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Determinants of mHealth App Quality: A Case Study of CHRONIQ Framework to Manage Chronic Disease in South Africa

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ABSTRACT

The rise of mobile health (mHealth) applications has raised concerns about their quality, especially in managing chronic diseases, where users rely on these apps for vital health-related decisions. Despite their potential, many mHealth apps lack standardised evaluation, compromising their effectiveness, safety, and user trust. This issue is particularly acute in resource-constrained settings like South Africa, where chronic diseases such as diabetes and cardiovascular conditions are prevalent.

The core problem this study has addressed is the need for a comprehensive framework to assess the quality of mHealth apps tailored for chronic disease management. Current evaluation tools, such as the MARS, Enlight Suite, and AQUA, still need to fully address these apps' unique requirements. This study aimed to validate and refine the CHRONIQ framework, a tool specifically designed to assess the quality of mHealth apps in chronic disease management, providing an integrated approach that considers information quality (IQ), system quality (SQ), service quality (SEQ), engagement quality (EQ), user satisfaction (US), health outcomes (HO), intention to use (IU), and net benefits (NB).

The research objective guiding this study was *to identify the determinants of the CHRONIQ framework to create a standardised tool for assessing and improving the responses to mHealth apps for chronic disease management in South Africa.* To address this, the study employed a quantitative research methodology, collecting data via an online survey from 250 users of chronic disease management mHealth apps, with a response rate of 80%. The survey instrument was designed based on the constructs of the CHRONIQ framework and was analysed using structural equation modelling (SEM) through SmartPLS 4.0.

The results from the study confirmed the validity and reliability of the CHRONIQ framework. The key findings comprise significant relationships between various constructs, such as SQ and EQ (coefficient: 0.276, $p < 0.001$) and between EQ and US (coefficient: 0.606, $p < 0.001$). Furthermore, it was found that US significantly influenced IU (coefficient: 0.698, $p < 0.001$). These study results indicate the importance of app features such as system performance, user satisfaction, and sustained engagement in achieving better health outcomes through mHealth apps. It is worth noting that the IQ construct did not significantly impact EQ; this finding suggests that while important, more than information alone is needed to drive user interaction

with robust system performance and service quality. The findings of this study provide significant implications for app developers, healthcare providers, and policymakers. The CHRONIQ framework can serve as a standardised tool to evaluate the effectiveness of mHealth apps in chronic disease management, ensuring that these apps meet user needs for accuracy, reliability, and engagement. For healthcare providers, the framework can aid in recommending the most appropriate apps for chronic disease patients, improving patient self-management and health outcomes. Policymakers can use CHRONIQ to align mHealth app standards with national healthcare objectives, such as South Africa's National Digital Health Strategy.

In conclusion, this study recommends the widespread adoption of the CHRONIQ framework to enhance the quality and effectiveness of mHealth apps for chronic disease management, ensuring that these digital tools contribute meaningfully to public health goals.

Keywords: Mobile Health; mHealth applications; chronic disease management; CHRONIQ; South Africa.

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This work is dedicated to my youngest sister, Chulumanco Charlie, whose courage and resilience in the face of chronic kidney disease continue to inspire me every day. Her fight has highlighted the urgency and importance of improving healthcare solutions for chronic disease patients like her. Her unwavering tenacity fuels my dedication to advancing knowledge in this critical domain.

Additionally, I dedicate this work to my sister, Tarchima, who was diagnosed with stomach cancer earlier this year. Despite undergoing life-changing procedures, her strength and determination to fight daily have been a profound source of inspiration. Her journey underscores the importance of resilience and hope in adversity. Her battle has deepened my commitment to research that contributes to improving healthcare systems.

To everyone who has been part of this journey, both seen and unseen, thank you for your continued support.

DECLARATION OF OWNERSHIP, AUTHORSHIP, AND ETHICAL CLEARANCE

I, Chumani Charlie, student number 202001174, now declare that I am fully aware of the University of Fort Hare's policy on plagiarism, and I have taken every precaution to comply with the regulations. I now declare that this master's dissertation is my original work submitted to the University of Fort Hare to fulfil the requirements for the degree Masters: Information Systems in the Faculty of Management and Commerce. Where other authors' works have been consulted, due acknowledgement has been given in-text and in the reference list at the end. In addition, I affirm that I am fully aware of and have followed every precaution to comply with the University of Fort Hare's policy on research ethics. The University of Fort Hare's research ethics committee has given me ethical clearance, and my reference number is CIL031SCHA01.

