functionality or attributes, yet it does not fully address aspects of quality (Gupta et al., 2021; Nascimento et al., 2018). To address these gaps, researchers have modified ECT to accommodate better the complexities associated with contemporary information systems. A prominent modification is Bhattacherjee's (2001) Expectation Confirmation Model (ECM), shown in Figure 2. This model argues that when users feel satisfied with a technology, they are more inclined to keep using it (Bhattacherjee, 2001).

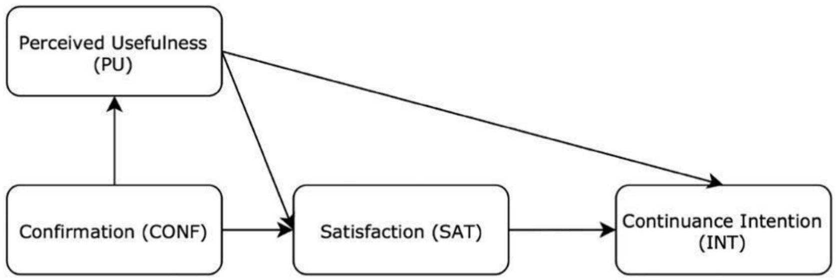

Figure 2: Expectation Confirmation Model
Source: Bhattacherjee (2001)

Bhattacherjee (2001) proposed that a user's intention to continue using a digital tool is similar to a consumer's decision to repurchase. In light of this, he developed the expectation confirmation model, a post-adoption framework suggesting that the ongoing use of a digital tool is shaped by three main factors: the confirmation of initial expectations, the perceived usefulness, and the satisfaction experienced with the digital tool. Confirmation of expectation refers to how well the actual performance of a technology product or service matches the initial expectations of the user. Perceived usefulness refers to the user's belief in the advantages they anticipate receiving from using a technology product or service. Satisfaction is assessing a user's first experience with the product or service (Bhattacherjee, 2001).

The expectation confirmation model suggests that perceptions of usefulness after adoption and alignment of prior expectations are key factors in shaping user satisfaction. Furthermore, the alignment of expectations directly impacts perceived usefulness. Ultimately, the model argues that perceived usefulness and satisfaction are key drivers of the intention to continue using the technology product or service (Bhattacherjee, 2001). It also posits that user satisfaction is positively influenced by both perceived usefulness and confirmation of expectations, while the intention to continue using the information systems is strongly and positively affected by user satisfaction and perceived usefulness (Bhattacherjee, 2001). This study addresses gaps in prior ECM adaptations by tailoring the model to incorporate ageing-specific factors, such as technology anxiety, health anxiety, self-efficacy, ageing satisfaction, health motivation, and health-consciousness, to better capture the nuances of older users' engagement with digital healthcare technologies. The expectation confirmation model (Bhattacherjee, 2001) is considered groundbreaking as it specifically addresses the gap between users' initial acceptance of an IT product or service and their continued use over time. Traditional models like the Technology Acceptance Model (TAM) by Davis et al. (1989) and the Theory of Planned Behaviour (TPB) by Ajzen (1991) have been comprehensively studied to understand what drives the initial acceptance of emerging digital tools. However, these models are limited in their ability to describe what occurs beyond the initial adoption phase. Bhattacherjee (2001) and Ambalov (2018) emphasise that while getting users to accept a product initially is crucial, the long-term success of any digital tool depends heavily on its continued usage.

In this study, the expectation confirmation model has been selected as the theoretical foundation for examining the intention to continue using digital healthcare technologies for several vital reasons. The expectation confirmation model is highly regarded among scholars as a robust framework for understanding post-adoption behaviour in the context of information systems (Lee and Kwon, 2011; Tam et al., 2020). Since its introduction, the expectation confirmation model has been widely employed by researchers to explore information systems continuance intention across various contexts, including mobile banking (Amin et al., 2023; Jusuf et al., 2017; Poromatikul et al., 2020; Rabaa'i and AlMaati, 2021; Susanto et al., 2012), e-learning systems (Alraimi et al., 2015; Alshurideh et al., 2019; Cheng, 2021; Dağhan and Akkoyunlu, 2016; Lee, 2010; Mtebe and Gallagher, 2022; Rabaa'i et al., 2021), e-Health/mHealth (Kumar and Natarajan, 2020; Nie et al., 2023; Wang and Chao, 2023; Zhang et al., 2018), mobile apps (Hsu and Lin, 2015; Park and Lee, 2023; Tam et al., 2018; Wang et al., 2021), fintech (Nurdin et al., 2023; Shiau et al., 2020), mobile instant messaging (CC and Prathap, 2020; Oghuma et al., 2016), e-commerce (Gunawan et al., 2022; Zhang et al., 2015), wearable technology devices (Dehghani et al., 2018; El-Gayar and Elnoshokaty, 2023; Gupta et al., 2021; Li et al., 2019; Nascimento et al., 2018; Ogbanufe and Gerhart, 2017; Park, 2020), and mobile shopping (Rahi et al., 2022; Shang and Wu, 2017; Susanto et al., 2016). Given that digital healthcare technologies fall under the category of IS-related products, applying the expectation confirmation model as a theoretical foundation to study the post-adoption behaviour of digital healthcare technology users is both relevant and insightful.

The Expectation Confirmation Model (ECM) has been used in this study to address the unique characteristics of digital healthcare technologies and the needs of older users. Unlike general IS contexts, DHTs serve critical health-related functions, such as chronic disease management, fitness tracking, and telehealth consultations, which inherently involve higher stakes for user satisfaction and continuance intention (Nie et al., 2023; Zhang et al., 2018). Users' expectations of DHTs are shaped not only by perceived technological benefits (e.g., usefulness and ease of use) but also by health-specific factors, such as improvements in health outcomes, self-management of conditions, and alignment with health objectives (Kumar and Natarajan, 2020). Thus, the confirmation of expectations for DHTs goes beyond general functionality to include measurable health improvements and usability for diverse health needs (Cao et al., 2022). Moreover, the behaviour of digital healthcare technology users closely parallels the post-adoption behaviour observed in technology users (Tam et al., 2020). Before using a digital healthcare technology, users form expectations regarding the device. Upon usage, they gain firsthand experience and assess its performance. This leads to either confirmation or disconfirming the alignment between their initial expectations and the actual performance. This confirmation process subsequently influences user satisfaction with digital healthcare technologies (Chiu et al., 2020). Furthermore, other prominent theories like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) fail to account for potential shifts in consumers' expectations and perceptions after the initial adoption phase, treating continuous use simply as a continuation of the initial adoption process. However, previous research suggests that individuals in the pre-adoption and post-adoption stages have different needs and motivations (Karahanna, 1999; Agarwal and Karahanna, 2000; Montazemi and Qahri-Saremi, 2015). Moreover, studies have shown that the expectation confirmation model provides a more robust explanation than TAM for understanding individuals' intentions to continue using information systems (Bhattacherjee, 2001; Halilovic and Cicic, 2013; Larsen et al., 2009).

In addition to its broad applicability across various IS contexts, the expectation confirmation model is particularly well-suited for studying older users' intentions to continue using digital healthcare technologies. Older users often approach technology with preconceived expectations shaped by prior experience, ease of use, and perceived usefulness (Mitzner et al., 2010; Vroman et al., 2015). The expectation confirmation model's focus on the confirmation or disconfirmation of these expectations after initial use makes it valuable for examining older users, who may be more sensitive to discrepancies between expectations and actual performance due to potential technology anxiety or lower self-efficacy (Czaja et al., 2006; Ha and Park, 2020). Studies have shown that confirmation of expectations significantly influences satisfaction and continued use intentions among older users, making the expectation confirmation model an ideal framework for this population (Su and Thong, 2021; Xie et al., 2020).

Also, older users may have different needs and motivations compared to younger users, particularly in the context of health-related technologies (Garcia Reyes et al., 2023; Heart and Kalderon, 2013). The expectation confirmation model's ability to account for shifts in user expectations after initial adoption is crucial for understanding the long-term engagement of older users with digital healthcare technologies (Barnard et al., 2013). As older users become more familiar with technology, they may reassess its usefulness and ease of use, impacting their intention to continue using it (Su and Thong, 2021; Tian and Wu, 2022). In contrast, other models like TAM and UTAUT, which emphasise initial adoption factors, may not adequately capture these dynamics in older populations (Lee and Xie, 2018). Furthermore, research indicates that satisfaction with technology plays a critical role in older users' continued usage, and the expectation confirmation model's emphasis on satisfaction as a mediator between confirmation and continued use intentions aligns well with this demographic (Cao et al., 2022; Heart and Kalderon, 2013). The expectation confirmation model's ability to capture these nuanced post-adoption factors makes it suitable for studying older users' interactions with digital healthcare technologies. Since the expectation confirmation model is rooted in actual user experiences and emphasises sustained technology use or ongoing engagement (Premkumar and Bhattacherjee, 2008), this study suggests that a theoretical framework based on this model may offer a more in-depth perspective on the topic under investigation. Table 2 provides a summary of key theories, comparing major information systems and technology adoption models to showcase the strengths of the expectation confirmation model.

Theory	Key Constructs	Strengths	Limitations
Expectation Confirmation Model (ECM) (Bhattacherjee, A. 2001)	Confirmation of Expectation, Perceived Usefulness, Satisfaction, Continuance Intention	Addresses post-adoption behaviour; Solid theoretical framework for IS contexts; Validated across various IS domains; Captures user experience dynamics; Higher explanatory power than some other models; Focuses on long-term IT usage; Recognises changing user perceptions; Applicable to digital healthcare technology context (Bhattacherjee, 2001; Hong et al., 2006; Hsu and Lin, 2015; Larsen et al., 2009; Lee and Kwon, 2011; Tam et al., 2020).	Does not consider ageing-specific characteristics, needs, expectations, capabilities, and physical limitations; Focuses mainly on cognitive aspects; oversimplifies complex decision processes; Limited consideration of external factors (Bhattacherjee and Barfar, 2011; Chiu et al., 2005; Hossain and Quaddus, 2012; Ghazali et al., 2024; Meng et al., 2022; 2013; Obeid et al., 2024; Tao et al., 2009).
Technology Acceptance Model (TAM) (Davis, 1989)	Perceived Usefulness, Perceived Ease of Use, Attitude, Behavioural Intention	Simple, easy to apply and test; Widely validated across numerous studies and contexts; Can be extended with additional variables; Provides apparent factors for improving acceptance (Davis, 1989; King and He, 2006; Lee et al., 2003; Venkatesh and Bala, 2008; Venkatesh and Davis, 2000; Yousafzai et al., 2007).	Does not consider external factors like facilitating conditions, which were later added in the Unified Theory of Acceptance and Use of Technology (UTAUT); Neglects social influences; Focuses only on initial adoption; Oversimplifies technology acceptance (Bagozzi, 2007; Bhattacherjee, 2001; Benbasat and Barki, 2007; Legris et al., 2003).
Theory of Planned Behaviour (TPB) (Ajzen, 1991)	Attitudes, Subjective Norms, Perceived Behavioural Control, Intentions, Behaviour	Considers social and control factors; Applicable across various domains; Strong predictive power for behavioural intentions; Allows addition of other predictors; Useful for intervention design (Ajzen, 1991; Ajzen, 2011; Armitage and Conner, 2001; Conner and Armitage, 1998; Godin and Kok, 1996; Sheeran, 2002).	The gap between intention and actual behaviour Assumes rational decision-making and does not account for habitual behaviours (Ogden, 2003; Perugini and Bagozzi, 2001; Sniehotta et al., 2014).
	Relative Advantage, Compatibility, Complexity, Trialability,	Explains adoption across different innovations; Considers multiple factors (includes innovation and adopter characteristics); Useful for	Does not explain organisational adoption; Lacks predictive power for adoption rate; Does not

Diffusion of Innovations (DOI) (Rogers, 2003)	Observability, Innovation Adoption	marketing strategies; Helps in promoting new products/ideas; Explains adoption process over time; Applicable at individual and organisational levels (Greenhalgh et al., 2004; Kapoor et al., 2014; Rogers, 2003).	account for resource limitations (Fichman, 2004; Karch et al., 2016; Meyer, 2004).
Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. 2003)	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioural Intention	Integrates multiple theories (Combines elements from eight models); Considers moderating factors (age, gender, experience, voluntariness); Applicable in organisational contexts; Provides a unified view and merges key elements from various theories (Dwivedi et al., 2011; Venkatesh et al., 2003; Venkatesh et al., 2012; Venkatesh et al., 2016; Williams et al., 2015).	Complex with many variables; Difficult to apply in all contexts; Focuses mainly on organisational settings (Bagozzi, 2007; Im et al., 2011; van Raaij and Schepers, 2008; Rana et al., 2017).
Technology Readiness Index (TRI) (Parasuraman, 2000)	Optimism, Innovativeness, Discomfort, Insecurity	Predicts acceptance and usage behaviour; Identifies readiness levels for adopting new technologies; Applicable in diverse contexts; Useful for segmenting users based on their technology readiness; Helps in designing targeted interventions (Parasuraman, 2000; Lin et al., 2007; Walczuch et al., 2008).	Overemphasis on psychological traits; Does not fully capture situational factors affecting technology adoption; Does not account for all barriers to technology adoption (Parasuraman and Colby, 2015; Caison et al., 2008; Liljander et al., 2006).

Table 2: Comparative Analysis of Expectation Confirmation Model and Other Major Technology Adoption Theories
(Developed by the author)

2.5 Theoretical Applications and Continuance Intention in Digital Healthcare Technologies

2.5.1 Expectation Confirmation Model in Digital Healthcare Technologies Contexts

The Expectation Confirmation Model (ECM) has been frequently applied to understand the continuance intention to use digital healthcare technologies. Initially introduced by Bhattacharjee in 2001, this model explains how users' initial expectations, actual experiences, and subsequent beliefs after adopting the technology shape their satisfaction and intention to keep using it. Applying expectation confirmation model in digital health has shed light on the elements that encourage continuous engagement with digital healthcare technologies, including eHealth services, mobile health (mHealth) apps, telemedicine platforms, and wearable devices (Cho, 2016; Gupta et al., 2021; Kumar et al., 2019; Min et al., 2017; Nascimento et al., 2018; Reychav et al., 2021; Sun and Gu, 2024; Yousaf et al. 2021). The following section discusses various studies that have applied the expectation confirmation model to different digital healthcare technologies.

Electronic Health (eHealth) Services

Research on eHealth services has widely employed the expectation confirmation model to understand user behaviour, particularly in relation to continued use. For instance, Leung and Chen (2019) identified confirmation and perceived usefulness as key predictors of lifestyle improvements through eHealth adoption. Their study highlights how user expectations and perceptions of usefulness can significantly drive engagement with eHealth, particularly when users participate in specific activities like recording health data or using health tutorials. Innovativeness, age, and participation in these activities were also found to influence outcomes, reflecting the diverse factors that shape user experiences with eHealth technologies. Building on this, Kumar et al. (2019) expanded the expectation confirmation model by integrating constructs from the Technology Acceptance Model (TAM). Their study emphasised the importance of social influence, trust, perceived service quality, and perceived privacy and security as critical factors shaping users' continued engagement with eHealth services. By merging these constructs with the expectation confirmation model, they highlighted how post-adoption beliefs, such as perceived ease of use and usefulness, combined with trust and privacy concerns, significantly impact continued engagement with eHealth technologies. In a related study, Kumar and Natarajan (2020) further highlighted the important role of post-adoption expectation beliefs in influencing the continued use of eHealth services. They emphasised that factors such as perceived trust, perceived privacy and security, combined with traditional expectation confirmation model constructs, are essential in shaping users' ongoing engagement with these services.

When looking at specific user groups, Mou et al. (2017) focused on college students' acceptance of online health services. They found that trust in both the website and provider, combined with

TAM variables, influences continued use. As students gained more experience, the importance of perceived ease of use diminished, suggesting that as familiarity with the system grows, other factors like trust and service quality take precedence in shaping behaviour. Similarly, Ju and Zhang (2020) explored the broader population's engagement with online healthcare services, finding that service quality, expectation confirmation, privacy concerns, and satisfaction are crucial drivers of continued use. They emphasised that privacy concerns and satisfaction directly affect users' intention to continue using these services, echoing findings from Kumar et al. (2019) and Mou et al. (2017), but across a wider demographic.

Mobile Health (mHealth) Apps

A variety of research has explored the application of the expectation confirmation model within the realm of mHealth apps. These studies shed light on the complex factors influencing users' intention to continue using mHealth apps, and each study provides unique insights into the different elements that drive continued usage. Post-adoption satisfaction has consistently been identified as a key driver of continuance intention in mHealth research. Cho (2016) emphasised the importance of post-adoption beliefs, showing that confirmation, satisfaction, perceived usefulness, and ease of use are critical predictors of the intention to continue using health apps. This further supports the notion that satisfaction, driven by perceived usefulness and confirmation, plays a pivotal role in user engagement. Similarly, Kaium et al. (2020) extended this understanding by identifying system quality, performance expectancy, facilitating conditions, and social influence as significant factors influencing confirmation and satisfaction, although they found service and information quality to be non-significant. These findings suggest that while technical and performance factors are crucial, some quality aspects may have less impact on long-term engagement. Furthermore, Chiu et al. (2020) highlighted the relationship between user investment and satisfaction. Their research demonstrated that both satisfaction and user investment enhance commitment, thereby boosting the intention to continue using fitness and health apps. These studies underscore the central role of satisfaction in driving continuance intention and highlight the various factors, ranging from IT mindfulness to system quality that influence it.

Several studies have expanded the expectation confirmation model by incorporating additional theoretical frameworks to better capture the dynamics of continuance intention. For example, Wu et al. (2022) made a notable contribution by expanding the expectation confirmation model with the introduction of IT identity and IT mindfulness. They demonstrated that IT identity directly influences continuance intention, while IT mindfulness serves as a mediator. Moreover, they found that satisfaction completely mediates the relationship between perceived usefulness and continuance intention. This study exemplifies how extending the expectation confirmation model with personal factors like identity and mindfulness can offer deeper insights into post-adoption behaviour. Li et al. (2019) also extended the expectation confirmation model by integrating social comparison theory, showing that rankings based on activity positively influence confirmation and continuance intention, although the effect is moderated by upward comparison. This demonstrates how psychological factors, such as how users perceive their performance relative to others, can moderate traditional expectation confirmation model relationships.

Moreover, Wang and Cao (2023) applied the theory of consumption value to the expectation confirmation model, identifying functional, social, emotional, and conditional values as important factors influencing perceived value and satisfaction. Their findings, along with those of Akter et al. (2013), which emphasised the importance of perceived service quality and trust in developing countries, show how incorporating additional value-based and trust-related constructs can enhance the expectation confirmation model's ability to predict continuance intention. Together, these studies provide a richer understanding of how users' value perceptions and trust in the service affect their ongoing use of mHealth apps. Similarly, Tian and Wu (2022) expanded the expectation confirmation model by integrating it with UTAUT and ECM, showing that factors like performance expectancy and effort expectancy, along with confirmation, are key drivers of satisfaction and continuance intention. This combination of theoretical models offers a more comprehensive view of how user expectations and effort influence long-term engagement with mHealth apps. In contrast to the focus of studies on post-adoption behaviour, Yousaf et al. (2021) looked into pre-adoption expectations and found that performance expectancy, effort expectancy, social influence, and trust positively influence neutral confirmation. This neutral confirmation then affects perceived privacy, which in turn impacts satisfaction. Additionally, the quality of the user interface impacts perceived usefulness and self-efficacy, with continual usage affecting health satisfaction. This study brings attention to the role of privacy concerns and user interface design in shaping users' satisfaction and pre-adoption expectations.

The role of feedback mechanisms and information quality has also been central to several studies on mHealth continuance intention. For example, Min et al. (2017) investigated these factors from an information ecology perspective, highlighting the importance of information accuracy, system responsiveness, and perceived health threats in shaping confirmation and perceived usefulness. Their findings suggest that system responsiveness and information accuracy play critical roles in shaping user satisfaction and engagement. Also, Reychav et al. (2021) focused on feedback in mobile health reporting systems, demonstrating that users' effort in self-disclosure and their expectations for feedback shape their perceptions of feedback quality and the sense of confirmation they experience. These perceptions subsequently influence user satisfaction and willingness to continue sharing medical information. Although the perceived quality of feedback does not directly enhance the sense of confirmation, both perceived feedback quality and confirmation factors positively contribute to user satisfaction. This increased satisfaction, in turn, strengthens the intention to continue disclosing health-related data. Nie et al. (2023) and Xu et al. (2022) both explored external factors that shape users' perceptions and behaviours. Nie et al. (2023) found that subjective norms positively impact perceived service and information quality, while Xu et al. (2022) showed that system ease of use influences perceived usefulness and attitudes, which in turn affect continuance intention. These studies illustrate the critical role of external perceptions in shaping users' engagement with mHealth technologies.

Telemedicine

Research on telemedicine has also applied the expectation confirmation model to explore user behaviour and continuance intention. For example, Zhu et al. (2023) studied remote telemedicine technologies and found that three different aspects of trust moderate how perceived usefulness translates into satisfaction. Their study also revealed that privacy concerns can weaken the relationship between structural assurance-based trust and continuance intention. Similarly, Grenier Ouimet et al. (2020) examined patients' intention to continue using teleconsultation and found that expectation confirmation impacts continuance intention, perceived usefulness, and quality, with quality further influencing perceived usefulness. Both studies emphasise the importance of trust and perceived usefulness in shaping user satisfaction and continued engagement while highlighting how privacy concerns can serve as a barrier to the continued use of telemedicine services.

Amin et al. (2022) proposed an integrative model for telemedicine services that identifies several key factors influencing users' intentions to continue using these services. They found that performance expectancy, information quality, satisfaction, engagement, and contamination avoidance are significant predictors of continuance intentions. Additionally, engagement and satisfaction were shown to act as mediators between performance expectancy, information quality, and continuance intention, further strengthening the relationship between these factors and the intention to continue using telemedicine services. Shifting the focus to emotional factors, Gong and Liu (2023) explored the role of technology anxiety and perceived ease of use in telemedicine adoption during the COVID-19 pandemic. They found that technology anxiety negatively impacts both perceived ease of use and usage intention, while health information consumption through social media positively affects perceived usefulness. Additionally, prior satisfaction with telemedicine services enhances both perceived ease of use and perceived usefulness, although it does not directly influence usage intention. Perceived ease of use was found to mediate the relationship between technology anxiety and usage intention, highlighting its central role in telemedicine adoption.

Wearable Technology Devices

Research on wearable technology devices has extensively used the expectation confirmation model to understand user behaviour and continuance intention to use. A core theme across many studies is the role of confirmation, perceived usefulness, and satisfaction in driving continued use of wearable devices. For instance, Nascimento et al. (2018) found that confirmation, perceived usefulness, and satisfaction significantly enhance the intention to continue using smartwatches, with habit and perceived usability also playing crucial roles, particularly as habit was identified as the most influential factor in determining continued use. Similarly, Siepmann and Kowalczuk (2021) confirmed the relevance of the expectation confirmation model in the smartwatch context, highlighting that self-quantification behaviour influences perceived usefulness, goal pursuit motivation, and confirmation. However, their study also pointed out that device annoyance is a significant barrier to continued use, highlighting a potential obstacle to continued use.

Pal et al. (2020) explored additional factors influencing the continuous use of smartwatches. They found that perceived usefulness, hedonic motivation, perceived comfort, and self-socio motivation positively influence the intention to continue using smartwatches. Conversely, concerns about privacy, battery life, perceived accuracy and functional limitations negatively affect usage, with functional limitations being the strongest predictor of discontinuance. This aligns with earlier studies, such as those by Nascimento et al. (2018) and Siepmann and Kowalczuk (2021), in terms of how user satisfaction and functionality drive long-term engagement. Gupta et al. (2021) combined social comparison theory with expectation confirmation model to examine smart fitness wearables. They found that perceived health outcomes and satisfaction significantly contribute to the intention to continue using these devices and to recommend them to others. Their study also revealed that a tendency for social comparison enhances both perceived health outcomes and satisfaction. Additionally, factors like perceived usefulness, confirmation, perceived health outcomes, and social comparison tendency were all found to positively influence user satisfaction, highlighting how social elements can shape engagement with fitness wearables. Sun and Gu (2024) also focused on fitness devices, discovering that users who are more innovative with technology and have higher levels of eHealth literacy are more likely to continue using wearable fitness devices. They also revealed that male users are more likely to maintain usage if their eHealth literacy is improved through specific training. This highlights the potential of tailored interventions to significantly improve long-term engagement with wearable fitness technology, particularly among men.

Expanding on satisfaction drivers, El-Gayar and Elnoshokaty (2023) found that satisfaction is key for fostering continued use of wearable devices. They identified perceived benefits, enjoyment, and confirmation as primary factors driving satisfaction. In addition, they pointed out that battery life, device compatibility, dialogue support, and overall appeal play significant roles in influencing confirmation. Similarly, Park (2020) applied the expectation confirmation model to smart wearable devices, finding that satisfaction, enjoyment, usefulness, flow state, and cost influence users' intentions to continue using their devices. User confirmation and system quality also emerged as significant factors in their model, further supporting the central role of satisfaction in wearable device usage.

Taking a broader approach, Zhao and Wang (2024) expanded the expectation confirmation model to examine users' willingness to continue using wearable devices. They discovered that self-efficacy, conversion costs, and perceived usefulness significantly affect continuance intention, with innovativeness and subjective references also playing a role. Interestingly, their study found that privacy concerns did not impact continuance intention, contrasting with Pal et al. (2020) and highlighting how different user populations may perceive privacy differently. Finally, Shen et al. (2018) introduced a revised expectation-disconfirmation model to explain why users might temporarily stop using wearable health information systems. They discovered that when expectations neither exceed nor fall short (neutral disconfirmation), it leads to neutral satisfaction and attitudinal ambivalence, both of which contribute to intermittent discontinuance. They further found that attitudinal ambivalence positively influences neutral satisfaction. It suggests that the interaction between satisfaction and ambivalence plays a role in short-term discontinuation. Table 3 provides a summary of studies using the expectation confirmation model in the context of digital health technologies, along with their key constructs and main findings.

Authors (Year)	Technology Context	Additional Constructs	Main Findings
Wu et al. (2022)	mHealth technology	IT identity, IT mindfulness	IT identity positively influences IT mindfulness; IT identity and IT mindfulness influence continuance intention.
Tian and Wu (2022)	mHealth	performance expectancy, effort expectancy, social influence, facilitating conditions	Confirmation influences satisfaction, performance expectancy, and effort expectancy; performance expectancy and confirmation impact satisfaction; effort expectancy, performance expectancy, social

			influence, and facilitating conditions positively influence continuance intention.
Cho (2016)	Health apps	Perceived ease of use	Confirmation, satisfaction, perceived usefulness, and perceived ease of use are significant predictors of continuance intention to use.
Kaium et al. (2020)	mHealth	System quality, information quality, service quality, performance expectancy, social influence, facilitating conditions	System quality, performance expectancy, facilitating conditions, and social influence affect confirmation, satisfaction, and continuance usage intention.
Wang and Cao (2023)	mHealth	Functional value, social value, emotional value, conditional value, perceived value, habit, epistemic value	Functional, social, emotional, and conditional values positively affect perceived value; epistemic value does not affect perceived value; satisfaction, perceived value, and habit positively affect continuance intention to use; satisfaction mediates the relationship between confirmation and continuance intention to use.
Nie et al. (2023)	mHealth services	E-health literacy, subjective norm, perceived service quality, perceived system quality, perceived information quality	Subjective norm positively impacts perceived service quality and perceived information quality; e-health literacy affects perceived usefulness, perceived service quality, and perceived information quality; perceived usefulness, customer satisfaction, and subjective norm influence continuance intention to use.
Xu et al. (2022)	mHealth applications	External characteristics, perceived ease of use, subjective norms, attitude	External characteristics positively influence perceived ease of use; perceived ease of use impacts perceived usefulness; perceived usefulness, perceived ease of use, and subjective norms positively impact attitude; perceived usefulness and attitude affect continuance intention to use; attitude mediates the relationship between perceived usefulness and continuance intention to use.
Li et al. (2019)	Social fitness-tracking apps	Activity amount ranking, activity frequency ranking, upward comparison tendency	Activity amount ranking and activity frequently ranking positively influence confirmation and continuance intention; expectation confirmation moderates the relationship between activity amount ranking and activity frequently ranking and continuance intention; the high level of upward comparison tendency decreases the positive effect of confirmation on continuous intention.

Yousaf et al. (2021)	Fitness applications	Performance expectancy, effort expectancy, trust, social influence, health satisfaction, technology self-efficacy, user-interface quality, perceived privacy	Performance expectancy, effort expectancy, social influence, and trust positively affect neutral confirmation; neutral confirmation affects perceived privacy; perceived privacy impacts satisfaction; user-interface quality impacts perceived usefulness and self-efficacy; self-efficacy has a positive effect on self-efficacy; continual usage impacts health satisfaction.
Min et al. (2017)	Health apps	Information accuracy, consensus, perceived health threats, system responsiveness, ease of use, network externality	Information accuracy, consensus, perceived health threats, system responsiveness, ease of use, and network externalities positively influence confirmation and perceived usefulness.
Reychav et al. (2021)	Mobile technology	Self-disclosure effort, feedback expectation, perceived feedback quality, disclosed intention	Self-disclosure effort and feedback expectation influence perceived feedback quality and confirmation; perceived feedback quality and confirmation impact satisfaction; satisfaction affects intention to disclose.
Chiu et al. (2020)	Fitness and health apps	Quality of alternative, investment size, commitment	Satisfaction and investment size positively impact commitment; confirmation of expectations positively impacts investment size.
Akter et al. (2013)	mHealth services	Perceived service quality, perceived trust	Perceived service quality and trust significantly determine continuance intention.
Leung and Chen (2019)	E-health/m-Health	Technology readiness, lifestyle improvements	Confirmation and perceived usefulness are the strongest predictors of lifestyle improvement; age, innovativeness, and use of e-health/m-health activities significantly affect continuance intention to use.
Kumar and Natarajan (2019)	E-health services	Trust, social influence, perceived service quality, perceived privacy and security, perceived ease of use	Trust, social influence, perceived service quality, perceived privacy and security, satisfaction, confirmation, perceived ease of use, and perceived usefulness significantly influence e-health services' continuance usage.
Kumar and Natarajan (2020)	E-health services	Perceived trust, perceived privacy and security, perceived ease of use	Perceived trust, perceived privacy and security, confirmation, perceived ease of use, and perceived usefulness are significantly associated with continuance intention.
Mou et al. (2017)	Online health services	Trust in website, trust in provider, perceived ease of use	Trust in both the website and provider integrates well with Technology Acceptance Model (TAM) variables to influence behaviour; perceived ease of use is less important in behaviour intentions.

Ju and Zhang (2020)	Online healthcare services	Interactive quality, service quality, perceived supervision, secondary use of personal information, privacy focus, anxiety	Service quality, expectation confirmation degree, privacy concern, and satisfaction positively influence continuous use intention and continuous use behaviour; satisfaction and privacy concern directly impact users' continuous use intention; satisfaction and concern positively affect continuance intention to use and continuous use behaviour; service quality and privacy concern affect satisfaction and concern.
Zhu et al. (2023)	Non-face-to-face telemedicine	Structural assurance trust, platform-based trust, physician-based trust, privacy concerns	The link between perceived usefulness and satisfaction is influenced by three aspects of trust; privacy concerns reduce the strength of the relationship between structural assurance-based trust and the intention to continue use.
Grenier Ouimet et al. (2020)	Teleconsultation	Quality of ease of use, service quality, security and confidentiality, trust	Confirmation of expectation influences continuance intention, usefulness, and quality; quality influences usefulness.
Amin et al. (2022)	Telemedicine	Performance expectancy, effort expectancy, information quality, contamination avoidance, engagement, facilitating condition, price value, functionality	Performance expectancy, information quality, contamination avoidance, engagement, and satisfaction influence continuance intention to use; engagement and satisfaction mediate these relationships; performance and effort expectancies impact engagement.
Gong and Liu (2023)	Telemedicine	Technology anxiety, perceived ease of use, social media health information consumption, previous telemedicine satisfaction	Technology anxiety negatively affects perceived ease of use and usage intention; perceived ease of use mediates the relationship between technology anxiety and usage intention; social media health information consumption influences perceived usefulness; previous telemedicine satisfaction impacts perceived ease of use and perceived usefulness.
Nascimento et al. (2018)	Smartwatches	Habit, perceived usability, perceived enjoyment	Expectation confirmation model relationships impact continuance intention to use; habit is the most important factor in explaining continuance intention.
Siepmann and Kowalczuk (2021)	Smartwatches	Self-quantification behaviour, goal pursuit motivation, device annoyance, enjoyment	Self-quantification behaviour impacts goal pursuit motivation, perceived usefulness, and device annoyance; device annoyance is a significant barrier to continuance intention to use.
Pal et al. (2020)	Smartwatches	Hedonic motivation, perceived comfort, self-socio motivation, perceived privacy, battery-life concern,	Perceives usefulness, hedonic motivation, perceived comfort, and self-socio motivation positively affect continuous usage; perceived privacy, battery-life concern, and perceived accuracy and functional limitations

		perceived accuracy and functional limitations	negatively affect continuous usage; hedonic motivation does not affect perceived usefulness.
Gupta et al. (2021)	Smart fitness wearables	Perceived health outcome, social comparison tendency, intentions to recommend	Satisfaction and perceived health outcome influence intention to continuance using and intention to recommend; social comparison tendency enhances perceived health outcome and satisfaction; perceived usefulness, confirmation, perceived health outcomes, and social comparison tendency positively all contribute to satisfaction.
Sun and Gu (2024)	Fitness wearable technology	Perceives usability, technology innovativeness, eHealth literacy	Technology innovativeness and eHealth literacy indirectly impact continuance intention; male consumers increase continuance intention when eHealth literacy is enhanced through training.
El-Gayar and Elnoshokaty (2023)	Wearable devices	Appeal, social support, personalisation, device battery, readability, trust, dialogue support, hedonic motivation	Satisfaction is an antecedent for continued use intention; perceived benefits, enjoyment, and confirmation are significant antecedents for satisfaction; device battery, integration with other devices, dialogue support, and appeal affect confirmation the most.
Park (2020)	Smart wearable devices	Perceived ease of use, perceived enjoyment, flow state, perceived cost, service and system quality	Satisfaction, enjoyment, usefulness, flow state, cost influence continuance intention to use; confirmation and service quality significantly affect usage intention.
Zhao and Wang (2024)	Wearable devices	Self-efficacy, conversion costs, innovation, subjective references, privacy concerns	Self-efficacy, conversion costs, and perceived usefulness significantly affect continuance intention to use; innovation and subjective references also play a role; privacy concerns do not affect continuance intention to use.
Shen et al. (2018)	Wearable health information systems	Attitudinal ambivalence, intermittent discontinuance, neutral disconfirmation	Neutral disconfirmation affects neutral satisfaction and attitudinal ambivalence, which influence intermittent discontinuance; attitudinal ambivalence impacts neutral satisfaction.

Table 3: Overview of Expectation Confirmation Model Applications in Digital Health Technology Studies (Developed by the author)

2.5.2 Continuance Intention to Use Digital Healthcare Technologies Among Older Users

While numerous studies have examined the initial adoption of digital healthcare technologies by older users, research on continuance intention is still emerging. This section critically examines key studies in this area, categorising them based on limitations identified in the literature related to wearable technologies, mHealth apps, eHealth services, and telemedicine platforms. This approach highlights the current state of knowledge and identifies areas where further investigation is necessary.

Wearable Technologies

One major issue observed in the literature is the lack of attention to ageing-specific factors in relation to continuance intention. For example, Ahmad et al. (2020) applied the Technology Acceptance Model (TAM) to explore factors influencing the continued use of digital health wearables by older users. Their study provides valuable insights into how perceived ease of use and usefulness influence continuance intention. However, the study does not fully address the age-related challenges older users face when using technology, such as usability issues or physical limitations that may hinder long-term engagement. Similarly, Wang et al. (2023) combined the Value-Attitude-Behaviour (VAB) model with the TAM to examine continuance intention in digital healthcare technologies. They found that perceived reliability, usefulness, self-perceived ageing, and health promotion positively influenced older users' willingness to continue using technology. While the study incorporates self-perceived ageing, it does not fully address broader ageing-related factors such as cognitive decline or changing sensory abilities that could affect the long-term use of digital health technologies. Both studies provide valuable insights, but they underscore the need for research that more deeply considers the specific challenges associated with ageing in this context.

Another limitation observed in the literature is the inadequacy of certain theoretical frameworks when examining continuance intention among older users. Talukder et al. (2021) employed the Theory of Consumption Values (TCV) to identify key factors influencing the continuance intention of older users using digital healthcare technologies. They identified social value as the most significant factor promoting continued use. However, by focusing primarily on consumption values, the study overlooks critical psychological and ageing-related factors that can significantly impact older users' decisions to continue using digital healthcare technologies. Important aspects, such as cognitive decline, physical limitations, and motivation for health management, are not adequately addressed in this model. Li et al. (2020), in contrast, investigated the influence of sociodemographic factors, health status, activity levels, and usage patterns on the long-term use of wearable activity trackers among older users. Their study provides valuable insights into how characteristics such as frequent exercise, higher education, and daily wear contribute to continued use. However, the lack of a solid theoretical foundation limits the study’s ability to explain why these factors influence continuance intention. This absence of a guiding theory also makes it difficult to generalise the results to other contexts or populations, highlighting a gap in theoretical depth when studying older users’ continued use of digital healthcare technologies.

A further issue in the literature is the lack of attention to psychological and social factors in the context of continuance intention to use digital healthcare technologies among older users. For instance, Zhang et al. (2024) utilised the fit-viability model and empowerment theory, placing emphasis on autonomy, competence, involvement, and health impact. Their approach effectively captures some psychological factors that are crucial for understanding continuance intention. However, while the model addresses general psychological needs, it does not fully consider the unique challenges and motivations of older users when using digital healthcare technologies. Similarly, Ku et al. (2020) combined the Theory of Planned Behaviour and Flow Theory to explain the continuous use of wearable technology among middle-aged and older users. Their findings highlight that concentration, attitude, subjective norm, and perceived enjoyment are positive predictors of continuous use. While their model effectively captures general predictors of continuance, it may not fully address the age-related psychological challenges (such as anxiety around technology use or declining cognitive function) that older users might face in maintaining long-term engagement with digital healthcare technologies.

Finally, there is an issue with the generalisability of findings from studies focused on specific devices. For instance, Jorbonyan et al. (2024) studied the long-term use of hearing aids among older users, examining factors such as satisfaction, confirmation, self-efficacy, extraverted personality, self-perceived hearing handicaps, perceived benefits, and social support. Although this study sheds light on key aspects of hearing aid users’ continued use intentions by addressing both psychological and social factors, the findings may not be entirely applicable to other digital healthcare technologies, such as fitness trackers or telemedicine platforms, due to the specific characteristics of hearing aids. This highlights the need for more comprehensive studies that can apply findings across a broader range of digital health devices used by older users.

mHealth Applications

Meng et al. (2020, 2022) and Kim and Han (2021) explored key psychological factors influencing older users' continuance intentions to use mHealth applications, though they approached the topic from different theoretical perspectives. Meng et al. (2020, 2022) emphasised the role of technology and health anxiety using trust theory, underscoring how psychological barriers can hinder older users' engagement with digital healthcare technologies. This focus on anxiety provides valuable insights but does not fully account for other age-related challenges, such as cognitive decline or physical limitations. Similarly, Kim and Han (2021) utilised the social cognitive theory of health behaviour to examine psychological factors like self-efficacy and outcome expectations, offering a broader understanding of health-related behaviours. However, like Meng et al. (2020, 2022), their model fails to address the specific age-related barriers that might hinder continued use.

eHealth Services

Forquer et al. (2014) and Hurmuz et al. (2022) underscored the importance of enjoyment in the continued use of eHealth services by older users. While Forquer et al. (2014) focused on how utilitarian (perceived usefulness) and hedonic (enjoyment) beliefs influence engagement with a specific eHealth service like a newsletter, Hurmuz et al. (2022) extended this by exploring enjoyment in a more interactive and gamified eHealth service, where aesthetics also play a key role. Both studies highlighted how positive emotional experiences can drive sustained engagement; however, the scope of each study limits their applicability across diverse digital healthcare contexts. Forquer et al.'s (2014) focus on a newsletter restricts generalisability to other dynamic eHealth services, while Hurmuz et al. (2022), through their use of the Technology Acceptance Model (TAM), failed to account for ageing-related barriers like cognitive decline and technological anxiety.

Telemedicine platforms

Hsieh et al. (2022) and Hsu et al. (2016) explored the factors influencing the continuance intention of older users to use telemedicine platforms, employing similar theoretical frameworks but with different focuses. Hsieh et al. (2022) integrated the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), and Self-Determination Theory (SDT) to investigate the continuance intention to use telemedicine by older users. Their results indicated that perceived behavioural control attitude, perceived usefulness, and autonomy support are key influences on older users' intentions to sustain telemedicine use. Similarly, Hsu et al. (2016) applied SDT and TPB to investigate predictive factors for continued use of telemedicine services among older users. They found that subjective norms, autonomy, relatedness, and attitudes toward technology significantly influence continuance intention. However, they also noted that perceived competence and behavioural control are not significant predictors of intention in the context of telemedicine. Both studies demonstrated the importance of psychological and social factors, particularly autonomy and relatedness, in shaping older users' continuance intentions to use telemedicine services.

The studies reviewed in this section highlight the complexity of continuance intention to use digital healthcare technologies among older users. While each study contributes valuable insights, they often focus on specific technologies or theoretical models, limiting their generalisability. Many of these studies fail to adequately capture the unique aspects of ageing that influence continuance intention to use technology. These limitations point to the need for a more comprehensive framework that addresses the multifaceted challenges older users face. To address these gaps, this study proposes a framework that integrates the expectation confirmation model with a more comprehensive set of factors relevant to older users' continuance intention to use digital healthcare technologies. By grounding the analysis in an established theoretical model and incorporating a wider range of contextual factors, this framework offers both theoretical and practical relevance. It is designed to be adaptable across various digital healthcare technologies, making it a versatile tool for understanding and enhancing long-term engagement among older users. Table 4 provides a summary of these studies, detailing the technology focus, theoretical frameworks used, key factors influencing continuance intention, and key findings.

Author (Year)	Technology Context	Theoretical Framework	Key Constructs	Main Findings
Ahmad et al. (2020)	Wearable Technology	Technology Acceptance Model	Perceived ease of use, perceived usefulness, perceived irreplaceability, perceived credibility, compatibility, social influence	Perceived ease of use, perceived usefulness, perceived irreplaceability, perceived credibility, compatibility, and social influence impact continuance intention to use.
Talukder et al. (2021)	Wearable Technology	Theory of Consumption Value	Social value, emotional and epistemic values, device quality, inertia, technology anxiety	Social, emotional, and epistemic values and device quality increase continuance intention to use; Inertia and technology anxiety are inhibitors.
Zhang et al. (2024)	Wearable Technology	Fit-viability model, Empowerment theory	Autonomy, competence, involvement, impact on health, task-technology fit, elderly-oriented fit	Autonomy, competence, involvement, and impact on health (four dimensions of empowerment) influence continuance intention to use; Task-technology fit and elderly-oriented fit influence empowerment dimensions.
Wang et al. (2023)	Wearable Technology	Value-Attitude-Behaviour, Technology Acceptance Model	Perceived reliability, perceived usefulness, self-perceived ageing, health promotion, perceived ease of use	Perceived reliability, perceived usefulness, self-perceived ageing, and health promotion influence continuance intention to use; Perceived ease of use had no effect.
Li et al. (2020)	Wearable Activity Trackers	-	Sociodemographic factors, health status, activity levels, factors related to long-term use such as usage patterns and initial adoption motivations	Diverse usage patterns and individual characteristics play significant roles in sustaining long-term engagement.
Ku et al. (2020)	Wearable Technology	Theory of Planned Behaviour, Flow Theory	Concentration, attitude, subjective norm, perceived enjoyment, perceived control	Concentration, attitude, subjective norm, and perceived enjoyment affect continuance intention to use; Perceived control was not considerable; Concentration and perceived enjoyment affect attitude.
Jorbonyan et al. (2024)	Wearable Medical Device	Patient Activation Model	Actual use, perceived benefits, satisfaction, confirmation, self-efficacy, extraverted personality,	Actual use, perceived benefits, satisfaction, confirmation, self-efficacy, an extraverted personality,

			self-perceived hearing handicap, perceived social support	self-perceived hearing handicap, and perceived social support influence continuance intention to use.
Meng et al. (2020)	mHealth	Trust Theory	Cognitive trust, affective trust, health anxiety, technology anxiety	Cognitive and affective trust enhance continuance intention; health and technology anxieties have complex moderating effects.
Meng et al. (2022)	mHealth	Trust Theory	Cognitive trust, affective trust, health anxiety, technology anxiety	Cognitive and affective trust increase continuance intention; Health anxiety amplifies cognitive trust and diminishes affective trust; Technology anxiety strengthens affective trust but not cognitive trust.
Kim and Han (2021)	mHealth Apps	Social Cognitive Theory of Health Behaviour	Technology self-efficacy, self-evaluative outcome expectations, self-regulation, privacy risk	Technology self-efficacy, self-evaluative outcome expectations, self-regulation, and privacy risk increase continuance intention to use.
Forquer et al. (2014)	eHealth	IT adoption and Continuance Theories	Utilitarian beliefs, hedonic beliefs, previous use	Utilitarian and hedonic beliefs predict continuance intention to use; Utilitarian beliefs have direct and indirect effects mediated by hedonic beliefs; Previous use is a stronger predictor of continued use than intention alone.
Hurmuz et al. (2022)	Gamified eHealth Service	Technology Acceptance Model	Perceived ease of use, perceived usefulness, enjoyment, aesthetics	Ease of use influences frequency and service use; Perceived usefulness affects continuance intention to use; Enjoyment impacts perceived usefulness; Aesthetics influences perceived ease of use.
Hsu et al. (2016)	Telemedicine	Self-Determination Theory, Theory of Planned Behaviour	Perceived competence, autonomy, relatedness, subjective norm, attitude, perceived behavioural control	Autonomy, relatedness, subjective norm, and attitudes affect continuance intention to use; perceived competence and perceived behavioural control are insignificant.

Hsieh et al. (2022)	Telemedicine	Technology Acceptance Model, Theory of Planned Behaviour, Self-Determination Theory	Attitude, perceived ease of use, perceived usefulness, perceived behavioural control, autonomy, subjective norm	Attitude, perceived behavioural control, autonomy affect continuance intention to use; Perceived autonomy, perceived usefulness, and ease of use affect older users' attitude.

Table 4: Summary of Studies on Continuance Intention to Use digital healthcare technologies Among Older Users
(Developed by the author)

2.5.3 Definitions of Constructs

To establish a clear understanding of the constructs used in this study, this section provides definitions developed based on existing literature. These definitions are tailored to the context of digital healthcare technologies and form the foundation for the theoretical framework and empirical analysis.

Health Motivation refers to the internal drive and desire that encourage individuals to actively engage in behaviours aimed at maintaining and improving their health, often driven by a desire to prevent health issues and achieve wellness goals (Asadi et al., 2019; Cox, 1982; Croyle, 1992; Dehghani et al., 2018; Jayanti and Burns, 1998; Kraft and Goodell, 1993; Li et al., 2019; Moorman and Matulich, 1993).

Health Consciousness refers to an individual's awareness and proactive approach towards maintaining and improving their health by integrating health-related behaviours and decisions into their daily lives, driven by the belief that personal health is essential (Alam et al., 2020; Basu and Dutta, 2008; Dellande et al., 2004; Dutta-Bergman, 2004; Jayanti and Burns, 1998; Lee et al., 2014).

Confirmation of Expectation refers to the cognitive evaluation where users perceive that their experience with technology meets or exceeds their anticipated benefits, ensuring that the outcomes align with their initial expectations during use (Bhattacherjee, 2001; Khayer and Bao, 2019; Lee, 2010; Lim et al., 2019; Oghuma et al., 2016; Rahi et al., 2018).

Perceived Usefulness refers to an individual's belief that using technology will significantly improve their ability to complete tasks or achieve goals, reflecting the value it adds to their personal or professional activities (Chiu, 2009; Davis, 1989; Davis et al., 1989; Loh et al., 2022; Park et al., 2009).

Satisfaction refers to an individual's assessment of a technology based on how well it aligns with prior expectations, resulting in an emotional reaction ranging from contentment to disappointment that contributes to their overall attitude towards the technology, influenced by both the quality of the experience and perceived value (Bhattacherjee, 2001; Chow and Shi, 2014; Doll et al., 1998; Kim et al., 2016; Lam et al., 2004; Oliver, 1981; Oliver, 2014; Oliver and Swan, 1989; Swan and Trawick, 1981; Ye and Titheridge, 2017).

Ageing Satisfaction refers to an individual's evaluation of their ageing journey, reflecting their sense of fulfilment or acceptance of the physical, emotional, and social changes associated with growing older. It encompasses personal feelings of well-being, energy, and usefulness and is linked to positive outcomes in health, mental well-being, and social engagement (Kleinspehn-Ammerlahn et al., 2008; Kim et al., 2014; Lawton, 1975; Levy, 2009; Nakamura et al., 2022; Sargent-Cox et al., 2012; Shirahada et al., 2019).

Health Anxiety refers to a persistent and intense concern about personal health, where all bodily sensations are often perceived as warning signs of serious illness. This excessive focus on health frequently leads to heightened stress and behaviours such as constant checking or seeking reassurance (Asmundson et al., 2010; Bailer et al., 2016; Cooper et al., 2017; Lee, 2018; Meng et al., 2020; Özdin and Bayrak Özdin, 2020; Ravaldi et al., 2021; Salkovskis et al., 2002; Tyrer, 2018; Warwick and Salkovskis, 1990).

Technology Anxiety refers to the feelings of nervousness, discomfort, or fear that arise when individuals interact with or think about using technology. It often stems from concerns about their ability to effectively use technological tools and the potential adverse outcomes associated with their use (Ahmad and Khalid, 2017; Bixter et al., 2019; Cambre and Cook, 1985; Hoque and Sorwar, 2017; Kohnke et al., 2014; Liljander et al., 2006; Lytras and Visvizi, 2018; Meuter et al., 2003; Sam et al., 2005; Troisi et al., 2022; Venkatesh, 2000; Venkatesh et al., 2003).

Self-efficacy refers to an individual's confidence in their capacity to organise and execute the necessary actions to achieve specific goals, particularly in contexts that challenge their skills and abilities. It is a judgment focused on one's perceived potential for future accomplishment rather than a reflection on prior achievements (Bandura, 1997; Bhatt, 2022; Compeau and Higgins, 1995; Saeed Al-Maroof et al., 2020; Shiferaw and Mehari, 2019; Susanto et al., 2016; Troisi et al., 2022; Venkatesh et al., 2003).

Continuance Intention to Use refers to an individual's ongoing commitment to using technology after its initial adoption, shaped by their experiences with it and reflecting their decision to integrate the technology into their daily routine (Dağhan and Akkoyunlu, 2016; Franque et al., 2021; Lee and Kwon, 2011; Limayem and Cheung, 2008; Susanto et al., 2016; Yoon and Rolland, 2015).

2.6 Gaps in Older Users' Continued Use of Digital Healthcare Technologies

The existing literature on the continuance intention to use digital healthcare technologies among older users has several noteworthy gaps. First, while there is considerable literature on the initial adoption of digital healthcare technologies, studies specifically examining continuance intention among older users are limited, with most research focusing on younger populations or the general public (Ahmad et al., 2020; Talukder et al., 2021). This leaves a critical gap in understanding the factors that influence older users to continue using these technologies over time. Second, many existing studies overlook critical psychological and age-related factors which are particularly relevant for understanding older users' sustained use of technology (Meng et al., 2020; Kim and Han, 2021). These factors require deeper exploration to understand this phenomenon better (Jorbonyan et al., 2024; Ku et al., 2020; Talukder et al., 2021). Third, there is a need for more comprehensive theoretical frameworks that specifically address the unique challenges and motivations of the older users' demographic (Ahmad et al., 2020; Talukder et al., 2021; Zhang et al., 2024; Wang et al., 2023). Many of the existing models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), while valuable, may not fully capture the complex ageing-related factors that influence continuance intention (Kim and Han, 2021; Hurmuz et al., 2022). Fourth, another limitation of the current literature is the lack of generalisability across different types of digital healthcare technologies. Most studies have focused on specific technologies, such as wearable devices, telemedicine, mHealth apps, or eHealth services (Forquer et al., 2014; Hsieh et al., 2022; Jorbonyan et al., 2024; Meng et al., 2022), which restricts the broader applicability of the findings. There is a need for a more holistic approach that can be applied to the diverse range of digital healthcare solutions utilised by older users (Li et al., 2020).

To address these gaps, this study proposes the development of a comprehensive framework that integrates the expectation confirmation model with a broader set of ageing-related factors to examine the continuance intention of older users across a diverse range of digital healthcare technologies. By doing so, this research aims to provide a better understanding of the factors influencing long-term engagement with digital healthcare technologies among older users. This study will go beyond traditional models like the TAM and UTAUT by leveraging the expectation confirmation model as the theoretical framework. Additionally, it will incorporate ageing-specific factors that are crucial for understanding older users' continued use of digital healthcare technologies. By integrating these ageing-related constructs into the expectation confirmation model, this research aims to provide a more accurate representation of the experiences and needs of older users in the context of digital healthcare technologies. Furthermore, this study will expand the scope of existing research by examining continuance intention across various types of digital healthcare technologies rather than focusing on a single technology. This broader approach will allow for a more generalisable understanding of how different digital healthcare technologies can support older users in managing their health over time. By considering a wide range of technologies, including wearable devices, mHealth apps, eHealth services, and telemedicine platforms, this research will generate insights that can be applied across multiple contexts, enhancing the practical relevance of the findings.

2.7 Working Conceptual Model

Based on the literature review and the integration of the expectation confirmation model (Bhattacherjee, 2001), this study proposes a working conceptual model that identifies the key factors influencing older users' continuance intention to use digital healthcare technologies. The expectation confirmation model serves as the theoretical foundation, particularly focusing on the constructs of confirmation of expectations, perceived usefulness, satisfaction, and continuance intention to use. These constructs highlight the importance of users' confirmation of their initial expectations and their perceived usefulness of the technology in determining their satisfaction and ongoing use. In addition to the expectation confirmation model constructs, this model incorporates additional ageing-related factors identified from the broader literature, such as health motivation, health consciousness, health anxiety and technology anxiety, to understand their effect on the continuance intention to use digital healthcare technologies by them. The working conceptual model is presented in Figure 3 below, showing the relationships between these constructs.

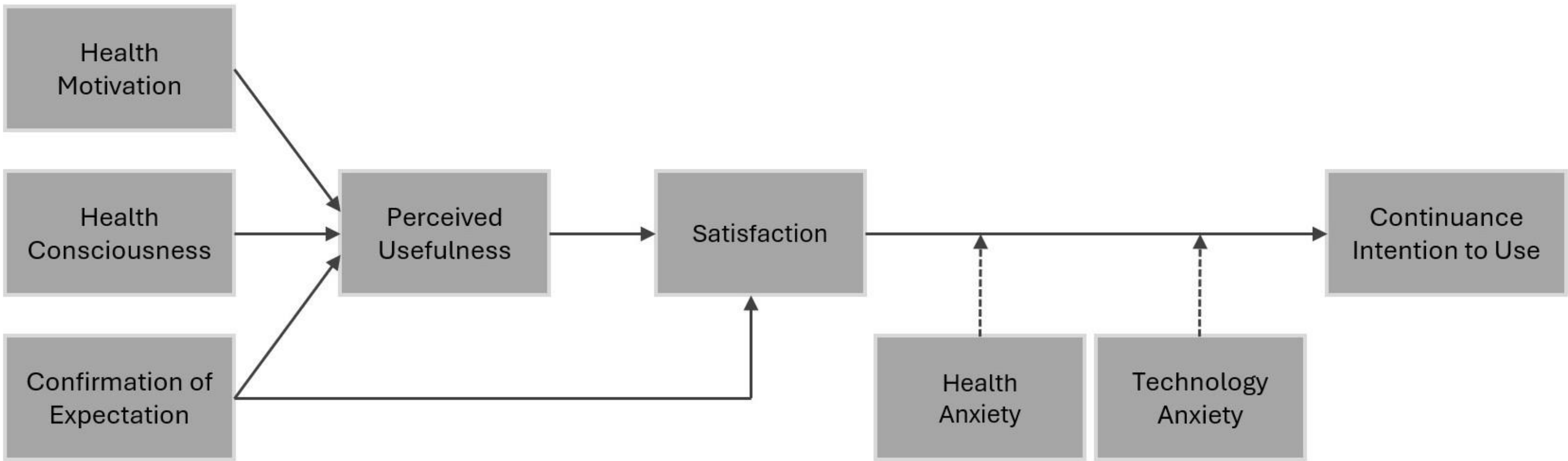

Figure 3: Working Conceptual Model
(Developed by the author)

Chapter 3: Research Methodology

3.1 Introduction

This chapter explains the methodological path used to explore the factors affecting older users' continuance intention to use digital healthcare technologies. The primary aim of this research is to fill the gap in the existing body of knowledge by exploring the factors influencing older users' continuance intention to use digital healthcare technologies as tools to manage their health and improve healthy ageing. To achieve this aim, the chapter outlines the philosophical basis, research strategy, and specific methods used, justifying each choice in relation to the study's objectives and existing literature. The study employs an exploratory sequential design, a type of mixed-methods approach that begins with a qualitative phase followed by a quantitative phase (Creswell and Clark, 2017). It begins with an exploratory qualitative phase using semi-structured interviews. This phase allows for an in-depth exploration of older users' experiences, motivations, and concerns regarding digital healthcare technologies, providing rich insights that inform the subsequent survey design (Creswell and Clark, 2017). These insights help to ensure that the survey captures relevant factors and relationships specific to this population, thereby enhancing the rigour and relevance of the quantitative phase. Following the qualitative phase, an explanatory quantitative survey is conducted to test the relationships between the identified factors and their influence on digital healthcare technology continuance intention.

The research adopts a pragmatic research philosophy, which is well-suited for integrating both qualitative and quantitative methods. Pragmatism allows the research to focus on the research problem and the practical implications of the findings (Creswell and Clark, 2017; Morgan, 2007). The qualitative phase provides a foundation for the quantitative phase by generating insights that guide the survey design. The quantitative phase then tests and confirms the relationships hypothesised based on the qualitative findings, ensuring a thorough understanding of the factors influencing digital healthcare technology use among older users. An abductive research approach is employed, allowing the refinement and adaptation of the expectation confirmation model based on empirical data from a two-phased, mixed-methods design. This design benefits from both qualitative and quantitative methods for a thorough understanding. Phase 1 uses semi-structured interviews with older digital healthcare technology users to explore their experiences, motivations, concerns, and perceptions. Thematic analysis with NVivo software is used to analyse the interview data (Braun and Clarke, 2006). Phase 2 builds on the qualitative findings with a survey questionnaire to test the relationships between factors influencing digital healthcare technology continuance intention. The questionnaire uses validated items from previous studies for rigour and reliability. Partial Least Squares Structural Equation Modelling (PLS-SEM) is selected for data analysis due to its ability to handle complex models, non-normal data distributions, and smaller sample sizes (Hair et al., 2019; Ringle et al., 2020). An overview of the research methodology is summarised in Table 5 below.

Aspect	Phase 1 (Exploratory)	Phase 2 (Explanatory)
Research Method	Qualitative	Quantitative
Research Philosophy	Pragmatism	Pragmatism
Research Approach	Abductive	Deductive
Data Collection Method	Semi-structured Interviews	Survey Questionnaire
Data Analysis Technique	Thematic Analysis (NVivo)	SPSS, PLS-SEM (SmartPLS)

Table 5: Overview of the Research Methodology
(Developed by the author)

3.2 Research as a Process

Saunders (2009) emphasises that scientific research must follow a structured process rather than being conducted arbitrarily. To exemplify this systematic process, Saunders (2009) introduced the Saunders Research Onion, as shown in Figure 4.

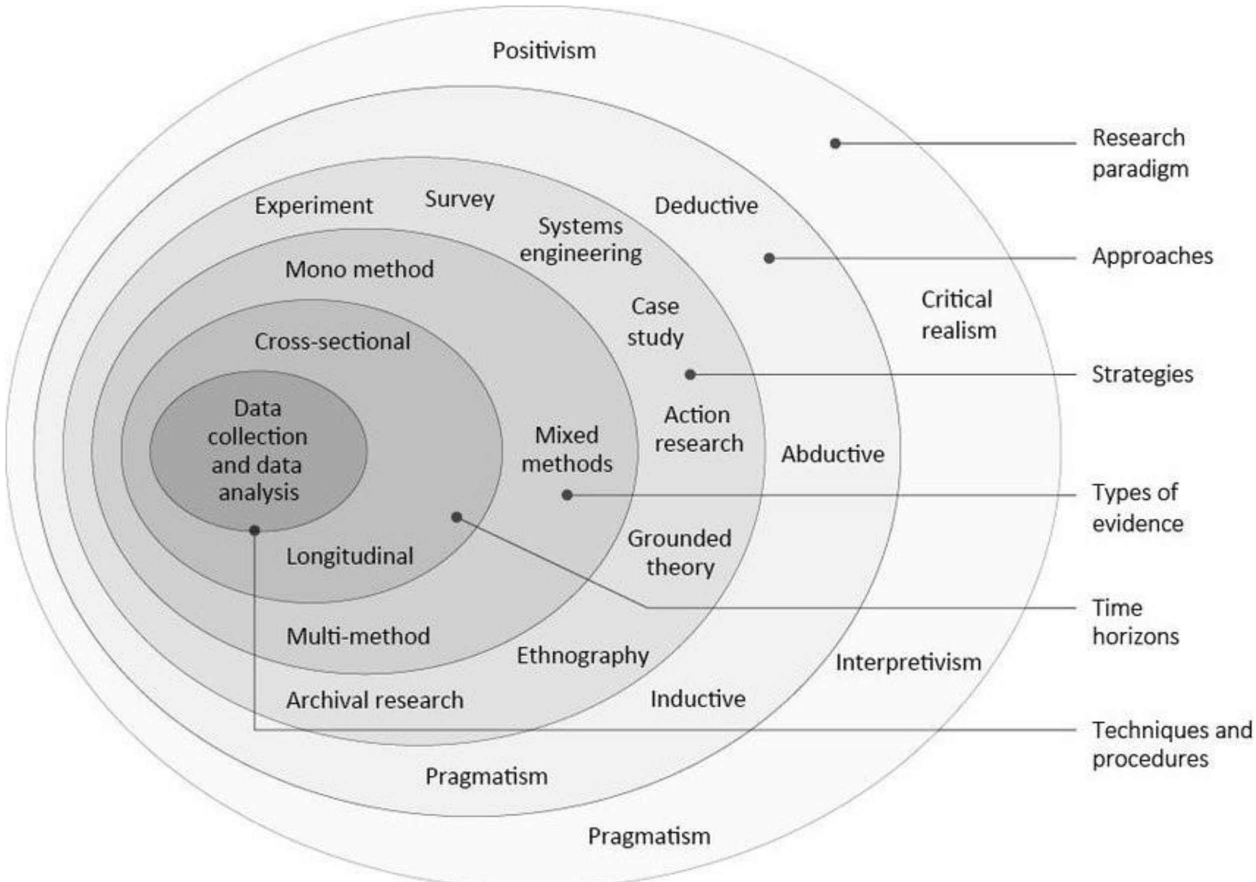

Figure 4: The Research Onion
Source: Saunders (2009)

Figure 4 shows that the research process is organised and systematic. It starts with establishing the research philosophy, then selecting the approach, developing a strategy, and determining the methods and tools for data collection. Following this, researchers choose the appropriate tools for data analysis, conduct the analysis, and conclude by identifying the key findings.

3.3 Research Philosophy

The philosophical approach of a research method is rooted in its assumptions about the nature of reality, including aspects such as mind, matter, reason, and evidence that support knowledge. Thus, the philosophical dimension is essential for the investigation process (Ponterotto, 2005). This study aims to identify key factors influencing older users' continued use of digital healthcare technologies and to understand the relationships among these factors. The debate over adopting a positivist or interpretivist perspective for investigating social phenomena is inevitable. Positivism, which focuses on predicting relationships between predefined variables, often leads to a shallow understanding of problems, lacking the depth needed to explore human behaviours fully. It struggles to account for the motivations, causes, and attitudes that drive human behaviour, as it relies on evidence used in the natural sciences (Veal, 2017). Unlike positivism, interpretivism emphasises an interactive process between the subject of study and the researcher. Instead of seeking broad generalisations, this approach aims to construct a deep understanding of existing phenomena (Collis and Hussey, 2009; Hair et al., 2019). However, the main limitation of interpretivism is the risk of researcher bias due to the close involvement in the study (Andrade, 2009; Ponelis, 2015).

According to Saunders et al. (2015), instead of focusing only on the pros and cons of various philosophical approaches, researchers should select a paradigm based on the specific scope, aims, and objectives of their research, as these are critical to making an informed decision. This argument aligns closely with the pragmatic approach, emphasising the practical application of research methods to answer research questions effectively. Pragmatism prioritises the research question over the method, allowing for a combination of qualitative and quantitative approaches that best address the problem (Creswell and Clark, 2017). It is particularly suitable for this study because digital healthcare technologies are a relatively new and complex development, especially among older users (Mace et al., 2022). From both ontological and epistemological standpoints, this study aims to explore a novel phenomenon. The inherent complexity of digital healthcare technology adoption among older users requires a flexible and adaptive research approach that pragmatism provides. Pragmatism allows for the use of multiple methods, acknowledging that different aspects of the research problem may require different types of data collection and analysis (Creswell and Clark, 2017). For example, while quantitative methods (associated with positivism) can identify key factors influencing digital healthcare technology adoption and continuance, qualitative methods (associated with interpretivism) can provide deeper insights into the lived experiences and attitudes of older users (Creswell and Creswell, 2017).

This study adopts a mixed-methods approach, which is well-supported by the pragmatic paradigm. Pragmatism endorses the integration of both qualitative and quantitative methods, emphasising the importance of using whatever tools are necessary to answer the research questions effectively (Tashakkori and Teddlie, 2010). By combining both methods, this study aims to enhance the robustness and depth of the research findings. Quantitative data will help to quantify the relationships between key factors influencing digital healthcare technology use. In contrast, qualitative data will provide contextual insights, ensuring a comprehensive understanding of older users' interactions with digital healthcare technologies. By adopting a pragmatic approach, the study aims to generate actionable insights that can directly inform the design and implementation of digital healthcare technologies for older users. The combination of qualitative and quantitative data will enable a more nuanced understanding of user needs, preferences, and barriers to adoption. This understanding can be translated into practical recommendations for healthcare providers, policymakers, digital healthcare technology developers, and brand managers, ultimately contributing to more effective and user-friendly digital healthcare technologies. Furthermore, the findings could influence training and support programs tailored for older users, ensuring they can fully benefit from these technologies. While pragmatism may be critiqued for its flexibility and lack of a singular philosophical stance, this very flexibility is what makes it particularly valuable for addressing complex, real-world problems like digital healthcare technology continuance intention to use among older users (Morgan, 2014). Critics may argue that pragmatism lacks the philosophical rigour of more traditional paradigms, but its strength lies in its ability to adapt to the research context and prioritise the research question (Yvonne Feilzer, 2010). By allowing the integration of multiple methods, pragmatism ensures that the study is not limited by the constraints of a single paradigm and can instead provide a more comprehensive and relevant understanding of the research problem. Therefore, despite potential criticisms, pragmatism remains the most appropriate choice for this study due to its practical orientation and ability to address complex phenomena (Creswell and Clark, 2017).

3.4 Research Approach

The research approach, alongside research philosophy, is crucial for researchers. It involves the logical reasoning methods that underpin the research and create a strategy to achieve valid social science research results (Frankfort-Nachmias and Nachmias, 2007). One notable research approach gaining traction is the abductive approach (Dubois and Gadde, 2002). Selecting an appropriate research approach is vital because it aligns with the data collection method, directly influencing the research outcomes. The abductive approach merges deductive and inductive reasoning, fostering an iterative and flexible process for theory development and refinement (Dubois and Gadde, 2002; Thompson, 2022; Timmermans and Tavory, 2012). This method is particularly effective in marketing research, allowing the researcher to move back and forth between empirical data and theoretical insights, thereby refining the understanding of the studied phenomenon (Timmermans and Tavory, 2012; Timmermans and Tavory, 2022). This iterative nature is valuable in marketing research, where consumer insights must be integrated with theoretical concepts to formulate effective strategies. Moreover, the abductive approach aids in identifying new variables and relationships, which is essential for uncovering fresh consumer insights and market dynamics (Dubois and Gadde, 2002).

The decision to use an abductive approach is justified because, although there is extensive research on technology continuance intention, few studies focus on digital healthcare technologies, especially among older users. This gap calls for a flexible approach that allows for the discovery of new variables and themes that may not have been previously explored. The abductive approach was crucial in this context as it allowed the research to remain adaptable, iteratively refining the theoretical framework in response to insights drawn directly from participants' experiences (Saunders et al., 2015; Timmermans and Tavory, 2022). Given the under-researched nature of older adults' continued use of digital healthcare technologies, an abductive approach enabled the researcher to modify and extend existing theories by moving between empirical data and theoretical insights (Dubois and Gadde, 2002). For instance, constructs that emerged during the data analysis were not initially part of the expectation confirmation model but became crucial for understanding older users' intentions. This method is precious when addressing gaps in existing models, as in this study, where the expectation confirmation model lacked ageing-specific constructs. The abductive process facilitated the identification of these new variables and relationships, ensuring that the theoretical framework was not only grounded in literature but also responsive to the lived experiences of older adults (Thompson, 2022; Timmermans and Tavory, 2012). This iterative dialogue between theory and data resulted in a more nuanced understanding of the factors influencing older adults' continuance intention to use digital healthcare technologies, aligning the findings with both theoretical insights and practical realities.

In the first phase of the research, semi-structured interviews were conducted with current digital healthcare technology users over 65 years old in the UK. This phase intended to gain deep, abductive insights into the factors influencing their intention to continue using digital healthcare technologies by iteratively moving between empirical data and theoretical insights (Dubois and Gadde, 2002). In the second phase of the research, a survey questionnaire was employed using a deductive approach. This method was chosen to empirically validate the theoretical framework that had been developed in the first phase through abductive reasoning (Crabtree and Miller, 1999). The framework tested in this phase was built upon the literature review and findings from the semi-structured interviews. Although survey questionnaires are typically aligned with a deductive approach, this study informed them by the abductive reasoning established in the previous phase (Timmermans and Tavory, 2012). Combining abductive reasoning in Phase 1 with deductive testing in Phase 2 provides a complete understanding of the factors influencing older users' continuance intention to use digital healthcare technologies (Dubois and Gadde, 2002). This methodology enables the development of a theoretical framework that is grounded in empirical data and literature, followed by subsequent empirical validation. Hence, the overall study employed a mixed approach that integrates both inductive and deductive reasoning (Thompson, 2022). To elaborate, Phase 1 involved conducting semi-structured interviews aimed at exploring older individuals' perspectives, employing an abductive inquiry logic. In contrast, Phase 2 utilised a survey questionnaire to empirically confirm the perspectives obtained in Phase 1, employing a deductive approach that was informed by the abductive reasoning established earlier. The following section details the research design and justifies the chosen research methods for this study.

3.5 Research Design

This study adopts a mixed-methods research strategy with a predominant focus on the quantitative approach. The mixed-methods design integrates both qualitative and quantitative methodologies, grounded in pragmatism, to provide a more comprehensive understanding of the research problem by collecting and analysing data either sequentially or concurrently (Creswell and Clark, 2017). This design effectively addresses research challenges by combining qualitative and quantitative data collection and analysis. It enables a more integrated and synergistic use of data, which strengthens the overall strength and reliability of the research findings (Tashakkori and Teddlie, 2010). Triangulation, an essential aspect of mixed-methods research, uses multiple data sources, methods, or theories to corroborate findings and enhance the research's credibility and validity (Denzin, 1978; Patton, 1999). By employing triangulation, researchers can mitigate the biases and weaknesses associated with single-method studies (Denzin, 1978). Since all data collection and analysis methods have limitations (Hill et al., 2005), mixed-methods help neutralise these biases, enhancing rigour and relevance (Johnson and Onwuegbuzie et al., 2004). Mixed-methods also leverage the strengths and mitigate the limitations of both qualitative and quantitative methods. This approach supports triangulation, which strengthens the research by combining and cross-validating multiple data sources and methods (Denzin, 1978). Triangulation minimises individual methods' limitations and provides a more comprehensive understanding of the studied phenomenon (Patton, 1999). By using mixed-methods, researchers can make meaningful contributions to both practical applications and theoretical knowledge (Creswell and Clark, 2017).

While the mixed-methods design enhances the comprehensiveness of the research findings, it is important to address the generalisability of the results (Turner et al., 2017). The qualitative phase, which focuses on in-depth exploration, provides insights that are more context-specific. However, the quantitative phase aims to generalise findings to a broader population by leveraging a large, representative sample of older adults in the UK. The qualitative findings are not intended to be statistically generalisable but can offer transferability to similar populations or settings (Aspers and Corte, 2019). For instance, the results may be relevant to older adults in regions with comparable healthcare systems and technology adoption trends. The mixed-methods design balances depth and generalisability, ensuring both contextually rich insights and broader applicability (Venkatesh et al.,2013). The use of a large, representative sample in the quantitative phase enhances the external validity of the study by ensuring that findings can be generalised to older adults in similar contexts. Meanwhile, the qualitative phase ensures that nuanced, context-specific insights provide a solid foundation for understanding behaviours and preferences in digital healthcare adoption. This layered approach ensures that both detailed contextual relevance and broader generalisability are achieved (Dawadi et al.,2021).

This study focuses on gaining a detailed understanding of older users' continuous use of digital healthcare technologies through qualitative data while also aiming to generalise these insights to a broader population with quantitative methods. Combining open-ended qualitative data with closed-ended quantitative data offers a significant advantage for achieving a more thorough analysis. The decision to use a mixed-methods approach arises from a thorough review of relevant literature on continuance intention to use, aligning with this study's objectives. Most existing research on continuance intention is quantitative and centred on technology-based theories, but it frequently misses the comprehensive perspective needed for more in-depth analysis (Yan et al., 2021). Qualitative research is valuable for capturing the complex relationships older users have with digital healthcare technologies, including their values, emotions, and feelings (Ienca et al., 2021). Additionally, qualitative research is crucial for capturing novel insights to inform the scale development process (Churchill, 1979). Quantitative methods, on the other hand, ensure the objectivity and credibility of the findings. A mixed-methods design bridges the gap between paradigms, leveraging the strengths of both approaches while minimising their weaknesses. This integration enriches the diversity of research approaches and effectively addresses complex problems (Curry et al., 2009).

The extensive literature review highlighted the factors influencing older users' continuance intention to use digital healthcare technologies, but a more in-depth evaluation of these factors concerning the expectation confirmation model is needed. It is essential to determine and test the relationships between these factors and moderators of the extended expectation confirmation model to assess their relevance to older users. Therefore, this study adopts an exploratory sequential mixed-methods design, starting with qualitative data collection to deeply explore older users' perspectives, followed by quantitative data to test hypotheses and examine relationships on a broader scale (Creswell et al., 2011). According to Creswell and Clark (2017), the exploratory sequential design is particularly useful when the research problem is not well understood and the researcher needs to explore qualitative data to inform the development of quantitative instruments. The sequential design contributes to generalisability by allowing the quantitative phase to build on the rich, context-specific findings of the qualitative phase (Dawadi et al., 2021). While the qualitative phase provides depth and uncovers nuanced experiences, the subsequent quantitative phase ensures that these findings can be tested and generalised to a broader population. This approach strengthens the external validity of the study by integrating specific insights into a representative survey instrument (Gibson, 2017; Turner et al., 2017).

This study begins with semi-structured interviews to delve into older individuals' experiences and perspectives using digital healthcare technologies. These interviews are suitable for collecting personalised data and examining respondents' experiences and perceptions (Kallio et al., 2016; Moser and Korstjens, 2018), offering more profound insights into the social and behavioural aspects of the research topic (Dawadi et al., 2021). The qualitative findings will inform the development of survey questions for the quantitative phase, ensuring the survey is grounded in these insights. The subsequent quantitative phase involves a questionnaire survey to test the hypotheses generated from the qualitative findings. This phase aims to quantify relationships between different variables and generalise the findings to a larger population. Using structured questionnaires, the study can measure the extent and prevalence of the identified factors influencing older users' continuance intention to use digital healthcare technologies. The quantitative data will be analysed using statistical methods to test the hypotheses and explore the strength and direction of the relationships between variables.

The choice of an exploratory sequential design was made to ensure that the research framework and survey instrument were informed by the initial qualitative exploration. By starting with qualitative interviews, the study allows for the identification of key themes and factors that may not be fully captured in existing literature. These themes then inform the development of the quantitative survey, ensuring that it is both comprehensive and contextually relevant (Creswell and Clark, 2017). While considering different approaches, a quantitative-first approach was considered but deemed less suitable for this study. Given the lack of a prior comprehensive understanding of older users' continuance intention to use digital healthcare technologies, a purely quantitative approach might miss important nuances and context-specific factors. Without qualitative exploration, the survey could overlook key variables, leading to incomplete or irrelevant data collection (Bryman, 2016; Maxwell, 2013). Therefore, the qualitative-first sequence ensures that the survey is both theoretically and practically grounded (Creswell and Clark, 2017).

This sequential design also addresses potential gaps in understanding that might arise if the study had started with a survey. A purely quantitative approach may overlook subtle nuances and contextual factors important to older users, which can be captured through qualitative exploration (Creswell and Clark, 2017). Therefore, the sequence of qualitative followed by quantitative methods ensures that the survey is both theoretically and practically grounded. While the study begins with qualitative exploration, the overall emphasis is on using the findings from both phases to build a comprehensive understanding of the research problem. After completing both phases, the qualitative and quantitative results will be synthesised, examining how the quantitative findings extend or challenge the initial qualitative insights. In summary, the exploratory sequential mixed-methods design is chosen for its ability to generate and test theories by combining qualitative data's depth with quantitative data's generalisability. Figure 5 illustrates the exploratory sequential design, showing how the qualitative phase informs the quantitative phase, as proposed by Creswell and Clark (2017).

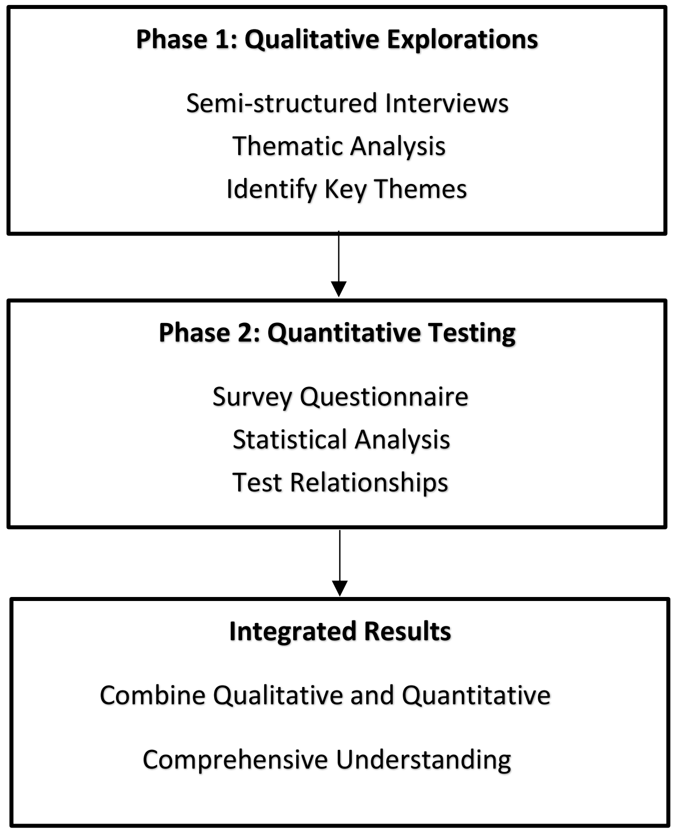

Figure 5: Exploratory Sequential Design
(Developed by the author)

3.6 Research Methods

This section describes the research methods and data analysis techniques applied in the study, expanding on the research paradigm and strategy previously discussed. Each subsection begins by explaining the rationale for the chosen methods, followed by a description of how participants were identified. The procedures for data collection and analysis are then outlined. The following section will cover the research method used in Phase 1.

3.6.1 Phase 1: Semi-structured Interviews

In this phase, the aim was to explore factors influencing the continuance intention to use digital healthcare technologies for health management and to validate the initial hypothesis that various factors and moderators impact the continued use of digital healthcare technologies among older users. Semi-structured interviews are especially suitable for research where understanding the nuanced experiences, emotions, and perceptions of individuals is crucial (Patton, 2014). Furthermore, Bryman (2016) highlight the value of semi-structured interviews in organising additional information, which can then be used to cross-check and validate the data collected, a process known as triangulation.

To ensure the validity and reliability of the qualitative phase, several measures were undertaken. Validity was enhanced through triangulation by comparing themes and patterns across multiple interviews to identify consistent findings. This ensured that the insights derived were not based on isolated accounts but reflected broader trends in participant experiences (Bans-Akutey and Tiimub, 2021). The use of a structured interview guide further supported validity by providing consistency in the topics covered while allowing flexibility to explore individual perspectives in depth. Reliability was maintained through an iterative coding process during thematic analysis (Campbell et al., 2013; Saunders et al., 2023. Initial codes were generated after carefully reviewing the transcripts, followed by refinement through multiple cycles to ensure consistency and alignment with the research objectives. NVivo software was used to manage and organise the data systematically, which further contributed to reliability by reducing the risk of manual errors. To minimise researcher bias, the coding process was reviewed by an independent qualitative researcher, ensuring that the identified themes accurately represented the participants' views.

Given the smaller number of participants in the qualitative phase compared to the quantitative phase, it was decided to focus the qualitative phase specifically on wearable technology devices. Wearable technology devices are widely used by older adults (Chandrasekaran et al., 2021; Kekade et al., 2018; Kyytsönen et al., 2023), making them an appropriate subject for in-depth qualitative exploration. This focus allows for a more detailed examination of a technology that many older adults are familiar with, ensuring richer, more insightful data despite the smaller sample size. Wearable technology devices are a critical component of digital healthcare technologies and represent a significant portion of the digital healthcare technology landscape. Research has shown that older adults often prefer wearable devices due to their ease of use and the immediate feedback they provide on health conditions (Peek et al., 2014; Li et al., 2020).

Focusing on wearable technology devices allows a deeper understanding of specific challenges and opportunities related to their use and insights applicable to other digital healthcare technologies. Moreover, the feasibility, time, and practical constraints of the study also support the decision to focus on wearable technology devices in the qualitative phase. Conducting qualitative research across all digital healthcare technology categories would have been challenging to manage and would require significantly more time, effort, and resources. The time constraints of the study made it impractical to explore all categories of digital healthcare technologies in-depth. By concentrating on wearable technology devices, the research process becomes more manageable within the available time frame, allowing for richer, more detailed insights. Older adults may also find it easier to articulate their experiences with wearable devices, as they involve more tangible and direct interactions than abstract technologies like telemedicine or health information systems (Mitzner et al., 2010). This focus on wearable technology devices also addresses a research gap in the application of the expectation confirmation model to older users. By concentrating on wearable devices, this study is able to extend the expectation confirmation framework to include constructs that reflect the specific needs and capabilities of older users.

3.6.1.1 Justification for Employing Semi-structured Interviews in Phase 1

Interviews provide an excellent opportunity to explore participants' views and collective experiences in-depth, offering insights that are difficult to obtain through other methods (Patton, 2014). As Kvale (2009) notes, interviews are particularly effective for collecting detailed information. This study employed semi-structured interviews, which combine elements of both structured and unstructured questioning. This hybrid approach involves using a set of predetermined questions while giving the researcher the flexibility to ask for clarifications or explore topics in more depth when necessary, as highlighted by Rubin and Rubin (2011). Semi-structured interviews were chosen because they encourage open discussion on topics of interest and offer the flexibility to introduce new questions as the research progresses (Patton, 2014). This flexibility allows participants to share their detailed experiences without being restricted by a strict set of questions, which is often the case with structured interviews (Bryman, 2016).

Moreover, the researcher has the ability to adjust the sequence and phrasing of questions or even add new ones as needed based on how the interview progresses (Cohen et al., 2002; Lune and Berg, 2017). Additionally, semi-structured interviews are particularly effective when studying emerging and newly implemented technologies (Rogers et al., 2014). This method allows researchers to delve into the reasons behind technology use and to explore how individuals react to and engage with these innovations (Dawadi et al., 2021). Therefore, semi-structured interviews were considered appropriate for this study's first phase, given their effectiveness in exploring continuance intention studies. The following section will discuss the development of the interview questions.

3.6.1.2 Interview Questions Development

The interview questions were formulated after conducting a thorough review of existing literature on the adoption and continued use of digital healthcare technologies by older users. These questions were further refined through consultations with two academic experts in qualitative research. The primary goal was to explore the factors influencing older users' continuance intention to use digital healthcare technologies, focusing on their experiences and perspectives. The design of the interview questions was informed by several studies, such as:

- Nikou et al. (2020) on digital healthcare technologies adoption by older adults through a capability approach model.
- Abouzahra and Ghasemaghaei (2020) on the antecedents and outcomes of older adults' use of wearable activity tracking devices.
- Vaghefi and Tulu (2019) on factors influencing the continued use of mobile health apps.
- Pal et al. (2020) on the continuous usage of smartwatches using an extended expectation confirmation model.

The questions were categorised into four sections:

Section 1 - Older users' background: This section gathered contextual information about the participants, such as their general health status, specific health concerns, methods of monitoring these concerns, and the types and brands of digital healthcare technologies they used. Also, the questions encouraged participants to elaborate on their daily health considerations and actions taken to maintain or improve their health.

Section 2 - Initial adoption: This section explored the initial motivations for using digital healthcare technologies, the specific applications and features used, and personal experiences with the technology. It examined perceived benefits, initial concerns, and the usefulness of the devices. Probing questions sought to uncover specific uses, adaptation periods, and satisfaction levels, aiming to draw out detailed experiences and clarify interviewees' responses.

Section 3 - Continued use: This section, the core focus of the study, delved into reasons for continuous usage of digital healthcare technologies. It investigated usage frequency, ongoing purposes, sustained benefits, and persistent concerns. Probing questions aimed to understand value retention, changes in application usage, and specific reasons for continued use, providing a comprehensive understanding of the participants' experiences.

Section 4 - Closing questions: This final section summarised and confirmed the discussions, gathering demographic information like age and confirming major discussion points to ensure data accuracy. Participants were thanked for their participation. Detailed interview questions are provided in Appendix 1.

3.6.1.3 Sampling Design

The target population for this phase comprised individuals over 65 years old living in the UK who currently use digital healthcare technologies. Older adults are defined as individuals aged 65 years or older (Orimo et al., 2006). Three main criteria were established for recruiting interviewees: they must have relevant experience with digital healthcare technologies, be over 65 years old, and be UK citizens. Experienced users are crucial as they can provide insightful feedback and understand the interview questions comprehensively. Interested and eligible participants who met these criteria were then invited to take part in the study. Different methods of data collection use a range of sampling techniques (Taherdoost, 2016). In this phase, purposive sampling was selected. Purposive sampling is a method often employed in qualitative research where participants are chosen based on specific criteria (Creswell and Poth, 2016; Patton, 2014). The reason for choosing purposive sampling was to ensure that the participants had relevant knowledge and experience with the phenomenon being studied (Creswell and Clark, 2017). This is particularly important when investigating current users of digital healthcare technologies, as those without sufficient experience might find it challenging to articulate their thoughts and opinions about the technology. The focus on users over 65 aimed to explore why they use digital healthcare technologies and how these devices support their continuance usage intentions.

Participants for this study were sourced from the Brunel Older People's Reference Group (BORG), a resource maintained by Brunel University London. This group consists of local individuals aged 50 and above who have expressed an interest in engaging with the university's research projects (Brunel University London, 2021). These individuals were contacted via email. Additionally, participants were recruited through social media platforms like X (formerly Twitter) and Meetup. An online invitation calling for 'Over 65 current users of wearable technology devices in the UK' was publicised on these platforms. The invitation to participate in the interview can be found in Appendix 2. Once participants were confirmed to meet the research criteria, they were provided with an explanation of the study's purpose and were asked to participate. Upon their agreement, an interview was arranged. More details on this procedure are provided in the interview process section.

3.6.1.4 Sample Size

The question of determining the right sample size for qualitative research is a topic that continues to be debated among scholars. An excessively large sample can raise ethical concerns, while a too-small sample can undermine the validity of the findings (Francis et al., 2010). Various scholars have offered guidelines for sample sizes in qualitative studies. Morse (1994) suggested that for phenomenological research, at least six participants are necessary, while ethnographic and grounded theory studies typically require a larger sample size of 30 to 50 participants. Cresswell

(2013) suggested involving 5 to 25 participants for phenomenological studies and 20 to 30 for grounded theory research. In qualitative research, the concept of data saturation is often used to justify the number of participants. It refers to the point in data collection where no new themes, patterns, or insights emerge from the interviews, indicating that further data collection would be redundant (Francis et al., 2010). For this study, data saturation was carefully monitored during the interview process. After conducting 20 interviews, it was clear that the major themes relating to older adults' experiences with digital healthcare technologies had been identified, with no significant new information emerging. Guest et al. (2006) suggest that saturation typically occurs around the 12th interview, but important themes can begin to emerge as early as the 6th interview, which aligns with the findings in this study. However, as Saunders et al. (2018) point out, saturation is not solely dependent on the number of interviews but is influenced by the study design, scope, and the qualitative traditions being followed. This approach ensures that the data collected sufficiently covers the research topic without unnecessary repetition.

Given the need to thoroughly explore older users' experiences, perceptions, and attitudes toward wearable technology devices, this study conducted 20 interviews. This number was chosen to ensure a robust exploration of the research questions while considering practical constraints like participant availability and resources. Using an abductive approach, this sample size allowed for identifying new constructs and refining the pre-existing expectation confirmation model and its additional constructs (Dubois and Gadde, 2002). The aim was to achieve data saturation, ensuring no new themes or insights emerged, thus providing thorough coverage of the older users' experiences and opinions. The abductive approach involves iteratively moving between empirical data and theoretical insights, enabling a flexible and iterative process of theory development and refinement (Dubois and Gadde, 2002; Timmermans and Tavory, 2012). This approach ensures that the findings are representative of the studied population, enhancing the validity and reliability of the conclusions (Saunders et al., 2015). The chosen sample size facilitated an in-depth analysis within the expectation confirmation model framework, offering a sufficient understanding of the influence of additional constructs on the core model.

3.6.1.5 Data Collection Process

The interviews for this study were conducted in the UK from June to August 2022. Given the post-pandemic context, face-to-face interviews were not practical, so online interviews were conducted instead. Previous studies have found that data collected through online interviews, such as those conducted via Skype or telephone, is of a quality comparable to data collected through face-to-face interactions. This equivalence in data quality suggests that the insights and information gathered through online methods can be just as reliable and valid as those obtained through traditional in-person interviews (Deakin and Wakefield, 2014; Weller, 2017). Before conducting each interview, participants were provided with a participant information sheet and a consent form, as required by the ethical approval from Brunel University London (see Appendix 3). These documents, outlined in Appendices 4 and 5, clarified the interview process and the rights of the participants. The information sheet included details about the study's purpose, topic, and the expected duration of the interview. Participants were also informed about ethical issues, the anonymity of their involvement, and their right to withdraw at any time. Signed consent forms were collected before starting the interviews.

Despite careful planning, the data collection process faced several challenges. Recruiting participants was difficult due to privacy concerns and digital fatigue post-pandemic, making individuals less inclined to participate in online research. To overcome this, targeted recruitment strategies were employed, including leveraging the Brunel Older People's Reference Group (BORG) database and social media platforms like X (formerly Twitter) and Meetup. An online invitation specifically targeted 'Over 65 current users of wearable technology devices in the UK'. Technological barriers also posed challenges, as some participants were unfamiliar with Zoom, leading to hesitancy, scheduling issues, and last-minute cancellations. To address this, step-by-step guides for using Zoom were provided, ensuring smooth interview sessions despite the extra time required. Maintaining participant engagement during the interviews was another hurdle. The impersonal nature of online interactions sometimes led to disinterest, potentially compromising data quality. To counter this, regular check-ins were conducted to ensure participants felt comfortable and valued. This approach helped keep their interest and willingness to share their thoughts. Technical difficulties, such as poor internet connections, also disrupted some interviews, causing audio and video issues. In such cases, interviews were rescheduled to ensure clear communication. Additionally, transcribing some of the interviews was challenging due to poor audio quality from technical issues, requiring significant time for reviewing and editing transcripts to ensure accuracy. Despite these challenges, a determination to collect high-quality data for the research remained. By being patient, flexible, adaptable, and proactive in finding solutions, these obstacles were successfully navigated, and the data for the study was gathered.

In the initial part of the interviews, participants were encouraged to share details about their background, general health, specific health concerns, and how they typically monitor their health. They were also asked about the types of wearable technology devices they use to track or manage their health, the brand of their devices, steps they take to maintain or improve their health, and how often they think about their health and well-being in their daily life. These open-ended questions allowed them to express their thoughts freely and provided valuable context for the rest of the interview. After that, in the second section, they were asked to discuss their initial adoption of wearable technology devices, including what drove them to use them, which features they used the most on them, and what they used those features for (e.g., communications, health, fitness, timekeeping tasks). They were also asked to describe their experience using the device, the benefits they noticed, and any concerns they had. Additionally, they were asked to compare their actual experience with the device to what they thought it would be like before using it. Probing and follow-up questions were used to further explore their responses on experience, such as how useful the device was to them, how long it took them to get used to the device, how satisfied they were with the device, and if using the device caused them any anxiety or stress. These open-ended questions encouraged participants to elaborate on their responses, which helped the researcher gather more in-depth stories and clarify the language used by the interviewees. This method proved effective in drawing out detailed narratives, making the participants' experiences clearer and more insightful (Ryan and Deci, 2000; Saunders et al., 2015).

In the continued use section, the interviewees were asked about how often they use the device if they still have the same purpose for using the device, and if they still use the same applications on their device. They were also asked to explain their reasons for continuing to use wearable technology devices and their overall satisfaction with using them to manage their health. Probing and follow-up questions were used to gather more information on whether they still see value or benefits from using the device if they still have concerns about using the device, and if using the device helps ease any health-related anxieties. In the last section, the interviewees were asked about their age and presented with a summary of the major discussion points to confirm whether they agreed. Each interview was recorded and transcribed precisely, ranging from 50 to 80 minutes. The transcripts were prepared right after the interviews to enable the researcher to assess more accurately when data saturation was reached. Table 6 below provides detailed information on the in-depth interviews that were conducted.

Interviewee ID	Interview Date	Age	Gender	Interview Approx. Duration
1	14/06/22	65	Male	70
2	15/06/22	67	Male	60
3	20/06/22	72	Female	55
4	22/06/22	66	Female	65
5	24/06/22	68	Female	60
6	27/06/22	70	Male	70
7	29/06/22	68	Female	80
8	01/07/22	75	Male	50
9	04/07/22	72	Male	65
10	05/07/22	64	Male	70
11	05/07/22	69	Female	60
12	07/07/22	73	Female	65
13	11/07/22	65	Male	55
14	14/07/22	77	Female	70
15	18/07/22	66	Male	85
16	20/07/22	72	Female	60
17	26/07/22	66	Male	65
18	02/08/22	65	Female	70
19	05/08/22	76	Male	80
20	10/08/22	69	Male	65

Table 6: Details of In-Depth Interviews of Older Users of Digital Healthcare Technologies
(Developed by the author)

3.6.1.6 Data Analysis Process

After considering different analytical methods such as narrative analysis (Riessman, 2008), interpretative phenomenological analysis (Smith et al., 2009), and discourse analysis (Gee, 2014), thematic analysis was eventually chosen for the interview assessment. This method was chosen due to its reliability and well-established standing in the field of qualitative research (Braun and Clarke, 2006). Thematic analysis is a process that involves detecting, examining, and describing themes or patterns that emerge within a data set (Saunders et al., 2015). This method has been effectively used to study the continuous use of fitness trackers (Becker et al., 2017) and to understand user perceptions of mobile health apps (Anderson et al., 2016). For this study, thematic analysis is considered suitable, as it enables the researcher to concentrate on a select set of themes and categories to interpret the data in connection with the research questions (Braun and Clarke, 2006). By identifying and describing themes and codes, the study aims to determine the main factors influencing older users' continued use of digital healthcare technologies and to contribute theoretically by proposing new constructs to the expectation confirmation model. This study utilised the six-phase approach to thematic analysis proposed by Braun and Clarke (2006). This approach includes familiarising oneself with the data, generating initial codes, identifying themes, reviewing them, defining and naming them, and ultimately creating the report (Braun and Clarke, 2006). Table 7 demonstrates the application of these six steps in the thematic analysis process, as described by Braun and Clarke (2006).

	Phase	Actual Procedure in The Research
1	Data Familiarisation	Engaging deeply with the data by reading transcripts multiple times; Taking notes on initial impressions and identifying potential insights
2	Code Generation	Identifying and labelling significant patterns, keywords, and phrases within the data; Organising these codes systematically to capture key ideas
3	Theme Identification	Grouping related codes into broader themes that capture recurring concepts and patterns relevant to the research questions
4	Theme Review	Refining themes by cross-checking them with the dataset to ensure they are distinct, coherent, and genuinely representative of the data
5	Theme Definition and Naming	Clearly defining each theme's scope and meaning; Assigning names that reflect their core ideas for easy interpretation and discussion
6	Reporting Findings	Synthesising themes into a comprehensive narrative; Using quotes to illustrate findings; Discussing implications in the research context

Table 7: Thematic Analysis Process
Source: Braun and Clark (2006)

In this study, NVivo 12, a qualitative analysis software developed by QSR International, was used for data storage, exploration, and organisation. This software is particularly useful for interpreting qualitative data because it offers multi-dimensional analysis features. These capabilities allow researchers to effectively manage data and identify patterns within complex textual information (Bazeley and Jackson, 2013). The choice to use NVivo was driven by its ability to efficiently extract detailed insights from a large volume of multimedia information. The analysis of interview data using NVivo involved identifying each construct or theme from the 20 interviews conducted. In this phase, data analysis was carried out using an abductive coding method (Timmermans and Tavory, 2022), which facilitates an iterative and adaptable approach to theory development and refinement (Dubois and Gadde, 2002). This method enables the researchers to move between theoretical insights and empirical data, enhancing the understanding of participants' perceptions, experiences, and feelings regarding the use of digital healthcare technologies while incorporating established theories and frameworks (Dubois and Gadde, 2002). The findings of this phase contributed to developing the conceptual framework and provided insights that addressed the research questions. A comprehensive discussion of the findings is presented in section 4.2. The following section will outline the data collection methods and analysis procedures used in Phase 2.

3.6.2 Phase 2: Questionnaire Survey

To examine the relationship between factors influencing the continuance intention to use digital healthcare technologies, a quantitative approach was adopted for Phase 2. The insights gained from Phase 1, combined with the literature review, informed the creation of the survey instrument used in this phase. Specifically, the qualitative findings from the wearable technology interviews helped guide the development of the survey instrument and hypotheses, ensuring that key insights from the interviews were reflected in the broader quantitative phase. In contrast to the qualitative phase, which focused on wearable technology devices, the quantitative phase extends the scope to include all categories of digital healthcare technologies such as wearable technology devices, telemedicine platforms, mHealth apps, and eHealth services. This broader inclusion is critical for understanding continuance intention across different types of technologies. It allows for a more holistic assessment of older users' interactions with a variety of digital healthcare technologies.

3.6.2.1 Justification for Employing Survey Questionnaire in Phase 2

During this phase, quantitative data was gathered through a self-administered questionnaire with open-ended questions. The structured format of questionnaires allows participants to respond in a sequential manner, making them an effective tool for gathering data (Brace, 2018). This method is beneficial for assessing the prevalence of certain behaviours or exploring a vast population's perspectives, views, or mindsets (De Vaus and de Vaus, 2013). A survey questionnaire was selected due to its capacity to provide quantifiable data crucial for validating the proposed model, a primary objective of this study, and it has proven to be effective in similar research fields. The web-based surveys were used in this study. Research indicates that internet-based surveys are a suitable alternative for data collection, and they enable the researcher to reach a wider audience (Dillman et al., 2014). The following section provides a detailed discussion of the questionnaire design for this study.