3 September 2025

Sign **Date**

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CHAPTER ONE - INTRODUCTION

1.1. Introduction

Chronic diseases such as cancer, cardiovascular diseases, and diabetes are significant contributors to global mortality, accounting for approximately 74% of all deaths worldwide, with particularly severe impacts in low- and middle-income countries (World Health Organisation, 2023). In South Africa, the increasing mortality rates from such diseases highlight an urgent need for innovative management strategies (Statistics South Africa, 2023).

Mobile health applications (mHealth apps) have emerged as vital tools in managing chronic diseases, significantly enhancing patient engagement and self-management. These apps facilitate monitoring vital health parameters, medication adherence, and lifestyle changes, which are crucial for diabetes, hypertension, and cardiovascular diseases (Gong et al., 2020; Debon et al., 2019). MHealth apps offer personalised healthcare interventions and are often less labour-intensive and more cost-effective than traditional approaches (Mahmood et al., 2019).

Moreover, mHealth apps can improve health outcomes by fostering better patient-provider communication and enabling real-time health monitoring, which is especially critical in regions with limited access to healthcare services (Ndayizigamiye, Kante, & Shingwenyana, 2020). Despite these advantages, the effectiveness of mHealth apps can be compromised by the lack of quality, evidence-based content, and issues related to data security (Vervier et al., 2019; Diano et al., 2023), underscoring the need for rigorous evaluation frameworks to ensure their efficacy and reliability in chronic disease management

The Chronic Disease Mobile Health Application Quality Evaluation Framework (CHRONIQ) proposes a tailored evaluation scheme for mHealth apps targeting chronic disease management (Charlie & Cilliers, 2024). Crafted to elevate chronic disease management via mHealth apps, CHRONIQ integrates insights from established evaluation tools like MARS, the Enlight Suite, and AQUA and is grounded in the Delone and McLean IS Success Model. This foundation allows CHRONIQ to address the nuanced demands of chronic disease management by synthesising aspects such as system quality, information quality, and user satisfaction (Stoyanov et al., 2015; Baumel, Faber, Mathur, Kane, & Muench, 2017; O'Rourke, Pryss, Schlee, & Probst, 2020; DeLone & McLean, 2003; Charlie & Cilliers, 2024).

Despite its theoretical robustness, CHRONIQ must still be validated empirically to support adoption within the research community. The framework introduces innovative constructs like Engagement Quality and Health Outcome, designed to enhance user interaction and assess the health impacts of mHealth applications, ensuring the apps are effective, user-centric, and secure (Charlie & Cilliers, 2024).

The current study has tested and validated the CHRONIQ framework's effectiveness and reliability. This study assessed the framework's application in real-world settings and refined the tool based on the findings. This process has aimed to establish the CHRONIQ framework as a credible tool for improving the quality of mHealth apps, thereby enhancing chronic disease management in South Africa and potentially beyond.

1.2. Problem Statement

Despite the rapid proliferation of mHealth apps (Goklani, 2023), ensuring their quality and safety remains a significant challenge. Most of these apps lack evidence-based content, proper scientific validation, and the involvement of healthcare professionals during the design phase, which can lead to potential medical hazards and the dissemination of misinformation (Nouri et al., 2018; Wayne, 2022; Charbonneau et al., 2020). Furthermore, the quality assessment tools currently available, such as the MARS, Enlight Suite, and AQUA, have been critiqued for not adequately addressing the unique requirements of chronic disease management apps, leading to significant variability in app quality and safety (Guo & Lyu, 2023; O'Rourke et al., 2020; Stoyanov et al., 2015).

For instance, despite initiatives such as the National Health Service's (NHS) curated app collection, concerns about data security and the accuracy of health information remain unresolved, with many apps found transmitting unencrypted personal data (Grundy, 2022; Huckvale et al., 2015). Additionally, existing frameworks for app evaluation lack a standardised approach, resulting in a fragmented understanding of what constitutes "quality" in mHealth apps (Grundy, 2022).