3.6.2.2 Questionnaire Design

To implement the proposed conceptual framework, established and validated measurement items were used to enhance the reliability of the framework (Adcock and Collier, 2001). Following the guidance of Frongillo et al. (2019), who emphasise the importance of validity across different contexts, some of the questionnaire instruments were adopted from prior studies, with some items adapted to fit the specific context of continuing to use digital healthcare technologies (DHTs). The constructs and their measurement items are listed in Table 8.

Item	Statements	Source
Health Motivation	I try to prevent health issues before I feel symptoms.	Moorman and Matulich (1993); Ha et al. (2023)
	I try to protect myself against the health issues I hear about.	
	I do not take action against health issues I hear about until I know I have a problem.	
	I try to maintain a healthy lifestyle.	
	I try to manage my health risk factors in my daily life.	

	I have an interest in maintaining a healthy lifestyle.	
	I usually value my health.	
Health Consciousness	My health depends on how well I take care of myself.	Dutta-Bergman (2004); Ahadzadeh et al. (2015)
	I am actively engaged in the prevention of disease and illness.	
	Taking preventive measures will keep me healthy for life.	
	Living a healthy life is important to me.	
	I am constantly examining my health.	
	I realise that bad living habits will harm my health.	
	I hope to reduce the harm to the body by changing bad living habits.	
	I think I can improve my health effectively in various ways, such as through exercise.	
Confirmation of Expectation	My experience with using digital healthcare technologies is better than what I expected.	Bhattacherjee (2001); Sinha and Singh (2022)
	The function provided for digital healthcare technologies in general is better than I expected.	
	Digital healthcare technologies fit my requirements better than I expected.	
	Digital healthcare technologies are more useful than I expected.	
	The features provided by digital healthcare technologies are better than what I expected.	
	Overall, most of my expectations from using digital healthcare technologies were confirmed.	
Perceived Usefulness	I find digital healthcare technologies useful in my daily life.	Davis (1989); Thong et al. (2006); Nguyen et al. (2022)
	Using digital healthcare technologies enables me to check my health condition quickly.	
	Using digital healthcare technologies increases my productivity.	
	Using digital healthcare technologies is useful to check my health condition more conveniently.	
	Digital healthcare technologies are beneficial to manage health.	
	Using digital healthcare technologies makes it easier to check my health condition.	
	Using digital healthcare technologies save my time and effort.	
Satisfaction	Experience of using digital healthcare technologies has been satisfactory.	Bhattacherjee (2001); Purohit et al. (2022)
	I am satisfied with my digital healthcare technologies.	
	I think I made the correct decision in using digital healthcare technologies.	
	My overall experience of digital healthcare technologies use was very pleasant.	
	Using digital healthcare technologies makes me feel very contented.	

	I am very pleased after using digital healthcare technologies.	
	Using digital healthcare technologies makes me feel delighted.	
	Digital healthcare technologies are very satisfactory to me.	
Ageing Satisfaction	Things keep getting worse as I get older.	Lawton (1975); Nakamura et al. (2022); Shirahada et al. (2019)
	I have as much as pep as I did last year.	
	The older I get, the more useless I feel.	
	I am as happy now as I was when I was younger.	
	As I get older, things are better than I thought they would be.	
	So far, I am satisfied with the way that I am ageing.	
	The older I get, the more I have had to stop doing things that I liked.	
	Getting older has brought with it many things that I do not like.	
Health Anxiety	I am afraid that I have a serious illness.	Salkovskis et al. (2002); Peng (2022)
	I worry about my health.	
	If I hear about an illness, I think I have it myself.	
	I usually feel at risk for developing a serious illness.	
	I usually feel at very high risk for developing a serious illness.	
	I usually think I have a serious illness.	
	If I have a bodily sensation or change, I wonder what it means.	
Technology Anxiety	Using digital healthcare technologies makes me very nervous.	Hoque and Sorwar (2017); Maduku et al. (2023)
	Using digital healthcare technologies makes me feel worried.	
	Using digital healthcare technologies makes me feel uncomfortable.	
	Using digital healthcare technologies makes me feel uneasy and confused.	
	Using digital healthcare technologies is somewhat intimidating to me.	
	I have difficulty understanding most technological matters with regard to using digital healthcare technologies.	
Self-efficacy	It is easy for me to self-monitor my physical condition by using digital healthcare technologies.	Lee and Larsen (2009); Malodia et al. (2023)
	I have the capability to use digital healthcare technologies to self-monitor my physical condition without much effort.	
	I believe I have the ability to use digital healthcare technologies.	

	I am confident that I can use skilfully use digital healthcare technologies.	
	I can learn how to use digital healthcare technologies.	
	I am confident in being able to use digital healthcare technologies independently.	
	I can meet my medical needs through digital healthcare technologies.	
	I can confidently handle common operational problems when using digital healthcare technologies.	
Continuance intention to use	I intend to continue using digital healthcare technologies, rather than discontinue its use.	Bhattacherjee (2001); Ha et al. (2023); Gupta et al. (2020)
	I will keep using digital healthcare technologies.	
	I predict that I will keep using digital healthcare technologies.	
	I plan to continue using the digital healthcare technologies.	
	I will always try to use digital healthcare technologies in my daily life.	
	I will keep using my digital healthcare technology as regularly as I do now.	
	I intend to increase my use of this digital healthcare technology in the future.	
	I will continue to use digital healthcare technologies to record my health status.	
	I intend to continue using digital healthcare technologies to monitor and manage my health status.	

Table 8: Constructs and Measurement Items Used in This Study
(Developed by the author)

The items for health motivation were adopted from Moorman and Matulich (1993) and Ha et al. (2023). Similarly, health consciousness items were adopted from Dutta-Bergman (2004) and Ahadzadeh et al. (2015). Ageing satisfaction items were directly sourced from Lawton (1975), Nakamura et al. (2022), and Shirahada et al. (2019), and health anxiety items were adopted from Salkovskis et al. (2002) and Peng (2022). These constructs remained unchanged from their original formulations. In contrast, perceived usefulness items were adapted from Davis (1989), Thong et al. (2006), and Nguyen et al. (2022) to align with the DHT context. Confirmation of expectation items were derived from Bhattacherjee (2001) and Sinha and Singh (2022) with minor modifications to reflect the expectations specific to DHTs. Satisfaction items were adapted from Bhattacherjee (2001) and Purohit et al. (2022). Similarly, technology anxiety items from Hoque and Sorwar (2017) and Maduku et al. (2023), and self-efficacy items from Lee and Larsen (2009) and Malodia et al. (2023), were modified to ensure they resonated with the context of older adults using DHTs. To measure the dependent variable, continuance intention to use, items were adopted from Bhattacherjee (2001), Ha et al. (2023), and Gupta et al. (2020). These items are widely recognised for their validity and reliability in capturing continuance behaviours across various contexts. Ageing Satisfaction and Self-Efficacy were initially identified during the qualitative phase of this study. These constructs emerged as critical factors influencing older adults' engagement with DHTs, reflecting their ageing-specific needs and individual capabilities. To operationalise these constructs in the quantitative phase, validated scales from prior research were employed to ensure robust measurement while maintaining relevance to the study's context. This approach ensured alignment with existing literature while addressing the unique characteristics of the target demographic. All constructs were measured using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), following established guidelines (Joshi et al., 2015; Likert, 1932). The final questionnaire underwent pre-testing and pilot testing to ensure clarity and relevance, as detailed in later sections. The full survey questionnaire is provided in Appendix 6.

3.6.2.3 Sampling Design

The target population and sampling technique for the quantitative phase of this study align with those used in Phase 1. While qualitative research emphasises depth over breadth and less focuses on sample size (Bryman, 2016), quantitative research typically requires larger sample sizes, especially when using Structural Equation Modelling (SEM). There is no fixed rule for determining sample sizes in quantitative research, but the goal is often to achieve generalisability. However, determining an appropriate sample size involves various complexities, such as the correlation between factors or indicators, the impact of missing data, and the number of factor indicators (Hair et al., 2017). To guide this study, Bollen's (2014) recommendation of a ratio of five samples per variable was applied. This guideline is well-regarded in structural equation modelling literature for ensuring robust model estimation and reliable results (Kline, 2023). Given that the questionnaire included 74 items, Bollen's guideline indicated that a minimum sample size of 370 respondents would be necessary. However, to further strengthen the study and accommodate potential complexities in the model, 479 completed questionnaires were collected. This sample size not only exceeds the minimum requirements based on Bollen's (2014) guideline but also provides a strong foundation for the analysis, thereby enhancing the stability of parameter estimates and the reliability of the findings. Moreover, this sample size is consistent with previous research on continuance intention to use technology, where sample sizes ranged from 100 to 600 respondents in studies utilising factor analysis and structural equation modelling (Dehghani et al., 2018; Pal et al., 2019; Bölen, 2020).

3.6.2.4 Questionnaire Validation Process

Face and Content Validity

The face and content validity of the questionnaire was established through expert review before conducting the pre-test and pilot study (Bolarinwa, 2015). Two academics specialising in marketing and healthy ageing were consulted to assess whether the questionnaire was appropriate and comprehensive for measuring the factors that influence the continuance intention to use digital healthcare technologies among older users. The experts provided feedback on the clarity, relevance, and comprehensiveness of the items related to constructs such as health motivation, health consciousness, confirmation of expectation, perceived usefulness, satisfaction, ageing satisfaction, health anxiety, technology anxiety, self-efficacy, and continuance intention to use. Additionally, the two academic researchers assessed the overall appropriateness of the questionnaire. To create a balanced questionnaire, both positively and negatively worded items were included, following the guidelines for scale development by Churchill (1979) and Oppenheim (2000). This approach ensured a mix of positive and negative statements, all of which were rated using a five-point Likert scale (Roszkowski and Soven, 2010). Some items were slightly reworded to better align with the specifics of the current study. This validation process ensured that the survey accurately measured the intended constructs, following the guidelines set out by Churchill (1979) for scale development and validity testing. The experts' feedback contributed to enhancing the face validity by ensuring the items appeared to measure the constructs as intended and the content validity by confirming that the questionnaire comprehensively covered the relevant aspects of digital healthcare usage among older adults.

Pre-test

Following the validation of the questionnaire through expert review, a pre-test was conducted with 12 participants. The participants were all over 65 years old, residing in the UK, and currently using digital healthcare technologies. This phase was crucial for assessing the practical aspects of the questionnaire, such as its clarity, structure, and ease of understanding for the target population (Bloomfield and Fisher, 2019). Participants were asked to complete the questionnaire and provide feedback on any difficulties they encountered, including ambiguous or unclear wording, as well as the flow and structure of the survey. Based on the feedback from the pre-test participants, a few items in the questionnaire instrument were revised to improve clarity and ensure better understanding. For example, certain questions were reworded to ensure that older adults could easily comprehend them, particularly in sections involving screening questions and the criteria for continuance intention. This phase ensured that the questionnaire was user-friendly and comprehensible for older adults, the target demographic of this study. The feedback received during the pre-test allowed the questionnaire to be fine-tuned, enhancing its usability and ensuring that it was ready for the larger pilot study.

Pilot Study

Pilot studies are an essential step to ensure the quality and validity of a measurement tool (Bryman, 2016; Thabane et al., 2010). After refining the questionnaire based on pre-test feedback, a pilot study was conducted with 188 participants, all of whom met the same criteria as those in the pre-test. Purposive sampling was employed to ensure that participants represented the study's target population (Creswell and Poth, 2016; Patton, 2014). Participants were recruited through a combination of digital and physical channels to ensure a representative sample, with all data collected through an online survey. The pilot study aimed to test the clarity, logic, and ease of understanding of the survey design, identify any issues with question phrasing, response options, or structure, and assess the reliability of the measurement tool. The study also evaluated the data collection process, including timing and response rates, to ensure the survey process would be efficient and appropriate for the main study (Srinivasan et al., 2017; Van Teijlingen and Hundley, 2002).

The questionnaire included 74 items across ten constructs, two of which, self-efficacy and ageing satisfaction, were developed from the qualitative phase of the research. The remaining constructs were adapted from established literature. SmartPLS was used to assess the initial reliability of the constructs through the pilot study. To ensure the internal consistency of the scales, Cronbach's Alpha was calculated for each construct. This measure of reliability assesses how well the items within a construct consistently measure the same underlying concept (Cronbach, 1951; Tavakol and Dennick, 2011). The reliability coefficients should range from 0 to 1, with values closer to 1 indicating more robust reliability (Koo and Li, 2016). Sekaran (2016) suggests that a Cronbach's Alpha value of 0.7 is acceptable, while a value of 0.8 or higher is considered to indicate good reliability. Hair et al. (2017) recommend aiming for coefficients between 0.7 and 0.9 for better reliability. As shown in Table 9, all constructs demonstrated strong internal consistency, with Cronbach's Alpha values ranging from 0.882 to 0.976. These results indicate that the scales measure the intended constructs.

Constructs	Number of Items	Cronbach's Alpha
Health Motivation	7	0.893
Health Consciousness	8	0.882
Confirmation of Expectation	6	0.944
Perceived Usefulness	7	0.943
Satisfaction	8	0.965
Ageing Satisfaction	8	0.951
Health Anxiety	7	0.948
Technology Anxiety	6	0.948
Self-efficacy	8	0.936
Continuance Intention to Use	9	0.976

Table 9: Reliability Test Results for Constructs
(Developed by the author)

The pilot study also tested the feasibility of the online survey distribution method in reaching older adults effectively. This was a critical step in ensuring that the main study's data collection would be efficient and accessible to the target population. Participants completed the survey with minimal difficulty, and according to their feedback, the survey took no more than 20 minutes to complete, indicating that the length was appropriate for the target population. Furthermore, no issues related to response rates or technical challenges were identified, ensuring that the scales and distribution methods were appropriate for the main data collection. Since the reliability of all constructs exceeded the recommended threshold of 0.7, no further modifications to the items were necessary, and the constructs were considered suitable for use in the main study.

3.6.2.5 Data Collection Process

Questionnaires can be administered through various methods, including face-to-face, telephone, and electronic formats. The popularity of electronic methods has surged due to advancements in software and mobile technology, making the process more efficient (Ruel et al., 2015). Consequently, self-completion questionnaires have become more cost-effective, user-friendly, and convenient compared to interviews (Belisario et al., 2015; Taherdoost, 2021). This tool's ability to reach a larger audience led to its use in this research. The survey of this study was promoted via digital and physical channels to attract a diverse participant pool. It was posted on social media platforms such as Twitter and Facebook groups related to digital healthcare technologies. Also, it was promoted on the Meetup. Additionally, members of the Brunel Older People's Reference Group (BORG) received email invitations.

Physical advertisements were displayed in gyms and on bulletin boards at Brunel University London. The advertisement provided a website link and a QR code to the online survey on Google Forms. Participants were also recruited through Prolific (Palan and Schitter, 2018), a crowdsourcing platform that has proven effective for recruiting participants for surveys across various disciplines, such as management, finance, psychology, and computer science (Queiroz et al., 2022; Kumar et al., 2022; Wise et al., 2020; Jakesch et al., 2023). Prolific's diverse participant pool ensures a representative sample of the general population (Prolific, 2023). The first page of the survey contained a participant information sheet (Appendix 7), which outlined all the essential details participants needed to know. It clearly explained the purpose of the research and what was expected from participants, assured them that their responses would remain confidential and anonymous, and emphasised that they could withdraw from the study at any point without facing any consequences. The quantitative data collection phase lasted from November 2023 to January 2024, ensuring sufficient sample size and data robustness. The ethical approval letter from Brunel University London and the survey advertisement are available in Appendices 8 and 9, respectively.

While self-completed questionnaires offer several benefits, this study encountered challenges that needed to be resolved to maintain the validity and relevance of the research findings. A major hurdle was finding and recruiting participants who met the study's specific inclusion criteria. These criteria were crucial for ensuring the quality of the data but led to a recruitment pace that was slower than anticipated. Identifying and recruiting participants who met the specific inclusion criteria proved to be a time-consuming and challenging process. Despite the initial slow pace of recruitment, I persisted in searching for individuals who fit the study's requirements, dedicating a significant amount of time and effort to this task. This extended the data collection period, as it took more time to find individuals who not only were willing to participate but also fulfilled all the necessary conditions for inclusion in the research. The use of the Prolific platform was a turning point in this challenge, as it allowed to access a larger pool of potential participants and streamline the recruitment process. The platform's advanced screening features made it possible to pre-select participants who met the study's specific demographic and behavioural criteria, effectively streamlining the recruitment phase. This approach not only shortened the duration of data collection but also ensured that the sample remained representative and aligned with the research requirements.

Additionally, the reliability of self-reported data was anticipated as a potential limitation in this study. Self-reported data can sometimes be biased due to social desirability or inaccurate memory recall (Althubaiti, 2016). The reliability of self-reported data was a significant concern, as biased or inaccurate responses could have severely compromised the validity of the study's findings. Recognising this potential limitation, proactive steps were taken to minimise its impact (Krumpal, 2013). To mitigate this limitation, participants were assured that their responses would be kept confidential and anonymous. This approach is known to encourage more accurate and honest responses, reducing the likelihood of social desirability bias and improving the reliability of the data collected (Nederhof, 1985; Ong and Weiss, 2000; Tourangeau, 2018). Additionally, questions were carefully designed to be clear and straightforward to reduce the likelihood of misinterpretation or biased responses. The survey questions were carefully designed to be clear and unambiguous, minimising the risk of misinterpretation or biased responses. This process required multiple revisions and pilot testing to ensure the questions were optimally designed. Technical issues posed another obstacle, as it had been expected that some participants might encounter difficulties accessing the online questionnaire. To address this, a QR code system was implemented, allowing for quick and direct access to the survey via mobile devices. While this solution was effective, it required additional time and resources to develop and test. It had to be ensured that the QR code functioned properly across various devices and platforms, which involved extensive compatibility testing and troubleshooting.

Ensuring data quality was another challenge faced with self-completed questionnaires. There was a risk of participants providing inaccurate, inconsistent, or frivolous responses, which could compromise the quality of the data. Ensuring data quality was a critical challenge, as inaccurate, inconsistent, or frivolous responses could have undermined the entire study. To mitigate this risk, a substantial amount of time and effort had to be allocated to screen and clean the data before analysis thoroughly. This process involved meticulously examining each response, identifying any inconsistencies or outliers, and making informed decisions on how to handle them based on established statistical procedures. This was a painstaking and time-consuming task, but it was essential to maintain the integrity of the study's findings. By addressing these challenges through targeted recruitment strategies (using the Prolific platform), ensuring participant anonymity and confidentiality, providing easy access to the questionnaire (using a QR code), and implementing measures to ensure data quality (screening and cleaning data), the obstacles were successfully navigated, and the data required for the study was gathered. The following section focuses on the data analysis process, detailing how the data was analysed and the reasoning behind the choice of statistical technique.

3.6.2.6 Data Analysis Process

The data analysis was conducted in two parts. Initially, the data were imported into SPSS version 29 for preliminary data analysis. This part involved data cleaning, generating descriptive statistics, evaluating response rate, and checking for non-response bias. In the second part, the proposed model, as detailed in Chapter 3, was evaluated using the PLS-SEM technique with SmartPLS 3 software (Sarstedt and Cheah, 2019), a technique frequently employed in research on the intention to continue using digital healthcare technologies (e.g., Kim et al., 2021; Lu et al., 2023; Meng et al., 2020; Yang et al., 2022). Phase 2 of this study adopts a deductive approach, building on the abductive reasoning from the qualitative phase (Phase 1). The theoretical framework developed in Phase 1 is empirically tested in Phase 2 using survey data and PLS-SEM analysis. This process demonstrates the iterative nature of the research process, where insights from Phase 1's abductive reasoning guide the deductive testing in Phase 2 (Creswell and Clark, 2017).

PLS-SEM enhances the functionality of earlier multivariate methods like regression, factor analysis, and discriminant analysis. It allows for the simultaneous examination of the relationships between independent and dependent variables (Sarstedt et al., 2021). Although both methods seek to analyse construct relationships, they differ in how they statistically test the measurement model (Sarstedt et al., 2016). CB-SEM focuses on estimating the variance-covariance matrix, while PLS-SEM is concerned with explaining the variance of an unobserved dependent variable (Hair et al., 2020; Schuberth, 2021; Rönkkö et al., 2016). Table 10, sourced from Hair et al. (2020), illustrates that CB-SEM's weaknesses are PLS-SEM's strengths, and vice versa, suggesting that the two techniques should be viewed as complementary rather than competitive (Hair et al., 2019; Henseler et al., 2016).

Criteria	PLS-SEM	CB-SEM
Research Goal	Develop or expand current theories or identify the main drivers	Validate or compare theories
Formative Indicators	Supported	Challenging to analyse
Sample Size	Suitable for smaller samples	Suitable for larger samples
Data Distribution	No assumption of normal distribution	Assumes normal distribution
Handling Complex Model	Performs more effectively	Supported
Handling Recursive Model	Not supported	Supported

Table 10: The Differences Between PLS-SEM and CB-SEM
Source: Hair et al. (2020)

This research uses the PLS-SEM method through SmartPLS version 3.3.3 (Ringle et al., 2023) to conduct data analysis, aligning with methodologies adopted in prior studies examining the continuance intention to use digital healthcare technologies (e.g., Kim et al., 2021; Lu et al., 2023;

Meng et al., 2020; Yang et al., 2023). The choice of PLS-SEM aligns with the study's unique research context and objectives for several reasons:

1. The study investigates a complex network of relationships among latent constructs such as health motivation, health consciousness, perceived usefulness, confirmation of expectation, satisfaction, ageing satisfaction, and continuance intention. Additionally, it explores the moderating effects of self-efficacy, health anxiety, and technology anxiety. PLS-SEM is ideal for complex models, handling numerous constructs and paths without strict requirements for sample size or data distribution (Hair et al., 2019; Ringle et al., 2020). Unlike first-generation multivariate methods that cannot assess latent variables, causal models, indirect effects, and complex relationships, PLS-SEM addresses these limitations (Henseler et al., 2009; Rencher, 2005). This capacity makes it well-suited for examining the factors influencing the continuance intention to use digital healthcare technologies among older users.
2. In the relatively underexplored field of digital healthcare technologies for older users, PLS-SEM's flexibility in assessing and refining hypothesised relationships without strict model fit criteria is advantageous for extending existing theories (Sarstedt et al., 2017). Given that the questionnaire data may not follow normal distribution patterns, PLS-SEM's ability to handle non-normal data distributions (Hair et al., 2014) and small sample sizes (Kock and Hadaya, 2018) is particularly beneficial. These features are crucial for ensuring the validity and reliability of findings, especially considering the challenges associated with studying older users and the exploratory nature of this research (Memon et al., 2021).
3. PLS-SEM excels in managing models with numerous independent and dependent variables, making it highly suitable for this comprehensive study on digital healthcare technology continuance intention among older users. Typically, PLS-SEM models include around seven to eight constructs (Ali et al., 2018; Hair et al., 2017; Ringle et al., 2012; Ringle et al., 2020) and approximately 27 measurement indicators (Hair et al., 2012; Ringle et al., 2012; Ringle et al., 2020). In contrast, CB-SEM models often include fewer constructs and indicators, which may negatively impact model fit as

complexity increases (Sarstedt et al., 2017). These features of PLS-SEM make it particularly well-suited for detailed analysis of complex interactions within this study's model.

4. PLS-SEM is implemented through intuitive and visually attractive software such as SmartPLS (Hair et al., 2021). SmartPLS offers a comprehensive suite of tools required for model evaluation, including analysis of the measurement model, path analysis, and multigroup comparisons (Hair et al., 2017).
5. PLS-SEM prioritises predictive capabilities over traditional model fit criteria, making it valuable in applied research where outcome prediction is essential. This is particularly relevant in the context of digital healthcare technologies, where assessing and enhancing predictive accuracy directly supports practical decision-making. PLS-SEM's adaptability and extensive use across fields like marketing (Arbabi et al., 2022; Sharma et al., 2022), education (Ghasemy et al., 2020; Purwanto, 2021), psychology (Al-Takhayneh et al., 2022), and social sciences (Li et al., 2020) underscore its robustness and versatility, supporting its application in studying complex phenomena like continuance intention to use digital healthcare technologies among older users.

Chapter 4: Qualitative Findings

4.1 Introduction

This chapter presents the qualitative data analysis and findings of semi-structured interviews conducted with UK residents over 65 who use digital healthcare technologies. This analysis represents the first methodological phase of this study. It employs the NVivo technique to identify key themes and sub-themes that influence the continued use of digital healthcare technologies among older users. From the findings of this phase and the literature review, this chapter aims to refine and enhance the conceptual framework that will be tested in the subsequent quantitative phase (chapter 5) using SPSS and Structural Equation Modelling (SEM). Through an abductive coding approach, this analysis explores the experiences and perspectives of participants, shedding light on the factors driving their continuance intentions regarding digital healthcare technologies. The chapter addresses the main themes identified from the interviews. Each theme is discussed in detail, highlighting its influence on the continued use of digital healthcare technologies among older users. It further proposes a refined conceptual framework grounded in the qualitative findings and literature review. Following this, the hypotheses for each identified construct are developed based on these qualitative findings. These hypotheses will be tested in phase 2 of the study to validate the relationships between the constructs.

4.2 Thematic Analysis Process

As discussed in Chapter Three, the interview data was thematically analysed using a coding approach that combined deductive and inductive reasoning (Timmermans and Tavory, 2022). This iterative process involved moving between empirical data and theoretical insights, refining and developing the theoretical framework based on qualitative findings (Dubois and Gadde, 2002; Timmermans and Tavory, 2012). It allowed the researcher to capture insights from participant stories in the qualitative phase, aiding in a deeper understanding of the factors influencing the continuous use of digital healthcare technologies. The analysis began with creating an initial coding framework inspired by existing literature and the Expectation

Confirmation Model (ECM) by Bhattacherjee (2001), identifying preliminary themes about older users' perceptions, attitudes, and concerns towards digital healthcare technologies. The expectation confirmation model, which includes constructs like perceived usefulness, expectation confirmation, and satisfaction, along with additional factors such as health motivation, health consciousness, health anxiety, and technology anxiety, served as a basis for categorising data in line with research aims and theoretical insights (Bingham and Witkowsky, 2021; Crabtree, 1999). However, consistent with this flexible approach (Timmermans and Tavory, 2022), the coding framework remained adaptable and was refined throughout the analysis. As new themes and patterns emerged from the data, the initial coding scheme was modified and expanded. This iterative process maintained a continuous dialogue between empirical data and theoretical insights, ensuring the final coding framework was grounded in participants' experiences and perspectives while also being informed by relevant literature and the expectation confirmation model (Neale, 2016).

Simultaneously, an abductive approach was employed to identify and categorise themes for participants' views on their intention to continue using digital healthcare technologies. This analytical process revealed Ageing Satisfaction and Self-efficacy as significant constructs. These constructs were not initially included in the coding framework but emerged from the data analysis, highlighting their importance in influencing participants' intentions to continue using these technologies. This approach facilitated the discovery of new insights and allowed for the refinement of the theoretical framework based on empirical evidence (Timmermans and Tavory, 2012). Following this, a thorough examination of the collected data was conducted to extract first-order themes from participants' experiences with digital healthcare technologies. These themes, identified during the coding phase, detailed participants' interactions with digital healthcare technologies. For example, themes included specific references to health-related motivations and behaviours, such as Personal Health Goals, Desire for Active Ageing, and Awareness of Health Benefits, which fell under broader themes like Health Motivation. Building on the initial phase, the analysis progressed to developing second-order themes, which synthesised the first-order themes into more aggregate concepts. These second-order themes went beyond the specifics of participants' accounts, identifying underlying patterns and processes. For instance, the first-order themes such as Personal Health Goals, Desire for Active Ageing, and Awareness of Health Benefits were abstracted into second-order themes termed Health Goals and Benefits that encapsulated broader health-related intentions and practices.

In the final stage of analysis, the thematic analysis was completed by aligning the newly identified constructs with the original themes. This ensured that the theoretical framework was grounded in empirical data and supported by the broader research context. The iterative coding process incorporated insights derived from both the data and theoretical perspectives. The final set of constructs represented a robust collection of themes, where second-order themes were refined into theoretical constructs. This involved interpreting and integrating these themes into a coherent framework that resonated with the research objectives and aligned with the expectation confirmation model. The final set of constructs, as shown in Table 11, includes Health Motivation, Health Consciousness, Confirmation of Expectation, Perceived Usefulness, Satisfaction, Ageing Satisfaction, Health Anxiety, Technology Anxiety, Self-efficacy, and Continuance Intention to Use. Each construct was accurately identified and validated through a rigorous coding process, providing a detailed understanding of the elements that influence the continued intention to use digital healthcare technologies among older users. The following table illustrates this analytical journey, demonstrating the development from initial, broad themes to a refined understanding of the specific constructs that influence older users' continuance intention to use digital healthcare technologies.

A priori themes	First-order themes from data	Second-order themes from data	Final set of constructs
Health Motivation	Personal Health Goals Desire for Active Ageing Awareness of Health Benefits Concern for Health Monitoring Motivation for Preventive Care	Health Goals and Benefits Health Monitoring for Prevention	Health Motivation
Health Consciousness	Regular Health Monitoring Preventive Mindset Proactive Health Behaviours Lifestyle Adaptations Behavioural Consistency	Health Monitoring for Prevention Proactive Consistent Behaviour	Health Consciousness
Confirmation of Expectation	Health and Fitness Improvement Accuracy and Reliability Easiness of Use Integration Health Awareness and Empowerment	Positive Confirmation of Expectations	Confirmation of Expectation
Perceived Usefulness	Health Monitoring and Management Activity and Lifestyle Enhancement Convenience Communicational Features Enjoyment Social and Emotional Aspects Empowerment and Control Personalisation	Useful Functional Features Enjoyable Use Relevant Use	Perceived Usefulness
Satisfaction	Perceived Health Improvement Goal Achievement Level of Accuracy User-Friendly Interface Emotional Experience and Support	Satisfaction with Functionality Ease of Use Overall Satisfaction	Satisfaction
Health Anxiety	Perceived Health Concerns Fear of Declining Functionality Fear of Health Deterioration Fear of Dependency Vulnerability to Health Risks Medical Appointments and Tests Managing Medications	Health concerns Managing Health Concerns	Health Anxiety
Technology Anxiety	Unfamiliarity and Inexperience Perceived Complexity Fear of Making Mistakes Privacy and Security Worries	Technological Concerns	Technology Anxiety

	Rapid Technological Change Technical Issues	Technology Difficulties	
N/A	Technological Inexperience Inadequacy Feeling Limited Technological Confidence Learning Beliefs	Self-confidence in Technology	Self-efficacy
N/A	Fulfilment with Life Stage Embracing Physical Changes Adaptability and Resilience Sense of Accomplishment Physical Wellbeing Engagement in Active Lifestyle	Ageing Contentment Engagement in Active Lifestyle	Ageing Satisfaction
Continuance of Use	Likelihood of Continuing to Use the Same Device Likelihood to Upgrade	Continuance of Using the Digital Healthcare Technologies	Continuance Intention to Use

Table 11: List of *a Priori* and Data-Driven Themes
(Developed by the author)

In the following of this chapter, the themes and sub-themes derived from the analysis will be outlined. The connections between the different constructs that were identified will also be discussed. This will help to show how these factors are linked and affect the continuance intention to use digital healthcare technologies by older users in the UK.

4.3 Themes and Constructs

4.3.1 Health Motivation

Using an abductive approach, Health Motivation was explored as a construct influencing older users' perceptions of digital healthcare technologies. Initially identified in prior research (Bianchi et al., 2023; Hsieh, 2023), it reflects intrinsic motivations toward health. The Health Belief Model (HBM) (Rosenstock, 1974) and Self-Determination Theory (SDT) (Deci and Ryan, 2000) underpin these findings. HBM explains that health behaviours are driven by perceived threats, benefits, and confidence in action, highlighting how awareness of digital healthcare technologies' health benefits motivates adoption. SDT suggests that intrinsic values and personal health goals encourage sustained use of these technologies (Ryan and Deci, 2000).

This study integrates these theories to reveal how intrinsic motivation, perceived benefits, and health beliefs shape the perceived usefulness of digital healthcare technologies. Interviews uncovered two second-order themes under Health Motivation: (1) Health Goals and Benefits, encompassing Personal Health Goals, Desire for Active Ageing, and Awareness of Health Benefits; and (2) Health Monitoring for Prevention, including Concern for Health Monitoring and Motivation for Preventive Care. These themes contribute to understanding the constructs within the Health Motivation framework (see Figure 6).

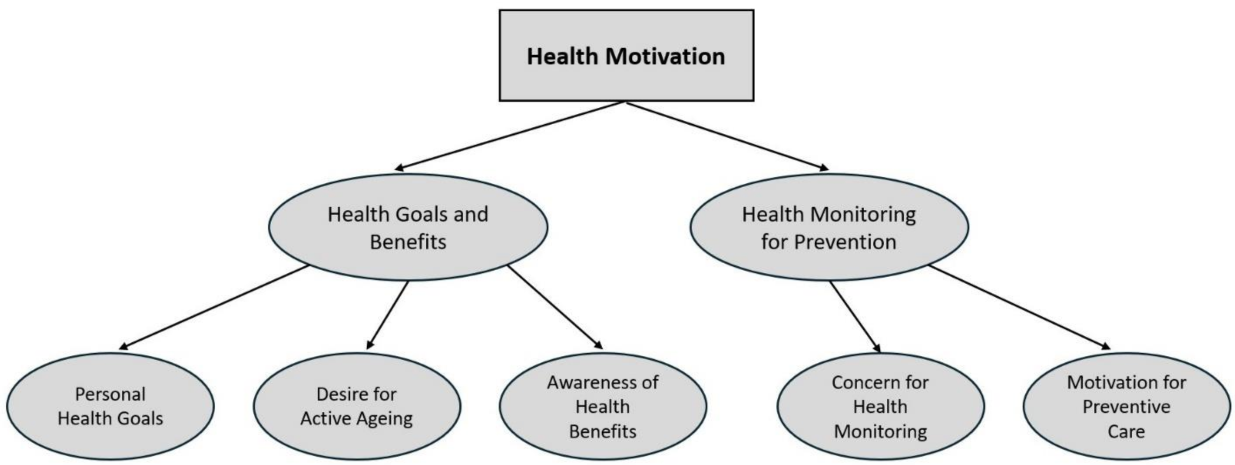

Figure 6: Health Motivation Theme Hierarchy
(Developed by the author)

Health Goals and Benefits

Health Goals and Benefits, a key second-order theme within Health Motivation, included three first-order themes: Personal Health Goals, Desire for Active Ageing, and Awareness of Health Benefits. These themes highlighted how older users' health goals, desire to stay active, and understanding of digital healthcare technologies' benefits shaped their motivation and perception of usefulness. These insights reveal how Health Goals and Benefits contribute to Health Motivation and influence the continued use of these technologies. Each first-order theme is discussed in detail below.

Personal Health Goals

Participants demonstrated a proactive commitment to well-being by setting health objectives, such as weight management, increasing physical activity, and managing chronic conditions like monitoring blood pressure or improving sleep quality. Digital healthcare technologies were frequently used to track steps, monitor heart rate, or manage diets, providing a sense of purpose and serving as valuable tools to monitor progress. Participant 9 shared, *"When I realised it could help me track my daily walks and monitor my heart rate, I saw how it perfectly fits my goal of staying active."* This illustrates how aligning personal health goals with technology enhances its perceived usefulness. This finding aligns with Chen and Chan (2014), who note that older adults are more likely to adopt technology that supports their health goals.

Desire for Active Ageing

Participants expressed a desire to maintain physical fitness, social connections, and emotional well-being as they age, aligning with the concept of successful ageing (Rowe and Kahn, 1997; Strawbridge et al., 2002). This intrinsic motivation drove behaviours like healthier eating, regular exercise, and chronic illness management. Digital healthcare technologies were often viewed as valuable in supporting these goals. For instance, Participant 2 stated, *"I want to stay active and independent as I age, and the smartwatch supports that. It keeps me motivated and reminds me to stay active."* This demonstrates how health motivation and tracking capabilities enhance perceived usefulness. However, some participants, such as Participant 7, doubted the effectiveness of these tools, stating, *"I have always tried to keep active as I have gotten older… but I feel like some of this technology is more flashy than functional, so I am not motivated to fully embrace it."* These doubts reduce perceived usefulness, affecting motivation and adoption, consistent with findings on technology acceptance (Venkatesh et al., 2003; Wang et al., 2023).

Awareness of Health Benefits

Awareness of the positive impacts of healthy behaviours, supported by digital healthcare technologies, shaped older adults' perceived usefulness of these tools. Understanding these benefits influenced participants' health-related choices, consistent with research showing that health knowledge promotes preventive behaviours in older adults (Geboers et al., 2015). For example, Participant 8 stated, *"It can improve health outcomes … It guides me toward healthier choices, both physically and mentally."* This illustrates how awareness of health benefits enhances perceived usefulness, with participants recognising these technologies as valuable for improving health outcomes and supporting well-being.

Health Monitoring for Prevention

Health Monitoring for Prevention was another significant second-order theme within the broader Health Motivation construct. This sub-theme was supported by two first-order themes that emerged directly from the participant interviews: Concern for Health Monitoring and Motivation for Preventive Care. These first-order themes provided evidence of how older users' desire to actively monitor their health status and take preventive measures to maintain their well-being contributed to the Health Monitoring for Prevention sub-theme and, in turn, the overarching Health Motivation construct. The insights gained from these themes shed light on how older users' motivation to engage in health monitoring and preventive care shaped their perceived usefulness and continued use of digital healthcare technologies, which aligned with the concept of health motivation as defined by Moorman and Matulich (1993).

Concern for Health Monitoring

The Concern for Health Monitoring reflects participants' prioritisation of staying informed about their physical condition, demonstrating proactive health motivation. They valued health monitoring for early detection, prevention, and maintenance, viewing it as a commitment to promoting well-being. Digital healthcare technologies were seen as valuable tools that fostered a sense of control and empowerment by enabling proactive health management. Participant 20 shared, *"With its ability to monitor my vitals and provide insights regularly, I have gained a sense of control over my health that goes beyond doctor's appointments."* This illustrates how health monitoring concerns enhance perceived usefulness, as these technologies offer convenience and autonomy in managing health. This aligns with Cho et al. (2014), who found that individuals motivated by health concerns benefit from self-monitoring capabilities, supporting active health management.

Motivation for Preventive Care

Participants highlighted their motivation to prevent health issues and recognised the value of digital healthcare technologies for early detection, reflecting high levels of health motivation. Understanding these technologies' role in preventive care significantly enhanced their perceived usefulness. Participant 15 shared, *"It is all about staying one step ahead of any health issues … It is about early detection … It has helped me to spot potential health concerns before they escalate."* This illustrates how health motivation influences the perceived usefulness of these tools by emphasising prevention and early detection.

The interviews consistently revealed that participants who exhibited higher levels of health motivation demonstrated a more favourable view of the utility of digital healthcare technologies. Their intrinsic drive to prioritise their health and well-being appeared to enhance their appreciation of how digital healthcare technologies could assist them in achieving their health goals. This alignment between health motivation and perceived usefulness underscores the pivotal role that psychological factors play in shaping older individuals' adoption and continued usage of these technologies. By understanding the influence of health motivation, the motivational dynamics that underpin the utilisation of digital healthcare technologies by the elderly population can be better appreciated.

4.3.2 Health Consciousness

During the interviews, Health Consciousness, a construct from existing literature (Barua and Barua, 2021; Chen and Lin, 2018; Meng et al., 2019), was revisited to explore its influence on older adults' perceptions of digital healthcare technologies. Defined by Kraft and Goodell (1993) as awareness and proactive engagement in health-promoting behaviours, Health Consciousness shapes how individuals perceive these technologies. The Health Belief Model (HBM) (Rosenstock, 1974) explains that awareness of health risks and benefits drives health-conscious behaviours, while Self-Determination Theory (SDT) (Deci and Ryan, 2000) highlights the role of intrinsic motivation in consistent adoption of health-supporting technologies. Two second-order themes emerged: (1) Health Monitoring for Prevention, including Regular Health Monitoring and Preventive Mindset, and (2) Proactive Consistent Behaviour, encompassing Proactive Health Behaviours, Lifestyle Adaptations, and Behavioural Consistency. These themes contribute to understanding the role of Health Consciousness (see Figure 7).

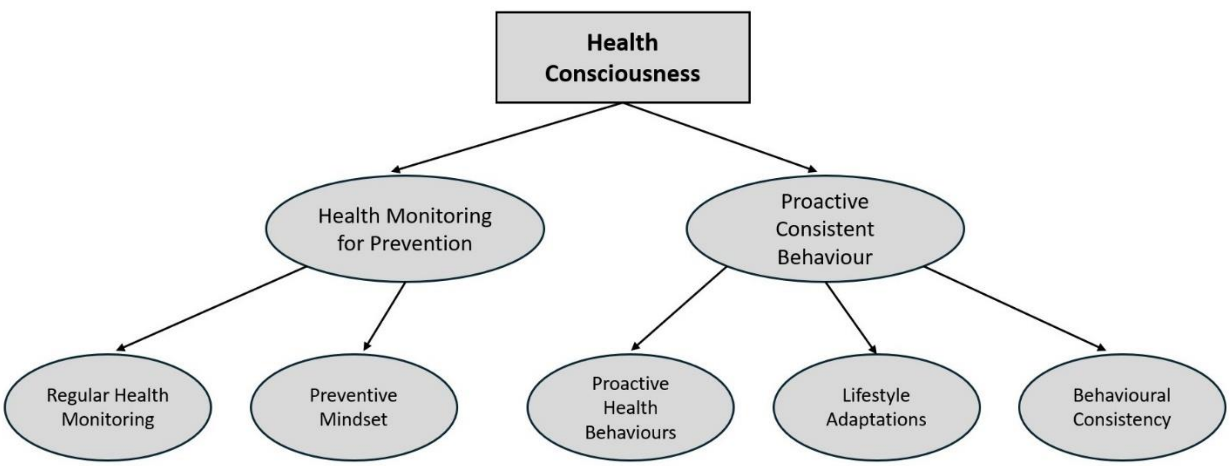

Figure 7: Health Consciousness Theme Hierarchy
(Developed by the author)

Health Monitoring for Prevention

Health Monitoring for Prevention, a key second-order theme within Health Consciousness, was supported by two first-order themes: Regular Health Monitoring and Preventive Mindset. These themes illustrate how older users' proactive health management through monitoring and prevention shaped their health-conscious behaviours, influencing their perceived usefulness and continued use of digital healthcare technologies. This aligns with Mercer et al. (2016) and Peng et al. (2016), who found that health-conscious individuals prioritise monitoring and preventive measures, driving the adoption of these technologies. Each first-order theme is discussed in detail below.

Regular Health Monitoring

Regular Health Monitoring reflects participants' proactive use of digital healthcare technologies to track health indicators like heart rate, activity levels, and sleep quality. Most participants valued these tools for providing real-time insights into their well-being, aligning with the concept of health consciousness, which emphasises awareness of one's physical state (Hong, 2009; Kraft and Goodell, 1993). This behaviour enhanced their perception of the technologies' usefulness, consistent with research showing that self-monitoring capabilities increase the perceived value of wearables and apps (Mercer et al., 2016; Peng et al., 2016).

Participant 5 shared, *"I am having a dedicated health companion right on my wrist … It is as if my body has a voice, and the watch helps me understand it better … Its real-time updates make me feel more in tune with myself."* This illustrates how real-time tracking fosters perceived usefulness by enabling active health monitoring. However, not all participants shared this view. Participant 11 stated, *"I believe that our bodies have a way of letting us know how they are doing ... I do not like to monitor myself with the smartwatch."* This reliance on instinct over technology reflects lower health consciousness and reduced perceived usefulness, highlighting variations in how individuals value digital healthcare technologies (Ancker et al., 2015).

Preventive Mindset

The Preventive Mindset reflects participants' focus on preventing and detecting health issues early. They valued the ability of digital healthcare technologies to track changes in health status, enabling timely action and reducing risks. This proactive approach aligns with the Health Belief

Model (Rosenstock, 1974), which suggests that individuals with a strong prevention focus are more likely to adopt technologies that support early detection and intervention.

Participants reported that tracking health metrics empowered them to catch potential issues early, enhancing the perceived usefulness of these technologies. This is consistent with findings that health-conscious individuals with a prevention focus are more likely to adopt digital tools with alert features (Ancker et al., 2015). For instance, Participant 17 shared, *"It keeps an eye on my heart rate and blood pressure ... I find its alerts really helpful. When it sends me alerts about any changes, I know that I should take an action before it gets worse."* This demonstrates how alert features support a preventive mindset, reinforcing the technology's usefulness for early detection and intervention.

Proactive Consistent Behaviour

Another significant second-order theme within the Health Consciousness theme was Proactive Consistent Behaviour. This sub-theme was supported by three first-order themes that emerged from the participant interviews: Proactive Health Behaviours, Lifestyle Adaptations, and Behavioural Consistency. These first-order themes provided evidence of how older users' proactive and consistent approach to managing their health contributed to the Proactive Consistent Behaviour sub-theme and, consequently, the key Health Consciousness theme.

Proactive Health Behaviours

Proactive Health Behaviours reflect participants' active engagement in promoting their well-being through regular exercise, healthy eating, and staying informed about their health. Many participants found digital healthcare technologies helpful for providing personalised guidance, reminders, and motivation to sustain these habits, aligning with research that health-conscious individuals adopt tools supporting wellness behaviours (Ancker et al., 2015). Features like prompts and feedback reinforce healthy routines and enhance perceived usefulness (Mercer et al., 2016).

Participant 1 shared, *“It reminds me to stay active throughout the day. Whether I am taking the stairs instead of the elevator or going for a walk during my lunch break, it congratulates me for trying to keep up with my exercise.”* This highlights how reminders and positive reinforcement from fitness trackers motivate ongoing health behaviours, showcasing the technology's usefulness for proactive users. However, some participants, like Participant 3, struggled to see the benefits. *“I am not really sure what all those numbers mean. My doctor takes care of that stuff. I still have not understood how this watch would help me.”* This lack of understanding diminished perceived usefulness, highlighting the importance of user awareness in recognising the potential of digital healthcare technologies for supporting wellness.

Lifestyle Adaptations

Lifestyle Adaptations involve changes participants made to their routines to support health needs and goals. Participants noted that integrating digital healthcare technologies into daily life facilitated healthy habits and streamlined routines, enhancing the technologies’ perceived usefulness. This aligns with research showing health-conscious individuals value tools that integrate with and promote healthier routines (Peng et al., 2016). Features like reminders and prompts acted as cues to sustain these changes.

Participant 9 shared, *“It is amazing how something so small can make such a big difference … When it is time for a walk, it gently vibrates, reminding me to stretch my legs and get moving … It also reminds me to stay hydrated.”* This highlights how wearables support daily routines and healthy habits, enhancing their usefulness. Similar findings from Mercer et al. (2016) show that personalised prompts and routine integration reinforce the value of wearables for health-conscious users.

Behavioural Consistency

Behavioural Consistency emphasises maintaining proactive health behaviours over time to achieve lasting benefits. Participants who consistently monitored their health highlighted the role of digital healthcare technologies in providing reminders and tracking mechanisms that supported their long-term habits. This consistency fostered positive outcomes, reinforcing the technologies' perceived usefulness. For instance, Participant 13 shared, *"I have been using it to monitor my activities and health trends over 7 years … It captures the story of my well-being; from the steps I take to the quality of my sleep."* This highlights how regular self-monitoring with a smartwatch supports ongoing health assessments and aligns with sustaining healthy habits, as supported by research showing self-monitoring features increase adoption among health-conscious users (Sergueeva et al., 2020).

In contrast, Participant 19 stated, *"I have always believed that good health comes from factors like a balanced diet or sometimes just luck. While this gadget is interesting, I do not rely on it too much."* This external health locus of control led them to undervalue consistent tracking, reflecting findings by Wallston et al. (1978) on how perceived control impacts technology adoption. These contrasting perspectives illustrate how personal beliefs shape the perceived usefulness of sustained monitoring.

These first-order themes revealed how a health-conscious mindset among older users translated into proactive, consistent behaviours that shaped their perceptions of digital healthcare technologies. Participants with higher health consciousness were more likely to view these technologies as valuable tools for managing their health, enhancing perceived usefulness and encouraging continued use. The interviews underscored that older individuals who prioritise their health tend to find greater value in these technologies, aligning with their proactive approach to maintaining and monitoring well-being. Conversely, older users with lower health consciousness showed less enthusiasm, perceiving digital healthcare technologies as less relevant to their lifestyles and needs.

4.3.3 Confirmation of Expectation

In exploring factors influencing older adults' continued use of digital healthcare technologies, the construct of Confirmation of Expectation, central to the Expectation Confirmation Model (ECM) (Bhattacharjee, 2001; Oliver, 1980), was revisited. This study expanded on the ECM framework to examine how confirmation of expectations shapes older users' decisions. Analysis of interview data aligned with the established concept and provided deeper insights into older users' beliefs and experiences, supporting prior findings that expectation confirmation is vital for continued technology use (Gupta et al., 2021). The second-order theme, Positive Confirmation of Expectations, emerged from the data with five first-order themes: Health and Fitness Improvement, Accuracy and Reliability, Easiness of Use, Integration, and Health Awareness and Empowerment. These themes highlight how digital healthcare technologies meet or exceed user expectations, fostering continued engagement (see Figure 8).

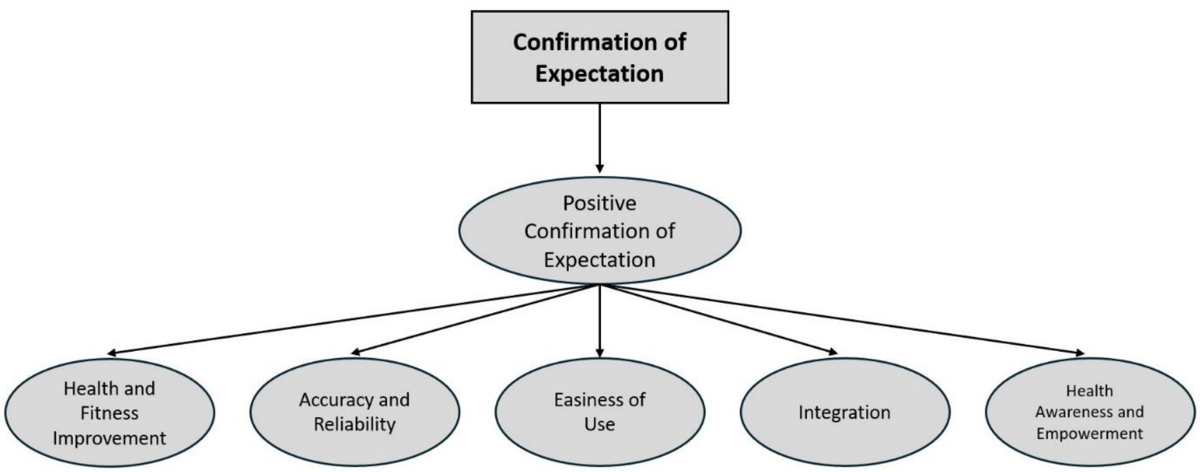

Figure 8: Confirmation of Expectation Theme Hierarchy
(Developed by the author)

Positive Confirmation of Expectations

Positive Confirmation of Expectations, a second-order theme within Confirmation of Expectation, was supported by five first-order themes: Health and Fitness Improvement, Accuracy and Reliability, Easiness of Use, Integration, and Health Awareness and Empowerment. These themes illustrate how the alignment between older users' expectations and their experiences with digital healthcare technologies reinforces the Confirmation of Expectations theme.

Health and Fitness Improvement

Participants expressed expectations of positive changes in their health and fitness levels through digital healthcare technologies, influenced by goals like weight loss, managing chronic conditions, and staying active. Participant 10 shared, *"I was really hoping that this smartwatch would help me get more active. When I started using it and saw that it is tracking my steps and calories burned, I realised that this is what I wanted."* Similarly, Participant 16 noted, *"But then I saw it monitors so many things … It elevated my perception of its usage."* When participants' expectations were met, their perceived usefulness and satisfaction increased, reinforcing the importance of aligning expectations with experiences (Bhattacherjee and Lin, 2014; Mercer et al., 2016).

Participant 2 highlighted how setting goals enhanced motivation: *"It was a personal challenge when I saw that I could set goals for daily steps. And now, reaching those goals makes me feel accomplished."* However, unmet expectations, as noted by Participant 6: *"I thought the smartwatch would monitor all my vitals, but it only tracks heart rate ... Maybe I should buy a newer version"*, led to disappointment, reducing perceived usefulness. These findings demonstrate that meeting health improvement expectations positively impacts perceptions of digital healthcare technologies, while unmet assumptions hinder satisfaction and continued use.

Accuracy and Reliability

The accuracy of digital healthcare technologies played a crucial role in shaping older users' perceptions, with many emphasising the importance of precise health monitoring. Participants often validated the accuracy of their devices by comparing their data to other sources, which increased trust, perceived usefulness, and satisfaction.

Participant 5 shared, *"My son told me that is not accurate especially with the stairs, but then, when I bought it, I compared the tracker's count with my pedometer, and they matched.* Similarly, Participant 19 noted, *"I was sceptical about how well this smartwatch could monitor my sleep. But I started looking at the sleep data it provided, and it was surprisingly close to how I felt."*

These examples demonstrate how accurate and reliable data reinforced users' trust and perception of the technology as a valuable tool, consistent with findings by Chen and Lin (2018). However, inaccurate data undermined confidence and reduced perceived usefulness. Participant 7 remarked, *"The data readings are way off. I expected accurate data."* Such experiences highlight the negative impact of unmet expectations regarding reliability on user satisfaction and adoption.

Easiness of Use

Participants initially worried about complex setup processes and confusing interfaces but often found the devices more intuitive than expected. Participant 8 shared, *"When I set up the smartwatch, it was not that complicated. The whole process was quite straightforward, and I could start using it without any major issues."* Similarly, Participant 20 stated, *"I wanted something that I could easily understand without needing to read a whole manual. When I got it, I wanted it to be easy to use. The buttons were clear, and the display showed me exactly what I needed to know."*

These positive experiences aligned with participants' expectations, boosting satisfaction and perceived usefulness, consistent with the expectation confirmation model (Bhattacherjee, 2001). However, unmet expectations regarding customer support negatively impacted the ease of use. Participant 14 noted, *"I had a question about my device's battery and its sync issue ... Whenever I contacted them, they did not reply."* This lack of timely assistance undermined user satisfaction, highlighting the importance of responsive support in maintaining ease of use.

Integration

Integration explores how digital healthcare technologies fit into participants' daily routines, reflecting their expectations and experiences. This aligns with research highlighting integration as a key usability factor for older users (Kim and Lee, 2017; Wildenbos et al., 2018). For example, Participant 13 shared, *"When I started using it, I found that it is actually quite comfortable to* *wear throughout the day. It is not bulky, and I barely notice it … It fits in perfectly with my daily activities. I have it on all day, except when I take a shower.”* Similarly, Participant 17 noted, *“I was concerned that wearing a smartwatch all the time would feel odd. But it became part of my routine.”*

These experiences demonstrated how seamless integration into routines enhanced perceived usefulness, consistent with Füller et al. (2019). However, some participants highlighted limitations. Participant 3 stated, *“It would have been better if I could customise the alerts and reminders on my device … It is not very flexible.”* The lack of customisation reduced satisfaction, reflecting the importance of personalisation in digital health tools (Kim and Lee, 2017).

Health Awareness and Empowerment

Health Awareness and Empowerment reflect participants' beliefs about gaining insights and feeling more in control through digital healthcare technologies. Participant 15 shared, *“When I saw that my smartwatch is tracking not just steps but also heart rate, blood pressure, and even stress levels, I felt more connected to my health than before.”* Similarly, Participant 11 noted, *“Seeing my steps and activity minutes every day made me realise how much or how little I was moving … It shows me trends over time and how small changes can lead to big improvements.”* These experiences align with research showing that self-monitoring enhances health awareness and empowerment (van Os et al., 2017). When technologies meet expectations by providing actionable data, they increase perceived usefulness and satisfaction, consistent with the expectation confirmation model (Bhattacherjee, 2001; Cho et al., 2020).

The findings align with prior research, showing that confirming expectations fosters perceived usefulness and satisfaction (Bhattacherjee, 2001; Bhattacherjee and Lin, 2014; Gupta et al., 2021). This study extends existing knowledge by exploring specific aspects of expectation confirmation, such as health and fitness improvements, accuracy, ease of use, integration, and health empowerment. These insights underscore the importance of designing digital healthcare technologies that align with older users' unique expectations and needs to encourage sustained use.

4.3.4 Perceived Usefulness

The analysis of interview data emphasised Perceived Usefulness, a key construct of the expectation confirmation model (Bhattacherjee, 2001; Davis, 1989), which reflects the belief that using technology enhances performance. In this study, Perceived Usefulness was reaffirmed and expanded through participants' narratives, showcasing its crucial role in influencing satisfaction and continuance intention (Venkatesh and Davis, 2000). Participants highlighted various valued aspects of digital healthcare technologies, such as health monitoring, empowerment, activity enhancement, convenience, integration with health practices, and personalization, consistent with findings by Yang et al. (2016). These insights provided a deeper understanding of how these factors contribute to perceived usefulness for older users.

Three second-order themes emerged within the broader theme of Perceived Usefulness. The first, Useful Functional Features, encompassed aspects like health monitoring, activity enhancement, convenience, and communicational features. The second, Enjoyable Use, included elements of enjoyment and social or emotional aspects. The third, Relevant Use, captured themes of empowerment, control, and personalisation. Together, these themes underline the multifaceted nature of perceived usefulness in shaping older users' adoption and continued use of digital healthcare technologies.

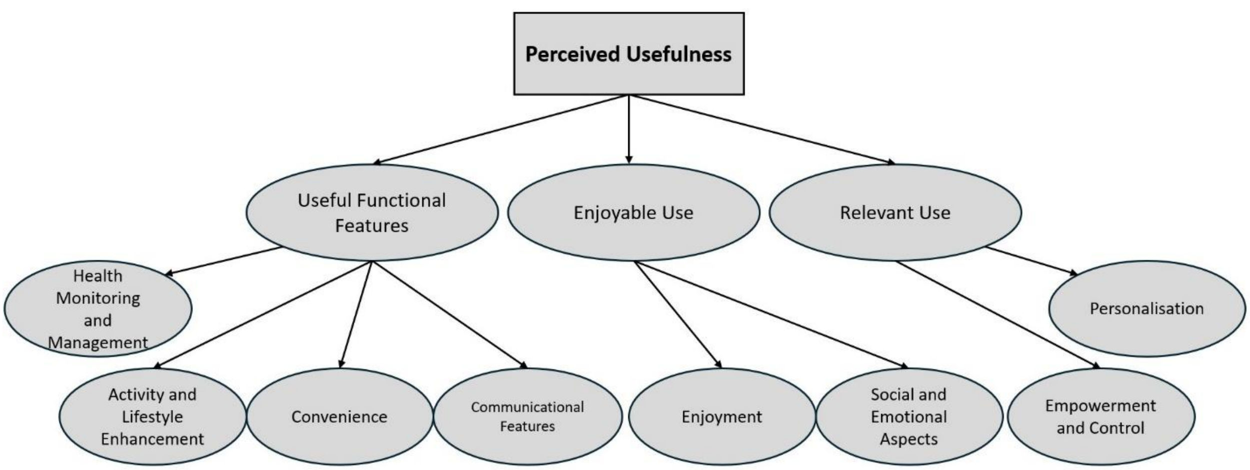

Figure 9: Perceived Usefulness Theme Hierarchy
(Developed by the author)

Useful Functional Features

Useful Functional Features was a second-order themes within the broader Perceived Usefulness theme. This sub-theme was supported by four first-order themes that emerged from the participant interviews: Health Monitoring and Management, Activity and Lifestyle Enhancement, Convenience, and Communicational Features. These first-order themes provided evidence of how the useful functional features of digital healthcare technologies contributed to the Perceived Usefulness theme and, consequently, the overall satisfaction with these technologies among older users.

Health Monitoring and Management

Health Monitoring and Management reflect how digital healthcare technologies enable effective tracking and management of health, contributing to user satisfaction (Wannheden et al., 2021). Participants highlighted features like vital sign monitoring, medication reminders, and early illness detection as valuable. Participant 8 shared, *"It gives me a sense of security and helps me track my health each day."* This illustrates how continuous heart rate monitoring fosters a sense of security and awareness, enhancing perceived usefulness. Prior research supports this, showing self-monitoring technologies improve satisfaction by offering personalised insights (Jiang and Cameron, 2020; Nadal et al., 2023). Similarly, Participant 16 noted, *"I never used to remember my medication on time. It buzzes and reminds me to take my medications."* This highlights how medication reminders improve adherence and health management, aligning with findings that such features enhance satisfaction by supporting self-care (Tran et al., 2022).

Activity and Lifestyle Enhancement

Activity and Lifestyle Enhancement reflects how digital healthcare technologies encourage participants to lead more active and healthier lives by setting goals, tracking steps, and staying motivated. Participant 20 shared, *"It gives me a reason to move more. It is a friendly challenge I have with myself every day."* This highlights how setting and tracking activity goals enhances satisfaction by supporting health objectives, consistent with research showing that such features boost perceptions of usefulness and satisfaction (Lunney et al., 2016). Similarly, Participant 12 noted, *"It pushes me to be more active. Seeing my steps and getting reminders to move keeps me on my toes. It has made me to stay active throughout the day."* This demonstrates the role of reminders and progress tracking in fostering commitment and a sense of achievement. Studies confirm that perceived usefulness for lifestyle enhancement increases satisfaction (Leung and Chen, 2019; Windasari et al., 2021).

Convenience

Participants valued the convenience of having health information readily accessible on their smartwatches, which enhanced satisfaction. Integration with other devices or services, such as syncing with smartphones or sharing data with healthcare providers, was seen as particularly useful. Participant 13 shared, *"My smartwatch syncs seamlessly with my phone. I can see my health data and notifications without having to pull out my phone all the time"*, highlighting how seamless integration improved daily routines and increased perceived usefulness. Research supports that integration in mHealth technologies enhances satisfaction through efficient self-monitoring and data access (Huang et al., 2020; Jakob et al., 2022). Similarly, Participant 10 noted, *"I can share heart rate logs and activity summaries with my doctor right from my watch."* This underscores the value of efficient data sharing in doctor-patient interactions, which has been linked to higher satisfaction with digital healthcare technologies (Qudah and Luetsch, 2019).

Communicational Features

The Communicational Features reflect how messaging and social interaction capabilities in digital healthcare technologies influenced participants' perceptions of usefulness and satisfaction. Participant 2 shared*, "I can read my messages on it and answer my calls … It is not just about health; it is about staying connected too."* This highlights how these devices extend beyond health tracking to support social connections. By fulfilling social needs through features like messaging and video chat, these technologies enhanced perceived usefulness and satisfaction, showing their value in maintaining both health and meaningful interactions.

Relevant Use

Relevant Use was a significant second-order theme within the broader Perceived Usefulness theme. This sub-theme was supported by two first-order themes that emerged from the participant interviews: Empowerment and Control and Personalisation. These first-order themes provided evidence of how the relevant use of digital healthcare technologies contributed to the Perceived Usefulness theme and, consequently, in turn, positively influenced overall user satisfaction with these technologies among older users.

Empowerment and Control

Digital healthcare technologies empowered participants to take a proactive role in managing their health, providing real-time data and insights that increased their sense of control and satisfaction. Participant 1 shared, *"Now, with this, I can check my vitals whenever I want. I feel like I have more control over my own health."* This highlights how self-monitoring capabilities enhance autonomy and perceived usefulness.

Similarly, Participant 17 noted, *"When I see my sleep patterns and heart rate trends, I understand that I am actively managing my health."* This demonstrates how engaging with health data fosters empowerment and satisfaction. These findings align with research showing that features enabling active health management increase satisfaction and perceived usefulness by enhancing control over health outcomes (Ghose et al., 2021; Kruse et al., 2017; Vo et al., 2019).

Personalisation

Personalisation emerged as a key factor influencing older adults' perceptions of digital healthcare technologies. Participants appreciated customisable features tailored to their health needs and preferences. Participant 15 stated, *"I can set my own personal goals and targets that match my fitness level … that keeps me engaged."* This highlights how personalised goals and progress tracking enhance perceived usefulness and satisfaction.

Research supports that customisation fosters greater perceived usefulness and satisfaction (Jimenez et al., 2023), aligning with the Technology Acceptance Model (Davis, 1989). However, when technologies failed to address specific needs, they were seen as irrelevant. Participant 4 noted, *“I do not see how this tracker helps me with my health concerns.”* This mismatch reduced perceived usefulness and hindered satisfaction, emphasising the importance of aligning features with individual needs.

Enjoyable Use

Enjoyable Use was another second-order theme within the broader Perceived Usefulness theme. This sub-theme was supported by two first-order themes that emerged from the participant interviews: Enjoyment and Social and Emotional Aspects. These first-order themes provided evidence of how the enjoyable use of digital healthcare technologies contributed to the Perceived Usefulness theme, which in turn positively influenced overall user satisfaction with these technologies among older users.

Enjoyment

Participants highlighted how enjoyable experiences with digital healthcare technologies enhanced their satisfaction and perceived usefulness. Participant 10 shared, *“Using it is surprisingly enjoyable. The graphics are pleasing, and the little achievements I earn make it feel like a game.”* This demonstrates how aesthetics and gamification elements evoke positive emotions, creating a sense of fun and engagement. Incorporating design features that enhance enjoyment not only improves user satisfaction but also strengthens the connection between perceived usefulness and acceptance of digital health technologies.

Social and Emotional Aspects

The social and emotional benefits of digital healthcare technologies significantly influenced older users’ perceptions of usefulness and satisfaction. Participant 17 shared, *“Sometimes, I share my* *activities with my granddaughter. She sends me encouraging messages whenever she sees I have hit my activity goals."* This highlights how social connections and emotional support, facilitated by these technologies, enhanced satisfaction and perceived usefulness.

These findings align with prior research demonstrating the role of perceived usefulness in shaping user satisfaction (Davis, 1989; Malik and Annuar, 2021; Venkatesh and Davis, 2000). In the healthcare context, Shin et al. (2020) found that older users who viewed health technologies as useful reported higher satisfaction. This study expands on these insights by exploring how functional, relevant, and enjoyable features contribute to perceived usefulness and satisfaction among older individuals.

4.3.5 Satisfaction

Satisfaction, a central construct in the Expectation Confirmation Model (ECM) (Bhattacharjee, 2001), significantly influences users' continuance intention (Tam et al., 2020). This study explores satisfaction among older individuals using digital healthcare technologies, confirming its fundamental role in the ECM and uncovering additional insights through abductive analysis of interview data. Three second-order themes emerged within the Satisfaction construct (see Figure 10). The first, Satisfaction with Functionality, includes Perceived Health Improvement, Goal Achievement, and Level of Accuracy. The second, Ease of Use, highlights the importance of a User-Friendly Interface. The third, Overall Satisfaction, focuses on Emotional Experience and Support. These themes collectively reveal the key factors shaping older users' satisfaction, encompassing functionality, usability, and emotional support, and their influence on continued use of digital healthcare technologies.

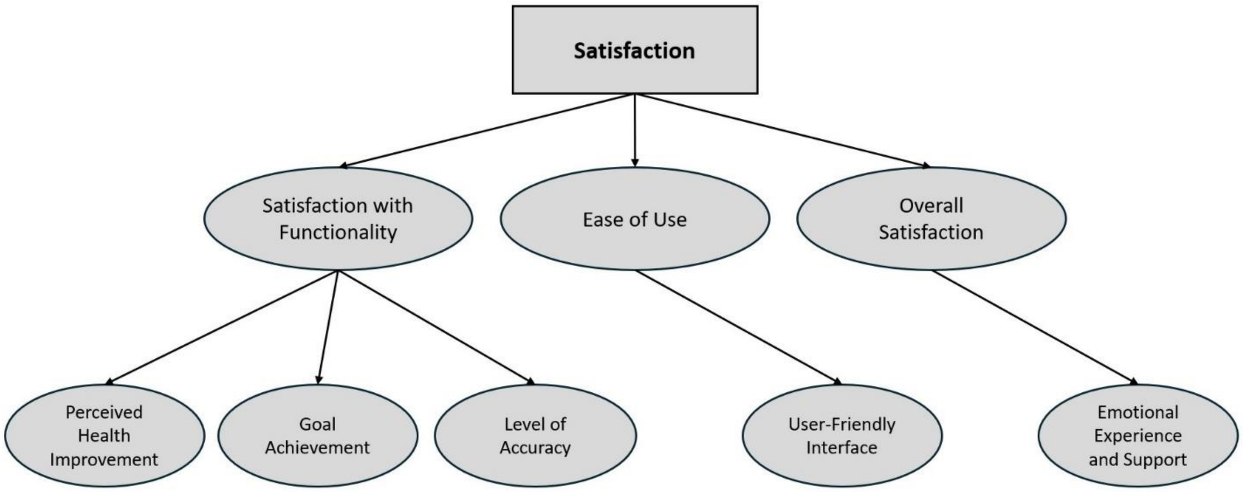

Figure 10: Satisfaction Theme Hierarchy
(Developed by the author)

Satisfaction with Functionality

Satisfaction with Functionality was a significant second-order theme within the broader Satisfaction theme. This sub-theme is supported by three first-order themes that emerged from the participant interviews: Perceived Health Improvement, Level of Accuracy, and Goal Achievement. These first-order themes provided evidence of how satisfaction with the functionality of digital healthcare technologies contributed to the overall Satisfaction theme, which in turn positively influenced ageing satisfaction and continuance intention among older users.

Perceived Health Improvement

Older individuals' satisfaction increased when they perceived digital healthcare technologies positively impacted their health and well-being, fostering a more positive view of ageing and reinforcing their intention to continue using the technology. Participant 1 shared, *"Since using it, I have noticed my stamina improving. Seeing the numbers on its screen reminds me that I should not give up on my health."*

Similarly, Participant 12 noted, *"Since I started using the smartwatch, I have actually lost weight."* These perceived health improvements enhanced satisfaction and continuance intentions, aligning with findings by Mitzner et al. (2019), which show that positive health outcomes increase satisfaction and sustained technology use.

Level of Accuracy

Participants reported that accurate health insights from digital healthcare technologies significantly enhanced their satisfaction, aligning with research showing accuracy as a key driver of user satisfaction (Nascimento et al., 2023). Accurate metrics provided older users with a sense of control, positively influencing ageing satisfaction and reinforcing continuance intentions.

Participant 17 shared, *"Its health readings' accuracy has made me more confident about my health."* This highlights how trustworthy data increased confidence, satisfaction, and proactive health management. By delivering precise health insights, these technologies empowered users with autonomy and efficacy, promoting a fulfilling and confident approach to ageing. Trust in accuracy also reinforced the technology's perceived value, encouraging continued use as an integral part of their health routines.

Goal Achievement

Participants' satisfaction increased when digital healthcare technologies helped them achieve health and wellness goals. This sense of accomplishment positively impacted ageing satisfaction, enhancing well-being, self-esteem, and motivation to continue using the technology. Participant 5 shared, *"When I hit my daily steps' goal, it celebrates my successes and keeps me hungry for more. That encourages me to set new goals and keep moving forward."* This highlights how meeting goals reinforced satisfaction and intention to sustain progress.

However, unmet goals diminished satisfaction, as Participant 7 noted, *"The other day when I went for a long walk, it said I did not reach my step goal for the day which annoyed me."* This underscores how goal frustration can reduce motivation, highlighting the importance of accurate tracking and encouraging feedback. These findings align with research showing that unmet expectations hinder satisfaction and technology adoption (Bhattacherjee, 2001). Accurate goal tracking and positive reinforcement are crucial for sustaining engagement and satisfaction.

The Perceived Health Improvement, Level of Accuracy, and Goal Achievement themes emphasised the importance of functionality and reliability in digital healthcare technologies for enhancing user satisfaction, ageing satisfaction, and continuance intention. These findings underscore the role of the Satisfaction with Functionality second-order theme in shaping older users' overall satisfaction and continued use of these technologies.

Ease of Use

Ease of Use was another significant second-order theme within the broader Satisfaction theme. This sub-theme was supported by the first-order theme User-Friendly Interface that emerged from the participant interviews. This first-order theme provides evidence of how the ease of use of digital healthcare technologies contributed to the overall Satisfaction theme, which in turn positively influenced ageing satisfaction and continuance intention among older users.

User-Friendly Interface

A user-friendly interface emerged as a key factor influencing participants' satisfaction with digital healthcare technologies. Simple menus and minimal complexity enhanced their experiences. Participant 9 shared, *"From day one, it has been very helpful and simple to use … not a confusing gadget. No complicated menus or confusing buttons … completely hassle-free."* This demonstrates how an intuitive interface fosters satisfaction, supports independent health management, and encourages continued use, aligning with research on ease of use as a critical factor for satisfaction and continuance intention (Venkatesh and Davis, 2000; Yan et al., 2021). In contrast, Participant 3 noted, *"I find it confusing to navigate through all those settings ... Adjusting its setting was like being lost in a digital jungle without a map."* This highlights how technical complexity causes frustration, reduces satisfaction, and diminishes ageing satisfaction by introducing inefficiency and disempowerment. Such barriers can discourage continued use, underscoring the importance of intuitive design.

Overall Satisfaction

Overall Satisfaction was the final second-order theme within the broader Satisfaction theme. This sub-theme was supported by two first-order themes that emerged from the participant interviews: Emotional Experience and Support. These first-order themes provided evidence of how the overall satisfaction with digital healthcare technologies contributed to the Satisfaction theme, which in turn positively influenced ageing satisfaction and continuance intention among older users.

Emotional Experience

A positive emotional experience with digital healthcare technologies, such as feelings of empowerment and accomplishment, significantly enhanced participants' satisfaction and ageing satisfaction. Participant 8 shared, *"Every time I glance at my smartwatch and see my achievements, it is like a little burst of joy."* This demonstrates how positive emotions foster satisfaction and motivation to continue using the technology.

In contrast, some participants noted a lack of emotional support. Participant 6 stated, *"I miss having those encouraging chats about my progress with my doctor. The isolation does not make me feel good."* This highlights how the absence of human interaction reduced satisfaction and motivation, consistent with research emphasising the importance of social support in health technologies (Khan et al., 2022).

Additionally, responsive customer support positively influenced satisfaction. Participant 15 noted, *"The support team guided me through it patiently."* This aligns with findings that timely assistance sustains user satisfaction (Negash et al., 2003). The Emotional Experience and Support themes underscore the importance of positive, supportive user experiences in enhancing satisfaction, ageing satisfaction, and continuance intention.

The findings of this research align with Tian and Wu (2022), who found that satisfaction positively influences older users' intention to continue using mHealth technologies. These results support existing studies emphasising the role of satisfaction in driving continuance intention among older adults. While previous research has not directly examined the link between satisfaction with technology and ageing satisfaction, studies suggest that technology use and acceptance can enhance overall satisfaction in older users (Li et al., 2022; Peek et al., 2014; Smith, 2014). This research expands on these findings by identifying a direct positive relationship between satisfaction with digital healthcare technologies and ageing satisfaction.

4.3.6 Ageing Satisfaction

In this study, Ageing Satisfaction emerged as a distinctive construct through interviews with older individuals, reflecting their positive evaluation of the ageing process. It encompasses acceptance of age-related changes and a sense of purpose in later life (Nakamura et al., 2022), offering valuable insights into how ageing perceptions influence the continuance intention to use digital healthcare technologies. This construct was adopted from existing literature (Nakamura et al., 2022) and enriched by qualitative findings, which provided a deeper contextual understanding of how older adults perceive and navigate their ageing process. Two second-order themes emerged within Ageing Satisfaction (see Figure 11). The first, Ageing Contentment, includes five first-order themes: Fulfilment with the Life Stage, Embracing Physical Changes, Adaptability and Resilience, Sense of Accomplishment, and Physical Well-being. These aspects highlight how satisfaction with the ageing process shapes engagement with digital healthcare technologies. The second, Engagement in Active Lifestyle, emphasises the importance of staying physically and mentally active. Together, these themes establish Ageing Satisfaction as a crucial factor influencing older users' continued use of digital healthcare technologies and provide a nuanced understanding of their experiences and attitudes.

Figure 11: Ageing Satisfaction Theme Hierarchy
(Developed by the author)

Ageing Contentment

Ageing Contentment was a second-order theme that contributed to the broader Ageing Satisfaction theme. This sub-theme was supported by five first-order themes that emerged from the participant interviews: Fulfilment with Life Stage, Embracing Physical Changes, Adaptability and Resilience, Sense of Accomplishment, and Physical Wellbeing. These first-order themes provide evidence of how ageing contentment influenced the overall Ageing Satisfaction theme, which in turn positively affected satisfaction and continuance intention among older users of digital healthcare technologies.

Fulfilment with Life Stage

Participants expressed contentment and acceptance with their current stage of life, contributing to ageing satisfaction and positive attitudes towards digital healthcare technologies. For instance, Participant 10 shared, *"I enjoy simple things and connect with people … With technology by my side, I can ensure my wellbeing."* This highlights how fulfilment with life enhances openness to technologies that support well-being. This finding aligns with Ryff (2013), who noted that life satisfaction and positive attitudes towards ageing promote engagement with health-promoting behaviours, including the adoption of digital healthcare technologies.

Embracing Physical Changes

Participants who embraced the physical changes of ageing exhibited higher ageing satisfaction, fostering self-acceptance and openness to digital healthcare technologies. Participant 16 shared, *"I appreciate the natural changes my body has gone through. It is a reminder of the journey I have been on."* This positive outlook reflected contentment with ageing and a proactive approach to well-being, encouraging the adoption of technologies that support health. This finding aligns with Wurm et al. (2017), who observed that positive attitudes toward ageing and physical changes are linked to greater engagement in health management behaviours, including technology use.

Adaptability and Resilience

Participants demonstrated adaptability and resilience in facing age-related challenges, which enhanced their ageing satisfaction and positively influenced their use of digital healthcare technologies. For instance, Participant 5 shared, *"Life is full of surprises, and I have learned to roll with the punches … When simple problems pop up, I remind myself that I have faced tougher things."* This resilient mindset enabled them to overcome technological barriers and maintain their intention to use digital healthcare tools. These findings align with Mayordomo et al. (2021), who noted that resilience and flexible thinking improve well-being among older adults, fostering greater satisfaction and engagement with health technologies.

Sense of Accomplishment

Participants who reflected on their life achievements derived satisfaction, fostering ageing contentment and motivating the adoption and continued use of digital healthcare technologies. Participant 8 shared, *"As I look back on my life, I cannot help but feel I have achieved so much. I am eager to see how it will enhance my life, just like all the other things I have achieved along the way."* This sense of accomplishment encouraged a positive outlook on technology use and ageing satisfaction. These findings align with Tovel et al. (2019), who noted that life satisfaction and a sense of achievement in older adults predict greater engagement in health-promoting activities.

Physical Wellbeing

Participants prioritised their physical health as a key aspect of ageing satisfaction, positively influencing their attitudes toward digital healthcare technologies. Participant 17 shared, *"I prioritise my health, and it is paid off … I have realised that feeling good physically is the secret way of a happy life."* This focus on physical well-being enhanced their quality of life and motivated the continued use of digital healthcare tools, which supported their health goals and contributed to their ageing satisfaction.

The themes of Fulfilment with Life Stage, Embracing Physical Changes, Adaptability and Resilience, Sense of Accomplishment, and Physical Wellbeing underscore the role of ageing contentment in enhancing ageing satisfaction. This, in turn, positively influences satisfaction and continuance intention among older users of digital healthcare technologies, highlighting the importance of ageing contentment in shaping attitudes and behaviours toward these tools.

Engagement in Active Lifestyle

Engagement in an Active Lifestyle was a second-order theme that contributed to the broader Ageing Satisfaction theme. This sub-theme was supported by the first-order theme Engagement in Active Lifestyle, which emerged from the participant interviews. This first-order theme provided evidence of how engagement in an active lifestyle influences the overall Ageing Satisfaction theme, which in turn positively affected satisfaction and continuance intention among older users of digital healthcare technologies.

Engagement in Active Lifestyle

An active lifestyle, including travel and outdoor activities, positively impacted ageing satisfaction and attitudes toward technology use. Participant 2 shared, *"I enjoy staying active and trying out new things, like exploring new places or enjoying the outdoors. It keeps me feeling good and makes me happier."* This adventurous spirit and active engagement reinforced positive intentions to use digital healthcare technologies, driven by ageing satisfaction.

In contrast, Participant 18 stated, *"I barely leave my house these days, I mostly just watch TV alone",* highlighting how social isolation diminished ageing satisfaction and enthusiasm for technology. Courtin and Knapp (2017) found that social isolation negatively affects physical and mental health, reducing engagement with new activities and technologies. These contrasting experiences demonstrate the significant impact of lifestyle engagement on ageing satisfaction and technology adoption.

The interviews revealed that contentment with ageing significantly influences older individuals' willingness to engage with digital healthcare technologies. Those satisfied with their life stage were more likely to view continued use positively, while dissatisfaction led to less favourable attitudes. The Engagement in Active Lifestyle emphasised fostering active lifestyles to enhance ageing satisfaction, which in turn improved satisfaction and continuance intention with digital healthcare technologies, highlighting its critical role in shaping attitudes and behaviours.

4.3.7 Health Anxiety

Health Anxiety, identified early in the study as a key factor (Meng et al., 2022), was further validated and enriched through participant narratives during the qualitative phase. Using an abductive approach, the analysis deepened understanding of how health anxiety influences the use and perception of digital healthcare technologies, significantly contributing to the theoretical framework. Two second-order themes emerged under Health Anxiety (see Figure 12). The first, Health Concerns, includes five first-order themes: Perceived Health Concerns, Fear of Declining Functionality, Fear of Health Deterioration, Fear of Dependency, and Vulnerability to Health Risks. The second, Managing Health Concerns, comprises Medical Appointments and Tests and Managing Medications. Together, these themes define the constructs of Health Anxiety and its role in shaping engagement with digital healthcare technologies.

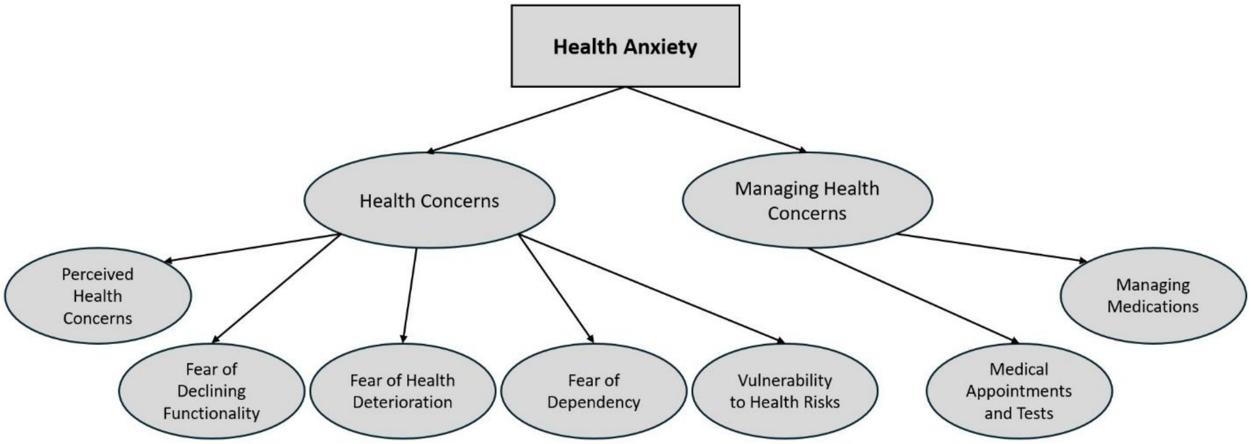

Figure 12: Health Anxiety Theme Hierarchy
(Developed by the author)

Health Concerns

Health Concerns was a significant second-order theme within the broader Health Anxiety theme. This sub-theme was supported by five first-order themes that emerged from the participant interviews: Perceived Health Concerns, Fear of Declining Functionality, Fear of Health Deterioration, Fear of Dependency, and Vulnerability to Health Risks. These first-order themes provided evidence of how health concerns contribute to the overall Health Anxiety theme, which in turn influenced continuance intention among older users of digital healthcare technologies.

Perceived Health Concerns

Perceived health concerns, particularly about chronic conditions and age-related issues, influenced older users' satisfaction and continuance intentions with digital healthcare technologies. Health-related worries, which tend to increase with age (Lebel et al., 2020; Wolitzky-Taylor et al., 2010), heightened health anxiety for some participants, making them more attentive to the benefits of these technologies. Participant 6 noted, *"As I have grown older, I worry more about my blood pressure and cholesterol levels … This device makes me feel that I am actively taking care of my health and gives me a sense of security."* This highlights how technologies tailored to specific health needs can reduce anxiety and encourage continued use. However, participants with fewer health concerns, like Participant 18, expressed less dependence on these devices: *"I feel good about where my health is at for my age … My watch helps me stay active, but I am not too anxious if I miss a day here and there."* These findings suggest that while health anxiety can enhance satisfaction and usage, lower anxiety may reduce perceived benefits and diminish engagement with digital healthcare tools.

Fear of Declining Functionality

Fear of losing physical and cognitive abilities as they age heightened participants' health-related distress but also motivated them to use digital healthcare technologies. Devices like fitness trackers helped maintain functionality, boosting satisfaction and encouraging continued use. Participant 17 shared, *"*It reminds me to be grateful for every little step I take … Staying active is a priority for me as I age*."* This highlights how tracking progress and achieving goals countered fears of decline, fostering satisfaction and commitment to using the technology. By helping older users maintain or improve abilities, these technologies reduced health anxiety and strengthened the link between satisfaction and continued use.

Fear of Health Deterioration

Participants' fear of health decline amplified health anxiety but also motivated regular use of digital healthcare technologies. Satisfaction with these devices increased as they provided a sense of security and control. Participant 1 shared, *"I fear that something might go wrong with my health, and it scares me."* This demonstrates how real-time monitoring alleviated fear, reduced anxiety, and enhanced satisfaction. These findings align with McMullan et al. (2019), who found that health-monitoring technologies help reduce anxiety by offering timely health information and a sense of control.

Fear of Dependency

Participants expressed a fear of becoming dependent on others, which heightened health anxiety and motivated them to use digital healthcare technologies to maintain independence. Participant

13 stated, *"I do not want to become a burden to my family and lose control over my life … My smartwatch provides a sense of security and empowerment, reminding me that I can still take charge of my health independently."* This highlights how these technologies reduce reliance on caregivers and promote self-reliance, enhancing satisfaction and continuance intention. In contrast, Participant 4 shared, *"I feel confident I can take care of myself … My smartwatch helps me stay on top of things, but knowing I am in control of my health gives me peace of mind."* This self-assurance reduced dependency-related anxiety but also diminished the perceived benefits and satisfaction with the technology, lowering the intention to continue its use.

Vulnerability to Health Risks

Participants' sense of vulnerability to age-related health risks heightened their health anxiety and motivated greater attention to health management. Digital healthcare technologies addressing these concerns through preventive measures and early detection increased satisfaction and usage intentions. Participant 20 shared, *"I worry about my body's ability to fight illnesses … This smartwatch offers me a lifeline to better manage health risks."* This reflects how perceived vulnerability drove active engagement with technology, empowering users to take control of their health. The satisfaction from proactive health management reinforced their intention to continue using these tools.

In summary, the Health Concerns, encompassing themes like Perceived Health Concerns, Fear of Declining Functionality, Fear of Health Deterioration, Fear of Dependency, and Vulnerability to Health Risks, emphasised the need to address health-related worries among older adults. Alleviating health anxiety through these technologies enhanced satisfaction and strengthened continuance intention, underscoring the importance of the Health Anxiety theme in shaping user engagement.

Managing Health Concerns

Managing Health Concerns was a significant second-order theme within the broader Health Anxiety theme. This sub-theme was supported by two first-order themes that emerged from the participant interviews: Medical Appointments and Test and Managing Medications. These first-order themes provided evidence of how managing health concerns contributed to overall Health Anxiety, which in turn influenced continuance intention among older users of digital healthcare technologies.

Medical Appointments and Tests

The theme Medical Appointments and Tests highlights how frequent medical visits and tests triggered health anxiety among participants. Digital healthcare technologies that provided access to medical records and test results helped alleviate this stress by simplifying healthcare management. Participant 12 noted, *"I have more and more medical stuff to deal with, like appointments and tests; managing them used to be overwhelming … My smartwatch has some helpful apps that make it all easier."* This streamlined process reduced anxiety, enhanced satisfaction, and encouraged continued use of the technology for managing healthcare needs, demonstrating its value in making the healthcare journey smoother and less daunting.

Managing Medications

Managing multiple medications was a significant challenge for some participants, contributing to health anxiety. Digital healthcare technologies offering reminders, interaction alerts, and medication tracking provided peace of mind and increased satisfaction. Participant 10 shared, *"It [smartwatch] sends me notifications to take my meds on time, and it even tells me all I need to know about each one."* These tools simplified medication management, reduced anxiety, and strengthened the intention to continue using the technology. Effective support for managing health concerns not only improved satisfaction but also reduced anxiety, promoting better health outcomes and well-being for older users.

Health Anxiety, encompassing Health Concerns and Managing Health Concerns, moderated the relationship between satisfaction and continuance intention for digital healthcare technologies among older users. The findings showed that heightened health anxiety amplified the impact of satisfaction on continuance intention. Participant experiences highlighted that greater anxiety increased sensitivity to the benefits of these technologies. Conversely, those with low health anxiety exhibited a weaker link between satisfaction and continued use, suggesting a less pronounced moderating effect in this group.

4.3.8 Technology Anxiety

Technology Anxiety, identified early as a significant construct in the theoretical framework (Meng et al., 2020; Gunasinghe & Nanayakkara, 2021; Inan et al., 2022), was elaborated upon during the qualitative phase through participant narratives. Using an abductive approach, the study refined and expanded understanding of how this anxiety affects attitudes and interactions with digital healthcare technologies. Two second-order themes emerged within Technology Anxiety (see Figure 13). The first, Technological Concerns, includes four first-order themes: Unfamiliarity and Inexperience, Perceived Complexity, Fear of Making Mistakes, and Privacy and Security Worries. The second, Technology Difficulties, comprises Rapid Technological Change and Technical Issues. These themes collectively enrich the understanding of Technology Anxiety and its impact on the use of digital healthcare technologies.

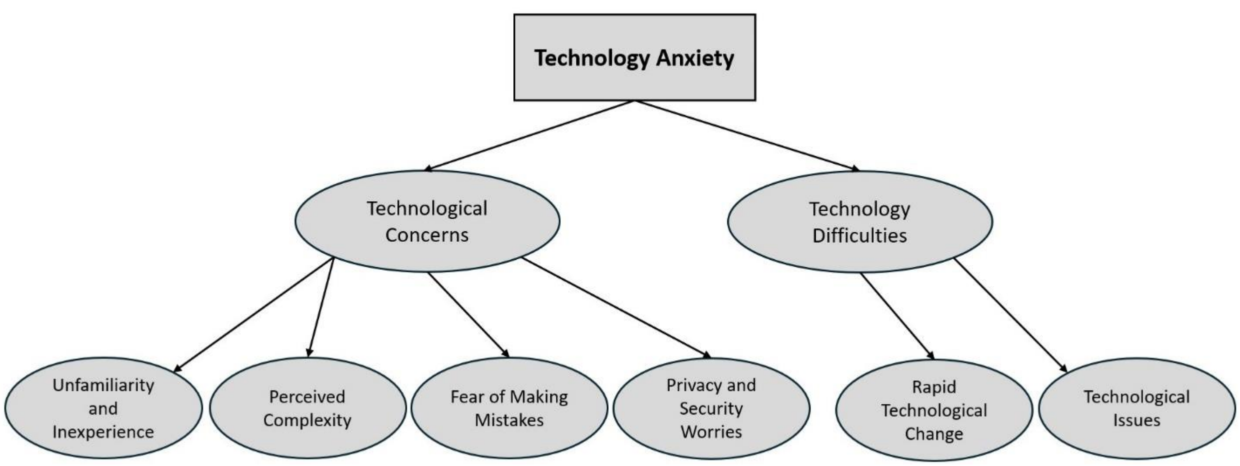

Figure 13: Technology Anxiety Theme Hierarchy
(Developed by the author)

Technological concerns

Technological Concerns was a significant second-order theme within the broader Technology Anxiety theme. This sub-theme was supported by four first-order themes that emerged from the participant interviews: Unfamiliarity and Inexperience, Perceived Complexity, Fear of Making Mistakes, and Privacy and Security Worries. These first-order themes provided evidence of how technological concerns contributed to the overall Technology Anxiety theme, which in turn negatively influenced satisfaction and continuance intention among older users.

Unfamiliarity and Inexperience

Participants with limited exposure to technology often felt anxious and out of their comfort zone, weakening the satisfaction-continuance intention relationship. Unfamiliarity caused frustration, lack of trust, and fear of mistakes, reducing willingness to continue using digital healthcare technologies. Participant 9 shared, *"If it was not a gift, I would not have bought it on my own. I did not grow up with all this technology stuff … Its apps just make my head spin. It is frustrating, and honestly, I am not sure I can trust it with something as important as my health."* This highlights how inexperience and mistrust hindered effective use, reducing satisfaction and continuance intention despite potential benefits.

Perceived Complexity

Participants who viewed digital healthcare technologies as overly complex experienced anxiety, frustration, and reduced satisfaction, discouraging continued use. Participant 14 shared, *"This smartwatch is so complicated, with all these buttons and settings. It is hard to know where to start … I am not sure I use it properly or not."* This highlights how intricate interfaces and self-doubt hindered confidence and satisfaction, weakening the intention to use these tools. In contrast, participants with familiarity and positive past experiences expressed ease and empowerment with technology. Participant 16 noted, *"The instructions are straightforward, and the design is simple. It is easy to use and enjoyable."* Similarly, Participant 6 said, *"I have used smartphones for years, so using this device is not a big deal."* Their low anxiety levels, driven by user-friendly design and familiarity, increased satisfaction and strengthened their commitment to continued use.

Fear of Making Mistakes

Many older users expressed anxiety about making errors with digital healthcare technologies, fearing unintended consequences or rendering the device unusable. This fear reduced satisfaction and weakened the intention to continue using the technology. Participant 3 shared, *“I am afraid I will press the wrong thing and mess it all up.”* This highlights how a lack of confidence and fear of errors created anxiety, diminishing satisfaction and engagement with these tools.

Privacy and Security Worries

Concerns about data privacy and security created significant anxiety among older users, reducing trust, satisfaction, and intention to continue using digital healthcare technologies. Participant 19 shared, *“I worry about my personal data getting into the wrong hands. It makes me wonder if I can really trust these systems to keep my information safe.”* This fear of data misuse or cybercrimes undermined confidence in the technology, highlighting the importance of addressing privacy and security concerns to maintain user satisfaction and trust.

The Unfamiliarity and Inexperience, Perceived Complexity, Fear of Making Mistakes, and Privacy and Security Worries underscored the importance of addressing technological concerns to reduce technology anxiety and, consequently, improve satisfaction and continuance intention among older users. Together, these findings highlighted the significance of Technological Concerns in influencing older users’ overall technology anxiety towards digital healthcare technologies and their subsequent impact on satisfaction and continuance intention.

Technology Difficulties

Technology Difficulties was another significant second-order theme within the broader Technology Anxiety theme. This sub-theme was supported by two first-order themes that emerged from the participant interviews: Rapid Technological Change and Technical Issues. These first-order themes provided evidence of how technology difficulties contributed to the overall Technology Anxiety theme, which in turn negatively influenced satisfaction and continuance intention among older users.

Rapid Technological Change

The fast pace of technological advancements caused anxiety among older users, who felt overwhelmed by the need to constantly adapt and learn new skills. This anxiety weakened the relationship between satisfaction and continuance intention. Participant 11 shared, *"Just when I get used to one thing, they introduce a new one with even more features and complexities."* This highlights how the struggle to adapt to evolving technology reduced satisfaction and discouraged continued use, as users feared their efforts to learn may quickly become outdated.

Technical Issues

Technical problems, such as setup challenges, syncing errors, and crashes, disrupted participants' experiences, causing frustration and anxiety. Participant 9 shared, *"I found myself so frustrated with the constant problems like freezes and crashes. It does not work as it should."* These issues weakened satisfaction and reduced the intention to continue using digital healthcare technologies. Addressing technical difficulties is essential to lowering technology anxiety and improving satisfaction and continuance intention among older users.

Technology Anxiety, encompassing the Technological Concerns and Technology Difficulties themes, moderated the relationship between satisfaction and continuance intention among older users. High levels of anxiety, driven by technology-related worries and fears, weakened this relationship by diminishing the impact of satisfaction on continuance intention. As interviews revealed, participants with heightened anxiety were less influenced by their satisfaction in deciding to continue using digital healthcare technologies. Conversely, those with low anxiety showed a reduced moderating effect, indicating that lower technology-related concerns lessened the impact on this relationship.

4.3.9 Self-efficacy

During the abductive analysis, Self-efficacy emerged as a significant yet unexpected construct. Defined by Bandura (1997) as an individual's belief in their ability to manage tasks or challenges, the interviews revealed how self-efficacy influenced older users' confidence and intentions to continue using digital healthcare technologies. This exploration highlighted the critical role of self-belief in shaping technological engagement. The second-order theme, Self-confidence in Technology, includes four first-order themes: Technological Inexperience, Inadequacy Feeling, Limited Technological Confidence, and Learning Beliefs (see Figure 14). These themes, rooted in participants' experiences, provide a nuanced understanding of how self-efficacy affects older users' engagement with digital healthcare technologies. Although the foundational definition of Self-efficacy was adopted from Bandura (1997), the qualitative findings enriched its contextual relevance, highlighting specific barriers and facilitators unique to older adults using these technologies. This construct establishes self-efficacy as a crucial factor influencing older users' ability to navigate and sustain engagement with digital healthcare technologies, offering insights into their lived experiences and attitudes.

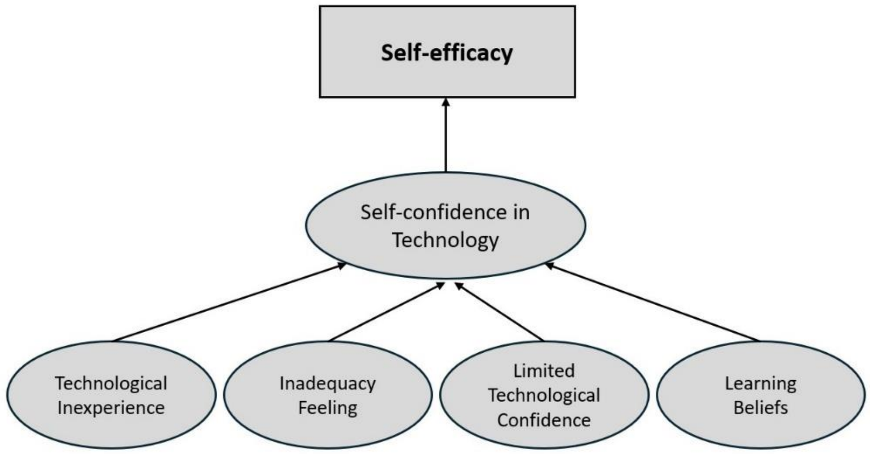

Figure 14: Self-efficacy Theme Hierarchy
(Developed by the author)

Self-confidence in Technology

Self-confidence in Technology was a significant second-order theme that contributed to the broader Self-efficacy theme. This sub-theme was supported by four first-order themes that emerged from the participant interviews: Technological Inexperience, Inadequacy Feeling, Limited Technological Confidence, and Learning Beliefs. These first-order themes provided evidence of how self-confidence in technology influenced the overall Self-efficacy theme, which in turn affected satisfaction and continuance intention among older users of digital healthcare technologies.

Technological Inexperience

Limited experience with digital technologies led to uncertainty and low self-efficacy among older users, reducing satisfaction and continuance intention. Participant 18 shared, *"I cannot figure out how to make it work … I am afraid I might mess something up, so I often end up not using some features at all."* This highlights how unfamiliarity with devices and interfaces caused frustration and reluctance to engage with digital healthcare technologies fully. In contrast, participants with prior experience felt more confident. Participant 5 noted, *"Having used similar health apps before, I find it easier to navigate and use the features effectively."* Familiarity enhanced self-efficacy, satisfaction, and the likelihood of continued use, showing that prior experience strengthens the satisfaction-continuance relationship for digital healthcare technologies.