The CHRONIQ framework was developed to assess and improve the quality of mHealth apps tailored for chronic disease management in response to these critical gaps (Charlie & Cilliers, 2024). This study sought to validate and refine the CHRONIQ framework, aiming to establish a standardised, reliable tool that enhances the credibility and effectiveness of chronic disease mHealth apps. By doing so, the research will contribute to safer, more effective digital health solutions for chronic disease patients, aligning with broader public health goals.

1.3. Research Aim

This study aimed to identify the determinants of the CHRONIQ framework to create a standardised tool for assessing mHealth apps for chronic disease management in South Africa.

1.4. Secondary Objectives

The following secondary objectives were identified to answer the primary objective.

- To quantitatively measure the impact of the CHRONIQ framework on improving user satisfaction and health outcomes by deploying high-quality mHealth apps for chronic disease management in South Africa.
- To determine which constraints of the CHRONIQ framework are necessary to determine the quality of health apps for chronic disease management in South Africa.
- To analyse the limitations of current mHealth app evaluation tools and standards within South Africa's healthcare context.

1.5. Hypotheses

To answer the primary objective, the following ten hypotheses were identified. The hypotheses test the relationships between the various constructs of the CHRONIQ framework, which are visually presented in Figure 1.1.

H1: Higher information quality in mHealth apps will lead to more excellent app engagement.

H01: Higher information quality in mHealth apps will not lead to greater app engagement.

H2: Higher system quality in mHealth apps will lead to better app engagement.

H02: Higher system quality in mHealth apps will not lead to better app engagement.

H3: Higher service quality in mHealth apps will lead to higher app engagement.

H03: Higher service quality in mHealth apps will not lead to higher app engagement.

H4: Enhanced engagement in mHealth apps will positively affect user satisfaction.

H04: Enhanced engagement in mHealt inh apps will not affect user satisfaction.

H5: Enhanced user satisfaction with mHealth apps will increase the intention to use these apps.

H05: Enhanced user satisfaction with mHealth apps will not increase the intention to use these apps.

H6: Greater intention to use mHealth apps will lead to better health outcomes.

H06: Greater intention to use mHealth apps will not lead to better health outcomes.

H7: Greater intention to use mHealth apps will increase perceived net benefits.

H07: Greater intention to use mHealth apps will not increase perceived net benefits.

H8: Higher health outcomes will increase user satisfaction.

H08: Higher health outcomes will not increase user satisfaction.

H9: Higher perceived net benefits will increase user satisfaction.

H09: Higher perceived net benefits will not increase user satisfaction.

H10: Higher user satisfaction will further reinforce user engagement with the mHealth apps, creating a feedback loop that sustains continued app usage.

H010: Higher user satisfaction will not reinforce user engagement with the mHealth apps nor create a feedback loop that sustains continued app usage.