Inadequacy Feeling

Participants who perceived digital healthcare technologies as overly complex experienced reduced self-efficacy, frustration, and limited use, diminishing satisfaction and continuance intention. Participant 7 shared, *"I struggle to understand how to use these new gadgets … I ended up not using it as much as probably should."* This highlights how low confidence and a sense of inadequacy hindered satisfaction and engagement. In contrast, confident users saw challenges as opportunities. Participant 12 noted, *"I enjoy exploring new features … When I face an issue, I prefer to work through it myself."* This demonstrates how self-assurance fostered empowerment, leading to higher satisfaction and a stronger commitment to continued use.

Limited Technological Confidence

Participants' doubts about their technological skills created a barrier that weakened the link between satisfaction and the intention to continue using digital healthcare devices. This lack of confidence led to avoidance, dependency, and anxiety about making mistakes. Participant 4 stated, *"I am not tech-savvy at all, and I get help from my daughter whenever I face a difficulty with this device",* highlighting reduced self-efficacy and reliance on others. Similarly, Participant 3 shared, *"I am afraid I will press the wrong button and break the fitness tracker."* This fear of errors discouraged engagement, reduced satisfaction, and diminished the intention to continue using the technology. Low confidence in using these devices undermined users' ability to fully benefit from them.

Learning Beliefs

Participants' doubts about acquiring new skills hindered the relationship between satisfaction and the motivation to continue using digital healthcare technologies. Participant 9 shared, *“Learning to use all the features of this device seems like a lost cause”.* This highlights how low self-efficacy led to feelings of being overwhelmed, reduced satisfaction, and decreased usage intentions.

The findings emphasise the role of self-efficacy in strengthening the connection between satisfaction and continued use. High self-efficacy enhanced this relationship, while low confidence weakened it. Themes such as Technological Inexperience, Inadequacy Feeling, Limited Technological Confidence, and Learning Beliefs underscore the need to foster self-confidence in technology to improve satisfaction and continuance intention among older users.

4.3.10 Continuance Intention to Use

The analysis of Continuance Intention to Use, a key construct of the Expectation Confirmation Model (ECM) (Bhattacherjee, 2001), identified a second-order theme, Continuance of Using Digital Healthcare Technologies. This theme is supported by two first-order themes: Likelihood of Continuing to Use the Same Device and Likelihood to Upgrade. Through abductive analysis, factors such as satisfaction with current technology, ageing satisfaction, health anxiety, technology anxiety, and self-efficacy were identified as influencing older users’ decisions to continue using or upgrade their digital healthcare technologies. These insights provide a deeper understanding of the factors driving sustained usage among older adults (see Figure 15).

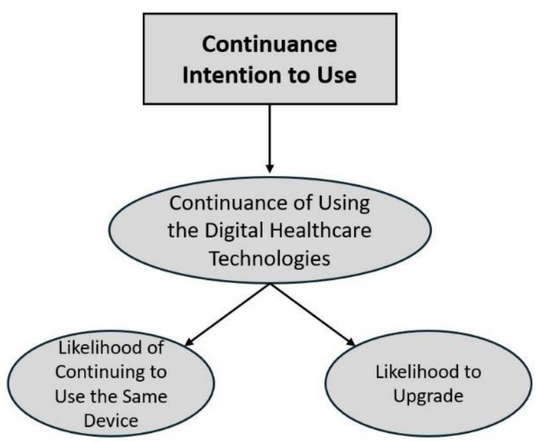

Figure 15: Continuance Intention to Use Theme Hierarchy
(Developed by the author)

Continuance of Using the Digital Healthcare Technologies

The second-order theme Continuance of Using Digital Healthcare Technologies within Continuance Intention to Use focuses on factors influencing older users' decisions to continue using their current devices or upgrade to new ones. Supported by two first-order themes, Likelihood of Continuing to Use the Same Device and Likelihood to Upgrade, this sub-theme highlights how factors like satisfaction, ageing satisfaction, health anxiety, technology anxiety, and self-efficacy shape continuance intention among older individuals. These themes provide insights into the drivers of sustained engagement with digital healthcare technologies.

Likelihood of Continuing to Use the Same Device

User satisfaction strongly influenced older individuals' likelihood of continuing to use digital healthcare technologies. High satisfaction levels indicated that users found the technology valuable and effective for managing their health, enhancing their intention to continue using it. Participant 16 reflected: *"It has all the health features I need, and I am used to how it works … It helps me stay healthy."* In addition to satisfaction, ageing satisfaction emerged as another critical factor. Older users who embraced their ageing process were more likely to sustain usage. Participant 15 shared: *"Technology has really improved my quality of life, and it helped me maintain my health and social connections … I am committed to continuing to use it daily."* Conversely, dissatisfaction with technology or one's ageing process reduced continuance intention. Participant 7 expressed: *"I started using an online app to improve my mobility, but I have not seen any real progress."*

While satisfaction and ageing satisfaction encouraged continued use, health anxiety played a dual role. For some, technologies that alleviated worries heightened continuance intentions. Participant 6 stated: *"Using it to monitor my heart rate and activity gives me comfort … I will keep using it."* However, unfulfilled needs could lead to discontinuance, as Participant 4 noted: *"I realised I was getting obsessed with perfecting sleep data … I felt better after removing that tracker from my routine."*

Not all experiences with digital healthcare technologies were positive. Technology-related anxieties and low self-efficacy also shaped users' engagement. Participant 11 highlighted concerns about privacy: "*Just having a watch that operates smoothly is not enough … I worry about my personal data being compromised."* Similarly, low self-efficacy hindered usage, as Participant 7 noted: *"I often feel overwhelmed and give up on understanding the smartwatch."* These findings underscore how satisfaction, ageing contentment, health anxiety, technology anxiety, and self-efficacy interact to shape older users' continuance intentions for digital healthcare technologies.

Likelihood to Upgrade

Some participants expressed interest in upgrading their digital healthcare technologies to access improved features, even when satisfied with their current device. Participant 10 noted: *"It is really important to stay up to date with technology these days … I like to try the new ones to see what the new features in them are, as I have had mine for five years."* While some participants were eager to explore new features, their likelihood to upgrade was also influenced by how they felt about their ageing experience. High ageing satisfaction encouraged older users to embrace upgrades as a means to improve well-being. Conversely, low ageing satisfaction reduced upgrade intentions. Participant 3 stated: *"I am doubtful that a more advanced smartwatch would make any big difference. I have told my kids, until you can find something that actually enhances my well-being, do not buy me anything."*

In addition to ageing satisfaction, health concerns also played a pivotal role in shaping upgrade intentions. Health anxiety motivated participants to upgrade for features that alleviated their worries. Participant 14 shared: *"I heard about a new model that measures blood oxygen levels and provides stress management tips. Upgrading to that device could give me even more peace of mind."* However, not all factors were motivating; for some, technological apprehension and low confidence posed significant barriers to upgrading. Heightened technology anxiety and low self-efficacy discouraged upgrading. Participant 8 explained: *"I am not very confident in learning how to use a new device. I would need a lot of guidance and support to feel ready to make that change."* Some participants expressed interest in upgrading their digital healthcare technologies to access improved features, even when satisfied with their current device.

The analysis of Continuance Intention to Use digital healthcare technologies among older users highlighted a complex interplay of factors shaping their decisions to maintain or upgrade their devices. Key influences included satisfaction, ageing satisfaction, health anxiety, technology anxiety, and self-efficacy, each uniquely affecting the likelihood of continued usage or upgrading. Understanding the nuanced roles of these factors provides valuable insights for developing targeted strategies to sustain engagement and encourage the adoption of new technologies that enhance older users' health and well-being.

4.4 Proposed Conceptual Framework (Post-Qualitative Findings)

Through a comprehensive analysis of the qualitative data using an abductive approach (Timmermans and Tavory, 2022), the research model was developed by integrating the established constructs from the Expectation Confirmation Model (ECM) (Bhattacherjee, 2001), additional constructs derived from the literature review, and the newly identified constructs that emerged from the interviews. The expectation confirmation model, which is the theoretical foundation for this study, suggests that users' decision to continuance using a technology depends on how satisfied they are with it. Their satisfaction comes from how well the technology meets their expectations and how useful they find it. In addition to the expectation confirmation model constructs, the research model incorporates health motivation, health consciousness, health anxiety, and technology anxiety, which were identified from the literature review as potential factors influencing older users' continuance intention to use digital healthcare technologies. Furthermore, the qualitative findings revealed the importance of ageing satisfaction and self-efficacy in the context of older users' continuance intention to use digital healthcare technologies. These two constructs emerged from the interviews. The abductive approach allowed for a more iterative and flexible process of theory development and refinement (Dubois and Gadde, 2002), enabling the researcher to integrate both the deductively derived and inductively emergent constructs into the existing theoretical framework, thereby enhancing the understanding of the factors influencing older users' intentions to continue using digital healthcare technologies.

The proposed conceptual framework (Post-Qualitative Findings), presented in Figure 16, is grounded in the review of the literature and the findings of the interviews with older users. The interviews revealed several key relationships among the constructs. It was found that health motivation and health consciousness have a positive direct effect on perceived usefulness. This suggests that older users who are more motivated to manage their health and are more aware of their health status are more likely to view digital healthcare technologies as useful. Additionally, confirmation of expectations was found to affect both perceived usefulness and satisfaction, indicating that when older users' expectations regarding digital healthcare technologies are met, they are more likely to find them useful and be satisfied with them. Furthermore, the interviews highlighted that perceived usefulness has a direct effect on satisfaction, implying that older users who find digital healthcare technologies useful are more likely to be satisfied with them. Satisfaction, in turn, was found to have an effect on both ageing satisfaction and continuance intention to use, suggesting that older users who are satisfied with the digital healthcare technologies are more likely to be content with their ageing experience and have a higher intention to continue using their digital healthcare technologies. The interviews also revealed that ageing satisfaction has a direct effect on continuance intention to use, indicating that older users who are more satisfied with their ageing experience are more likely to continue using digital healthcare technologies. Lastly, it was discovered that health anxiety, technology anxiety, and self-efficacy act as moderators in the relationship between satisfaction and continuance intention to use. This suggests that these factors can influence how strongly older users' satisfaction with the technology influences their decision to keep using it. These qualitative findings, derived through an abductive approach, have been instrumental in refining the proposed conceptual framework (Figure 16) and providing a more nuanced understanding of the factors influencing older users' continuance intention to use digital healthcare technologies. Based on the proposed conceptual framework, a set of hypotheses was developed, and they will be discussed in detail in the following section.

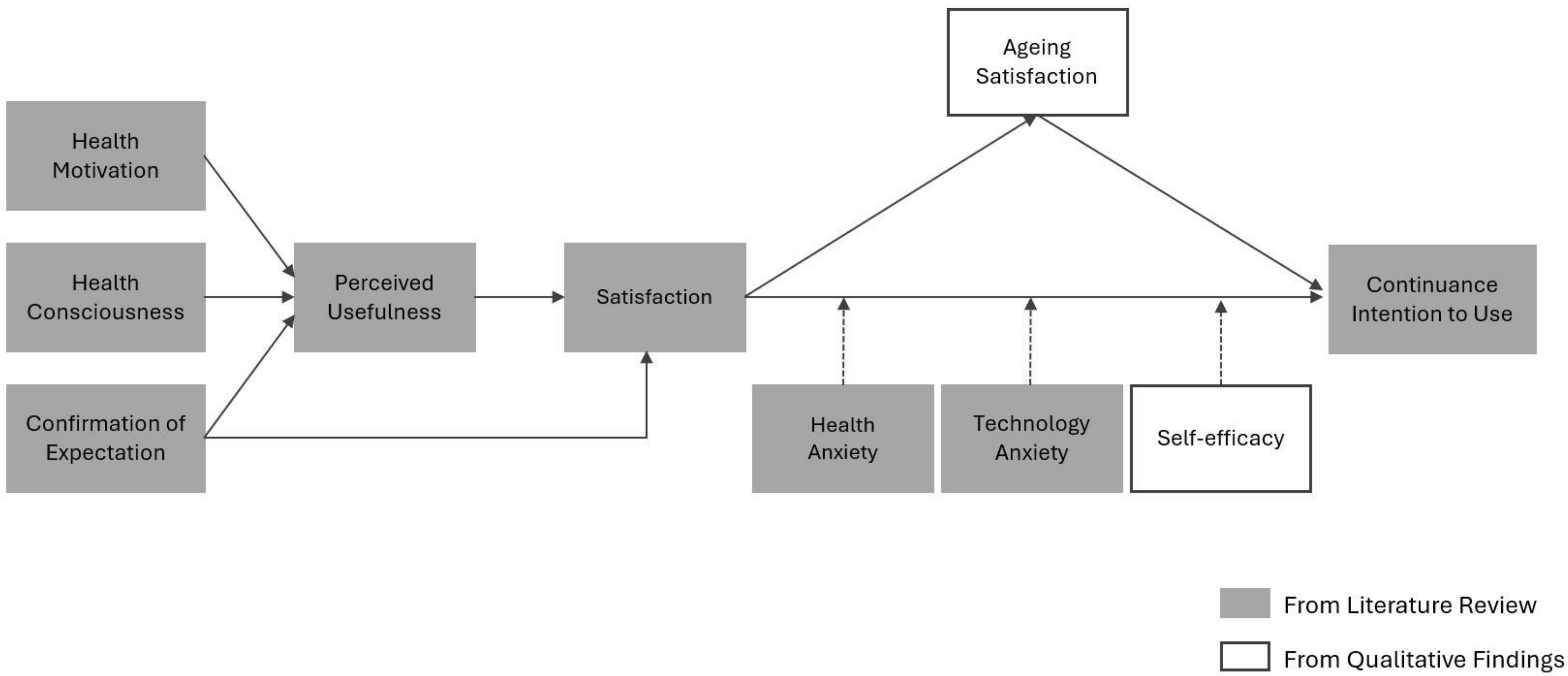

Figure 16: Proposed Conceptual Framework (Post-Qualitative Findings)
(Developed by the author)

4.5 Hypotheses Development

4.5.1 Health Motivation

The adoption of digital healthcare technologies has been extensively studied from the perspective of healthcare professionals (e.g., Borges do Nascimento et al., 2023; Ndayishimiye et al., 2023; Turnbull et al., 2024). However, it is essential to understand how consumers' health motivation influences their intention to use and continue using these technologies, especially among middle-aged and older adults (Bianchi et al., 2023; Ha et al., 2023; Hayat et al., 2024). Health motivation is an individual's internal drive or desire to actively engage in and sustain behaviours and practices that improve their overall well-being and physical health (Moorman and Matulich, 1993). This includes goal-directed arousal that motivates individuals to engage in preventive behaviours and make conscious choices to prioritise their health (Xu, 2009). The concept of health motivation is grounded in established health behaviour theories, particularly the Health Belief Model (HBM) developed by Rosenstock (1974) and the Self-Determination Theory (SDT) developed by Deci and Ryan (2000). Over time, researchers have adapted and refined these foundational theories to address specific contexts, such as technology adoption in healthcare. For example, Ahadzadeh et al. (2015) integrated the Health Belief Model (HBM) with the Technology Acceptance Model (TAM) to explore health-related internet use. Similarly, Dou et al. (2017) and Guo et al. (2015) integrated elements of HBM when examining mHealth and smartphone health technology acceptance, respectively. These studies illustrate how the original theories have evolved to offer a more nuanced understanding of health motivation in the context of digital health technology adoption.

As people age, they encounter various health issues, making the adoption of digital healthcare technology beneficial for managing their health effectively (Asadi et al., 2019; Hayat et al., 2024). Bianchi et al. (2023) suggest that health motivation is a key predictor of positive attitudes towards adopting wearable technologies, a form of digital healthcare technology. Many studies have examined the role of health motivation and its impact on behaviour change. Ryan and Deci's (2000) research on self-determination theory underscores the significance of intrinsic motivation, like personal values and enjoyment, in maintaining long-term health behaviours. They contend that individuals driven by intrinsic motivation are more likely to maintain healthy behaviours over time. Additionally, Piko and Bak (2006) study the influence of health motivation on adolescent health behaviours, emphasising its impact on developing healthy habits during a pivotal developmental stage. Older adults generally display strong health motivation, driven by the need to address age-related health issues and maintain their quality of life (Loeb et al., 2001). As they age, their recognition of health's importance increases, often leading to increased motivation to adopt health-promoting behaviours (Loeb et al., 2001; von Wagner et al., 2009). This heightened health motivation is also associated with specific personality traits (Loeb, 2004). For example, studies show that older adults with high conscientiousness are more health-motivated, as this trait is linked to a greater tendency to engage in planned, health-positive actions (Friedman and Kern, 2014). Moreover, traits like openness to experience can enhance the willingness to embrace new health technologies, including digital healthcare technologies (Roberts et al., 2009).

Recent research highlights the significance of health motivation in adopting digital healthcare technologies across different age groups and contexts. Ha et al. (2023) discovered that health motivation strongly predicts the habitual use of wearable health devices among middle-aged users. Similarly, Hayat et al. (2023) identified health motivation as a key factor in the widespread adoption of wearable fitness devices. Hayat et al. (2024) also showed that health motivation impacts the intention of middle-aged and older adults to use electronic health applications. Hasan et al. (2022) found that health motivation significantly predicts young adults' intention to adopt mHealth technologies. Zhang et al. (2023) emphasised the importance of understanding health motivations for adopting mobile health apps in China. Bianchi et al. (2023) underscored the role of health motivation in shaping attitudes and intentions towards adopting wearable technology for healthcare in South America. De et al. (2024) identified health motivation as crucial for engaging in preventive health behaviours, including using digital healthcare technologies. Yang et al. (2024) used the Unified Theory of Acceptance and Use of Technology (UTAUT) to forecast acceptance of mHealth and found that health motivation plays a crucial role in shaping the intention to use these services. It is predicted that older users who are highly motivated to maintain their health perceive digital healthcare technologies as valuable tools for effective health management because these technologies offer several benefits that align with their health-related goals and motivations. For example, digital healthcare technologies offer easy access to personalised health information, enabling older users to gain a clearer understanding of their health and make informed decisions regarding their care (Von Wagner et al., 2009; Zhang et al., 2023). By empowering them to take manage their health effectively, digital healthcare technologies can enhance older users' sense of control (Hayat et al., 2024). Moreover, digital healthcare technologies can boost the quality of life of older users by helping them in the early detection and prevention of health problems, as well as providing remote monitoring and support for chronic conditions (Bianchi et al., 2023; Dehghani, 2018). These technologies can also help address older users' specific health concerns, such as medication management, fall prevention, and social isolation (Ha et al., 2023). Highly motivated older users actively seek and process health information to make informed decisions about their care (Moorman and Matulich, 1993). Digital healthcare technologies can facilitate this process by providing personalised recommendations, reminders, and feedback based on their health data and preferences (Yang et al., 2024). Therefore, if older users with high health motivation engage with digital healthcare technologies and experience their benefits firsthand, their perceived usefulness of these technologies may increase. Thus, the following hypothesis is proposed:

H1: Older users' health motivation is positively related to the perceived usefulness of digital healthcare technologies.

4.5.2 Health Consciousness

Health consciousness describes how significantly health issues are part of a person's daily activities and life (Jayanti and Burns, 1998). Those who are health-conscious usually focus on wellness and have positive views on preventive measures like exercising and eating healthy (Kraft and Goodell, 1993; Tan et al., 2022). They are generally more supportive of healthcare activities (Lee and Lee, 2018; Paluch and Tuzovic, 2019) and are more likely to adopt digital healthcare technologies (Cho et al., 2014; Meng et al., 2019). For older adults, health consciousness is essential in the use of digital healthcare technologies, as these technologies aid in better health monitoring and management (Zhang et al., 2022). Health consciousness, though not part of the Health Belief Model (HBM) (Rosenstock, 1974), has been used alongside HBM constructs in health behaviour research. It emerged from efforts to understand how individuals' health-related attitudes and beliefs affect their behaviours. Researchers like Gould (1988) and Jayanti and Burns (1998) developed the concept to capture individuals' readiness to undertake health actions. While distinct from HBM constructs, health consciousness complements them by focusing on how health concerns are integrated into daily activities. Studies have combined health consciousness with HBM and other health behaviour theories to better understand health-related behaviours, particularly in technology adoption (e.g., Ahadzadeh et al., 2015; Cho et al., 2014). Self-Determination Theory (SDT) (Deci and Ryan, 2000) also provides a useful framework for understanding health consciousness. SDT focuses on how autonomous motivation, such as personal values and intrinsic interest in maintaining one's health, drives sustained health behaviour (Deci and Ryan, 2000). Health-conscious individuals, motivated by an internal desire to stay healthy, align closely with the SDT concept of intrinsic motivation (Teixeira et al., 2012). These individuals engage in health behaviours, such as using digital healthcare technologies, not because of external pressures but because it reflects their values and commitment to health (Fortier et al., 2012). This intrinsic motivation, central to SDT, supports long-term engagement with digital health technologies, contributing to better health outcomes and continued digital healthcare technology usage (Nahum-Shani et al., 2021).

Health consciousness significantly impacts older adults' use of digital healthcare technologies, as these tools enable better health monitoring and management (Zhang et al., 2022). Research indicates that health consciousness is a crucial value for older adults (Barbaccia et al., 2022) and influences decisions to adopt or reject new technology (Mustafa et al., 2022). However, this factor is often overlooked in technology adoption models (Kim et al., 2018; Venkatesh et al., 2012). Understanding the role of health consciousness in adopting and continuing to use digital healthcare technologies is crucial for identifying what drives technology acceptance and sustained usage. This knowledge can aid in developing strategies to encourage long-term use of these technologies (Yan et al., 2021). Studies show that health consciousness greatly affects both behavioural intention (Shah et al., 2021) and continued use intention (Yadav et al., 2024; Yan et al., 2021). Health-conscious individuals are more likely to focus on maintaining a healthy diet and lifestyle and to use digital healthcare technologies (Meng et al., 2019). They frequently engage in preventive health behaviours, such as monitoring their health indicators and using mobile health devices (Chen and Lin, 2018; Meng et al., 2019). Health consciousness is a key predictor of preventive health behaviour and the intention to use wearable medical devices (Sergueeva et al., 2019), as well as the continuance intention to use mobile health applications (Cho, 2016; Guo et al., 2020).

Several studies have explored how health consciousness affects the adoption and continued use of various digital healthcare technologies. For example, it influences the adoption of mobile health tools (Jacob et al., 2022), the continuance intention to use mHealth (Birkmeyer et al., 2021), attitudes towards mHealth apps (Vervier et al., 2019), continued use of fitness wearable technology (Sun and Gu, 2024), and the adoption of personal informatics (Shin and Biocca, 2017). Health consciousness also impacts the continued usage of mobile health applications (Guo et al., 2020; Wu et al., 2022; Yadav et al., 2024; Yan et al., 2021) and wearable health devices (Srivastava et al., 2022). Additionally, it moderates the relationship between various factors and the adoption and continued use of digital healthcare technologies (Ahadzadeh et al., 2015; Handayani et al., 2020; Shah et al., 2021). Health-conscious individuals recognise digital healthcare technologies as valuable tools for tracking health metrics, accessing personalised health information, and engaging in preventive health behaviours (Chen and Lin, 2018; Meng et al., 2019). As older adults increasingly prioritise their health and well-being (Abud et al., 2022; Anaby et al., 2011; Barbaccia et al., 2022), and since digital healthcare technologies help them monitor and manage their health more effectively (Liu et al., 2016; Meng et al., 2022), it is likely that health-conscious older users view digital healthcare technologies as beneficial for maintaining and enhancing their health. By using digital healthcare technologies, older users can access crucial information, practice personalised self-care, and feel empowered in their health management, thereby enhancing their health consciousness (Kim et al., 2023). These benefits can enhance the perceived usefulness of digital healthcare technologies for health-conscious older users, empowering them to actively participate in managing and enhancing their well-being (Talukder et al., 2020). Additionally, as health consciousness involves a proactive approach to managing health (Jayanti and Burns, 1998), older users with higher health consciousness may perceive digital healthcare technologies as valuable tools for taking control of their well-being.

Also, the advantages of digital healthcare technologies in supporting healthy ageing and maintaining functional abilities (Abud et al., 2022) are likely more evident to health-conscious older users, enhancing their perceived usefulness of these technologies. Thus, it is suggested that highly health-conscious older users are more likely to view digital healthcare technologies as essential tools for monitoring and managing their health. Based on these considerations, the following hypothesis is proposed:

H2: Older users' health consciousness is positively related to the perceived usefulness of digital healthcare technologies.

4.5.3 Confirmation of Expectation

The confirmation of expectations plays a crucial role in shaping perceived usefulness and satisfaction with digital healthcare technologies. According to the expectation confirmation model, confirmation is positively linked to user satisfaction and perceived usefulness (Bhattacherjee, 2001). This connection has been confirmed in various fields, including eHealth/mHealth (Kumar and Natarajan, 2020; Nie et al., 2023; Wang and Chao, 2023; Zhang et al., 2018), smartwatches and fitness trackers (El-Gayar and Elnoshokaty, 2023; Gupta et al., 2021; Li et al., 2019; Ogbanufe and Gerhart, 2017; Park, 2020), e-learning (Chow and Shi, 2014; Prasetya et al., 2021), mobile shopping (Rahi et al., 2022; Shang and Wu, 2017; Susanto et al., 2016), mobile banking (Jusuf et al., 2017; Poromatikul et al., 2020; Rabaa'i and AlMaati, 2021), mobile apps (Hsu and Lin, 2015; Tam et al., 2020), and e-commerce (Gunawan et al., 2022; Zhang et al., 2015). Furthermore, the positive impact of confirmation on perceived usefulness and satisfaction extends to fintech (Nurdin et al., 2023; Shiau et al., 2020), mobile instant messaging (Oghuma et al., 2016), contactless payment technologies (Puriwat and Tripopsakul, 2021), and mobile social networking sites (Cao et al., 2022).

In the context of digital healthcare technologies, potential users form initial expectations about the technology's benefits. As they engage with the technology, they develop perceptions of its usefulness. When these initial expectations are met through actual use, it positively impacts the perceived usefulness of these technologies (Ju and Zhang, 2020; Xu et al., 2022; Zhao and Wang, 2024). Essentially, when digital healthcare technologies deliver the expected benefits, satisfy user needs, and achieve their intended purposes, they are seen as valuable tools for healthcare (Gupta et al., 2021; Shen et al., 2022; Wu et al., 2022; Yousaf et al., 2021). Additionally, confirmation of expectation is closely linked to user satisfaction with digital healthcare technologies (Pal et al., 2020; Park, 2020; Wang and Cao, 2023). Users are more likely to be satisfied when the performance of digital healthcare technologies matches or surpasses their pre-use expectations. Conversely, dissatisfaction arises when the actual experience falls short of these expectations (Nascimento et al., 2018; Shen et al., 2018). Satisfaction is derived from the alignment between what users expect and the technology's actual performance or outcomes (Bhattacherjee, 2001; Kumar and Natarajan, 2020; Leung and Chen, 2019). When digital healthcare technologies meet users' needs, provide desired outcomes, and offer a positive experience, users feel satisfied with the technology (El-Gayar and Elnoshokaty, 2023; Siepmann and Kowalczuk, 2021; Sun and Gu, 2024).

In the context of older users' continued use of digital healthcare technologies, expectation confirmation significantly impacts their satisfaction and perceived usefulness (Cao et al., 2022; Talukder et al., 2020; Tian and Wu, 2022). For instance, if an older user expects a fitness tracker to monitor their heart rate during exercise accurately and it meets this expectation, they will find the device useful and feel satisfied with its performance (Ahmad et al., 2020; Palas et al., 2022). This confirmation of expectations directly influences perceived usefulness and satisfaction, promoting greater adherence to health and fitness routines as users gain trust in the technology's accuracy and benefits (Talukder et al., 2020). When users' expectations are met, they engage with the technology on an ongoing basis (Cho, 2016; Kaium et al., 2020). Positive experiences that align with initial expectations reinforce their commitment to use the technology (Cao et al., 2022). This is especially important for older users, who may have concerns or hesitations and uncertainties when it comes to adopting and using new technologies (Guo et al., 2013; Shen et al., 2022). If their expectations are confirmed, they are more likely to find digital healthcare technologies useful and feel satisfied with them. This concept is based on the expectation confirmation model (Bhattacherjee, 2001) and is supported by research showing the importance of expectation confirmation in encouraging older users to continue using technology (e.g., Kim and Han, 2021; Zhang et al., 2024). By meeting older users' expectations, digital healthcare technologies prove their value and effectiveness in meeting this group's specific needs and goals (Gupta et al., 2021). Consistently delivering expected benefits makes older users more likely to see digital healthcare technologies as reliable and effective tools for managing their health and well-being. Furthermore, the confirmation of expectations is closely linked to user satisfaction among older users (Su and Tong, 2021). When their initial expectations about digital healthcare technologies are met or exceeded by their actual experiences, they are more likely to be pleased and satisfied with the technology. This satisfaction arises from various factors, such as the ease of use, reliability, and effectiveness of digital healthcare technologies in meeting their healthcare needs (Kumar and Natarajan, 2020; Wang and Cao, 2023). Therefore, the following hypotheses are posited:

H3: Confirmation of expectation is positively associated with the older users' perceived usefulness of digital healthcare technologies.

H4: Confirmation of expectation is positively associated with older users' satisfaction with digital healthcare technologies.

4.5.4 Perceived Usefulness

In the expectation confirmation model, perceived usefulness refers to users' expectations of the benefits they will gain from using an IS after they have used it (Davis, 1989). This concept is about how well the system works (Bhattacherjee and Premkumar, 2004; Venkatesh et al., 2011) and is considered a strong predictor of users' intention to continue using the technology (Bölen, 2020). Perceived usefulness emphasises the practical advantages users gain, showcasing the effectiveness and utility of information technology (Zhou, 2014). It includes post-adoption expectations (Hew et al., 2017; Li and Liu, 2014), which can be influenced by their experience of confirmation, particularly when there is initial uncertainty about what to expect from the technology (Lee and Kwon, 2011). Several studies have found that perceived usefulness is a strong predictor of satisfaction across various technologies, including digital healthcare technologies (Gupta et al., 2021; Leung and Chen, 2019; Nascimento et al., 2018; Park, 2020; Shen et al., 2018; Wu et al., 2022), fintech (Nurdin et al., 2023; Shiau et al., 2020), mobile instant messaging (CC and Prathap, 2020; Oghuma et al., 2016), mobile apps (Hsu and Lin, 2015; Park and Lee, 2023; Tam et al., 2020), contactless payment systems (Al-Sharafi et al., 2022; Puriwat and Tripopsakul, 2021), mobile social networks (Cao et al., 2022; Jumaan et al., 2020), and e-learning platforms (Cheng, 2021; Lee, 2010; Rabaa'i et al., 2021). These studies suggest that when users find a technology useful, their satisfaction with it increases.

Additionally, perceived usefulness has been consistently found to significantly influence the intention to continue using IS-related products or services (Alraimi et al., 2015; Gupta et al., 2021; Lee, 2010; Lin et al., 2017; Oghuma et al., 2015). This is especially true for digital healthcare technologies, where perceived usefulness significantly impacts users' intentions to keep using these technologies (Bianchi et al., 2023; Cho, 2016; El-Gayar and Elnoshokaty, 2023; Gupta et al., 2021; Ha et al., 2023; Hayat et al., 2024; Ju and Zhang, 2020; Kaium et al., 2020; Kumar and Natarajan, 2020; Leung and Chen, 2019; Pal et al., 2020; Park, 2020; Siepmann and Kowalczuk, 2021; Sun and Gu, 2024; Tian and Wu, 2022; Wang and Cao, 2023; Wang et al., 2021; Wu et al., 2022; Xu et al., 2022; Zhao and Wang, 2024). However, this research deliberately avoids examining the effect of perceived usefulness on the continuance intention to use digital healthcare technologies by older users, as this has been investigated by Yan et al. (2021). Instead, the focus is on how perceived usefulness affects satisfaction, contributing new insights and addressing a gap in the literature concerning older users' satisfaction with digital healthcare technologies.

As a ubiquitous computing tool, digital healthcare technologies are expected to positively influence older users' satisfaction with these technologies, consistent with the expectation confirmation model and previous research on digital healthcare technology usage among older users (Ahmad et al., 2020; Kim and Han, 2021; Zhang et al., 2024). Several factors contribute to this relationship, tailored to the needs and preferences of older users. First, when digital healthcare technologies effectively meet older users' specific health needs, such as monitoring vital signs and providing medical information (Guo et al., 2013; Shen et al., 2022; Xie and He, 2020), they may enhance user satisfaction. Second, digital healthcare technologies that offer easy access to healthcare services, including online consultations and appointment scheduling (Nie et al., 2023; Shen et al., 2022), may reduce barriers for older users, resulting in higher satisfaction levels. Third, the ease of use and user-friendliness of digital healthcare technologies significantly affect older users' perceptions of usefulness and satisfaction. Given that some older users may have limited experience with technology or face age-related cognitive and physical limitations (Guo et al., 2013; Nie et al., 2023; Xie and He, 2020), digital healthcare technologies designed with intuitive interfaces, clear instructions, and accessible features are likely to be perceived as useful. Fourth, digital healthcare technologies that simplify healthcare routines, save time, and facilitate convenient tasks like medication tracking and remote communication with healthcare professionals (Li et al., 2019; Yousaf et al., 2021) may contribute to increased satisfaction among older users. Additionally, digital healthcare technologies that empower older users to manage their health, make informed decisions, and provide tools for self-management and personalised recommendations (Shen et al., 2018; Talukder et al., 2020) may foster independence and satisfaction. Finally, digital healthcare technologies that facilitate better communication and engagement with healthcare providers (Tian and Wu, 2022; Wu et al., 2022) may foster higher satisfaction by strengthening the patient-provider relationship, which is particularly important for older users. Therefore, this study postulates that:

H5: Perceived usefulness is positively associated with older users' satisfaction with digital healthcare technologies.

4.5.5 Satisfaction

User satisfaction reflects an end-user's emotional response to a specific computer application, as highlighted by Doll et al. (1998). Successful use of a product or service boosts satisfaction (Baroudi et al., 1986; Downing, 1999). In marketing literature, satisfaction is crucial for customer loyalty, playing a vital role in developing and maintaining a long-term consumer base (Limayem et al., 2007). Satisfaction also impacts the use of IS (Bhattacherjee, 2001), the success of the system (DeLone and McLean, 1992; Wixom and Todd, 2005), attitudes toward technology (Bhattacherjee and Premkumar, 2004), and acceptance of technology (Wixom and Todd, 2005). It plays a significant role in shaping post-adoption behaviour in the context of IS (Bhattacherjee, 2001; Bhattacherjee and Barfar, 2011; Limayem et al., 2007; Lin and Bhattacherjee, 2008; Wixom and Todd, 2005). The expectation confirmation model suggests high satisfaction levels encourage constant use of IS products or services, while low satisfaction can lead to discontinuation (Lee and Kwon, 2011). The link between satisfaction and continuance intention has been widely explored across various domains, including information systems (Bhattacherjee, 2001; Bhattacherjee et al., 2008; Steelman and Soror, 2017), e-learning (Alshurideh et al., 2019; Cheng, 2021; Mtebe and Gallagher, 2022; Rabaa'i et al., 2021), mobile apps (Tam et al., 2020; Wang et al., 2021), health informatics (Shin et al., 2017), mobile banking and digital payments (Amin et al., 2023; Chaveesuk et al., 2022; Chen and Li, 2017; Nguyen and Dao, 2024; Puriwat and Tripopsakul, 2021; Rabaa'i and AlMaati, 2021; Susanto et al., 2016), and digital healthcare (Ju and Zhang, 2020; Nie et al., 2023; Ogbanufe and Gerhart, 2017; Siepmann and Kowalczuk, 2021; Tian and Wu, 2022; Wang and Cao, 2023; Xu et al., 2022; Zhao and Wang, 2024). These studies consistently show that user satisfaction enhances the likelihood of continued technology use.

In the context of digital healthcare technologies, user satisfaction is a crucial determinant of continuance usage, especially given the numerous alternatives available (Pal et al., 2020). Improving satisfaction levels fosters brand loyalty and sustained usage, as only satisfied users will continue with a specific product or service (Oghuma et al., 2016; Taherdoost, 2018; Tam et al., 2020). This is particularly significant for older users, for whom digital healthcare technologies are still relatively new, and their continued use is highly dependent on their satisfaction (Cao et al., 2022; Guo et al., 2013; Shen et al., 2022; Xie and He, 2020). Older individuals often have less experience with technology and may encounter challenges in adopting new tools (Guo et al., 2013). Thus, their satisfaction with digital healthcare technologies is crucial for determining whether they will continue using these technologies (Shen et al., 2022). When digital healthcare technologies align with the needs and expectations of older users, offering clear benefits and ease of use, their satisfaction increases. This heightened satisfaction then enhances their likelihood of continued usage (Nie et al., 2023; Tian and Wu, 2022; Wu et al., 2022; Xie and He, 2020).

Furthermore, older users' satisfaction with digital healthcare technologies can significantly impact their overall satisfaction with ageing. Effective use of digital healthcare technologies helps older individuals manage their health, maintain independence, and improve their quality of life (El-Gayar and Elnoshokaty, 2023; Li et al., 2019; Yousaf et al., 2021), positively influencing their perception of ageing. Firstly, digital healthcare technologies that meet older users' health needs promote well-being, which is essential for ageing satisfaction (Van den Berg et al., 2012). Effective health management remains a top concern for older adults (Bowling and Dieppe, 2005). Secondly, digital healthcare technologies that enhance autonomy and independence boost older users' control over their lives, vital for psychological well-being and ageing satisfaction (Wurm et al., 2013). Managing health independently fosters a positive self-concept and higher ageing satisfaction. Thirdly, digital healthcare technologies that improve daily living by facilitating healthcare access, providing timely health information, and simplifying health tasks enhance comfort and security (Wang et al., 2019), thereby improving life quality and ageing satisfaction. Moreover, trust in the reliability and effectiveness of digital healthcare technologies builds confidence in managing ageing challenges, further increasing satisfaction (Yusif et al., 2016). Additionally, the psychological benefits of support and empowerment from using digital healthcare technologies contribute to a positive attitude towards ageing (Czaja and Lee, 2007; Heart and Kalderon, 2013). This empowerment and support can lead to a sense of fulfilment and contentment, raising overall ageing satisfaction. The following is hence posited:

H6: Satisfaction is positively associated with the older users' ageing satisfaction.

H7: Satisfaction is positively associated with the older users' continuance intention to use digital healthcare technologies.

4.5.6 Ageing Satisfaction

As populations age, understanding factors that promote health and well-being is crucial for mitigating the rise of chronic conditions and healthcare costs (Kubzansky et al., 2018; VanderWeele et al., 2020). There is a growing trend among researchers and policymakers to shift focus from disease risk factors to modifiable health assets that improve people's overall health and well-being (Kim et al., 2021; Kim et al., 2022; VanderWeele, 2017). One health asset of increasing interest to older adults, researchers, and healthcare systems is ageing satisfaction (Nakamura et al., 2022). Ageing satisfaction represents attitudes towards the ageing process, which is a key internal characteristic in older adults (Shirahada et al., 2019). Often referred to in the literature as individual perspectives on ageing or views toward one's own ageing experience (Kim et al., 2014; Kleinspehn-Ammerlahn et al., 2008; Lawton, 1975; Levy, 2009; Sargent-Cox et al., 2009).

Studies link ageing satisfaction with better physical health results, such as reduced risks of physical limitations, cognitive decline, and mortality (Brown et al., 2021; Levy et al., 2002; Robertson et al., 2016; Sargent-Cox et al., 2012; Wurm and Benyamini, 2014). It also correlates with positive health behaviours like increased use of preventive services, medication adherence, and healthier diets (Cohn-Schwartz et al., 2021; Wurm et al., 2008), as well as better social outcomes, including greater social involvement, perceived support, and new friendships (Menkin et al., 2017; Schwartz et al., 2021). Ageing satisfaction significantly influences older adults' attitudes, behaviours, and health outcomes (Nakamura et al., 2022). Those with higher ageing satisfaction tend to engage in healthier behaviours and are more likely to adopt technologies that support their well-being (Kim et al., 2014; Yap et al., 2022). Given that digital healthcare technologies can improve healthcare access, facilitate chronic condition management, and promote healthy habits (Shirahada et al., 2019), older users with greater ageing satisfaction may be more open to using these technologies. Additionally, older adults with higher ageing satisfaction see digital healthcare technologies as essential for maintaining independence, autonomy, and quality of life (Kleinspehn-Ammerlahn et al., 2008). By offering convenient health management solutions, digital healthcare technologies help fulfil their desire for successful ageing and health control (Nakamura et al., 2022). Consequently, older users with higher ageing satisfaction may be more motivated to continue using digital healthcare technologies, as these technologies align with their positive self-perceptions and goals for success.

The relationship between ageing satisfaction and the continued use of digital healthcare technologies is shaped by factors like technology readiness and perceived usefulness (Shirahada et al., 2019). Older adults with higher ageing satisfaction are often more willing to learn and adopt new technologies, viewing them as tools to enhance their health and well-being (Yap et al., 2022). When digital healthcare technologies offer clear benefits and meet the specific needs of older users, those with higher ageing satisfaction are more likely to find these technologies useful and continue using them (Kim et al., 2014). Building on existing research, the present study explores how ageing satisfaction influences older users' intention to continue using digital healthcare technologies. Ageing satisfaction is crucial in determining this intention, as it encourages older individuals to engage in healthy behaviours, embrace supportive technologies, and see digital healthcare technologies as essential for maintaining independence and quality of life. It is hypothesised that older users with higher ageing satisfaction will have a stronger intention to continue using digital healthcare technologies, thereby enhancing their overall health and well-being. This hypothesis aligns with previous studies that emphasise the significant impact of ageing satisfaction on older users' attitudes and behaviours. Therefore, it is hypothesised that:

H8: Ageing satisfaction is positively associated with older users' continuance intention to use digital healthcare technologies.

4.5.7 Health Anxiety

Health anxiety is characterised by an excessive, irrational fear triggered by perceived health threats (Abramowitz and Braddock, 2008). Symptoms, sensations, and health information, such as test results, can be misinterpreted as evidence of severe illness, resulting in significant distress (Salkovskis et al., 2002). Health anxiety varies in intensity, ranging from mild, which promotes healthy behaviours, to severe anxiety, which leads to maladaptive behaviour and ongoing distress (Asmundson et al., 2010; Ferguson, 2009; Longley et al., 2016). While it is not officially recognised as a medical diagnosis, it is closely related to conditions like hypochondriasis and illness anxiety disorder (Bailer et al., 2016; Starcevic, 2013). The concept of health anxiety stems from cognitive-behavioural theories of anxiety disorders, particularly the cognitive model of health anxiety proposed by Salkovskis and Warwick (1986). This model explains that health anxiety arises from dysfunctional beliefs about health and illness, which cause individuals to misinterpret bodily sensations and health-related information. The cognitive-behavioural perspective highlights that these misinterpretations and the subsequent anxiety are maintained by a cycle of maladaptive thoughts, emotions, and behaviours (Abramowitz et al., 2007). This framework clarifies how health anxiety develops, continues, and affects health-related behaviours, such as the adoption and use of digital healthcare technologies among older adults.

Health anxiety is a characteristic that becomes more prominent with age and is associated with health-related behaviours. Older adults, who often face more health issues, tend to engage in safety behaviours like frequent checking and seeking reassurance to alleviate their health-related concerns (Brown et al., 2020; El-Gabalawy et al., 2013). This heightened anxiety in older adults is partly due to the presence of various physical health conditions (El-Gabalawy et al., 2013). Health issues are often linked to negative emotions like worry and fear; for instance, individuals facing serious illnesses tend to feel heightened anxiety about their health condition (Dalton et al., 2009). Research indicates that people with elevated health anxiety are more prone to perform safety behaviours such as monitoring for illness symptoms, avoiding perceived risks, and seeking reassurance, in contrast to those with lower levels of health anxiety (Brown et al., 2020; Te Poel et al., 2016). These behaviours are negatively reinforced, leading to more dysfunctional health beliefs and sustaining health anxiety (Abramowitz and Moore, 2007; Olatunji et al., 2011). Therefore, older users with higher health anxiety tend to carefully process health-related information and assess the benefits of digital healthcare technologies, seeking reliable health services and data to reduce their fears about their health conditions (Kim and Han, 2021; Lagoe and Atkin, 2015; Meng et al., 2021).

Older adults experiencing increased health anxiety are more inclined to adopt health management practices, including using digital healthcare technologies to track their health, manage chronic conditions, and obtain health-related information (Bergman et al., 2020). These tools are especially useful for alleviating their anxiety and addressing health concerns (Goyal et al., 2022; Liu et al., 2022; Lu et al., 2023). The detailed health information provided by digital healthcare technologies enables older users to make more informed assessments about their conditions (Conboy et al., 2018; Özkan and İnal, 2022; Yang et al., 2022), assisting them in making health-related decisions and increasing their satisfaction with the technology. This increased level of satisfaction could enhance their commitment to continue using these technologies. While the relationship between satisfaction and the intention to continue using digital healthcare technologies among older users with health anxiety has not been extensively studied, it is assumed that older users with health concerns exhibit higher satisfaction with digital healthcare technologies. This increased satisfaction likely stems from the empowerment digital healthcare technologies provide by delivering relevant health information, which helps users make informed health decisions (Chen et al., 2023; Kim and Han, 2021; Meng et al., 2022; Zhang et al., 2023).

Furthermore, older users with high health anxiety may find a heightened sense of relief and control through the use of digital healthcare technologies, directly boosting their overall satisfaction. This increased satisfaction can strengthen their intention to continue using these technologies. As digital healthcare technologies address their health concerns by offering reliable data, monitoring capabilities, and personalised health insights, users see greater value in the technology, reinforcing their commitment to its ongoing use. Therefore, the interplay between health anxiety and satisfaction is key to understanding the continuance intention to use digital healthcare technologies. The more effectively digital healthcare technologies alleviate health anxiety by meeting the specific needs of these users, the stronger the link between satisfaction and the intention to keep using these technologies becomes. This suggests that high levels of health anxiety significantly enhance the positive impact of satisfaction on the continuance intention to use digital healthcare technologies among older users. Hence, it is hypothesised that:

H9: Older users' high level of health anxiety strengthens the relationship between satisfaction and continuance intention to use digital healthcare technologies.

4.5.8 Technology Anxiety

Technology anxiety, which has developed from the concept of computer anxiety, involves users' concerns or unease regarding their ability with technology tools (Cui et al., 2009; Hsu et al., 2021; Meuter et al., 2003; Venkatesh, 2000). Classic anxiety theories suggest that anxiety negatively affects cognitive responses, especially process expectations (Phillips et al., 1972). Technology anxiety is crucial in predicting the adoption and use of IS, with a negative correlation to user behaviour and adoption (Hasan and Ahmed, 2010). This anxiety is a significant barrier for older adults when it comes to using new technologies (Vroman et al., 2015; Zhu and Cheng, 2024). It is a discomfort and apprehension that some individuals experience when using computers, often leading to reluctance or avoidance of technology use (Compeau et al., 1999; Simonson et al., 1987; Venkatesh, 2000). Research indicates that older adults commonly report higher levels of technology anxiety than younger individuals, primarily because of age-related declines in sensory abilities (Berner et al., 2022; Dyck et al., 1998; Laguna and Babcock, 1997; Marquié et al., 2002; Vachon et al., 2020; Xue et al., 2012).

Age-related challenges, such as declining cognitive and physical abilities, contribute to higher levels of technology anxiety in older adults compared to younger users (Hsu and Peng, 2022; Kavandi and Jaana, 2020; Kim et al., 2023). This anxiety in older adults is also influenced by other factors, such as a lack of familiarity with technological tools, privacy and security concerns, and fears of making mistakes (Celik, 2016; Edo et al., 2023; Tsai et al., 2019). Additionally, older individuals experience greater technology anxiety when engaging with wireless computing devices, largely due to their complexity and the heightened uncertainty and risk they present (Bahli and Benslimane, 2004). This anxiety is frequently associated with self-imposed barriers, disinterest, and diminished motivation (Turner et al., 2007; Yusif et al., 2016).

Older adults often feel less comfortable and have less control over information and communication technology (ICT) compared to younger adults (Czaja et al., 2006; Morris and Venkatesh, 2000). Studies on Health Information Technologies (HITs) in older populations reveal that technology anxiety, particularly in the context of health matters, negatively impacts their willingness to continue using these technologies (Deng et al., 2014; Guo et al., 2013; Jeng et al., 2022). Technology anxiety significantly influences older users' attitudes, behaviours, and intentions to continue using digital healthcare technologies (Jeng et al., 2022; Kim et al., 2023; Zin et al., 2023). Older users with higher levels of technology anxiety may feel more apprehensive and fearful when using digital healthcare technologies, negatively affecting their satisfaction and intention to continue using these technologies. Various studies have explored the moderating role of technology anxiety on the adoption or continued use of technologies. Meng et al. (2020) discovered that technology anxiety moderates the relationship between affective trust and older users' intention to continue using mobile health services, enhancing the impact of affective trust. Lee et al. (2022) observed that technology anxiety moderates the adoption of augmented reality (AR) virtual try-on technology, affecting perceptions of its usefulness and ease of use. Sorwar et al. (2023) demonstrated that technology anxiety impacts older adults' acceptance and adoption of smart home technology, diminishing the perceived benefits. These studies indicate that high levels of technology anxiety can weaken the positive effects of perceived usefulness, trust, and ease of use on the intention to adopt or continue using technology.

When older users with high technology anxiety feel satisfied with digital healthcare technologies, their anxiety may still weaken the link between satisfaction and the intention to continue using these technologies. Despite satisfaction with the technology's performance, older users with high anxiety might hesitate to continue using digital healthcare technologies due to their ongoing apprehension and fear. Additionally, these individuals may require more time and effort to assess the benefits and drawbacks of digital healthcare technologies before developing satisfaction and forming intentions for continued use. The presence of technology anxiety can create a psychological barrier that hinders the translation of satisfaction into continued use. In light of the above arguments, the subsequent hypothesis is postulated:

H10: Older users' high technology anxiety weakens the relationship between satisfaction and continuance intention to use digital healthcare technologies.