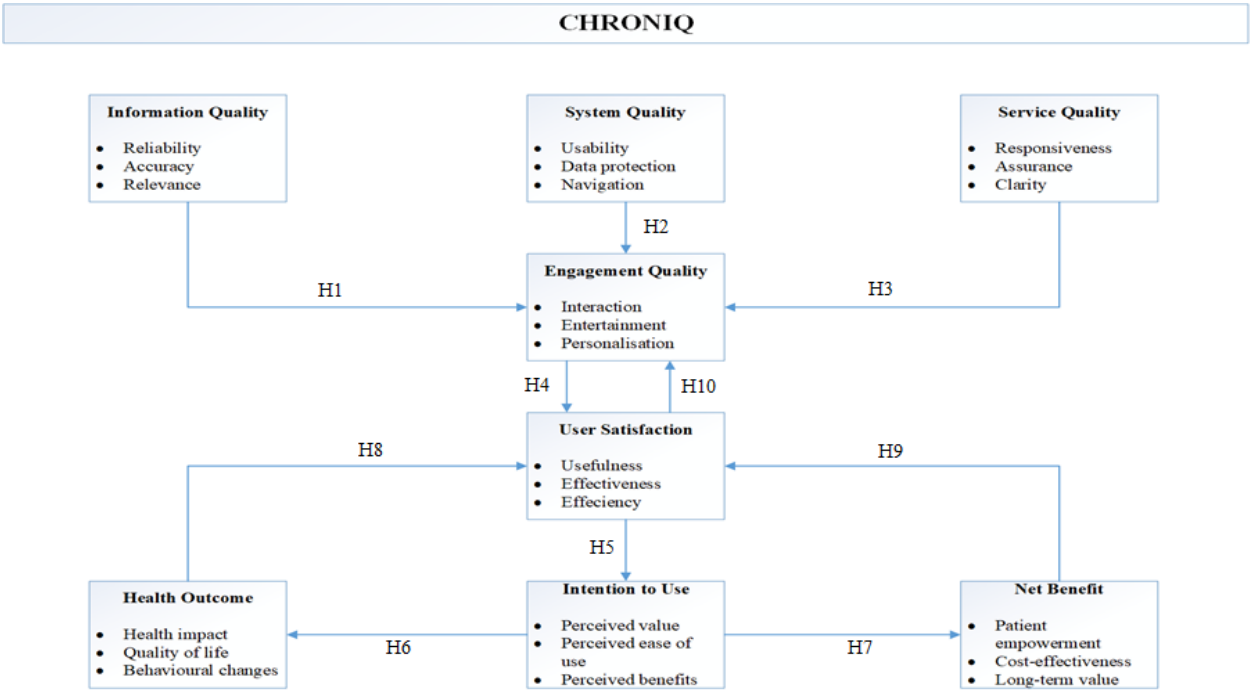

Figure 1.1: Diagrammatic representation of research hypotheses

(Source: Author)

1.6. Significance of the Study

This study is significant for its potential to enhance the quality assessment of mHealth apps through the CHRONIQ framework and the broader impact these high-quality apps can have on chronic disease management. The growing reliance on mobile technology by citizens offers a unique opportunity to improve healthcare delivery, particularly in regions like South Africa, where chronic diseases are prevalent (Watkins, et al., 2018; World Health Organisation , 2023). By ensuring mHealth apps meet high-quality standards, this research aims to contribute directly to better patient health outcomes.

High-quality mHealth apps have shown potential in improving treatment adherence and patient outcomes, particularly in managing chronic conditions such as diabetes, cardiovascular diseases, and respiratory diseases (Arshed, Mahmud, Minhat, Ying, & Umer, 2023; Eberle, Lohnert, & Stichling, 2021). Systematic reviews have indicated that mHealth interventions can significantly improve glycemic control in diabetes patients and enhance blood pressure monitoring in hypertensive patients, leading to better overall disease management (Eberle, Lohnert, & Stichling, 2021; Angelini, Alicastro, Dionisi, & Di Muzio, 2019).

Furthermore, this study has refined the CHRONIQ framework, enhancing its applicability across different cultural and socio-economic contexts. By aligning the framework with the specific needs and conditions of South African patients, the research aims to provide a credible and enhanced model that can be adapted for global use, thereby supporting the development of mHealth apps that are technically sound, user-centric, and contextually relevant.

1.7. Literature Review

This section explores various dimensions related to the regulation, theoretical underpinnings, and empirical evidence in mHealth apps. This section provides an overview of the theoretical and conceptual frameworks that underpin the study of mHealth apps for chronic disease management. Understanding the contextual literature is crucial for situating this research within the broader scholarly discourse and elucidating the theoretical foundations guiding this investigation.

1.7.1. Conceptual perspective

This section will cover the definitions and current research on chronic disease management, health apps, and the CHRONIQ framework. The section aims to clarify how these concepts are interlinked and their relevance to the study's objectives.

1.7.1.1. Chronic disease management

Chronic disease management involves the ongoing oversight and treatment of conditions that require long-term care and intervention, such as diabetes, hypertension, and cardiovascular diseases (Zhao et al., 2022). Effective management typically incorporates patient education, lifestyle modification, medication adherence, and regular health status monitoring (Chan, 2021). According to Reynolds et al. (2018), the success of chronic disease management hinges on coordinated interventions that combine patient engagement, healthcare provider insights, and supportive health technologies to sustain patient health and prevent exacerbations.