4.5.9 Self-efficacy

Self-efficacy, initially introduced by White (1959) and further developed by Bandura (1986) in the framework of social cognitive theory, is a motivational construct that focuses on an individual's belief in their ability to organise and accomplish specific tasks. It plays a critical role in behaviour acquisition and maintenance, shaping the activities people choose to engage in, the effort they put forth, and their perseverance when encountering challenges (Trepte and Reinecke, 2011). Bandura (1986) highlighted that self-efficacy is about one's judgment of what they can achieve with their skills rather than their actual abilities. The development of self-efficacy is influenced by experiences such as practising and succeeding, observing others, receiving positive feedback, and maintaining positive physiological and psychological states (Bandura et al., 1996). Self-efficacy is adaptable and can be relevant across different aspects of life (Schneider and Chein, 2003). Although some research examines self-efficacy as a broad concept, assessing it within specific areas is often more practical, as abilities tend to be specialised to particular domains. Domain-specific self-efficacy is valuable as it offers more accurate predictions within targeted contexts (Cassar and Friedman, 2009; Shiau et al., 2020). This focused approach to self-efficacy has been studied in diverse fields, including financial management, computer use, and fintech (Chen, 2017; Shiau et al., 2020; Shim et al., 2019). This study focuses on technology self-efficacy, which pertains to individuals' confidence in their ability to effectively use digital healthcare technologies (Huang and Ren, 2020).

Hsu and Chiu (2004) applied the theory of planned behaviour (TPB) to the context of information systems sustainable use, concluding that internet self-efficacy and satisfaction influence users' willingness to continue using technology. Similarly, Zhu et al. (2013) developed a model based on attribution theory and expectation inconsistency theory, finding that self-efficacy and satisfaction significantly affect the intention to continue using self-service technology. Wang et al. (2019) discovered that cognitive factors like self-efficacy positively impact user engagement with social media. Zhao and Wang (2022) also found that perceived self-efficacy in using digital healthcare technologies enhances users' willingness to continue using them. Additionally, empirical studies highlight that self-efficacy plays a moderating role in behaviours related to mobile technology, including mobile commerce (Islam et al., 2011) and mobile health interventions (Clarke et al., 2014).

In the context of technology and information systems, self-efficacy significantly influences user behaviour and confidence in mastering specific technologies or systems (Almaiah et al., 2019; Huang and Ren, 2020). Individuals with higher levels of self-efficacy feel more capable of overcoming technological challenges (Abdullah et al., 2016; Bandura, 1986). Conversely, those with lower levels of self-efficacy are more likely to give up, attribute failures to themselves, and experience greater anxiety or depression when facing difficulties (Bandura, 1986; Rahman et al., 2016). Generally, people are more inclined to engage in activities where they feel confident and avoid those where they lack confidence (Bandura and Watts, 1996; Berkowsky et al., 2017; Ezzi, 2014). Research indicates that self-efficacy is crucial for older adults' behaviour and health outcomes, yet it tends to decline with age. Older adults often have lower self-efficacy compared to younger individuals, significantly affecting their ability to manage health-related tasks and engage in proactive behaviours (McAuley et al., 2006; Medrano-Ureña et al., 2020). This age-specific decline is associated with psychological, social, and health-related challenges unique to older adults (Grembowski et al., 1993; McAuley et al., 2003; Whitehall et al., 2021; Woodward et al., 1987). As older adults often face age-related challenges, such as declining cognitive and physical abilities, they experience lower levels of self-efficacy compared to younger users (Alam et al., 2020; Cao et al., 2022; Jokisch et al., 2022). Additionally, older adults' unfamiliarity with technology, concerns about privacy and security, and fears of making mistakes or causing harm to their health through digital healthcare technologies further reduce their self-efficacy (Balapour et al., 2019; Hoque and Sorwar, 2017; Meng et al., 2019).

Technological self-efficacy has been found to be a determining factor in individuals' adaptability to technological innovations (Compeau and Higgins, 1995). This is particularly relevant for older adults, whose beliefs about their ability to use digital healthcare technologies significantly influence their adoption and continued use of these technologies (Askari et al., 2020; Singh et al., 2022). Research consistently shows that self-efficacy is a key determinant of older users' intention to use technology (De Veer et al., 2015; Liu et al., 2022). Older adults proficient in using computers and the internet generally show a higher intention to adopt new systems compared to those with limited skills (John, 2013). Consequently, technologically skilled older users may find new technologies easier to use than those with less experience (Omotayo, 2020). Studies underscore the significant role of self-efficacy in technology adoption among older adults. O'Neill et al. (2023) emphasised that self-efficacy affects older adults' engagement with technology, noting that low self-efficacy diminishes confidence and motivation, thus hindering technology use. Similarly, Yusif et al. (2016) identified self-efficacy as a major barrier to technology adoption, with older adults who have low self-efficacy perceiving new technologies as challenging to use, leading to lower adoption rates. Wang et al. (2018) explored the role of self-efficacy throughout the preadoption, adoption, and postadoption stages of technology use among older adults, finding that low self-efficacy negatively impacts their willingness to adopt new technologies. Moreover, Heart and Kalderon (2013) demonstrated that low self-efficacy significantly hampers the adoption of health-related ICTs, highlighting the importance of improving self-efficacy to enhance the effective use of these technologies among older adults. Berkowsky et al. (2017) concluded that self-efficacy, along with perceived usefulness and positive attitudes toward technology, is a strong predictor of technology adoption among older adults, with higher self-efficacy leading to greater adoption rates.

For older users with lower self-efficacy, experiencing satisfaction with digital healthcare technologies might not significantly increase their intention to keep using the technology. Despite being satisfied with the technology's performance or usefulness, older users with low self-efficacy may still hesitate to continue using digital healthcare technologies due to ongoing doubts about their ability to navigate and benefit from the technology. Their lack of confidence, perceived complexity, and fear of failure can create significant psychological barriers that hinder the translation of satisfaction into continued use, as less confident users may continually question their ability to navigate and benefit from the technology (Berner et al., 2022; Hussain et al., 2023; Liang et al., 2024). These psychological barriers are particularly challenging for older adults, who often face age-related cognitive and physical limitations that further undermine their self-efficacy and confidence in using technology (Czaja et al., 2019; Heinz, 2013). Additionally, the fast-paced evolution of digital healthcare technologies can intensify the impact of low self-efficacy, leaving older users feeling increasingly overwhelmed and disconnected from new features and updates (Vaportzis et al., 2017). As a result, even when older users are satisfied with digital healthcare technologies, their low self-efficacy can weaken the relationship between satisfaction and the intention to continue using the technology. Therefore, the following hypothesis is posited:

H11: Older users' low self-efficacy weakens the relationship between satisfaction and continuance intention to use digital healthcare technologies.

Table 12 below is the exemplar quotes from the findings of Phase 1 to support the hypotheses in this study and subsequently. Then, the hypothesised conceptual model is presented in Figure 17.

	Hypothesis	Construct	Exemplar Quotes
1	H1: Older users' health motivation is positively related to the perceived usefulness of digital healthcare technologies.	Health Motivation	Participant 9: "When I realised it could help me track my daily walks and monitor my heart rate, I saw how it perfectly fits my goal of staying active." Participant 2: "I want to stay active and independent as I age, and the smartwatch supports that. It keeps me motivated and reminds me to stay active." Participant 8: "It can improve health outcomes … It guides me toward healthier choices, both physically and mentally." Participant 20: "With its ability to monitor my vitals and provide insights regularly, I have gained a sense of control over my health that goes beyond doctor's appointments." Participant 15: "It is all about staying one step ahead of any health issues … It is about early detection … It has helped me to spot potential health concerns before they escalate."
2	H2: Older users' health consciousness is positively related to the perceived usefulness of digital healthcare technologies.	Health Consciousness	Participant 5: "I am having a dedicated health companion right on my wrist … It is as if my body has a voice, and the watch helps me understand it better … Its real-time updates make me feel more in tune with myself." Participant 17: "It keeps an eye on my heart rate and blood pressure ... I find its alerts really helpful. When it sends me alerts about any changes, I know that I should take an action before it gets worse." Participant 1: "It reminds me to stay active throughout the day. Whether I am taking the stairs instead of the elevator or going for a walk during my lunch break, it congratulates me for trying to keep up with my exercise." Participant 9: "It is amazing how something so small can make such a big difference … When it is time for a walk, it gently vibrates, reminding me to stretch my legs and get moving … It also reminds me to stay hydrated." Participant 13: "I have been using it to monitor my activities and health trends over 7 years … One of the things I really appreciate about using this is the ability to do frequent health assessments. It captures the story of my well-being; from the steps I take to the quality of my sleep."

3	H3: Confirmation of expectation is positively associated with the older users' perceived usefulness of digital healthcare technologies.	Confirmation of Expectation	Participant 10: "I was really hoping that this smartwatch would help me get more active. When I started using it and saw that it is tracking my steps and calories burned, I realised that this is what I wanted." Participant 16: "But then I saw it monitors so many things … It elevated my perception of its usage." Participant 15: "When I saw that my smartwatch is tracking not just steps but also heart rate, blood pressure, and even stress levels, I felt more connected to my health than before." Participant 11: "Seeing my steps and activity minutes every day made me realise how much or how little I was moving … It shows me trends over time and how small changes can lead to big improvements."
4	H4: Confirmation of expectation is positively associated with the older users' satisfaction with digital healthcare technologies.	Confirmation of Expectation	Participant 5: "My son told me that is not accurate especially with the stairs, but then, when I bought it, I compared the tracker's count with my pedometer, and they matched." Participant 19: "I was sceptical about how well this smartwatch could monitor my sleep. I started looking at the sleep data it provided, and it was surprisingly close to how I felt." Participant 20: "I wanted something that I could easily understand without needing to read a whole manual. When I got it, I wanted it to be easy to use. The buttons were clear, and the display showed me exactly what I needed to know." Participant 13: "When I started using it, I found that it is actually quite comfortable to wear throughout the day. It is not bulky, and I barely notice it … It fits in perfectly with my daily activities. I have it on all day, except when I take a shower." Participant 17: "I was concerned that wearing a smartwatch all the time would feel odd. But it became part of my routine." Participant 2: "It was a personal challenge when I saw that I could set goals for daily steps. And now, reaching those goals makes me feel accomplished."
5	H5: Perceived usefulness is positively associated with older users' satisfaction with digital healthcare technologies.	Perceived Usefulness	Participant 8: "It gives me a sense of security and helps me track my health each day." Participant 16: "I never used to remember my medication on time. It buzzes and reminds me to take my medications." Participant 20: "It gives me a reason to move more. It is a friendly challenge I have with myself every day."

			Participant 12: "It pushes me to be more active. Seeing my steps and getting reminders to move keeps me on my toes. It has made me to stay active throughout the day." Participant 13: "My smartwatch syncs seamlessly with my phone. I can see my health data and notifications without having to pull out my phone all the time." Participant 10: "I can share heart rate logs and activity summaries with my doctor right from my watch." Participant 2: "I can read my messages on it and answer my calls … It is not just about health; it is about staying connected too." Participant 1: "Now, with this, I can check my vitals whenever I want. I feel like I have more control over my own health." Participant 17: "When I see my sleep patterns and heart rate trends, I understand that I am actively managing my health." Participant 15: "I can set my own personal goals and targets that match my fitness level … that keeps me engaged." Participant 10: "Using it is surprisingly enjoyable. The graphics are pleasing, and the little achievements I earn make it feel like a game." Participant 17: "Sometimes, I share my activities with my granddaughter. She sends me encouraging messages whenever she sees I have hit my activity goals."
6	H6: Satisfaction is positively associated with the older users' ageing satisfaction.	Satisfaction	Participant 1: "Since using it, I have noticed my stamina improving. It is about progress … Seeing the numbers on its screen reminds me that I should not give up on my health." Participant 12: "Since I started using the smartwatch, I have actually lost weight." Participant 8: "Every time I glance at my smartwatch and see my achievements, it is like a little burst of joy."
7	H7: Satisfaction is positively associated with the older users' continuance intention to use digital healthcare technologies.	Satisfaction	Participant 17: "Its health readings' accuracy has made me more confident about my health." Participant 5: "When I hit my daily steps' goal, it celebrates my successes and keeps me hungry for more. That encourages me to set new goals and keep moving forward." Participant 9: "From day one, it has been very helpful and simple to use … not a confusing gadget. No complicated menus or confusing buttons … completely hassle-free."

			Participant 15: “The support team guided me through it patiently.”
8	H8: Ageing satisfaction is positively associated with older users’ continuance intention to use digital healthcare technologies.	Ageing Satisfaction	Participant 10: “I enjoy simple things and connect with people. With technology by my side, I can ensure my wellbeing.” Participant 16: “I appreciate the natural changes my body has gone through. It is a reminder of the journey I have been on.” “Life is full of surprises, and I have learned to roll with the punches. I am not one to back down from a challenge … When simple problems pop up, I remind myself that I have faced tougher things.” Participant 8: “Well, as I look back on my life, I cannot help but feel I have achieved so much. It has been full of ups and downs, but it is all added up to this wonderful story I can share with my grandchildren. I am eager to see how it will enhance my life, just like all the other things I have achieved along the way.” Participant 17: “I prioritise my health, and it is paid off … I have realised that feeling good physically is the secret way of a happy life.” Participant 2: “I enjoy staying active and trying out new things, like exploring new places or enjoying the outdoors. It keeps me feeling good and makes me happier.”
9	H9: Older users’ high level of health anxiety strengthens the relationship between satisfaction and continuance intention to use digital healthcare technologies.	Health Anxiety	Participant 6: “As I have grown older, I worry more about my blood pressure and cholesterol levels … This device makes me feel that I am actively taking care of my health and gives me a sense of security.” Participant 17: “It reminds me to be grateful for every little step I take … Staying active is a priority for me as I age.” Participant 1: “I fear that something might go wrong with my health, and it scares me.” Participant 13: “I do not want to become a burden to my family and lose control over my life. I have worked hard all my life to be self-independent, and the thought of relying on others is a difficult one to bear … That is why my smartwatch is valuable to me. It provides a sense of security and empowerment, reminding me that I can still take charge of my health independently. It is not just about staying healthy; I want to protect my dignity.” Participant 20: “I worry about my body's ability to fight illnesses, and I understand my increased vulnerability to health risks … This smartwatch offers me a lifeline to better manage health risks. It

			is constantly monitoring my vital signs and activity levels." Participant 12: "I have more and more medical stuff to deal with, like appointments and tests; managing them used to be overwhelming … My smartwatch has some helpful apps that make it all easier. They help me set up appointments, get my medical info, and see my results on my phone." Participant 10: "It [smartwatch] sends me notifications to take my meds on time, and it even tells me all I need to know about each one, like what they do and what to watch out for. I am manging all these medications much easier."
10	H10: Older users' high technology anxiety weakens the relationship between satisfaction and continuance intention to use digital healthcare technologies.	Technology Anxiety	Participant 9: "If it was not a gift, I would not have bought it on my own. I did not grow up with all this technology stuff … Its apps just make my head spin. It is frustrating, and honestly, I am not sure I can trust it with something as important as my health." Participant 14: "This smartwatch is so complicated, with all these buttons and settings. It is hard to know where to start … Back in my day, a doctor's visit was a simple affair, but now it feels like I need a degree in technology just to manage my own health … I am not sure I use it properly or not." Participant 3: "I am afraid I will press the wrong thing and mess it all up." Participant 19: "I have heard too many stories about people's personal info being stolen online. I worry about my personal data getting into the wrong hands. It makes me wonder if I can really trust these systems to keep my information safe and confidential." Participant 11: "I am trying my best to keep up with the changes in technology, but it seems like just when I get used to one thing, they introduce a new one with even more features and complexities." Participant 9: "I found myself so frustrated with the constant problems like freezes and crashes. It does not work as it should."
11	H11: Older users' low self-efficacy weakens the relationship between satisfaction and continuance intention to use digital healthcare technologies.	Self-efficacy	Participant 18: "Sometimes, I just cannot figure out how to make it work the way is supposed to, and I do not know how to navigate through all these buttons and menus on it … I am afraid I might mess something up, so I often end up not using some features at all." Participant 7: "Sometimes, I struggle to understand how to use these new gadgets … When something feels too hard to use, it is hard to stay satisfied with

			it. I question myself if it is worth the effort … I ended up not using it as much as probably should." Participant 4: "I am not tech-savvy at all, and I get help from my daughter whenever I face difficulty with this device." Participant 3: "I am afraid I will press the wrong button and break the fitness tracker." Participant 9: "Learning to use all the features of this device seems like a lost cause."

Table 12: Exemplar Quotes from The Findings of Phase 1 to Support the Hypotheses Development (Developed by the author)

4.6 Hypothesised Conceptual Model

The hypothesised conceptual model, presented in Figure 17, summarises the relationships proposed in the hypotheses developed earlier in this chapter. This model integrates both literature-based constructs and qualitative findings to illustrate the key factors influencing older users' continuance intention to use digital healthcare technologies. Each hypothesis (H1 to H11) is shown in the model, highlighting the expected connections between constructs. This figure serves as a comprehensive representation of the theoretical framework guiding this research.

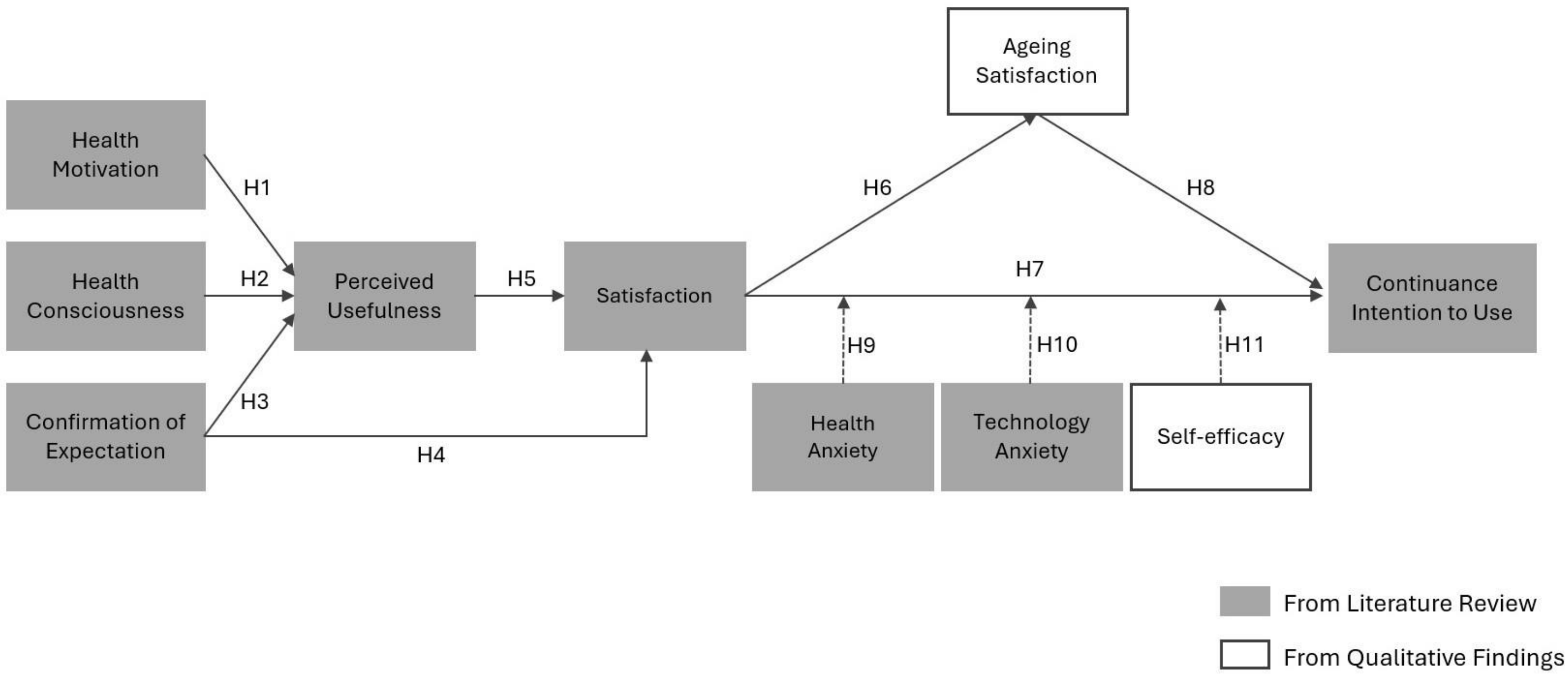

Figure 17: Hypothesised Conceptual Model
(Developed by the author)

Chapter 5: Quantitative Findings

5.1 Introduction

Findings from the qualitative analysis were discussed in the chapter 4. This chapter focuses on the results derived from survey data collected from participants. Data collected through Google Forms were exported to an Excel (xlsx) file, where each participant was assigned an identification number, and responses were encoded. These encoded data were then imported into SPSS for initial review and descriptive analysis. The chapter is structured to begin with an overview of preliminary data processing, covering data cleaning, handling missing values, outlier identification, and normality assessment. Following this, a profile of the respondents is presented, including demographic details such as age and gender. Finally, the chapter applies Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the validity and reliability of both the measurement and structural models.

5.2 Preliminary Data Analysis

Before beginning any analysis in SmartPLS, reviewing the data for potential errors or inconsistencies is critical. This preliminary stage, known as data cleaning or screening, seeks to discover and fix any data errors in order to assure reliable results in the PLS-SEM analysis (Chu and Ilyas, 2016). Osborne (2012) highlighted the necessity of screening and cleaning collected data to remove errors and incomplete responses. Although corrective measures may not always be needed, this examination is vital to ensure accurate multivariate analysis results (Hair et al., 2014). Hair et al. (2017) stressed the importance of checking for data issues, which are subsequently addressed using SPSS.

5.2.1 Data Cleaning and Missing Data

A total of 479 questionnaires were collected for the study, with participation criteria requiring individuals to be (1) 65 years or older, (2) residents of the UK, and (3) users of digital healthcare technologies. These criteria ensured the relevance of the study's findings to the target demographic engaged with digital healthcare in the UK. During the data cleaning process, participant profiles were thoroughly reviewed to ensure they met the inclusion criteria. As a result, 18 participants who were under the age of 65, 5 participants who were not using digital healthcare technologies, and 7 participants who did not reside in the UK were excluded. This process led to the removal of 30 individuals, ensuring the integrity and focus of the research. Following this process, 449 participants remained eligible for the final analysis, forming the foundation for all subsequent data evaluations and interpretations in this study.

In addition to data cleaning, handling missing data was a critical consideration. Missing values frequently arise in quantitative data collection due to various factors such as participants refusing to answer, misunderstanding questions, accidentally skipping questions, or researcher errors during data entry (Bryman, 2016). These missing values can diminish the dataset's completeness, potentially leading to biased and incorrect results (Hair et al., 2014; Kwak and Kim, 2017). Addressing this concern is particularly necessary when using structural equation modelling (SEM) techniques for data analysis (Hair et al., 2019), as structural equation modelling is not designed to handle datasets with missing values (Gorard, 2020). For example, the Bootstrapping feature in SmartPLS, which evaluates the connections between constructs, requires a complete dataset to function properly (Ramayah et al., 2018). To prevent this issue, the online survey was configured so that all questions were mandatory, ensuring that no responses could be submitted without full completion. As a result, the data collected had no missing data.

5.2.2 Outlier Analysis

The next step involves analysing the data for anomalies, known as outliers, which could indicate errors or reflect unusual variability that could potentially skew structural equation modelling analysis results (Bryman, 2016). This step is particularly crucial with smaller sample sizes, where a few extreme values can impact model reliability. Mowbray et al. (2019) describe univariate outliers as values that are unusually high or low compared to the rest of the dataset. Z-scores indicate how far each data point deviates from the mean, measured in standard deviations, allowing to detect these anomalies. By using Z-scores, researchers evaluate the possibility that a value falls in the expected range of a standard normal distribution (SND), with values typically centred around a mean of 0. In interpreting Z-scores, a positive score indicates that a data point is above the mean, while a negative score shows it is below. For instance, a Z-score of +1 indicates that the data point is one standard deviation above the mean, and a Z-score of -1 indicates it is one standard deviation below (Bryman, 2016). For this study's sample of 449 respondents, a threshold of four standard deviations from the mean was set, following Hair et al. (2019), who recommend this threshold for smaller sample sizes. Z-scores exceeding this limit were considered potential outliers. Using SPSS software, each data point was evaluated against this threshold. As shown in Table 13, no Z-scores exceeded the limit of 4, indicating the absence of univariate outliers in this dataset. The range of Z-scores across constructs suggests that data points are consistently within an acceptable range, reinforcing the reliability of the dataset and reducing concerns about data skewness or bias.

Constructs	Items	Minimum Z-score	Maximum Z-score
Health Motivation	HM1	-2.74709	0.85039
	HM2	-2.19263	0.81716
	HM3	-2.38506	1.05942
	HM4	-1.52957	0.66832
	HM5	-3.11073	0.75570
	HM6	-2.01294	0.86605
	HM7	-3.53627	0.66249
Health Consciousness	HC1	-2.91114	0.77424
	HC2	-1.59991	1.15485
	HC3	-2.08281	0.80510
	HC4	-2.45029	0.63260
	HC5	-2.41926	1.11267
	HC6	-3.26158	0.77452
	HC7	-2.45787	0.72187
	HC8	-2.49185	0.89890
Confirmation of Expectation	CON1	-2.10524	1.05875
	CON2	-2.77541	1.10726
	CON3	-0.95451	1.11798
	CON4	-1.82875	1.09925
	CON5	-2.60799	1.06512
	CON6	-2.91954	1.14356
Perceived Usefulness	PU1	-3.15182	1.05061
	PU2	-2.81853	1.08661
	PU3	-2.21548	1.09626
	PU4	-1.88814	1.09873
	PU5	-2.92019	0.93232

	PU6	-2.7424	1.07135
	PU7	-2.61173	1.11704
Satisfaction	SAT1	-2.07832	1.03781
	SAT2	-2.70633	1.04613
	SAT3	-2.83378	1.01016
	SAT4	-2.75312	1.07553
	SAT5	-0.59867	1.11428
	SAT6	-0.52634	1.00264
	SAT7	-2.37954	1.12165
	SAT8	-2.80455	1.02466
Ageing Satisfaction	AS1	-1.77076	1.50532
	AS2	-1.69752	1.41239
	AS3	-1.57934	1.26681
	AS4	-1.79413	1.18972
	AS5	-1.71489	1.57125
	AS6	-1.98562	1.29345
	AS7	-1.59287	1.51016
	AS8	-1.60361	1.47558
Health Anxiety	HA1	-2.23851	1.35076
	HA2	-2.35970	1.10144
	HA3	-1.92601	1.30582
	HA4	-1.88580	1.35391
	HA5	-1.86761	1.34674
	HA6	-1.70251	1.34511
	HA7	-2.43037	1.15969
Technology Anxiety	TA1	-1.57476	1.52844
	TA2	-1.80684	1.49046
	TA3	-1.79835	1.47709
	TA4	-1.70191	1.62391
	TA5	-2.11181	1.40038
	TA6	-1.52258	1.56872
Self-efficacy	SE1	-2.07161	1.47756
	SE2	-1.60951	1.62677
	SE3	-1.80798	1.28953
	SE4	-1.59707	1.35767
	SE5	-1.50936	1.49973
	SE6	-1.66843	1.50598
	SE7	-1.52962	1.70551
	SE8	-1.49157	1.38722
Continuance Intention to Use	CI1	-2.78216	1.27326
	CI2	-2.51631	1.18032
	CI3	-2.26954	1.18916
	CI4	-2.27962	1.13617
	CI5	-2.31292	1.18631
	CI6	-2.41700	1.1845
	CI7	-1.6365	1.38226
	CI8	-1.55652	1.11579

	CI9	-2.56300	1.06035

Table 13: Z-Scores Demonstrating the Minimum and Maximum Standard Scores (Developed by the author)

5.2.3 Assessing for Normality

The distribution pattern of a single variable of data is referred to as normality (Mishra et al., 2019). A bell curve, which is a sign of a normal distribution, should be seen in this distribution (Hair et al., 2013). An essential first step in ensuring that the data are suitable for statistical analysis is to test for normality. The validity and reliability of multivariate studies might be impacted by data that drastically depart from normality (Hair et al., 2014). Even though Hair et al. (2016) state that PLS-SEM does not need normally distributed data, it is nevertheless crucial to ensure that the data are not excessively skewed from normality. Researchers in SEM (Kline, 2023) recommend assessing data distribution using measures of skewness and kurtosis. Kurtosis assesses the height of the distribution's peak, whereas skewness reveals how asymmetrical it is (Hair et al., 2017). The distribution is skewed to the left when the skewness value is positive and to the right when it is negative. Similarly, a distribution with a higher peak is indicated by positive kurtosis, and a distribution with a flatter peak is indicated by negative kurtosis (Kline, 2023). The accepted thresholds for skewness and kurtosis vary somewhat despite the fact that zero is the ideal value for both (Joanes and Gill, 1998). According to Field (2024), thresholds of ±2.58 should be used at the significance level of .01 and ±1.96 at the significance level of .05. On the other hand, Kline (2023) suggests that kurtosis and skewness should be within ±1. Normality testing reveals that skewness and kurtosis values for each of the ten constructs in the model fall within the acceptable range of ±1 (see Table 14). This confirms that the data distribution is suitable for the constructs and appropriate for model testing.

Constructs	Items	Skewness		Kurtosis	
		Statistics	Std. Error	Statistics	Std. Error
Health Motivation	HM1	-1.351	0.113	2.055	0.225
	HM2	-1.238	0.113	1.456	0.225
	HM3	-0.784	0.113	-0.093	0.225
	HM4	-1.331	0.113	0.913	0.225
	HM5	-1.088	0.113	0.246	0.225
	HM6	-1.141	0.113	1.024	0.225
	HM7	-1.453	0.113	1.562	0.225
	HC1	-1.249	0.113	1.074	0.225

Health Consciousness	HC2	-0.691	0.113	-0.171	0.225
	HC3	-1.102	0.113	0.623	0.225
	HC4	-1.55	0.113	1.79	0.225
	HC5	-0.708	0.113	-0.247	0.225
	HC6	-1.212	0.113	1.052	0.225
	HC7	-1.19	0.113	0.601	0.225
	HC8	-0.84	0.113	-0.226	0.225
Confirmation of Expectation	CON1	-0.765	0.113	0.104	0.225
	CON2	-0.681	0.113	-0.314	0.225
	CON3	-0.781	0.113	0.339	0.225
	CON4	-0.893	0.113	0.233	0.225
	CON5	-0.706	0.113	-0.184	0.225
	CON6	-0.744	0.113	0.004	0.225
Perceived Usefulness	PU1	-0.747	0.113	-0.066	0.225
	PU2	-0.719	0.113	-0.006	0.225
	PU3	-0.621	0.113	-0.571	0.225
	PU4	-0.775	0.113	0.05	0.225
	PU5	-0.95	0.113	0.291	0.225
	PU6	-0.744	0.113	-0.142	0.225
	PU7	-0.725	0.113	-0.23	0.225
Satisfaction	SAT1	-0.797	0.113	0.063	0.225
	SAT2	-0.821	0.113	0.048	0.225
	SAT3	-0.846	0.113	0.106	0.225
	SAT4	-0.812	0.113	0.108	0.225
	SAT5	-0.583	0.113	-0.336	0.225
	SAT6	-0.764	0.113	-0.366	0.225
	SAT7	-0.711	0.113	-0.195	0.225
	SAT8	-0.751	0.113	-0.29	0.225
Ageing Satisfaction	AS1	-0.065	0.113	-1.15	0.225
	AS2	-0.273	0.113	-1.033	0.225
	AS3	-0.256	0.113	-1.257	0.225
	AS4	-0.352	0.113	-1.107	0.225
	AS5	-0.175	0.113	-1.023	0.225
	AS6	-0.283	0.113	-0.915	0.225
	AS7	0.015	0.113	-1.114	0.225
	AS8	-0.137	0.113	-1.12	0.225
Health Anxiety	HA1	-0.517	0.113	-0.653	0.225
	HA2	-0.529	0.113	-0.75	0.225
	HA3	-0.401	0.113	-0.782	0.225
	HA4	-0.234	0.113	-0.949	0.225
	HA5	-0.353	0.113	-0.851	0.225
	HA6	-0.28	0.113	-1.058	0.225
	HA7	-0.559	0.113	-0.464	0.225
Technology Anxiety	TA1	-0.014	0.113	-1.141	0.225
	TA2	0.003	0.113	-0.981	0.225
	TA3	0.03	0.113	-1.052	0.225
	TA4	0.021	0.113	-1.002	0.225

	TA5	-0.057	0.113	-0.898	0.225
	TA6	0.085	0.113	-1.159	0.225
Self-efficacy	SE1	-0.353	0.113	-0.389	0.225
	SE2	0.136	0.113	-1.028	0.225
	SE3	-0.415	0.113	-1.043	0.225
	SE4	-0.245	0.113	-1.191	0.225
	SE5	-0.072	0.113	-1.106	0.225
	SE6	-0.258	0.113	-0.993	0.225
	SE7	-0.072	0.113	-1.035	0.225
	SE8	-0.077	0.113	-1.33	0.225
Continuance Intention to Use	CI1	-0.395	0.113	-0.512	0.225
	CI2	-0.397	0.113	-0.77	0.225
	CI3	-0.514	0.113	-0.753	0.225
	CI4	-0.473	0.113	-0.764	0.225
	CI5	-0.435	0.113	-0.744	0.225
	CI6	-0.443	0.113	-0.747	0.225
	CI7	-0.229	0.113	-1.058	0.225
	CI8	-0.501	0.113	-0.667	0.225
	CI9	-0.529	0.113	-0.808	0.225

Table 14: Assessing for Skewness and Kurtosis Values
(Developed by the author)

5.3 Profile of Respondents

In addition to gathering data on variables potentially affecting older users' intentions to continue using digital healthcare technologies, the online survey also collected personal and demographic details about the respondents. These details included gender, age, UK residency status, and usage of digital healthcare technologies. The following subsections provide a detailed breakdown of the respondents' demographic profiles.

5.3.1 Gender

Participants were requested to indicate their gender by selecting from options such as female, male, prefer not to say, and other. In a sample of 449 respondents, males were more prevalent, with 253 (56.35%), followed by 180 females (40.09%). Additionally, 11 participants (2.45%) preferred not to disclose their gender, and 5 chose the other category (1.11%). Table 15 illustrates the gender distribution among the participants.

Gender	Frequency	Percent
Female	180	40.09
Male	253	56.35
Prefer not to say	11	2.45
Other	5	1.11
Total	449	100

Table 15: Gender Distribution among Participants
(Developed by the author)

5.3.2 Age

Participants were asked to provide their ages, and the responses are detailed in Table 16. The findings revealed that 265 participants (59.02%) were aged 65 to 70, 110 participants (24.50%) were aged 71 to 75, 64 participants (14.25%) were aged 76 to 80, and 10 participants (2.23%) were over 80 years old.

Age	Frequency	Percent
65-70	265	59.02
71-75	110	24.50
76-80	64	14.25
+80	10	2.23

Table 16: Age Distribution of Participants
(Developed by the author)

5.4 Descriptive Analysis of the Variables

The number of indicators, as well as the minimum, maximum, mean, and standard deviations, are displayed in the descriptive statistics for all the variables (See Table 17). To express how much they agreed with each indicator, participants scored each one on a five-point Likert scale. The constructs' average scores, which varied from 3.09 to 4.23, showed that older users' attitudes about continuing to use digital healthcare technologies were positive. Furthermore, the low standard deviation (SD) values for all indicators suggest that the responses are closely aligned with the mean.

Constructs	Indicators	Minimum	Maximum	Mean	Standard Deviation
Health Motivation	7	1	5	4.22	0.654
Health Consciousness	8	1	5	4.23	0.657
Confirmation of Expectation	6	1	5	3.89	0.888
Perceived Usefulness	7	1	5	3.88	0.905
Satisfaction	8	1	5	3.87	0.952
Ageing Satisfaction	8	1	5	3.20	1.12
Health Anxiety	7	1	5	3.45	1.05
Technology Anxiety	8	1	5	3.14	1.07
Self-efficacy	6	1	5	3.09	1.14
Continuance Intention to Use	9	1	5	3.62	1.03

Table 17: Descriptive Statistics of Dependant and Independent Constructs
(Developed by the author)

5.5 SmartPLS Structural Equation Modelling

The selection and justification of PLS-SEM for data analysis and model testing were rigorous, as covered in the methodology chapter (see Section 3.6.2.6). For this procedure, data were imported into SmartPLS for analysis after being originally exported from SPSS. A two-step process is involved in conducting model testing with PLS-SEM, according to several researchers (Hair et al., 2022; Henseler et al., 2017; Sarstedt et al., 2022): (1) evaluating the measurement model and (2) evaluating the structural model. While the structural model stage looks at the significance of relationships between variables to evaluate the given hypotheses, the measurement model stage focuses on verifying the validity and reliability of the constructs (Hair et al., 2023).

5.5.1 Measurement Model Assessment

The measurement model, also known as the outer model, assesses the effectiveness of constructs in being represented by their corresponding indicators (Sarstedt et al., 2019). It determines the effectiveness of these indicators in capturing the constructs (Hair et al., 2019). Structural equation modelling facilitates the measurement of a single construct through multiple indicators, enhancing accuracy (Hair et al., 2020). Therefore, verifying the validity and reliability of these indicators is essential in multivariate analysis (Hair et al., 2019).

Furthermore, assessing the structural model is less significant if the measurement model does not meet the necessary validity and reliability criteria (Cheung et al., 2024). Scholars (Hair et al., 2022; Henseler et al., 2017; Sarstedt et al., 2022) have established standards for assessing the measurement model, emphasising aspects such as indicator reliability, construct reliability, convergent validity, and discriminant validity. The criteria used for this evaluation are summarised in Table 18. According to reviews of PLS-SEM methodologies (Ali et al., 2018; Hair et al., 2020; Ringle et al., 2020), these criteria are standard in the assessment of measurement models.

Assessment Type	Criteria	Criteria Value
Indicator Reliability	Indicator Loadings	Each loading should meet or exceed 0.7
Construct Reliability	Cronbach's Alpha	Alpha (CA) should meet or exceed 0.7
	Composite Reliability	Composite Reliability (CR) should meet or exceed 0.7
Convergent Validity	Average Variance Extracted	Average Variance Extracted (AVE) values should meet or exceed 0.5
Discriminant Validity	Cross Loadings	Loadings on own construct should exceed cross-loadings
	Fornell-Larcker Criterion	√ AVE for each construct should surpass inter-construct correlations

Table 18: Criteria for Evaluating Measurement Model

5.5.1.1 Indicator Reliability

Indicator reliability is a key aspect of structural equation modelling analysis, evaluating how effectively the indicators represent the construct they are designed to measure. This involves analysing the outer loadings of indicators, with values exceeding 0.70 indicating that the indicators are strongly aligned with the construct, reflecting high reliability (Hair et al., 2020). Strong outer loadings suggest that the indicators for a construct are closely related, which is crucial for ensuring the validity of the construct (Sarstedt et al., 2019). Loadings, which vary from 0 to 1, indicate the reliability of indicators, with higher values signifying better reliability (Garson, 2016). Outer loadings in the range of 0.70 to 0.90 are considered strong, whereas loadings between 0.60 and 0.70 may be considered sufficient for certain situations, such as exploratory studies, though they generally reflect lower internal consistency reliability (Hair et al., 2019). To improve composite reliability and Average Variance Extracted (AVE), indicators with outer loadings between 0.40 and 0.70 may need to be removed. Indicators with loadings between 0.50 and 0.60 can be retained if they belong to the same construct as other stronger indicators (Hair et al., 2017). Hair et al. (2019) and Sarstedt et al. (2021) note that outer loadings above 0.70

generally indicate a reliable indicator. However, indicators with slightly lower loadings may be kept if the overall construct shows satisfactory validity, supported by other high-loading indicators (Franke and Sarstedt, 2019). All indicators in this research had outer loadings above the 0.7 threshold (see Table 19). This result highlights the robustness of each indicator and significantly strengthens the overall reliability of the construct measurements in the structural equation modelling analysis. Sarstedt et al. (2021) assert that such high outer loadings indicate a strong and consistent representation of the constructs, implying that the indicators used share a substantial degree of commonality and are highly effective in capturing the essence of the constructs they aim to measure.

Constructs	Indicators	Loadings>0.7
Health Motivation	HM1	0.765
	HM2	0.807
	HM3	0.728
	HM4	0.855
	HM5	0.824
	HM6	0.771
	HM7	0.777
Health Consciousness	HC1	0.794
	HC2	0.741
	HC3	0.811
	HC4	0.809
	HC5	0.755
	HC6	0.719
	HC7	0.761
	HC8	0.757
Confirmation of Expectation	CON1	0.888
	CON2	0.878
	CON3	0.875
	CON4	0.891
	CON5	0.885
	CON6	0.876
Perceived Usefulness	PU1	0.875
	PU2	0.851
	PU3	0.890
	PU4	0.863
	PU5	0.846
	PU6	0.866
	PU7	0.876
	SAT1	0.897
	SAT2	0.889
	SAT3	0.882

Satisfaction	SAT4	0.910
	SAT5	0.891
	SAT6	0.905
	SAT7	0.901
	SAT8	0.905
Ageing Satisfaction	AS1	0.865
	AS2	0.879
	AS3	0.899
	AS4	0.886
	AS5	0.853
	AS6	0.896
	AS7	0.894
	AS8	0.835
Health Anxiety	HA1	0.899
	HA2	0.869
	HA3	0.884
	HA4	0.879
	HA5	0.902
	HA6	0.899
	HA7	0.804
Technology Anxiety	TA1	0.894
	TA2	0.900
	TA3	0.902
	TA4	0.917
	TA5	0.875
	TA6	0.782
Self-efficacy	SE1	0.880
	SE2	0.910
	SE3	0.907
	SE4	0.898
	SE5	0.883
	SE6	0.889
	SE7	0.847
	SE8	0.910
Continuance Intention to Use	CI1	0.912
	CI2	0.912
	CI3	0.915
	CI4	0.928
	CI5	0.929
	CI6	0.948
	CI7	0.876
	CI8	0.954
	CI9	0.946

Table 19: Indicator Reliability Results
(Developed by the author)

5.5.1.2 Construct Reliability

In order to ensure that the structural model produces accurate results, it is essential to evaluate the measurement model's reliability (Hair et al., 2020). Indicators are considered reliable if they are internally consistent and consistently yield the same findings when tested under similar conditions (Sürücü and Maslakci, 2020). Traditionally, reliability in social science research is gauged using Cronbach's alpha (CA) (Cronbach, 1951). Studies in marketing that employ PLS-SEM frequently assess internal consistency using composite reliability (CR) and Cronbach's alpha (Guenther et al., 2023). Composite reliability has the potential to overestimate reliability, whereas Cronbach's alpha tends to underestimate it (Sarstedt et al., 2020; Tavakol and Dennick, 2011). According to Hair et al. (2021), an increase in the number of indicators can lead to an increase in Cronbach's alpha values. Therefore, it is recommended by Sarstedt et al. (2019) to report both Cronbach's alpha, which tends to show lower values, and composite reliability, which may present higher values.

Reliability coefficients closer to 1 indicate stronger reliability, with values expected to range between 0 and 1 (Koo and Li, 2016). Acceptable thresholds of reliability have been defined differently by various scholars. Sekaran (2016) suggest that a score of 0.7 is acceptable, while 0.8 is considered to indicate good reliability, while Hair et al. (2017) recommended aiming for coefficients between 0.7 and 0.9 for better reliability. The results of the reliability assessments in this study (Table 20) show that Cronbach's alpha coefficients range from 0.900 to 1.000, while composite reliability values span from 0.920 to 1.000. These values exceed standard thresholds for reliability, indicating strong internal consistency among the indicators used in the measurement model. The high degree of agreement among items within each construct validates their accurate reflection of the theoretical concepts being measured. The reliability of the constructs is validated by Cronbach's alpha and composite reliability values, which also enhance the structural model analysis's overall credibility. By exceeding the commonly accepted reliability thresholds of 0.7 for adequate and 0.8 for strong reliability (Sekaran, 2016), this research significantly reduces the potential risk of measurement error.

5.5.1.3 Convergent Validity

The degree to which one indicator connects with other indicators within the same construct is assessed by convergent validity (Cheung et al., 2024). It verifies that the indicators are appropriately describing the same concept, as mentioned by Henseler et al. (2009). Each indicator must have an outer loading more than 0.7 in order for convergent validity to be proven, and the construct's average variance extracted (AVE) must meet or exceed 0.5 (Hair et al., 2017). According to Sarstedt et al. (2017), the AVE is computed as the mean of the squared loadings of the construct's indicators. When a construct has an AVE of 0.5 or above, it is thought to account for more than half of the variance (Chin, 1998). The AVE values in this study are greater than 0.5, as shown in Table 20, indicating that the constructs have convergent validity. The constructs' relevance and strength are validated by the AVE values that are more than 0.5. This is more than the minimum threshold that Chin (1998) recommended, demonstrating strong internal consistency and a strong theoretical framework for this research. The elevated AVE values demonstrate that the indicators precisely depict their constructs, hence enhancing the measurement model's reliability. This adds to the constructs' reliability and increases trust in the analysis and findings of the study.

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Ageing Satisfaction	0.957	0.963	0.767
Confirmation of Expectation	0.943	0.955	0.778
Health Anxiety	0.950	0.959	0.769
Health Consciousness	0.901	0.920	0.591
Health Motivation	0.900	0.921	0.625
Perceived Usefulness	0.945	0.955	0.751
Satisfaction	0.966	0.971	0.806
Self-efficacy	0.941	0.953	0.773
Continuance Intention to Use	0.979	0.982	0.855
Technology Anxiety	0.963	0.968	0.793

Table 20: Construct Reliability and Convergent Validity Results
(Developed by the author)

5.5.1.4 Discriminant Validity

Discriminant validity confirms that each construct in a model is unique and accurately represents its associated variables, maintaining clear separation from other constructs (Hair et al., 2021). In practice, this means a construct should show stronger correlations with its own indicators than with those of any other construct in the model (Sarstedt et al., 2021). To confirm this uniqueness, statistical techniques such as Cross Loadings and the Fornell-Larcker criterion are employed, verifying that each construct is independently represented within the model.

Cross Loadings

It has been established that cross loadings are one of the most effective ways for determining the discriminant validity, as they allow for an indicator-level examination of each construct's distinctiveness (Hair et al., 2019). This method guarantees that the indicators are connected to the constructs that they belong to (Henseler et al., 2016). Specifically, according to Hair et al. (2017), an indicator should have a higher outer loading on the build that for which it was designed than it does on any other construct. The Fornell-Larcker criterion differs from cross loadings, as cross loadings assess discriminant validity at the level of individual indicators (Henseler et al., 2017). In this study, SmartPLS was employed to test discriminant validity, and the cross loadings are presented in Table 21. According to the results, each indicator demonstrates a higher loading on its designated construct than on any other construct, aligning with the guidelines by Hair et al. (2017). This pattern of loadings confirms that each construct is well-differentiated, thus providing strong evidence for discriminant validity. The high degree of alignment between indicators and their constructs supports the robustness of the measurement model, further validating that each construct independently captures its intended dimension of the research.

	AS	CON	HC	HM	Moderating Effect (HA)	Moderating Effect (SE)	Moderating Effect (TA)	PU	SAT	CI
Q1	0.450	0.607	0.654	0.765	-0.422	0.134	-0.265	0.565	0.572	0.408
Q10	0.482	0.656	0.811	0.730	-0.326	0.203	-0.395	0.628	0.621	0.458
Q11	0.448	0.611	0.809	0.718	-0.431	0.137	-0.312	0.612	0.611	0.469
Q12	0.428	0.636	0.755	0.654	-0.491	0.189	-0.330	0.598	0.594	0.451
Q13	0.425	0.554	0.719	0.651	-0.442	0.107	-0.283	0.524	0.501	0.472
Q14	0.430	0.599	0.761	0.676	-0.373	0.041	-0.246	0.594	0.567	0.436
Q15	0.471	0.601	0.757	0.613	-0.318	0.101	-0.276	0.570	0.575	0.373
Q16	0.624	0.888	0.706	0.730	-0.392	0.096	-0.274	0.765	0.785	0.617
Q17	0.627	0.878	0.672	0.676	-0.405	0.140	-0.307	0.757	0.767	0.563
Q18	0.584	0.875	0.742	0.723	-0.430	0.166	-0.371	0.773	0.787	0.591
Q19	0.626	0.891	0.701	0.691	-0.486	0.127	-0.321	0.813	0.806	0.626
Q2	0.463	0.675	0.690	0.807	-0.404	0.180	-0.271	0.613	0.642	0.489
Q20	0.636	0.885	0.671	0.677	-0.416	0.188	-0.336	0.799	0.798	0.597

Q21	0.571	0.876	0.701	0.687	-0.437	0.144	-0.337	0.779	0.794	0.611
Q22	0.663	0.823	0.691	0.663	-0.452	0.097	-0.305	0.875	0.832	0.638
Q23	0.620	0.745	0.655	0.599	-0.400	0.121	-0.326	0.851	0.766	0.650
Q24	0.638	0.799	0.686	0.675	-0.404	0.186	-0.383	0.890	0.793	0.617
q25	0.619	0.725	0.630	0.631	-0.496	0.196	-0.380	0.863	0.769	0.662
Q26	0.599	0.764	0.675	0.655	-0.532	0.219	-0.356	0.846	0.766	0.625
Q27	0.598	0.755	0.651	0.650	-0.435	0.175	-0.330	0.866	0.800	0.680
Q28	0.612	0.759	0.649	0.646	-0.460	0.166	-0.350	0.876	0.818	0.627
Q29	0.644	0.801	0.690	0.673	-0.504	0.157	-0.334	0.831	0.897	0.646
Q3	0.404	0.551	0.638	0.728	-0.311	0.133	-0.233	0.466	0.515	0.386
Q30	0.632	0.806	0.674	0.668	-0.500	0.162	-0.328	0.817	0.889	0.654
Q31	0.575	0.760	0.630	0.638	-0.476	0.184	-0.357	0.780	0.882	0.652
Q32	0.666	0.820	0.682	0.663	-0.489	0.183	-0.353	0.834	0.910	0.675
Q33	0.650	0.798	0.670	0.636	-0.437	0.183	-0.335	0.794	0.891	0.643
Q34	0.681	0.801	0.678	0.673	-0.459	0.198	-0.359	0.837	0.905	0.682
Q35	0.672	0.811	0.692	0.692	-0.474	0.159	-0.324	0.830	0.901	0.646
Q36	0.679	0.830	0.710	0.690	-0.475	0.171	-0.350	0.840	0.905	0.669
Q37	0.865	0.599	0.477	0.485	-0.324	0.077	-0.143	0.612	0.614	0.623
Q38	0.879	0.605	0.461	0.458	-0.326	0.078	-0.136	0.608	0.623	0.600
Q39	0.899	0.601	0.485	0.454	-0.318	0.083	-0.173	0.622	0.652	0.651
Q4	0.455	0.673	0.769	0.855	-0.370	0.161	-0.306	0.650	0.622	0.468
Q40	0.886	0.671	0.608	0.566	-0.392	0.112	-0.237	0.705	0.691	0.627
Q41	0.853	0.604	0.493	0.495	-0.270	0.026	-0.162	0.603	0.632	0.606
Q42	0.896	0.665	0.554	0.549	-0.381	0.068	-0.212	0.683	0.680	0.638
Q43	0.894	0.592	0.516	0.494	-0.320	0.057	-0.119	0.626	0.601	0.590
Q44	0.835	0.508	0.436	0.427	-0.289	0.052	-0.132	0.556	0.575	0.556
Q45	0.281	0.429	0.452	0.436	-0.213	0.172	-0.229	0.399	0.426	0.402
Q46	0.227	0.400	0.437	0.415	-0.278	0.126	-0.206	0.370	0.392	0.397
Q47	0.268	0.401	0.389	0.391	-0.239	0.160	-0.241	0.346	0.401	0.381
Q48	0.203	0.364	0.373	0.337	-0.249	0.099	-0.183	0.307	0.350	0.334
Q49	0.208	0.346	0.371	0.355	-0.229	0.089	-0.199	0.289	0.316	0.341
Q5	0.440	0.655	0.738	0.824	-0.388	0.165	-0.326	0.623	0.608	0.449
Q50	0.277	0.388	0.388	0.401	-0.212	0.133	-0.233	0.350	0.394	0.377
Q51	0.278	0.356	0.345	0.344	-0.229	0.032	-0.129	0.328	0.368	0.393
Q52	-0.372	-0.240	-0.177	-0.210	0.044	0.040	0.060	-0.273	-0.259	-0.380
Q53	-0.411	-0.301	-0.212	-0.245	0.080	0.010	0.099	-0.343	-0.332	-0.408
Q54	-0.401	-0.343	-0.277	-0.306	0.134	0.017	0.115	-0.373	-0.335	-0.467
Q55	-0.420	-0.324	-0.245	-0.265	0.102	-0.011	0.088	-0.362	-0.345	-0.477
Q56	-0.371	-0.291	-0.213	-0.243	0.126	0.004	0.092	-0.314	-0.301	-0.417
Q57	-0.487	-0.354	-0.262	-0.269	0.112	-0.029	0.054	-0.425	-0.402	-0.498
Q58	0.490	0.390	0.317	0.324	-0.118	0.104	-0.114	0.433	0.415	0.512
Q59	0.508	0.464	0.424	0.408	-0.175	0.115	-0.160	0.507	0.492	0.560
Q6	0.417	0.599	0.713	0.771	-0.417	0.205	-0.384	0.593	0.572	0.489

Q60	0.498	0.456	0.363	0.380	-0.156	0.090	-0.144	0.466	0.454	0.571
Q61	0.514	0.475	0.380	0.380	-0.190	0.095	-0.152	0.517	0.498	0.568
Q62	0.472	0.404	0.352	0.370	-0.221	0.083	-0.163	0.459	0.446	0.545
Q63	0.491	0.474	0.362	0.416	-0.176	0.026	-0.109	0.474	0.470	0.534
Q64	0.541	0.536	0.458	0.478	-0.313	0.124	-0.229	0.577	0.579	0.623
Q65	0.512	0.433	0.369	0.379	-0.142	0.079	-0.131	0.443	0.451	0.539
Q66	0.652	0.665	0.545	0.547	-0.377	0.055	-0.142	0.692	0.685	0.912
Q67	0.616	0.592	0.520	0.518	-0.327	0.051	-0.139	0.659	0.647	0.912
Q68	0.625	0.634	0.536	0.523	-0.415	0.082	-0.174	0.681	0.682	0.915
Q69	0.664	0.650	0.543	0.538	-0.389	0.065	-0.151	0.675	0.687	0.928
Q7	0.480	0.603	0.694	0.777	-0.458	0.000	-0.211	0.588	0.571	0.438
Q70	0.664	0.655	0.583	0.564	-0.402	0.096	-0.244	0.705	0.703	0.929
Q71	0.649	0.621	0.517	0.497	-0.347	0.054	-0.166	0.679	0.672	0.948
Q72	0.610	0.543	0.446	0.414	-0.306	0.080	-0.160	0.621	0.605	0.876
Q73	0.662	0.648	0.563	0.559	-0.386	0.069	-0.214	0.718	0.703	0.954
Q74	0.673	0.654	0.555	0.547	-0.399	0.085	-0.197	0.733	0.715	0.946
Q8	0.433	0.612	0.794	0.745	-0.366	0.206	-0.350	0.615	0.609	0.415
Q9	0.431	0.601	0.741	0.660	-0.425	0.225	-0.321	0.555	0.564	0.493

Table 21: Results of Cross Loadings
(Developed by the author)

Fornell and Larcker

An additional approach to evaluating discriminant validity is the Fornell-Larcker technique (1981), which states that a construct’s square root of its AVE must be greater than the correlations it has with other constructs. In other terms, the off-diagonal correlations within the same column must be less than the diagonal values, which represent the square roots of AVE. According to Hair et al. (2021), this suggests that a construct exhibits a higher degree of variance with its own indicators than with those of other constructs. The Fornell-Larcker criterion assesses discriminant validity at the construct level, as opposed to cross loadings (Henseler et al., 2015). The constructs meet the Fornell-Larcker criterion for discriminant validity, as demonstrated by Table 22, where each construct’s value on the diagonal exceeds its correlations with other constructs. This confirms that the constructs are distinct and capture different dimensions of the research.

	AS	CON	HA	HC	HM	PU	SAT	SE	CI	TA
AS	0.876									
CON	0.693	0.882								
HA	0.286	0.439	0.877							
HC	0.577	0.692	0.451	0.769						
HM	0.562	0.691	0.439	0.742	0.790					
PU	0.717	0.826	0.392	0.765	0.745	0.867				
SAT	0.725	0.795	0.434	0.756	0.743	0.801	0.898			
SE	-0.471	-0.356	-0.066	-0.267	-0.295	-0.402	-0.380	0.879		
CI	0.699	0.681	0.430	0.579	0.567	0.741	0.734	-0.508	0.935	
TA	0.566	0.512	0.102	0.427	0.443	0.547	0.537	-0.736	0.627	0.891

Table 22: Fornell-Larcker Discriminant Validity Results
(Developed by the author)
*Note: AS: Ageing Satisfaction; CON: Confirmation of Expectations; HA: Health Anxiety; HC: Health Consciousness; HM: Health Motivation; PU: Perceived Usefulness; SAT: Satisfaction; SE: Self-efficacy; CI: Continuance Intention to Use; TA: Technology Anxiety

5.5.1.5 Overview of the Structural Model

Figure 18 illustrates the structural model, offering an overview of the relationships among the latent constructs, represented as blue circles, and the paths that connect them, including the relevant path coefficients. This model evaluates the extent to which the independent variables account for the variance in the dependent variable (continuance intention to use). Notably, an R^2 value of 0.684 for the continuance intention to use indicates that the antecedents account for 68.4% of the variance in this dependent variable. This substantial explained variance highlights the importance of the constructs within the model and their strong predictive capabilities. In addition, the model includes several moderating effects (shown in green), such as health anxiety, technology anxiety, and self-efficacy, which influence the relationships between satisfaction and continuance intention to use. These moderating effects further refine our understanding of how different factors impact continuance intention to use. The path coefficients between the constructs are significant, confirming the hypothesised relationships in the model. For instance, the strong relationship between perceived usefulness and satisfaction, as well as the link between satisfaction and continuance intention to use, underscores the centrality of these constructs in predicting user behaviour.

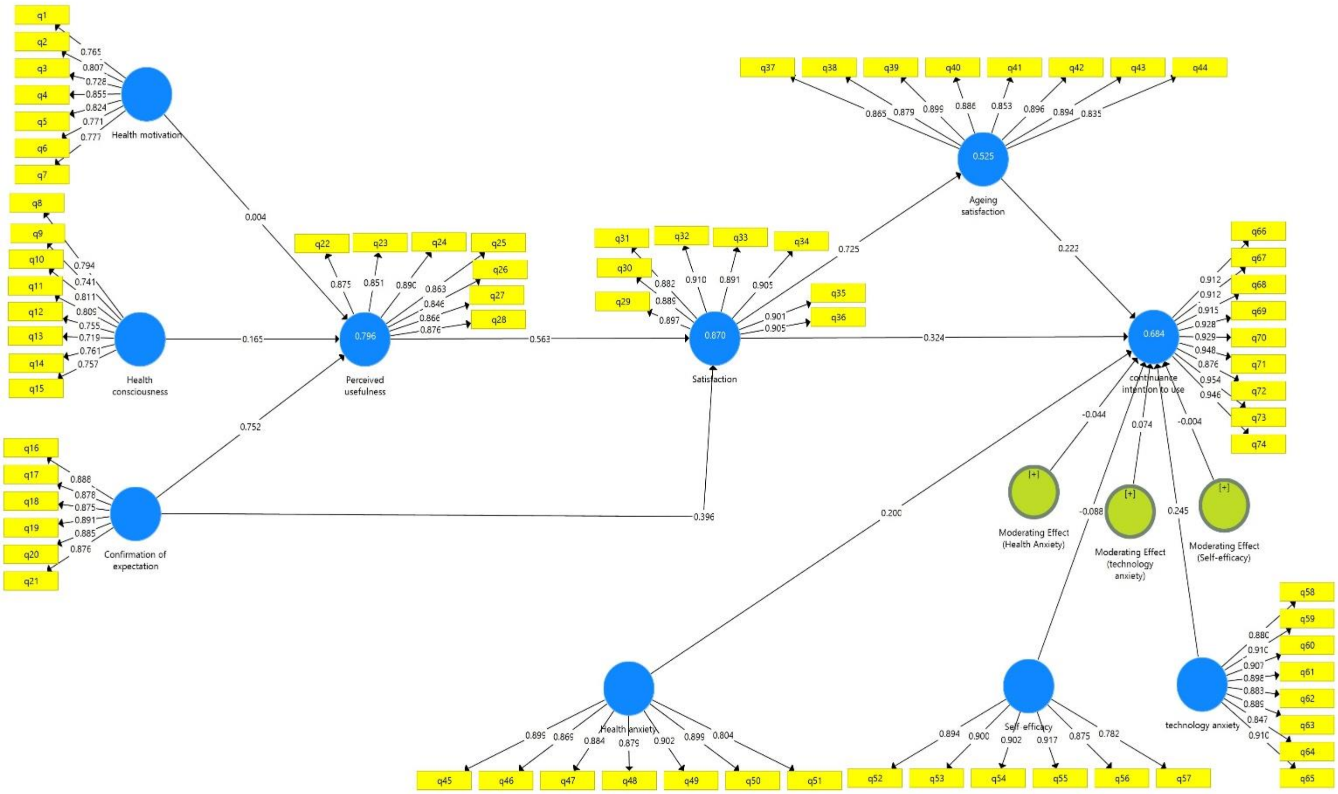

Figure 18: Overview of the Structural Model
(Developed by the author)

5.5.2 Structural Model Assessment

The examination of the connections between constructs is carried out by the structural model, which is also referred to as the inner model (Hair et al., 2022; Henseler et al., 2022). Additionally, the structural model analyses these interactions in the framework (Henseler et al., 2015; Ringle et al., 2023). To test the research hypotheses, this evaluation is carried out via bootstrapping (see Figure 19). Collinearity, coefficient of determination (R^2), path coefficients, and cross-validated redundancy (Q^2) are some of the major factors that should be evaluated, as stated in the guidelines that were provided by Hair et al. (2020). For the purpose of evaluating the structural model utilised in this investigation, the criteria are outlined in Table 23.

Criteria	Rules of Thumb
Collinearity	VIF should be under 5, or tolerance levels should be above 0.2
Path coefficients (β)	Greater path coefficients signify stronger predictor ability; p-value should be ≤ 0.05
Coefficient of determination (R2)	High = 0.67; Moderate = 0.33; Weak= 0.19
Cross-validated redundancy (Q2)	Above 0 = Meaningful; 0.25 - 0.50 = Medium; above 0.5 = Large predictive relevance
Effect Size (f2)	0.35 = Large effect; 0.15 = Medium effect; 0.02 = Small effect

Table 23: Criteria of Structural Model Assessment
Source: Cohen, 1998; Chin (1998); Hair et al. (2011); Hair et al. (2017); Hair et al. (2017).

Verifying that the variables in the structural model are independent by checking for collinearity is the first step in evaluating the model. Bootstrapping with 10,000 samples is then used to evaluate the significance of relationships within the model. Robust t-statistics for each path coefficient are generated (Ali et al., 2018). Next, the model's explanatory power is evaluated by measuring its ability to account for variations in the dependent variables. In the final stage, the model's predictive power, or its capacity to forecast future data, is assessed. Figure 19 (see below) illustrates the bootstrapping results, which are further discussed in this chapter. The path coefficients, represented by arrows between variables, indicate the strength and direction of relationships, with path coefficients having t-values over 1.96 considered statistically significant, thus providing strong evidence against the null hypothesis of no effect.

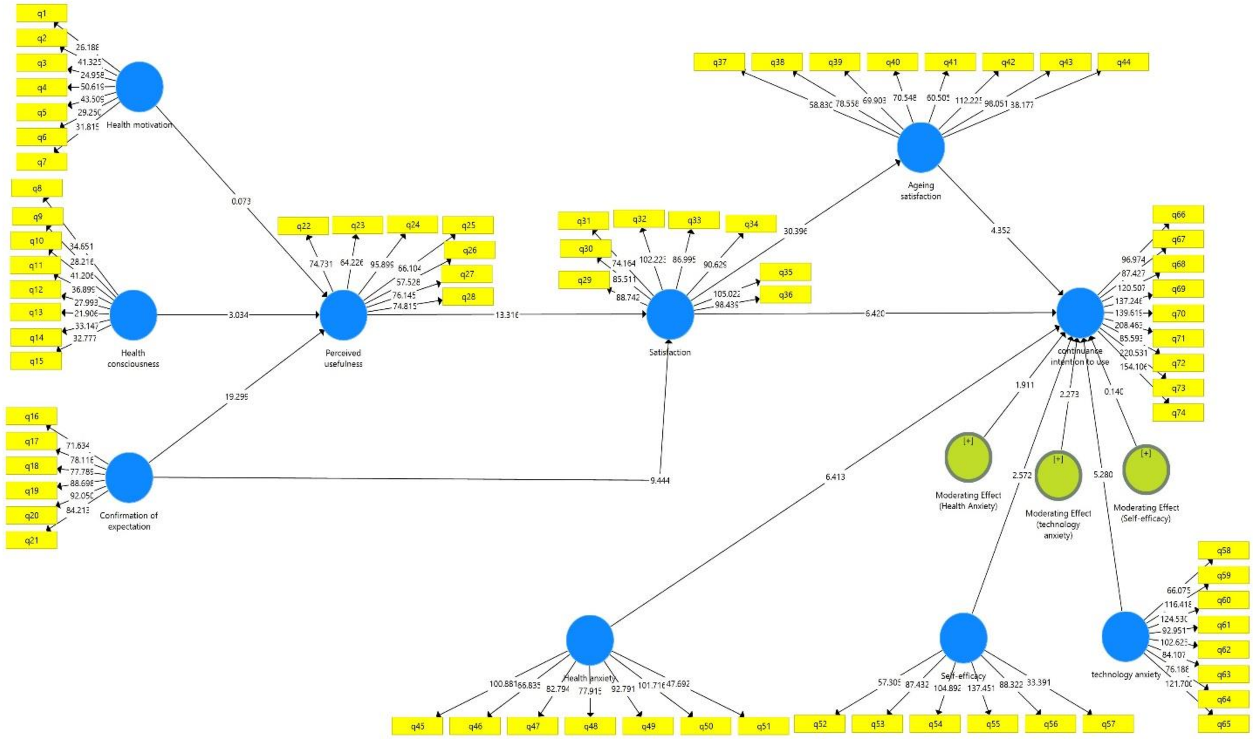

Figure 19: Bootstrapping Results (including individual item *t* values)
(Developed by the author)

5.5.2.1 Collinearity

The examination of collinearity is usually the first step in the process of evaluating the structural model (Koch and Lynn, 2012). Collinearity occurs when two constructs are substantially associated with one another, which makes interpretation complicated (Dormann et al., 2013; Hair et al., 2017). It can be a source of method bias in PLS-SEM, and the Variance Inflation Factor (VIF) is the methodology that is utilised to assess this phenomenon (Hair et al., 2020). According to Hair et al. (2022), the variance inflation factor (VIF) is determined by taking the reciprocal of the tolerance level. The tolerance level represents the proportion of variability in an independent variable that remains unexplained by other independent variables in the model. The construct may need to be deleted from the model or merged with another construct that is connected to it if the VIF values are greater than five or the tolerance values are less than 0.20. This indicates that the construct has a high degree of collinearity. VIF values that are lower than five are considered acceptable and indicate good collinearity (Hair et al., 2021). As shown in Table 24, all of the constructs have VIF values that are lower than the criterion of 5, which demonstrates that the collinearity levels are acceptable. The highest VIF values are for Perceived Usefulness and Confirmation of Expectation in relation to Satisfaction, both at 4.650, which are close to the threshold but still acceptable. Following these, Health Motivation in relation to Perceived Usefulness has a VIF of 4.174, and Health Consciousness in relation to Perceived Usefulness has a VIF of 3.211, both within acceptable limits. Other constructs, such as Ageing Satisfaction (2.413), Technology Anxiety (2.760), and Self-efficacy (2.276) in relation to Continuance Intention to Use, have lower VIF values, indicating lower collinearity. Satisfaction's VIF value with regard to Continuance Intention to Use is 3.269, also within acceptable bounds. The findings suggest that collinearity is not a significant concern in this study since all constructs exhibit VIF values below 5.

	Ageing Satisfaction	Perceived Usefulness	Satisfaction	Continuance Intention
Ageing Satisfaction				2.413
Confirmation of Expectation		2.978	4.650	
Health Anxiety				1.278
Health Consciousness		3.211		
Health Motivation		4.174		
Perceived Usefulness			4.650	
Satisfaction	1.000			3.269
Self-efficacy				2.276
Technology Anxiety				2.760

Table 24: Results of the Collinearity Testing
(Developed by the author)

5.5.2.2 Path Coefficient (β)

Execution of the PLS-SEM algorithm and interpretation of the path coefficient values should be performed in the subsequent phase. In order to highlight the hypothesised connections between model constructs, path coefficients (β) are utilised. The statistical significance of these connections is evaluated using *p*-values and t-values. Depending on the context, these coefficients can range from +1 to -1, where +1 indicates a strong positive relationship, 0 indicates a relationship that is minimal, and -1 indicates a relationship that is strongly negative (Garson, 2016). When analysing path coefficients, t-values and p-values are utilised to establish the importance of the findings. According to Sarstedt and Ringle (2010), a t-value greater than 1.96 with a p-value less than 0.05 ($p < 0.05$) is considered significant, while t-values above 2.57 with p-values below 0.01 ($p < 0.01$) indicate a high level of significance. Additionally, Hair et al. (2016) noted that in certain cases, t-values above 1.65 and p-values lower than 0.001 ($p < 0.001$) are interpreted as highly significant. For this analysis, bootstrapping was conducted with 10,000 sub-samples, and the path analysis results are displayed in Table 25.

Path Relationships	Path coefficient (β)	T statistics (|O/STDEV|)	P values	Hypotheses Results
HM->PU (H1)	0.004	0.073	0.942	Rejected
HC->PU (H2)	0.165	3.034	0.003	Accepted
CON->PU (H3)	0.752	19.299	0.000	Accepted
CON->SAT (H4)	0.396	9.444	0.000	Accepted
PU->SAT (H5)	0.563	13.316	0.000	Accepted
SAT->AS (H6)	0.725	30.396	0.000	Accepted
SAT->CI (H7)	0.324	6.420	0.000	Accepted
AS->CI (H8)	0.222	4.352	0.000	Accepted
SAT x HA->CI (H9)	-0.044	1.911	0.057	Rejected
SAT x TA->CI (H10)	0.074	2.273	0.023	Accepted
SAT x SE->CI (H11)	-0.004	0.140	0.889	Rejected

Table 25: Results of Path Analysis
(Developed by the author)

The path analysis results reveal that eight of the eleven hypotheses in the structural model were confirmed, exhibiting significant positive relationships. Particularly, the path from confirmation of expectation (CON) to Perceived Usefulness (PU) showed the most substantial effect (β = 0.752), signifying that confirmation of expectation is a key determinant of perceived usefulness. Conversely, the path Satisfaction (SAT) to Health Anxiety (HA) to Continuance Intention to Use (CI) had the least impact (β = -0.044) and was not statistically significant. Perceived Usefulness (PU) is significantly influenced by two independent variables: health consciousness (HC) and confirmation of expectation (CON). This suggests that both health consciousness and confirmation of expectation play critical roles in determining the perceived usefulness of digital healthcare technologies (DHTs). Regarding Satisfaction (SAT), it is positively and significantly influenced by both confirmation of expectation (CON) and Perceived Usefulness (PU). Additionally, satisfaction significantly affects ageing satisfaction (AS), highlighting its importance in the overall satisfaction with digital healthcare technologies among older users. In the context of continuance intention to use (CI), satisfaction (SAT) and ageing satisfaction (AS) have significant positive effects, with path coefficients of 0.324 and 0.222, respectively. This underscores the role of overall satisfaction and specific satisfaction with ageing in the continued use of digital healthcare technologies. Among the moderators, only the path SAT x TA → CI is significant (β = 0.074), suggesting that technology anxiety is a relevant factor in moderating the relationship between satisfaction and continuance intention to use digital healthcare technologies. However, several paths did not show significant effects: HM → PU (β = 0.004), SAT x HA → CI (β = -0.044), and SAT x SE → CI (β = -0.004). Consequently, hypotheses H2, H3, H4, H5, H6, H7, H8, and H10 are accepted based on their significant positive relationships, while hypotheses related to the non-significant paths are rejected.

5.5.2.3 Coefficient of Determination (R^2)

The coefficient of determination (R^2) quantifies the proportion of variance in dependent latent variables that is explained by independent variables in a structural model (Hair et al., 2020). This metric plays a vital role in assessing the effectiveness of a structural model in PLS-SEM studies (Purwanto, 2021). R^2 values range from 0 to 1, where higher values signify a larger amount of variance accounted for. The interpretation of R^2 can differ among various fields of study. Hair et al. (2021) classify R^2 values of 0.25, 0.50, and 0.75 as representing weak, moderate, and significant predictive power. Conversely, Chin (1998) indicates that R^2 values of 0.19, 0.33, and 0.67 reflect weak, moderate, and significant predictive power. The varying benchmarks highlight the importance of taking the specific context into account when analysing R^2 values. The R^2 values for the model's endogenous constructs of this study, as presented in Table 26, range from 0.525 to 0.870. The model demonstrates a significant power to explain 87% of the variance in satisfaction, 79% in perceived usefulness, 68% in continuance intention to use, and 52% in ageing satisfaction. The results indicate that the model demonstrates significant predictive power regarding satisfaction, perceived usefulness, and continuance intention to use while showing moderate predictive power for ageing satisfaction. The elevated R^2 values for satisfaction, perceived usefulness, and continuance intention to use suggest that the independent variables in the model serve as strong predictors for these outcomes. On the other hand, the moderate R^2

value for ageing satisfaction indicates that, while it explains a notable portion of the variance, there are likely additional influencing factors that the model does not capture. The R^2 values demonstrate the model's robust explanatory power, providing important insights into the relationships between the key constructs.

	R Square
Ageing Satisfaction	0.525
Perceived Usefulness	0.796
Satisfaction	0.870
Continuance Intention to Use	0.684

Table 26: R^2 Values of the Endogenous Constructs
(Developed by the author)

5.5.2.4 Cross-Validated Redundancy - Stone Geisser's Q2 Value

The Stone-Geisser Q^2 value test is employed to evaluate the predictive relevance of a structural model's endogenous constructs (Geisser, 1975; Hair et al., 2019; Stone, 1974). As part of the blindfolding procedure, this test requires estimating parameters while temporarily excluding some data associated with a construct; subsequently, the estimated parameters are used to predict the missing points (Hair et al., 2016). This method is especially valuable for models containing several constructs, allowing for a robust assessment of predictive relevance (Götz et al., 2009). Predictive relevance is shown by a Q^2 value greater than 0.05, according to Chin (2010). Q^2 values above zero indicate predictive significance, as further explained by Hair et al. (2016); benchmarks of 0.02, 0.15, and 0.35 indicate weak, moderate, and strong relevance, respectively. Stronger predictive significance is indicated by higher Q^2 values and smaller differences between the original and predicted data (Hair et al., 2011). Table 27 highlights that all dependent variables have Q^2 values above zero, indicating predictive relevance. Satisfaction (Q^2 = 0.653), perceived usefulness (Q^2 = 0.556), and continuance intention to use (Q^2 = 0.543) demonstrate strong predictive power. Ageing satisfaction (Q^2 = 0.375) has moderate predictive power. Furthermore, all constructs exceed Chin's (2010) threshold of $Q^2 > 0.05$, confirming their predictive validity.

	SSO	SSE	Q^2 (=1-SSE/SSO)
Ageing Satisfaction	3,592.000	2,245.751	0.375
Perceived Usefulness	3,143.000	1,396.611	0.556
Satisfaction	3,592.000	1,247.517	0.653
Continuance Intention to Use	4,041.000	1,845.450	0.543

Table 27: Results of Cross-Validated Redundancy (Q2)
(Developed by the author)
*Note: SSO: Sum of Squared Observations; SSE: Sum of Squared Prediction Errors; Q2: Predictive Relevance

5.5.2.5 Effect Sizes (f^2)

In a structural model, the effect size (f^2) assesses how strongly the variables are connected to one another. It determines how the removal of an exogenous variable influences the R^2 value of the endogenous variable (Fritz et al., 2012). The f^2 value signifies the magnitude of the effect, with benchmarks of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively (Cohen, 2013). Evaluating effect sizes is essential for understanding the practical importance of relationships within the model, extending beyond just their statistical significance (Funder and Ozer, 2019). Typically, effect sizes are reviewed after the Q^2 and R^2 values have been assessed. The effect sizes (f^2) for the endogenous constructs in the model are shown in Table 28. The findings reveal that perceived usefulness has a significant impact on satisfaction (f^2 = 0.525), whereas confirmation of expectation has a moderate effect on satisfaction (f^2 = 0.259). For continuance intention to use, ageing satisfaction (f^2=0.065), health anxiety (f^2=0.099), satisfaction (f^2=0.102), and technology anxiety (TA) (f^2=0.069) have a small to medium effect. Self-efficacy (f^2=0.011) has a small effect on continuance intention to use. Regarding ageing satisfaction, satisfaction (f^2=1.106) has a large effect size. For perceived usefulness, confirmation of expectation (f^2=0.928) demonstrates a large effect size, while health consciousness (f^2=0.026) exhibits a small effect size, and health motivation (f^2=0.000) has no effect.

The effect sizes for the relationships between exogenous and endogenous variables offered valuable insights into the relative significance of each predictor in accounting for the variance of the dependent variables. For example, the large effect size of perceived usefulness on satisfaction suggested that perceived usefulness plays a crucial role in determining user satisfaction with digital healthcare technology. Also, the small effect sizes of ageing satisfaction, health anxiety, and technology anxiety on continuance intention to use indicated that these factors have a relatively minor but still relevant influence on users' intention to continue using digital healthcare technology. The absence of an effect of health motivation on perceived usefulness (f^2=0.000) suggested that users' motivation to maintain or improve their health does not significantly contribute to their perception of the usefulness of digital healthcare technologies.

Exogenous Variables (Independent)	Endogenous Variables (Dependent)			
	Ageing Satisfaction	Perceived Usefulness	Satisfaction	Continuance Intention
Ageing Satisfaction				0.065
Confirmation of Expectation		0.928	0.259	
Health Anxiety				0.099
Health Consciousness		0.026		
Health Motivation		0.000		
Perceived Usefulness			0.525	
Satisfaction	1.106			0.102
Self-efficacy				0.011
Technology Anxiety				0.069

Table 28: Results on Endogenous Effect Sizes (f^2)
(Developed by the author)

5.5.3 Mediation Analysis of Ageing Satisfaction

5.5.3.1 Introduction to the Mediation Analysis

The decision to conduct a mediation analysis examining the role of ageing satisfaction was driven by the need to gain a deeper understanding of how older users' attitudes toward their ageing process influence their continued use of digital healthcare technologies. Since ageing satisfaction reflects these attitudes, exploring whether it mediates the relationship between satisfaction and continuance intention to use is crucial. This analysis allows for an assessment of how satisfaction with the digital healthcare technology may indirectly influence older users' intention to continue using it by shaping their perceptions of their ageing process. Positive feelings toward ageing may reinforce the decision to continue using the technology, making ageing satisfaction an essential factor in understanding long-term usage. Additionally, ageing satisfaction is an ageing-specific factor, and investigating its mediating role adds relevance to the study by capturing a key aspect of older adults' lives that general factors, such as satisfaction with technology alone, may not address.

5.5.3.2 Methodology

The mediation analysis was conducted using the PROCESS macro for SPSS (Hayes, 2022), which employs ordinary least squares regression to evaluate both direct and indirect effects. To ensure the robustness of the mediation effect, bootstrapping with 5,000 resamples was performed to test the significance of the indirect effects. The analysis examined four key relationships: first, the effect of satisfaction on ageing satisfaction (Path a); second, the effect of ageing satisfaction on continuance intention to use (Path b); third, the direct effect of satisfaction on continuance intention, controlling for the mediator (Path c'); and finally, the combined indirect effect of satisfaction on continuance intention through ageing satisfaction (ab). This approach allowed for a comprehensive understanding of the mediating role of ageing satisfaction in the relationship between satisfaction and continuance intention.

5.5.3.3 Results

The results of the mediation analysis, as presented in Table 29, provide evidence for the role of ageing satisfaction as a mediator in the relationship between satisfaction and continuance intention to use digital healthcare technologies. Specifically, satisfaction was found to significantly predict ageing satisfaction ($B = 0.493$, $SE = 0.119$, $p < 0.001$, $\beta = 0.305$), indicating that higher levels of satisfaction with digital healthcare technologies are associated with more positive attitudes toward ageing. This relationship represents **Path a** of the mediation model. Further analysis revealed that ageing satisfaction significantly predicts continuance intention to use ($B = 0.171$, $SE = 0.045$, $p < 0.001$, $\beta = 0.219$), establishing **Path b**. This suggests that positive perceptions of ageing, fostered by satisfaction with digital healthcare technologies, contribute to older users' intention to continue using such technologies. Importantly, even when accounting for the mediating role of ageing satisfaction, satisfaction retained a significant direct effect on continuance intention to use ($B = 0.214$, $SE = 0.068$, $p = 0.034$, $\beta = 0.142$). This direct effect, known as **Path c'**, indicates that satisfaction directly influences continuance intention, independent of the mediating variable.

The indirect effect of satisfaction on continuance intention through ageing satisfaction (ab = 0.109) was tested using bootstrapping procedures with 5,000 resamples. The confidence interval for this indirect effect ranged from 0.039 to 0.168, confirming that the mediation effect was statistically significant. These findings demonstrate that ageing satisfaction partially mediates the relationship between satisfaction and continuance intention to use digital healthcare technologies, underscoring its importance as an intermediary factor. The overall model explained 11.7% of the variance in ageing satisfaction ($R^2 = 0.117$, $F(1,121) = 23.811$, $p < 0.001$) and 12.1% of the variance in continuance intention ($R^2 = 0.121$, $F(2,012) = 12.675$, $p < 0.001$). These results highlight the substantive contributions of both satisfaction and ageing satisfaction in predicting older users' continuance intention. The relationships among satisfaction, ageing satisfaction, and continuance intention are visually represented in Figure 20, and the statistical results are detailed in Table 29.

Figure 20: Mediation Model of Ageing Satisfaction in the Relationship Between Satisfaction and Continuance Intention to Use
(Developed by the author)

		M (Ageing Satisfaction)					Y (Continuance Intention to Use)			
Antecedent		B	SE	p	β		B	SE	p	β
X (Satisfaction)	a	.493	.119	.000	.305	c’	.214	.068	.034	.142
M (Ageing Satisfaction)		-	-	-		b	.171	.045	.000	.219
		R2 = .117					R2 = .121			
		F (1.121) = 23.811, p < .001					F (2.012) = 12.675, p < .001			

Table 29: Results of Mediation Analysis

*Note: a = path from predictor to mediator (Satisfaction -> Ageing Satisfaction); b = path from mediator to outcome (Ageing Satisfaction -> Continuance Intention to Use); c’ = direct path from predictor to outcome excluding the mediator (Satisfaction -> Continuance Intention to Use); R^2 = Coefficient of Determination; F = degrees of freedom; p = p-value; B = unstandardised regression coefficient; SE = standard error; β = standardised regression coefficient

Chapter 6: Discussion, Implications, and Future Research

6.1 Introduction

This chapter concludes the thesis by summarising the key findings from both the qualitative and quantitative phases of the study. It provides an in-depth analysis of the theoretical and practical implications, highlighting the study's contributions to the existing body of knowledge on digital healthcare technologies and the factors influencing older users' continuance intention to use them. The chapter discusses how these findings can be applied in real-world settings, particularly by healthcare providers, policymakers, brand managers, and digital healthcare technology developers. Additionally, the study's limitations are acknowledged, and recommendations for future research are provided to further advance the understanding of older users' engagement with digital healthcare technologies.

6.2 Interpretation of Findings

In the qualitative phase of this research, a comprehensive understanding of the factors influencing older users' continued use of digital healthcare technologies was developed using an abductive approach. The Expectation Confirmation Model (ECM) served as the primary theoretical framework, with ageing-specific constructs incorporated to address the unique context of older users. Unlike prior studies that predominantly focus on general technology users or younger populations, this research highlights the distinctive challenges and needs of older users, such as technology anxiety, health anxiety, and ageing satisfaction. This study demonstrates how the ECM, traditionally applied in generic contexts, is insufficient for capturing the complexities of older users' post-adoption behaviours, necessitating the integration of ageing-specific constructs. Also, some previous research using the ECM to predict continuance intention to use digital healthcare technologies has failed to fully explain continuance behaviour (e.g., Pal et al., 2020; Shen et al., 2018; Wu et al., 2020; Yousaf et al., 2021), indicating that the traditional constructs in the ECM may not adequately account for all influencing factors. By adding novel contextual variables, such as ageing satisfaction, health consciousness, and technology anxiety, this study enriches the ECM and enhances its ability to predict continuance intention among older users.

These ageing-specific factors have been largely overlooked in existing ECM applications, making this study critical for addressing these gaps and adapting the model to the unique characteristics of this growing demographic. The core constructs of the expectation confirmation model, including confirmation of expectation, perceived usefulness, satisfaction, and continuance intention to use, provided the foundation for understanding post-adoption behaviours in this context (Al Amin et al., 2024; Bhattacherjee, 2001). This aligns with the first research objective, which aims to identify the factors influencing older users' continuance intention to use digital healthcare technologies by extending the ECM with ageing-specific constructs and developing a theoretical model based on this extension.

In addition to these expectation confirmation model constructs, several factors from previous literature, including health motivation, health consciousness, health anxiety, and technology anxiety, were initially identified in the literature and subsequently emerged from the qualitative interviews. These constructs were recognised as ageing-specific constructs that affect older users' interactions with digital healthcare technologies. Ageing-specific constructs, such as ageing satisfaction, introduce a psychological dimension that is absent from traditional ECM applications. By addressing how older users' attitudes toward their ageing process influence their engagement with technology, this study bridges IS research with broader ageing theories, adding a critical layer of emotional and psychological understanding. This demonstrates that by integrating psychological and contextual factors, the ECM can better capture older users' post-adoption behaviours, thereby addressing the limitations of the traditional model and enhancing its explanatory power. Unlike general user groups, older adults' interactions with these technologies are shaped by demographic and psychological nuances, such as lower digital literacy, dependency on healthcare, and emotional barriers like technology anxiety (Ferreira-Brito et al., 2024; Krishnaswami et al., 2020; Seifert et al., 2019). This contextualisation addresses prior gaps in ECM studies by tailoring the model to meet the specific needs of ageing populations. The interviews confirmed the relevance of these factors and highlighted their influence on older users' continued use of digital healthcare technologies.

Moreover, two additional ageing-specific factors, including ageing satisfaction and self-efficacy, emerged from the interviews as important constructs. These factors, which are unique to the experiences of older users, were added to the model to better capture the distinct attitudes and behaviours related to their continued use of digital healthcare technologies. By introducing constructs such as ageing satisfaction, this study bridges the ECM with broader theories on psychological well-being and ageing, offering a holistic understanding of older users' continuance intention. The integration of ageing-specific constructs significantly enhances the ECM's ability to account for the unique characteristics of older users, underscoring the importance of emotional and psychological factors in understanding continuance intention within this demographic. Additionally, this advancement aligns with the second research objective, which investigates how these constructs influence the continued use of digital healthcare technologies among older adults. Based on these findings, 11 hypotheses were developed and tested in the subsequent quantitative phase.

Confirmation of expectation was a construct that emerged from the qualitative phase. Older users who felt that their experience with digital healthcare technologies met or exceeded their expectations reported finding the technology more useful and experienced higher satisfaction. This supports the expectation confirmation model framework, where confirmation of expectation is a key driver of perceived usefulness and satisfaction (Bhattacherjee, 2001; Gupta et al., 2020). The interviews indicated that when digital healthcare technologies performed in line with or beyond what older users expected, their satisfaction and their perceived usefulness with digital healthcare technologies increased. Perceived usefulness also emerged as a significant construct during the qualitative phase, as older users expressed the importance of digital healthcare technologies in helping them manage their health. Those who found the technology useful were more likely to experience higher satisfaction. This observation aligns with the expectation confirmation model, where perceived usefulness is a strong predictor of satisfaction (Bhattacherjee, 2001; Rabaa'i et al., 2021). Older users who perceived digital healthcare technologies as effective tools for managing their health reported higher levels of satisfaction with the technology. Similarly, satisfaction emerged as a key determinant in older users' decisions to continue using digital healthcare technologies. When older users felt satisfied with the performance of digital healthcare technologies, they were more likely to have a positive attitude toward ageing and a stronger intention to continue using the technology. This confirmed the role of satisfaction in shaping post-adoption behaviour and influencing the overall experience of using digital healthcare technologies.

The interviews also revealed the importance of health motivation and health consciousness in shaping older users' perceptions of digital healthcare technologies. Health motivation, defined as the internal drive to engage in health-promoting behaviours (Asadi et al., 2019; Moorman and Matulich, 1993), was found to influence how older users perceived the usefulness of digital healthcare technologies in managing their health. Similarly, health consciousness, which refers to an individual's awareness and concern about their health (Alam et al., 2020; Jayanti and Burns, 1998), was linked to older users' recognition of the benefits of digital healthcare technologies for improving their well-being. This construct bridges the gap between health behaviour theories and the ECM, illustrating how health-focused concerns influence technology engagement. Its inclusion highlights the broader applicability of the ECM in health-critical contexts, where users prioritise technologies that align with their well-being goals.

Technology anxiety emerged as a key factor during the interviews. Defined as concerns or unease about interacting with technology (Hoque and Sorwar, 2017; Meuter et al., 2003), it was observed that it influences older users' decisions about whether to continue using digital healthcare technologies. This construct expands the ECM by incorporating psychological barriers that affect older adults. Furthermore, its relevance can extend to other vulnerable populations, such as individuals with limited digital literacy or those facing accessibility challenges. This finding underscores the necessity of refining continuance models to address the emotional and cognitive dynamics of specific user groups, particularly older users. Additionally, health anxiety, defined as an excessive and irrational fear of potential health threats (Abramowitz and Braddock, 2008; Meng et al., 2020), emerged as a relevant factor. Identifying health anxiety as a potential moderator shows how stress affects older users' engagement with digital healthcare technologies. This suggests that adjusting post-adoption models like the ECM to include emotional and mental states could make them more accurate.

Older users with heightened concerns about their health found the reassurance provided by real-time health monitoring particularly valuable, which strengthened their intention to continue using digital healthcare technologies. From the qualitative interviews, ageing satisfaction and self-efficacy emerged as key factors influencing older users' continued use of digital healthcare technologies. Ageing satisfaction, which represents attitudes toward the ageing process (Shirahada et al., 2019), was found to significantly influence older users' perception of digital healthcare technologies. The inclusion of ageing satisfaction as a mediator introduces a psychological dimension to the ECM, which has traditionally focused on cognitive and utilitarian factors. This adaptation underscores the importance of well-being in understanding older adults' post-adoption behaviours and extends the model's relevance to broader demographic contexts where psychological well-being is critical. Older users with higher ageing satisfaction viewed digital healthcare technologies more positively, seeing them as beneficial tools for maintaining their health and independence. Finally, self-efficacy, or confidence in one's ability to effectively use technology (Bandura, 1986; Susanto et al., 2016), was identified as a moderating factor. Older users with lower self-efficacy expressed doubts about their ability to navigate digital healthcare technologies, which suggested that lower self-efficacy might hinder the translation of satisfaction into a strong intention to continue using digital healthcare technologies. The identification and testing of moderators such as technology anxiety, self-efficacy, and health anxiety align with the third research objective, which aims to explore the effect of moderators on the relationship between satisfaction and continuance intention to use digital healthcare technologies in the context of older users.

In the quantitative phase of this study, a PLS-SEM analysis was conducted to test the proposed hypotheses and examine the factors influencing older adults' intention to continue using digital healthcare technologies. The analysis revealed several significant insights into the factors driving continuance intention, including the roles of health consciousness, confirmation of expectation, perceived usefulness, satisfaction, ageing satisfaction, and technology anxiety. These findings directly address the first research objective by identifying the factors influencing older users' continuance intention to use digital healthcare technologies and validating the theoretical model extended with ageing-specific constructs.

Health consciousness was shown to have a significant positive effect on perceived usefulness ($\beta = 0.165$, $p = 0.003$). This result suggests that older adults who are more aware of and attentive to their health are likely to perceive digital healthcare technologies as valuable tools for maintaining and improving their well-being. This finding is in line with research by Cho et al. (2014) and Meng et al. (2019), which highlighted how health-conscious individuals, particularly older adults, tend to adopt health-related technologies more readily. These individuals are more likely to seek out and use technologies that help them monitor their health, thus viewing digital healthcare technologies as useful resources. The analysis also showed a significant relationship between perceived usefulness and satisfaction ($\beta = 0.563$, $p = 0.000$), reinforcing the Technology Acceptance Model (TAM) proposition that perceived usefulness is a key driver of user satisfaction (Davis, 1989). This finding aligns with the work of Bhattacherjee and Premkumar (2004) and Zhou (2014), who demonstrated that satisfaction with technology is largely shaped by how useful users find it. In the context of older adults, when they perceive digital healthcare technologies as beneficial for their health, their satisfaction with the technology increases, which in turn positively affects their commitment to continue using it.

The strongest predictor of perceived usefulness was confirmation of expectation, which had a substantial impact on both perceived usefulness ($\beta = 0.752$, $p = 0.000$) and satisfaction ($\beta = 0.396$, $p < 0.001$). This result underscores the importance of meeting older adults' expectations when it comes to the functionality and performance of digital healthcare technologies. When users' expectations are confirmed or exceeded, they are more likely to find the technology useful and be satisfied with their experience. This finding is consistent with findings from Bhattacherjee (2001) in the expectation confirmation model context and Gupta et al. (2021), who found similar results in studies of a smart fitness wearable. This confirms that older users who have their expectations met by digital healthcare technologies are more likely to perceive the technology as useful and experience higher satisfaction, which aligns with broader research on post-adoption behaviours in technology use (Kumar and Natarajan, 2020; Talukder et al., 2020). Satisfaction was found to significantly influence both ageing satisfaction ($\beta = 0.725$, $p = 0.000$) and continuance intention to use digital healthcare technologies ($\beta = 0.324$, $p = 0.000$). This supports the hypothesis that older adults who are satisfied with their experience of using digital healthcare technologies are more likely to have positive attitudes toward ageing and are more inclined to continue using these technologies. This finding is consistent with Bhattacherjee (2001), who emphasised satisfaction as a critical factor in continued technology use, and Wixom and Todd (2005), who found that satisfaction is pivotal in shaping attitudes toward technology adoption. Moreover, studies on digital healthcare technologies, such as Shen et al. (2022) and Xie and He (2020), have shown that user satisfaction directly impacts their likelihood to continue engaging with digital health tools, particularly among older users. Furthermore, ageing satisfaction itself was shown to be a significant predictor of continuance intention ($\beta = 0.222$, $p = 0.000$), indicating that older adults who feel positive about their ageing process are more likely to embrace and continue using technologies that support their health and well-being. This finding is consistent with Shirahada et al. (2019), who highlighted the link between positive attitudes towards ageing and technology acceptance among older populations. In addition, technology anxiety was found to significantly moderate the relationship between satisfaction and continuance intention ($\beta = 0.074$, $p = 0.023$). This finding reveals psychological barriers that affect older users' engagement with digital healthcare technologies, suggesting a need to integrate such barriers into post-adoption models like the ECM. By acknowledging the moderating role of technology anxiety, this study emphasises the importance of designing user-friendly technologies to mitigate its effects, especially for older populations. Older adults with higher levels of technology anxiety were less likely to continue using digital healthcare technologies, even if they were satisfied with them. This finding supports research by Vroman et al. (2015) and Zhu and Cheng (2024), which noted that anxiety about using technology can be a significant barrier to adoption and continued use, particularly among older users. By exploring the moderating effect of technology anxiety, this phase also directly addresses a research objective, which focuses on the role of moderators in shaping the relationship between satisfaction and continuance intention.

While many hypotheses were supported, some were not confirmed in the quantitative analysis. Contrary to expectations and studies on the adoption of digital healthcare technologies, such as Hayat et al. (2023), health motivation did not have a significant effect on perceived usefulness in the context of continuance intention to use digital healthcare technologies among older users (β

= 0.004, p = 0.942). This suggests that while older users may be motivated by health concerns, this motivation does not necessarily lead them to perceive digital healthcare technologies as useful tools for managing their health. One possible explanation is that health motivation might influence digital healthcare technology use in more nuanced ways than initially hypothesised. For instance, health motivation could be more relevant in specific health contexts, such as managing chronic conditions, or interact with factors such as user experience or support from healthcare providers, which might mediate its influence on perceived usefulness (Wu et al., 2022). Additionally, health motivation in older users has been found to be situational and context-dependent, particularly in managing chronic conditions versus general health maintenance, where specific needs or social support networks play a crucial role (Turner et al., 2021).

Another unexpected result was that health anxiety did not significantly moderate the relationship between satisfaction and continuance intention (β = -0.044, p = 0.057). While previous research has suggested that health anxiety can drive the continued use of health technologies (Kim and Han,2021; Meng et al.,2021), this study found that health anxiety did not strengthen the relationship between satisfaction and the intention to continue using digital healthcare technologies among older users. This suggests that while health anxiety may drive continuance intention to use, its moderating influence between satisfaction and continuance intention may be more complex than initially anticipated. Health anxiety can vary greatly among individuals and may fluctuate over time (Te Peol et al., 2016). This makes its moderating effect more complex than initially expected. For some older users, digital healthcare technologies might reduce anxiety by offering real-time health monitoring and reassurance. Conversely, constant monitoring could increase anxiety for others, especially if it reveals potential health issues (Rosman et al., 2020). This could complicate any clear moderating effects. Additionally, individual differences in coping mechanisms and past technology experiences may influence how health anxiety impacts digital healthcare technology use in the long term.

Finally, self-efficacy did not significantly moderate the relationship between satisfaction and continuance intention (β = -0.004, p = 0.889). This finding contrasts with research that highlights self-efficacy as a key determinant in technology use. Studies like Hsu and Chiu (2004) and Zhu et al. (2013) have shown that self-efficacy positively impacts the intention to continue using technology. Additionally, research suggests that self-efficacy plays a crucial role in motivating older users to engage with and adopt new technologies (Berkowsky et al., 2017; Heart and Kalderon, 2013; O'Neill et al., 2023). However, in this study, low levels of self-efficacy in older users did not significantly weaken the relationship between satisfaction and continuance intention. This could be because the study focuses on continuance intention, where older users have already overcome the initial barriers related to self-efficacy. As these users gain more familiarity with the technology, self-efficacy might become less critical, reducing its relevance as a predictor of their intention to continue using digital healthcare technologies (Yousaf et al., 2021). General measures of self-efficacy might also have failed to capture the specific task-related skills required for using digital healthcare technologies. Research suggests that general self-efficacy does not predict user behaviour in health technology contexts as accurately as task-specific measures (Zhang et al., 2017). This context-specific self-efficacy is a more precise predictor of how users interact with health technology, as it directly relates to the tasks they need to perform (Rahman et al., 2016). This could explain why self-efficacy did not significantly moderate the relationship between satisfaction and continuance intention. In this post-adoption phase, older users' confidence in using digital healthcare technologies may have stabilised, minimising the impact of low self-efficacy on their future intentions. These findings provide valuable insights into the factors that influence older users' continued use of digital healthcare technologies, highlighting the importance of both technology-related and ageing-specific factors. The results also reinforce the relevance of the expectation confirmation model as a useful framework for understanding post-adoption behaviours in this context while underscoring the need for further exploration of individual differences when examining older users' engagement with digital healthcare technologies. By integrating ageing-specific constructs, this study contributes to theoretical advancements by demonstrating the model's adaptability to demographic-specific research. These contributions highlight the need to refine the expectation confirmation model to address unique psychological and behavioural dynamics, such as those observed among older users, and suggest broader implications for extending the model to other population groups or specialised contexts.

Following the PLS-SEM analysis, a mediation analysis was conducted to gain a deeper understanding of how older users' attitudes toward their ageing process influence their continued use of digital healthcare technologies. Since ageing satisfaction is an ageing-specific factor, investigating its mediating role adds relevance to the study by capturing a key aspect of older users' lives that general factors, such as satisfaction with the technology alone, may not address. The results of the mediation analysis, performed using the PROCESS macro for SPSS, revealed that satisfaction significantly predicts ageing satisfaction (a = 0.493), and ageing satisfaction, in turn, has a significant positive effect on continuance intention to use (b = 0.171). Furthermore, the direct effect of satisfaction on continuance intention to use remained significant even when the mediator was included (c' = 0.214), indicating that satisfaction independently influences older users' intention to continue using these technologies. Additionally, the indirect effect of satisfaction on continuance intention through ageing satisfaction was significant (ab = 0.109), ranging from 0.039 to 0.168, as tested through bootstrapping with 5,000 resamples. This highlights the mediating role of ageing satisfaction, which introduces a psychological and emotional dimension to the ECM. By demonstrating how positive attitudes toward ageing enhance continuance intention, this study extends the model's applicability to contexts where emotional well-being influences technology engagement. This confirms that ageing satisfaction partially mediates the relationship between satisfaction and continuance intention to use. The partial mediation suggests that while satisfaction plays a direct role in shaping older users' intention to continue using digital healthcare technologies, ageing satisfaction provides an additional pathway through which this relationship operates. This finding underscores the importance of considering ageing-specific factors, such as ageing satisfaction, in understanding the continued use of digital healthcare technologies among older users. It highlights that older users' perceptions of their ageing experience significantly influence how satisfied they are with these technologies, which in turn affects their intention to use them over the long term.

6.3 Theoretical Implications

This study conceptually expands and empirically validates the Expectation Confirmation Model (ECM) by integrating ageing-specific constructs such as health consciousness, ageing satisfaction, and technology anxiety, which have been previously overlooked in studies focused on older users (Meng et al., 2022). By empirically validating these constructs, the study addresses a critical limitation in the ECM, which has traditionally lacked consideration for ageing-specific characteristics, needs, and concerns. These constructs offer significant advancements in understanding post-adoption behaviour in older users, who experience unique health concerns and attitudes towards both ageing and technology (Kim et al., 2019; Xie and He, 2020). Introducing and testing these constructs demonstrates the necessity of extending the ECM to account for such factors when applied to older populations, which significantly advances its theoretical applicability.

Health consciousness was found to have a direct positive effect on perceived usefulness, highlighting that older users' awareness of their health status plays a critical role in their assessment of digital healthcare technologies. This demonstrates that health consciousness not only influences technology evaluation but also bridges a notable gap between health behaviour theories and Information Systems (IS) continuance models. By highlighting this connection, the study advances the theoretical understanding of how health awareness directly informs older users' engagement with health-related technologies, addressing a key interdisciplinary gap. Tailoring post-adoption frameworks like the ECM to include health-related considerations specific to older adults deepens the theoretical understanding of their unique health goals and needs. This enhanced understanding illustrates how older users' broader health priorities influence their engagement with digital healthcare technologies, adding depth to the traditional ECM framework.

In addition, technology anxiety was found to moderate the relationship between satisfaction and continuance intention, revealing that older users with higher levels of anxiety about technology are less likely to continue using digital healthcare technologies, even when satisfied with their experience. This finding extends the ECM by demonstrating the role of psychological barriers that uniquely affect older users. The inclusion of technology anxiety addresses a critical omission in prior ECM applications, underscoring the importance of emotional and cognitive barriers in shaping older users' technology use. Prior studies have not empirically tested such moderating effects within the expectation confirmation model, making this a key novelty of this research (Lee et al., 2022). By addressing this gap, the study emphasises the need for age-specific considerations in post-adoption models to fully capture how older users' concerns about technology can impact sustained engagement.

Furthermore, the introduction of ageing satisfaction as both a direct predictor of continuance intention and a mediator between satisfaction and continuance intention represents a significant theoretical contribution to the literature on ageing and technology use. This study is the first to empirically demonstrate the role of ageing satisfaction within the ECM framework, showing that older users who are more satisfied with their ageing process are more likely to continue using digital healthcare technologies. This finding situates ageing satisfaction as a critical psychological dimension within IS research, bridging the gap between user satisfaction and long-term technology engagement. The mediation effect suggests that while satisfaction directly influences continuance intention, the overall strength of this relationship is enhanced through its impact on ageing satisfaction. This adds a novel dimension to the expectation confirmation model by refining our understanding of how older users' psychological well-being drives long-term technology use. The importance of psychological well-being as a driver of technology use has been highlighted in other fields (Orben and Przybylski, 2019; Sequeiros et al., 2022), but its specific influence within ageing populations in the ECM context is a new contribution.

This research also addresses the limitations of the expectation confirmation model, which traditionally emphasises constructs such as confirmation of expectations, perceived usefulness, and satisfaction but does not account for the ageing-specific factors that influence technology use. By integrating constructs like ageing satisfaction, health consciousness, and technology anxiety, this research adapts the expectation confirmation model to more accurately reflect the factors driving long-term technology use among older adults. The findings suggest that post-adoption models should be tailored to different user demographics, particularly older adults, to better capture the complexities of technology engagement in this growing population. This emphasis on demographic-specific tailoring underscores the model's adaptability and sets a foundation for further demographic-focused research within IS literature. This is particularly significant as previous research has shown that the effectiveness of technology continuance models can vary significantly depending on the demographic profile of the users (Foroughi et al., 2019; Hsiao et al., 2016; Lin et al., 2017).

In terms of reinforcing core relationships within the expectation confirmation model, confirmation of expectations was found to have a positive effect on both perceived usefulness and satisfaction, reaffirming that older users' satisfaction with digital healthcare technologies depends on the alignment between their expectations and the actual performance of the technology. This supports the expectation confirmation model's fundamental assumption that fulfilled expectations are critical for both user satisfaction and the perceived usefulness of technology. Additionally, perceived usefulness has a direct positive effect on satisfaction, which confirms the importance of usefulness in driving satisfaction in the post-adoption phase, especially among older users (Bhattacherjee, 2001; Gupta et al., 2021). This highlights the centrality of perceived usefulness as a construct that integrates user expectations with actual experiences, reaffirming its relevance in both theory and practice. This is particularly significant in the context of digital healthcare technologies, where the perceived usefulness plays a key role in determining whether older adults will continue to engage with these tools over time.

Finally, satisfaction has a direct positive effect on ageing satisfaction, suggesting that positive experiences with digital healthcare technologies can enhance older users' overall satisfaction with the ageing process. This relationship bridges the IS literature and broader ageing research, presenting a dual pathway where technology use influences both functional outcomes and emotional well-being. This relationship introduces a new theoretical link between technology use and psychological well-being, offering valuable insights for both the ageing literature and the IS literature. It provides a cross-disciplinary contribution by showing how positive experiences with technology not only influence technology continuance but also contribute to broader life satisfaction, particularly in the context of ageing.

6.4 Practical Implications

The research identified health consciousness, confirmation of expectations, perceived usefulness, satisfaction, ageing satisfaction, and technology anxiety as key factors affecting older users' intention to continue using digital healthcare technologies. These findings align with the research aim of promoting the long-term use of digital healthcare technologies to support healthy ageing by addressing the specific needs, expectations, and limitations of older users. By addressing these factors, stakeholders such as healthcare providers, policymakers, digital healthcare technology developers, and brand managers can work together to create a more conducive environment for sustained engagement with these technologies. This collaborative effort can ultimately lead to improved health outcomes and a better quality of life for this demographic.

Healthcare providers can take a lead role by promoting health consciousness among older adults. They should take the lead by emphasising the health-related benefits of these technologies. By helping older users recognise the health-related benefits of these technologies, providers contribute to the aim of enabling older users to manage their health more effectively and improve their quality of life. These advantages include self-monitoring, personalised health recommendations, and early detection of health issues (Schroeder et al., 2023; Schulz et al., 2015). Healthcare providers can communicate these benefits during routine health check-ups, recommending digital healthcare technologies that align with individual health goals, such as managing chronic conditions like diabetes or hypertension (Hermes et al., 2020; Kruse et al., 2016). For instance, the integration of remote monitoring devices into standard care can help older users see the value of using these technologies to manage their health proactively (Piras and Miele, 2017). At the same time, digital healthcare technology developers can contribute by designing features that specifically address the health consciousness of older users. This aligns with the research aim by fostering long-term engagement through tools that empower older users to make informed health decisions, enhancing their independence and well-being. This includes offering health reports, medication reminders, and tailored health data insights, which can help older users stay informed and engaged (Lee and Coughlin, 2015). Also, brand managers can support this effort through targeted marketing campaigns that clearly communicate the health benefits of digital healthcare technologies. By framing these technologies as essential tools for achieving and maintaining good health, brand managers help align marketing efforts with the aim of supporting healthy ageing. For instance, advertisements and content on websites and social media should emphasise how digital healthcare technologies empower older adults to take control of their health, manage chronic conditions, and promote preventative care. These marketing messages should align with broader health promotion initiatives, helping to frame digital healthcare technologies as essential tools for achieving and maintaining good health (Mehmet et al., 2020). Policymakers also play a role by embedding digital healthcare technologies into public health programs, raising awareness of their potential through clinical and community health programs (World Health Organization, 2018).

Another key recommendation involves enhancing the confirmation of expectations, which is crucial for fostering satisfaction and long-term use of digital healthcare technologies. This supports the aim of promoting the long-term use of these technologies by ensuring older users feel confident in their value and usability. Healthcare providers can achieve this by offering comprehensive onboarding and training programs for older users, ensuring that the technology is presented in a way that aligns with their needs and expectations. This can be done through hands-on workshops, video tutorials, and step-by-step guides, with ongoing support to help users feel more confident over time (Chen and Chan, 2014). Developers can further facilitate this process by using participatory design approaches that involve older users in the creation of digital healthcare technologies (Branco et al., 2016). This ensures that the technology is tailored to their specific needs and limitations, with user-friendly interfaces and simplified navigation. In line with these efforts, brand managers should align their marketing strategies with these user experiences, ensuring that advertisements focus on ease of use and accessibility. These strategies contribute to long-term engagement by addressing older users' expectations and building trust in the technology. Effective communication strategies, such as personalised messaging and clear instructional content, can bridge the gap between user expectations and actual product experience (Berg and Liljedal, 2022). Testimonials from older users who have successfully adopted digital healthcare technologies can further build trust, making older users more likely to adopt and continue using these technologies (Vaportzis et al., 2017). Meanwhile, policymakers can contribute by creating guidelines and standards that promote user-centred design standards for health technologies and funding programs that train healthcare providers to integrate these tools effectively.

Perceived usefulness, a key driver of satisfaction in this study, can be enhanced by stakeholders through various actions. Healthcare providers, for example, should reinforce the perceived usefulness of digital healthcare technologies by integrating them into regular healthcare routines and showing older adults how these technologies support their health goals. This can involve demonstrating the real-world benefits of digital healthcare technologies during medical appointments or using digital healthcare technologies data to tailor treatment plans. For instance, a healthcare provider could explain how a wearable device's data on heart rate or physical activity can improve a patient's management of a chronic condition such as diabetes or hypertension, thereby increasing the perceived usefulness of the technology (Kamei et al., 2022). Digital healthcare technology developers can also boost perceived usefulness by focusing on personalised health tools that provide real-time data and actionable feedback that align with older adults' health needs (Jimenez et al., 2023). Tools that offer insights based on individual health information allow older users to feel more in control of their health, which, in turn, fosters satisfaction (De Veer et al., 2015). Marketing efforts by brand managers should play a key role in promoting the practical benefits of digital healthcare technologies to older adults. Marketing campaigns should emphasise how digital healthcare technologies help older adults maintain their independence, manage chronic health conditions, and improve their overall quality of life. By clearly communicating these benefits in targeted marketing messages, brand managers can help older adults understand the usefulness of digital healthcare technologies, which leads to higher satisfaction and greater intention to continue using them (Jokisch et al., 2022). Policymakers can further support these efforts by providing funding for training programs that help healthcare providers integrate digital healthcare technologies into their services and by offering subsidies to ensure broader access among older users, especially those in low-income groups.

Satisfaction with digital healthcare technologies is also critical for fostering positive ageing satisfaction and encouraging long-term usage among older adults. These implications support the research aim of promoting the long-term use of digital healthcare technologies by enhancing both user satisfaction and overall well-being during the ageing process. Healthcare providers should enhance satisfaction by offering ongoing support and guidance for older adults using digital healthcare technologies. Ensuring that older adults feel confident in their use of digital healthcare technologies and understand how these tools contribute to their overall health can significantly enhance their satisfaction with the technology. This enhanced satisfaction reinforces the aim of enabling older users to manage their health more effectively, thereby improving their quality of life. Regular follow-ups, individualised advice, and clear communication about the benefits of continued use can further strengthen this relationship (Mace et al., 2022). Developers should ensure that digital healthcare technologies are reliable, easy to use, and tailored to the specific health needs of older users. By focusing on intuitive designs and personalisation features, developers can greatly enhance user satisfaction. These features not only promote sustained engagement but also align with the goal of fostering independence and healthy ageing among older users. Brand managers can reinforce this satisfaction by focusing their marketing campaigns on the positive experiences older users have had with digital healthcare technologies, particularly in relation to maintaining independence and improving quality of life. By showcasing how digital healthcare technologies improve quality of life, maintain independence, and support successful ageing, brand managers can encourage older adults to stay engaged with these technologies. Policymakers also have an essential role in creating supportive policies that promote the use of digital healthcare technologies among older adults. By funding public health programs that integrate digital healthcare technologies into regular care routines and providing incentives for healthcare providers to recommend these technologies, policymakers can support environments that increase satisfaction and encourage long-term use. Additionally, policies aimed at improving access to digital healthcare technologies, such as grants for low-income older adults, can ensure that these technologies are more widely adopted, leading to greater satisfaction and sustained engagement (Nikou et al., 2020).

However, it is also important to note that the effect of satisfaction on continuance intention is not only direct but is also mediated through ageing satisfaction. This means that while satisfaction with digital healthcare technologies directly influences older users' intention to continue using them, their overall satisfaction with the ageing process further enhances this relationship. This dual pathway supports the research aim by demonstrating how digital healthcare technologies can simultaneously promote health management and improve attitudes toward ageing. In other words, satisfaction with digital healthcare technologies not only directly influences older users' intention to continue using them but is amplified when it also leads to improved satisfaction with their ageing process. This dual pathway, where satisfaction reinforces ageing satisfaction, strengthens the long-term use of these technologies. Healthcare providers should, therefore, emphasise how continued use of digital healthcare technologies can promote not just health management but overall well-being in the ageing process. For example, regular follow-ups that highlight how digital healthcare technologies are contributing to positive health outcomes may improve satisfaction with the technology, which in turn enhances ageing satisfaction, making it more likely that older adults will continue using the technology. Developers can support this mediation effect by integrating features that explicitly connect health improvements with successful ageing milestones, thus reinforcing how the technology supports healthy ageing over time. For example, providing reminders of health goals met (such as improvements in mobility or reductions in blood pressure) aligns with the aim of helping older users maintain their health and independence while fostering a sense of accomplishment. Brand managers should incorporate this dynamic into their marketing strategies by showing how satisfaction with digital healthcare technologies can lead to greater confidence and satisfaction with ageing itself. Marketing campaigns should include testimonials from older adults who feel that using the technology has not only improved their health but also positively impacted their view of ageing, which ultimately encourages long-term engagement with the technology. Furthermore, policymakers can invest in public health initiatives that integrate digital healthcare technologies into community health services and senior care programs, creating a supportive infrastructure that enhances ageing satisfaction. Such initiatives align with the research aim by promoting mental well-being, physical activity, and long-term engagement with digital healthcare technologies. By promoting mental well-being and physical activity through these programs, policymakers can help ensure that older users view digital healthcare technologies as valuable tools for maintaining their health and independence, encouraging long-term use.

The study also suggests that promoting ageing satisfaction can contribute to the continued use of digital healthcare technologies. Healthcare providers should develop programs that support successful ageing by fostering social engagement, promoting physical activity, and providing opportunities for lifelong learning. For example, programs that offer group fitness classes, social activities, or community learning opportunities can integrate digital healthcare technologies that track health progress or provide medication reminders, enhancing older adults' confidence in managing their health (Santini et al., 2020). These programs not only enhance satisfaction but also contribute to the aim of fostering healthy, active ageing through the sustained use of these technologies. Digital healthcare technology developers can further contribute to ageing satisfaction by designing tools that help older users maintain independence, such as medication reminders or physical activity trackers. Brand managers should align their messaging with the idea that digital healthcare technologies support healthy, active ageing and improve overall quality of life. Marketing campaigns should emphasise the psychological and emotional benefits of using digital healthcare technologies, such as increased independence, staying connected with healthcare providers, and a greater sense of control over one's health. These messages can resonate with older users, fostering positive associations with digital healthcare technologies and encouraging their continued use (Tam et al., 2021). Policymakers should invest in public health initiatives that integrate digital healthcare technologies into community health services and senior care programs, creating a supportive infrastructure that enhances ageing satisfaction. By promoting mental well-being and physical activity through these programs, policymakers can help ensure that older users view digital healthcare technologies as valuable tools for maintaining their health and independence, encouraging long-term use.

Finally, addressing technology anxiety is essential for the sustained use of digital healthcare technologies among older adults. Digital healthcare technology developers should design intuitive interfaces with customisable settings that allow older users to adjust features like font size and contrast. Additionally, they should provide step-by-step tutorials, easily accessible help functions, and troubleshooting guides within the user interface to ease the learning process. These efforts align with the research aim by ensuring older users feel empowered to use digital healthcare technologies without intimidation, fostering long-term engagement. To further reduce technology anxiety, healthcare providers can host regular digital literacy workshops at community centres, clinics, or senior living facilities to ensure ongoing support. Programs such as tech buddy initiatives, where younger or tech-savvy volunteers offer one-on-one support to older users, can significantly reduce technology anxiety by building confidence and trust in the use of digital healthcare technologies (Tsai et al., 2015). Brand managers should focus on promoting simplicity and accessibility in their marketing campaigns, reassuring older users that digital healthcare technologies are designed with their needs in mind (Sharma et al., 2022). Policymakers also can support efforts to reduce technology anxiety by funding digital literacy programs aimed at older users. These initiatives directly contribute to the aim of addressing limitations faced by older users, thereby enhancing both satisfaction and continued use. They should also collaborate with developers to create design standards that prioritise accessibility, ensuring that digital healthcare technologies are user-friendly for a broad range of users, regardless of their technical proficiency (Charness and Boot, 2016). These collective efforts can help create a supportive environment that mitigates technology anxiety, thereby enhancing both satisfaction and the continued use of digital healthcare technologies.

6.5 Limitations and Further Research

While this study makes significant contributions to the understanding of older users' continuance intention to use digital healthcare technologies, it is essential to acknowledge its limitations and provide recommendations for future research to address them. Addressing these limitations would further advance the understanding of older users' behaviours, aligning with the study's aim of promoting the long-term use of digital healthcare technologies to support healthy ageing.

Firstly, the study focuses on older users in the United Kingdom, which may limit the generalisability of the findings to other cultural contexts. Cultural factors, such as values, beliefs, and social norms, can influence individuals' attitudes and behaviours related to technology adoption and use (Srite and Karahanna, 2006). For instance, cultures with high power distance and collectivistic orientations may have different perceptions and expectations regarding the use of digital healthcare technologies compared to cultures with low power distance and individualistic orientations (Hofstede, 2001). Future research addressing these cultural variations could enhance the generalisability of findings, helping to better understand the diverse needs of older users in different cultural contexts and further advancing the aim of fostering global adoption and long-term engagement. Conducting cross-cultural studies that compare the experiences and perceptions of older users from different countries or regions would provide a more comprehensive understanding of the phenomenon. Researchers should consider adapting research instruments to ensure cultural relevance and validity and employing both quantitative and qualitative methods to explore cultural nuances in depth.

Secondly, the study employs a cross-sectional design, which captures older users' perceptions and intentions at a single point in time. While cross-sectional studies can provide valuable insights into the relationships between variables, they do not allow for the examination of causal relationships or changes over time (Levin, 2006; Sedgwick, 2014). This limitation is particularly relevant in the context of technology adoption and continued use, as users' attitudes, behaviours, and experiences may evolve as they become more familiar with the technology (Bhattacherjee and Premkumar, 2004). Longitudinal studies would provide insights into how older users' engagement with digital healthcare technologies changes over time, contributing to the aim of ensuring sustained use and understanding the long-term impact on health and well-being. Future research should consider longitudinal designs to examine how the factors influencing continuance intention evolve over time and how actual continued use of digital healthcare technologies affects older users' health outcomes and well-being. Longitudinal studies can involve collecting data from the same participants at multiple time points. They allow researchers to track changes in behaviours, attitudes, and outcomes related to digital healthcare technology use (Caruana et al., 2015; Ployhart and Vandenberg, 2010). This approach would provide a more dynamic and comprehensive understanding of the factors influencing older users' long-term engagement with digital healthcare technologies and the impact of these technologies on their health and quality of life.

Thirdly, while this study focused on key ageing-specific constructs influencing older users' continuance intention to use digital healthcare technologies, such as health motivation, health consciousness, ageing satisfaction, health anxiety, technology anxiety, and self-efficacy, there may be additional factors not included in our theoretical framework that could enhance understanding. For example, social influence, referring to the impact of significant others' opinions, and trust, the willingness to rely on technology based on expected performance, have been found to play significant roles in technology adoption and continued use (Meng et al., 2019; Zhang et al., 2022). Incorporating these factors in future research could provide a more holistic view of the influences on continuance intention, addressing gaps related to social and trust dynamics and enhancing the practical utility of the findings. In the context of older users and digital healthcare technologies, social influence may manifest through the recommendations and support of family members, friends, or healthcare providers. This external encouragement can significantly impact older adults' decision-making processes regarding technology use. Similarly, trust in the accuracy, reliability, and security of digital healthcare technologies may be particularly important, given their potential concerns about privacy and the impact of these technologies on their health and well-being. Trust issues may deter older adults from fully engaging with digital healthcare technologies, even if they perceive them as useful. Although these constructs are significant, they were not included in our theoretical framework to maintain a focused scope on ageing-specific factors unique to older users. To address this limitation, future research should explore the potential impact of these and other relevant factors on older users' continuance intention to use digital healthcare technologies. Expanding the theoretical framework to include these constructs would provide a more comprehensive understanding of the phenomenon, integrating both ageing-specific and general factors influencing technology use among older adults.

Another limitation is the reliance on self-reported data, which may be subject to biases, such as social desirability and recall bias (Althubaiti, 2016). Social desirability bias occurs when participants respond to survey questions in a way that presents them in a favourable light rather than providing honest answers (Krumpal, 2013). In the context of digital healthcare technology use, older users may overreport their intentions to continue using these technologies to appear more technologically savvy or health conscious. Recall bias, on the other hand, refers to the inaccuracies that can arise when participants are asked to remember and report on past experiences or behaviours (Raphael, 1987). Older users may have difficulty accurately recalling their past interactions with digital healthcare technologies, particularly if they have been using these technologies for an extended period or if they have experienced cognitive declines. Future studies incorporating objective usage data would improve the reliability of findings, contributing to the broader aim of accurately capturing older users' engagement with digital healthcare technologies over time. This can involve collaborating with digital healthcare technology providers or healthcare organisations to access and analyse data on older users' engagement with digital healthcare technologies over time, providing a more reliable and comprehensive picture of their post-adoption behaviours.

Additionally, the research focuses on older users' continuance intention to use digital healthcare technologies in general, without distinguishing between specific types of technologies or health conditions. However, the factors influencing continuance intention may vary depending on the characteristics and functionalities of different digital healthcare technologies, as well as the specific health needs and concerns of older users. Addressing this limitation would help tailor strategies to specific technologies and health contexts, aligning with the aim of meeting diverse user needs and expectations. For instance, the factors influencing the continued use of wearable fitness trackers may differ from those influencing the continued use of telemedicine platforms, as these technologies serve different purposes and require different levels of user engagement (Canhoto and Arp, 2017). Similarly, older users with chronic conditions, such as diabetes or heart disease, may have different motivations and challenges related to digital healthcare technology use compared to those who are relatively healthy. Future research should investigate the factors influencing continuance intention for specific digital healthcare technologies, such as wearable devices, mHealth apps, eHealth services, or telemedicine, and explore how these factors may differ across various health conditions. This can involve conducting more focused studies that examine the unique challenges and opportunities associated with specific types of digital healthcare technologies and health conditions, providing targeted insights for the design and implementation of these technologies.

Furthermore, while the study provides valuable insights into the factors influencing older users' continuance intention to use digital healthcare technologies, it does not directly examine the impact of continued use on health outcomes and well-being. Understanding the long-term effects of digital healthcare technology use on older users' physical, mental, and social health is crucial for demonstrating the value and effectiveness of these technologies (Kunonga et al., 2021). For example, continued use of digital healthcare technologies may contribute to improved disease management, increased physical activity, reduced healthcare utilisation, and enhanced quality of life among older users. Future research examining these outcomes would provide evidence-based support for the research aim, highlighting how these technologies directly contribute to healthy ageing. However, the evidence on the health benefits of digital healthcare technology use remains limited and mixed, particularly in the context of older users (Fox and Connolly, 2018; Volpp and Mohta, 2017). Future research should investigate the relationship between the continued use of digital healthcare technologies and various health indicators, such as disease management, functional ability, quality of life, and healthcare utilisation. This can involve conducting randomised controlled trials or observational studies that compare the health outcomes of older users who continue to use digital healthcare technologies with those who do not, controlling for potential confounding factors. By providing evidence on the health benefits of sustained digital healthcare technology use, researchers can contribute to the development of evidence-based guidelines and policies for the promotion and implementation of these technologies in healthcare settings. By addressing these limitations and pursuing these avenues for future research, the field can develop a more comprehensive, nuanced understanding of older users' continuance intention to use digital healthcare technologies. This will further support the aim of designing effective, user-friendly, and impactful digital healthcare technologies that enable older adults to manage their health and improve their quality of life, aligning with the overarching goal of promoting healthy ageing.

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Appendix 1. Interview Questions

What explains older users' continuance intention to use digital healthcare technologies (DHTs)?

Hi.

Thanks for participating in this interview and providing me your valuable time. (Not more than 90 minutes).

I am Masoumeh Jahangiri, and I am a doctoral researcher at Brunel University London, currently undertaking a research study on older users' continuance intention to use digital healthcare technologies (DHTs).

Please note, you must be over 65 years old, live in the UK, and use a wearable technology device to be eligible to participate in this interview. Participation in this interview is voluntary.

This study has been approved by Brunel University's Ethics Committee and I would like to reassure you that your feedback will remain anonymous, confidential, will be stored securely and shall not be used other than for the purpose of this study.

Please make sure that you answer all questions by explaining your opinion, viewpoint with the most appropriate responses and words as much as you can explain. In case you have any comment on the questions please feel free to add your comment.

Background

1. How would you describe your health, generally?
2. What aspects of your health cause you the most concern?

3. How do you monitor your health concerns?
4. What types of digital devices or applications do you use to track or manage your health?
5. What is the brand of your digital healthcare technologies?
6. What steps do you take to maintain or improve your health?
7. How often do you think about your health and well-being in your daily life?

Initial Adoption

When you used a digital healthcare technology for the very first time,

1. What did drive you to use a digital healthcare technology?
2. Which applications did you use on your digital healthcare technologies?
3. What features of the device did you use the most?
4. What did you use that feature for? (E.g., Communications, health, fitness, timekeeping tasks)
5. How would you describe your experience from using the device?
6. What benefits did you notice from using the device?
7. Did you have any concerns? What were they?
8. How did your experience with the device compare to what you thought it would be like before using it?

Probing and follow-up questions based on participants' responses on experience:

- how useful was the device to you?
- How long did it take you to get used to the device?
- How satisfied were you with the device?
- Did using the device cause you any anxiety or stress?

Continued Use

1. How often do you use the device?
2. Do you still have the same purpose for using the device?
3. Do you still use the same applications on your device?
4. Why do you choose to continue using the device?
5. Overall, how satisfied are you with using digital healthcare technology to manage your health?

Probing and follow-up questions based on participants' responses:

- Do you still see value/benefits from using the device?
- Do you still have concerns about using the device?
- Does using the device help ease any health-related anxieties?

We are now coming to the end of the interview, and I have just a few more general questions for you.

Closing questions

1. How old are you?

2. Let me summarise our major discussion today, do you agree with these points?

Thanks for your participation.

Appendix 2. Interview Invitation

Dear Invitee,

I hope you are well. My name is Masoumeh Jahangiri. I am a doctoral researcher at Brunel University London. The title of the research that I am conducting is:

‘What explains the older users’ continuance intention to use digital healthcare technologies?’

The intention is to investigate the attitudes of older users toward digital healthcare technologies and explore influential factors that may contribute to the continuance intention to use them as a means to manage their health, through the use of questionnaires and interviews.

I am looking for participants who are:

- Using wearable technology devices (such as Smartwatches, Fitness Trackers, Continuous Glucose Monitors (CGMs), Wearable Electrocardiograms (ECGs), Wearable Blood Pressure Monitors, Hearing Aids and Smart Earbuds)
- over 65 years old
- living in the UK

I am kindly requesting your participation in this study If you have all the criteria and you are interested in taking part in my research interview or/and questionnaire, please let me know by email.

Please be advised that the interview is expected to last no longer than one and a half hours.

Brunel University’s Ethics Committee has approved this study, and I would like to reassure you that your feedback will remain anonymous and confidential, will be stored securely and shall not be used other than for the purpose of this study.

Thank you for your time,

Masoumeh Jahangiri

1732776@brunel.ac.uk

Appendix 3. Interview Letter of Approval

College of Business, Arts and Social Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

4 February 2022

LETTER OF CONDITIONAL APPROVAL

APPROVAL HAS BEEN GRANTED FOR THIS STUDY TO BE CARRIED OUT BETWEEN 04/02/2022 AND 28/02/2023

Applicant (s): Ms Masoumeh Jahangiri

Project Title: What explains the elderly's continuance intention to use wearable technology devices? The case of smartwatches and fitness trackers.

Reference: 30922-LR-Feb/2022- 37808-2

Dear Ms Masoumeh Jahangiri

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has agreed that there is no objection on ethical grounds to the proposed study. Approval is given on the understanding that the conditions of approval set out below are followed:

- **You must replace the word 'elderly' with 'older people' or 'older adults' in your title and throughout all your documentation, participant information, interview schedule, survey questionnaire, consent form and recruitment email.**
- **Participant Information – Under "What are the indemnity arrangements?" delete the sentence: "If you can demonstrate that you experienced harm as a result of your participation in this study, you may be able to claim compensation."**
- **You are not required to resubmit your BREO form after making the changes/addressing the points listed above.**
- **Approval is given for remote (online/telephone) research activity only. Face-to-face activity and/or travel will require approval by way of an amendment.**
- **The agreed protocol must be followed. Any changes to the protocol will require prior approval from the Committee by way of an application for an amendment.**
- **Please ensure that you monitor and adhere to all up-to-date local and national Government health advice for the duration of your project.**

Please note that:

- Research Participant Information Sheets and (where relevant) flyers, posters, and consent forms should include a clear statement that research ethics approval has been obtained from the relevant Research Ethics Committee.
- The Research Participant Information Sheets should include a clear statement that queries should be directed, in the first instance, to the Supervisor (where relevant), or the researcher. Complaints, on the other hand, should be directed, in the first instance, to the Chair of the relevant Research Ethics Committee.
- Approval to proceed with the study is granted subject to receipt by the Committee of satisfactory responses to any conditions that may appear above, in addition to any subsequent changes to the protocol.
- The Research Ethics Committee reserves the right to sample and review documentation, including raw data, relevant to the study.
- If your project has been approved to run for a duration longer than 12 months, you will be required to submit an annual progress report to the Research Ethics Committee. You will be contacted about submission of this report before it becomes due.
- You may not undertake any research activity if you are not a registered student of Brunel University or if you cease to become registered, including abeyance or temporary withdrawal. As a deregistered student you would not be insured to undertake research activity. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Page 1 of 2

Appendix 4. Interview Participant Information Sheet

PARTICIPANT INFORMATION SHEET

Study title:

What explains the older users' continuance intention to use digital healthcare technologies (DHTs)?

Invitation Paragraph

You are invited to take part in a research study. You do not have to take part if you do not want to. It is important that you understand why the research is being done and what the questionnaire will entail. Please read the following information clearly, and if there is anything that you do not understand or if you would like more information, please feel free to let me know.

What is the purpose of the study?

The purpose of the study is to investigate older users' attitudes toward digital healthcare technologies and investigate influential factors that may contribute to the continuance intention to use digital healthcare technologies to manage their health through questionnaires and interviews.

Why have I been invited to participate?

You have been invited to participate in this study as you are a current user of wearable technology device (e.g., Smartwatches, Fitness Trackers, Continuous Glucose Monitors (CGMs), Wearable Electrocardiograms (ECGs), Wearable Blood Pressure Monitors, Hearing Aids and Smart Earbuds), over 65 years old, and living in the UK.

Do I have to take part?

Participation is completely voluntary, so it is up to you and you alone to decide if you would like to take part. If you do agree to participate, you will be given this information sheet to keep. If you do decide to take part, you are still able to withdraw until 28/02/2023.

What will happen to me if I take part?

If you decide to participate, you will be required to answer the interview questions. The interview is estimated to take you no more than 90 minutes. All I expect from you is to answer honestly.

Are there any lifestyle restrictions?

There are no commitments or lifestyle restrictions associated with participating.

What are the possible disadvantages and risks of taking part?

There are no disadvantages or risks associated with taking part in this study. All data is anonymous, and no personal information will be used or stored.

What if something goes wrong?

If you wish to make a complaint, the person to contact is the Chair of the College of Business, Arts and Social Sciences Research Ethics Committee (cbass-ethics@brunel.ac.uk.).

Will my taking part in this study be kept confidential?

All information which is collected about you during the course of the research will be kept strictly confidential. Any information about you which leaves the University will have all your identifying information removed. With your permission, anonymised data will be stored and may be used in future research – you can indicate whether or not you give permission for this by way of the Consent Form.

Will I be recorded, and how will the recording be used?

The interview will be audio-recorded the whole time. The recording will remain anonymous, confidential, and will be stored securely and shall not be used other than for the purpose of this study.

What will happen to the results of the research study?

The results of this study will be presented in my PhD thesis. If you wish to know the results of my study, then please feel free to contact me at the email address provided below.

Who is organising and funding the research?

The researcher in conjunction with Brunel Business School, College of Business, Arts and Social Sciences, Brunel University London. No external funds are being provided.

What are the indemnity arrangements?

Brunel University London provides appropriate insurance cover for research which has received ethical approval.

Who has reviewed the study?

This study has been reviewed by the College Research Ethics Committee.

Passage on the University's commitment to the UK Concordat on Research Integrity

Brunel University is committed to compliance with the Universities UK Research Integrity Concordat. You are entitled to expect the highest level of integrity from our researchers during the course of their research.

Contact for further information and complaints.

Researcher name and details:

Masoumeh Jahangiri - 1732776@brunel.ac.uk

Supervisors' names:

Dr Yousra Asaad - Yousra.Asaad@brunel.ac.uk

Dr Pantea Foroudi - Pantea.Foroudi@brunel.ac.uk

For complaints, Chair of the Research Ethics Committee:

Professor David Gallear

David.Gallear@brunel.ac.uk

Thank you for taking part in this study.

Appendix 5. Interview Consent Form

CONSENT FORM

What explains older users' continuance intention to use digital healthcare technologies (DHTs)?

Masoumeh Jahangiri

APPROVAL HAS BEEN GRANTED FOR THIS STUDY TO BE CARRIED OUT BETWEEN 04/02/2022 AND 28/02/2023

The participant (or their legal representative) should complete the whole of this sheet.		
	YES	NO
Have you read the Participant Information Sheet?	☐	☐
Have you had an opportunity to ask questions and discuss this study? (via email/phone for electronic surveys)	☐	☐
Have you received satisfactory answers to all your questions? (via email/phone for electronic surveys)	☐	☐
Do you understand that you will not be referred to by name in any report concerning this study?	☐	☐
Do you understand that:		
• You are free to withdraw from this study at any time.	☐	☐
• You don't have to give any reason for withdrawing.	☐	☐
• Choosing not to participate or withdrawing will not affect your rights.	☐	☐
• You can withdraw your data any time up to 28/02/2023	☐	☐
I agree to my interview being recorded.	☐	☐
I agree to the use of non-attributable quotes when the study is written up or published.	☐	☐
The procedures regarding confidentiality have been explained to me.	☐	☐

I agree that my anonymised data can be stored and shared with other researchers for use in future projects.	☐	☐
I agree to take part in this study.	☐	☐

Signature of research participant:	
Print name:	Date:

Appendix 6. Survey Questionnaire

What explains older users' continuance intention to use digital healthcare technologies (DHTs)?

Dear respondent,

Thanks for participating in this survey and providing me with your valuable time (Not more than 20 minutes).

I am Masoumeh Jahangiri, a doctoral researcher at Brunel University London, currently undertaking a research study on the continuance intention to use digital healthcare technologies (DHTs) by older people.

Please note you must be over 65 years old, live in the UK, and be a current user of a digital healthcare technology (e.g., wearable technology devices, mHealth, eHealth services, and telemedicine) to be eligible to participate in this survey. Participation in this questionnaire is voluntary.

Brunel University's Ethics Committee has approved this study, and I would like to reassure you that your feedback will remain anonymous and confidential, will be stored securely and shall not be used other than for the purpose of this study.

Please confirm the following:

☐ I have read the Participant Information Sheet included with this questionnaire.

☐ I am over the age of 18.

☐ I understand that no personal identifying data is collected in this study, therefore I know that once I have submitted my answers, I am unable to withdraw my data from the study.

☐ I agree that my data can be anonymised, stored and used in future research in line with Brunel University's data retention policies.

☐ I agree to take part in this study.

Before we get started with the main questionnaire, please tell me about yourself and your background:

1) What is your age? (Please write down the number): _____
2) Do you live in the UK? Yes ☐ No ☐
3) Do you use a digital healthcare technology? Yes ☐ No ☐

Please indicate/rate on a five-point scales the extent to which you strongly disagree or strongly agree with the following statements.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
1. I try to prevent health issues before I feel symptoms.	1	2	3	4	5
2. I try to protect myself against the health issues I hear about.	1	2	3	4	5
3. I do not take action against health issues I hear about until I know I have a problem.	1	2	3	4	5
4. I try to maintain a healthy lifestyle.	1	2	3	4	5
5. I try to manage my health risk factors in my daily life.	1	2	3	4	5
6. I have an interest in maintaining a healthy lifestyle.	1	2	3	4	5
7. I usually value my health.	1	2	3	4	5
8. My health depends on how well I take care of myself.	1	2	3	4	5
9. I am actively engaged in the prevention of disease and illness.	1	2	3	4	5
10. Taking preventive measures will keep me healthy for life.	1	2	3	4	5
11. Living a healthy life is important to me.	1	2	3	4	5
12. I am constantly examining my health.	1	2	3	4	5
13. I realise that bad living habits will harm my health.	1	2	3	4	5
14. I hope to reduce the harm to the body by changing bad living habits.	1	2	3	4	5

15. I think I can improve my health effectively in various ways, such as through exercise.	1	2	3	4	5
16. My experience with using digital healthcare technologies is better than what I expected.	1	2	3	4	5
17. The function provided for digital healthcare technologies in general is better than I expected.	1	2	3	4	5
18. Digital healthcare technologies fit my requirements better than I expected.	1	2	3	4	5
19. Digital healthcare technologies are more useful than I expected.	1	2	3	4	5
20. The features provided by digital healthcare technologies are better than what I expected.	1	2	3	4	5
21. Overall, most of my expectations from using digital healthcare technologies were confirmed.	1	2	3	4	5
22. I find digital healthcare technologies useful in my daily life.	1	2	3	4	5
23. Using digital healthcare technologies enables me to check my health condition quickly.	1	2	3	4	5
24. Using digital healthcare technologies increases my productivity.	1	2	3	4	5
25. Using digital healthcare technologies is useful to check my health condition more conveniently.	1	2	3	4	5
26. Digital healthcare technologies are beneficial to manage health.	1	2	3	4	5
27. Using digital healthcare technologies makes it easier to check my health condition.	1	2	3	4	5
28. Using digital healthcare technologies save my time and effort.	1	2	3	4	5
29. Experience of using digital healthcare technologies has been satisfactory.	1	2	3	4	5
30. I am satisfied with my digital healthcare technologies.	1	2	3	4	5
31. I think I made the correct decision in using digital healthcare technologies.	1	2	3	4	5
32. My overall experience of digital healthcare technologies use was very pleasant.	1	2	3	4	5
33. Using digital healthcare technologies makes me feel very contented.	1	2	3	4	5
34. I am very pleased after using digital healthcare technologies.	1	2	3	4	5

35. Using digital healthcare technologies makes me feel delighted.	1	2	3	4	5
36. Digital healthcare technologies are very satisfactory to me.	1	2	3	4	5
37. Things keep getting worse as I get older.	1	2	3	4	5
38. I have as much as pep as I did last year.	1	2	3	4	5
39. The older I get, the more useless I feel.	1	2	3	4	5
40. I am as happy now as I was when I was younger.	1	2	3	4	5
41. As I get older, things are better than I thought they would be.	1	2	3	4	5
42. So far, I am satisfied with the way that I am ageing.	1	2	3	4	5
43. The older I get, the more I have had to stop doing things that I liked.	1	2	3	4	5
44. Getting older has brought with it many things that I do not like.	1	2	3	4	5
45. I am afraid that I have a serious illness.	1	2	3	4	5
46. I worry about my health.	1	2	3	4	5
47. If I hear about an illness, I think I have it myself.	1	2	3	4	5
48. I usually feel at risk for developing a serious illness.	1	2	3	4	5
49. I usually feel at very high risk for developing a serious illness.	1	2	3	4	5
50. I usually think I have a serious illness.	1	2	3	4	5
51. If I have a bodily sensation or change, I wonder what it means.	1	2	3	4	5
52. Using digital healthcare technologies makes me very nervous.	1	2	3	4	5
53. Using digital healthcare technologies makes me feel worried.	1	2	3	4	5
54. Using digital healthcare technologies makes me feel uncomfortable.	1	2	3	4	5
55. Using digital healthcare technologies makes me feel uneasy and confused.	1	2	3	4	5
56. Using digital healthcare technologies is somewhat intimidating to me.	1	2	3	4	5
57. I have difficulty understanding most technological matters with regard to using digital healthcare technologies.	1	2	3	4	5
58. It is easy for me to self-monitor my physical condition by using digital healthcare technologies.	1	2	3	4	5
59. I have the capability to use digital healthcare technologies to self-monitor my physical condition without much effort.	1	2	3	4	5

60. I believe I have the ability to use digital healthcare technologies.	1	2	3	4	5
61. I am confident that I can use skilfully use digital healthcare technologies.	1	2	3	4	5
62. I can learn how to use digital healthcare technologies.	1	2	3	4	5
63. I am confident in being able to use digital healthcare technologies independently.	1	2	3	4	5
64. I can meet my medical needs through digital healthcare technologies.	1	2	3	4	5
65. I can confidently handle common operational problems when using digital healthcare technologies.	1	2	3	4	5
66. I intend to continue using digital healthcare technologies, rather than discontinue its use.	1	2	3	4	5
67. I will keep using digital healthcare technologies.	1	2	3	4	5
68. I predict that I will keep using digital healthcare technologies.	1	2	3	4	5
69. I plan to continue using the digital healthcare technologies.	1	2	3	4	5
70. I will always try to use digital healthcare technologies in my daily life.	1	2	3	4	5
71. I will keep using my digital healthcare technology as regularly as I do now.	1	2	3	4	5
72. I intend to increase my use of this digital healthcare technology in the future.	1	2	3	4	5
73. I will continue to use digital healthcare technologies to record my health status.	1	2	3	4	5
74. I intend to continue using digital healthcare technologies to monitor and manage my health status.	1	2	3	4	5

Appendix 7. Survey Participant Information Sheet

PARTICIPANT INFORMATION SHEET

Study title:

What explains the older users' continuance intention to use digital healthcare technologies (DHTs)?

Invitation Paragraph

You are invited to take part in a research study. You do not have to take part if you do not want to. It is important that you understand why the research is being done and what the questionnaire will entail. Please read the following information clearly, and if there is anything that you do not understand or if you would like more information, please feel free to let me know.

What is the purpose of the study?

The purpose of the study is to investigate older users' attitudes toward digital healthcare technologies and investigate influential factors that may contribute to the continuance intention to use digital healthcare technologies to manage their health.

Why have I been invited to participate?

If you are a current user of digital healthcare technology (e.g., wearable devices, mobile health, eHealth services, and telemedicine), over 65 years old, and living in the UK, you are invited to participate in this study.

Do I have to take part?

Participation is completely voluntary, so it is up to you and you alone to decide if you would like to take part.

What will happen to me if I take part?

If you decide to participate, you will be required to answer the questionnaire. Answering all the questions of the questionnaire is estimated to take you no more than 20 minutes. All I expect from you is to answer honestly.

Are there any lifestyle restrictions?

There are no commitments or lifestyle restrictions associated with participating.

What are the possible disadvantages and risks of taking part?

There are no disadvantages or risks associated with taking part in this study. All data is anonymous, and no personal information will be used or stored.

What if something goes wrong?

If you wish to make a complaint, the person to contact is the Chair of the College of Business, Arts and Social Sciences Research Ethics Committee (cbass-ethics@brunel.ac.uk.).

Will my taking part in this study be kept confidential?

All information which is collected about you during the course of the research will be kept strictly confidential. Any information about you which leaves the University will have all your identifying information removed. With your permission, anonymised data will be stored and may be used in future research – you can indicate whether or not you give permission for this by way of the Consent Form.

What will happen to the results of the research study?

The results of this study will be presented in my PhD thesis. If you wish to know the results of my study, then please feel free to contact me at the email address provided below.

Who is organising and funding the research?

The researcher in conjunction with Brunel Business School, College of Business, Arts and Social Sciences, Brunel University London. No external funds are being provided.

What are the indemnity arrangements?

Brunel University London provides appropriate insurance cover for research which has received ethical approval.

Who has reviewed the study?

This study has been reviewed by the College Research Ethics Committee.

Passage on the University's commitment to the UK Concordat on Research Integrity

Brunel University is committed to compliance with the Universities UK Research Integrity Concordat. You are entitled to expect the highest level of integrity from our researchers during the course of their research.

Contact for further information and complaints.

Researcher name and details:

Masoumeh Jahangiri

1732776@brunel.ac.uk

Supervisors' names:

Dr Yousra Asaad - Yousra.Asaad@brunel.ac.uk

Dr Pantea Foroudi - Pantea.Foroudi@brunel.ac.uk

For complaints, Chair of the Research Ethics Committee:

Dr Katja Sarmiento-Mirwaldt

cbass-ethics@brunel.ac.uk

Thank you for taking part in this study.

Appendix 8. Survey Letter of Approval

College of Business, Arts and Social Sciences Research Ethics Committee
Brunel University London
Kingston Lane
Uxbridge
UB8 3PH
United Kingdom

www.brunel.ac.uk

7 November 2023

LETTER OF APPROVAL

APPROVAL HAS BEEN GRANTED FOR THIS STUDY TO BE CARRIED OUT BETWEEN 07/11/2023 AND 31/01/2024

Applicant (s): Ms Masoumeh Jahangiri

Project Title: What explains the older people's continuance intention to use digital healthcare technologies?

Reference: 45554-LR-Nov/2023- 47708-2

Dear Ms Masoumeh Jahangiri

The Research Ethics Committee has considered the above application recently submitted by you.

The Chair, acting under delegated authority has agreed that there is no objection on ethical grounds to the proposed study. Approval is given on the understanding that the conditions of approval set out below are followed:

- **On the consent form, amend the start and end dates and the withdraw date as previously request.**
- **The agreed protocol must be followed. Any changes to the protocol will require prior approval from the Committee by way of an application for an amendment.**
- **Please ensure that you monitor and adhere to all up-to-date local and national Government health advice for the duration of your project.**

Please note that:

- Research Participant Information Sheets and (where relevant) flyers, posters, and consent forms should include a clear statement that research ethics approval has been obtained from the relevant Research Ethics Committee.
- The Research Participant Information Sheets should include a clear statement that queries should be directed, in the first instance, to the Supervisor (where relevant), or the researcher. Complaints, on the other hand, should be directed, in the first instance, to the Chair of the relevant Research Ethics Committee.
- Approval to proceed with the study is granted subject to any conditions that may appear above.
- The Research Ethics Committee reserves the right to sample and review documentation, including raw data, relevant to the study.
- If your project has been approved to run for a duration longer than 12 months, you will be required to submit an annual progress report to the Research Ethics Committee. You will be contacted about submission of this report before it becomes due.
- You may not undertake any research activity if you are not a registered student of Brunel University or if you cease to become registered, including abeyance or temporary withdrawal. As a deregistered student you would not be insured to undertake research activity. Research activity includes the recruitment of participants, undertaking consent procedures and collection of data. Breach of this requirement constitutes research misconduct and is a disciplinary offence.

Dr Katja Sarmiento-Mirwaldt

Chair of the College of Business, Arts and Social Sciences Research Ethics Committee

Brunel University London

Appendix 9. Survey Advertisement

Brunel University London

PARTICIPANTS NEEDED FOR RESEARCH IN MARKETING

I am looking for participants to take part in:

WHAT EXPLAINS OLDER PEOPLE'S CONTINUANCE INTENTION TO USE DIGITAL HEALTHCARE TECHNOLOGIES (DHTS)?

To participate, you need to be over 65 years old, live in the UK, and be a current user of digital healthcare technology (e.g., wearable devices, mobile health, electronic health records, telemedicine, and virtual care).
Participation in this questionnaire would not take more than 20 minutes.
Brunel University's Ethics Committee has approved this study, and I would like to reassure you that your feedback will remain anonymous and confidential, will be stored securely and shall not be used other than for the purpose of this study.

To take part in this study, please click on the link below or scan the QR code:
https://forms.gle/AtQ6zkTAcoFEHga3A

Thanks in advance for participating in this study,
Masoumeh Jahangiri