1.7.1.2. Mobile health applications (mHealth apps)

According to Haggag et al. (2022), mHealth apps are tools used on smartphones and other mobile devices to promote health and wellness, manage disease, and provide healthcare services. These apps can track health data, offer educational content, and connect users with healthcare providers. (Hamberger et al., 2022). While mHealth technologies are proliferating, their integration into standard care practices is often hampered by a lack of robust theoretical frameworks guiding their development and implementation (Bally & Cesuroglu, 2020; Ogundaini & de la Harpe, 2019; Ogundaini et al., 2021). This gap suggests a need for a more rigorous application of behaviour change theories to enhance the effectiveness of mHealth interventions.

1.7.1.3. CHRONIQ framework

Charlie and Cilliers (2024) underscore that the Chronic Disease Mobile Health Application Quality Evaluation Framework (CHRONIQ) is designed to assess the quality and effectiveness of mHealth applications tailored explicitly for chronic disease management. Developed by integrating components of existing models like the MARS and the Delone and McLean IS Success Model, the CHRONIQ framework aims to provide a comprehensive tool for evaluating mHealth apps through dimensions like Information Quality, System Quality, and User

Satisfaction (Charlie & Cilliers, 2024). The CHRONIQ framework is discussed in more detail in Sections 2.15 and 2.16.

1.7.2. Empirical perspective

To assess the quality of mHealth apps targeting pediatric anxiety, depression, and posttraumatic stress disorder (PTSD), Domhardt et al. (2021) systematically searched the Apple App Store and Google Play Store to identify relevant apps meeting inclusion criteria. The quality of eligible apps was independently evaluated using MARS and Enlight assessment tools. Results indicated subpar overall app quality, insufficient scientific development processes, and a lack of methodologically robust app evaluations. Similarly, Sander et al. (2020) examined the general characteristics, therapeutic backgrounds, content, and quality of PTSD apps. Their findings revealed that most evaluated apps needed more evidence-based approaches, with only one out of the 69 evaluated having undergone scientific evaluation through a randomised controlled trial. Data protection and privacy standards could have been more robust across most apps.

Terhorst et al. (2020) pursued a distinct investigation, focusing on evaluating the construct validity of the MARS tool. Their study noted a scarcity of validation research on the metric quality of the MARS tool, particularly in terms of the tool's construct and concurrent validity. Assessing 1299 mHealth apps spanning 15 health domains, the researchers found evidence supporting the MARS tool's suitability for assessing mHealth app quality. Concurrently, they explored the model's correlation with another quality assessment tool, Enlight, to gauge concurrent validity. Conversely, using the MARS tool, Amor-Garcia et al. (2020) examined the quality of mHealth apps catering to patients with genitourinary cancers. Their analysis revealed minimal involvement of healthcare professionals in app development, correlating with low-quality apps and indicating an absence of evidence-based offerings, consistent with findings from Sander et al. (2020) and Domhardt et al. (2021).

Although Sander et al. (2020) and Domhardt et al. (2021) aimed to evaluate the quality of mHealth apps using the MARS and Englight tools, both studies focused on evaluating apps targeting PTSD. Moreover, the MARS and Enlight have been developed for general-purpose mHealth apps and eHealth interventions, respectively, with neither tool specifically targeting mHealth apps for chronic disease management. The approach taken by Terhorst et al. (2020) aimed at considering a different perspective in their investigation, reporting good to excellent

reliability of the MARS tool; they were, however, investigating a tool with limited ability to appraise the quality of chronic disease mHealth apps effectively.

Moreover, the measure of the concurrent validity of the MARS tool was correlated against another tool (Enlight) of limited chronic disease mHealth app appraisal. Amor-Garcia et al.'s (2020) study was the only study that investigated the quality of chronic disease mHealth apps; however, the study was limited to investigating apps aimed at managing genitourinary cancers. Moreover, the MARS was the tool used to appraise these cancer mHealth apps, and, as has been discussed in this text, it is limited in its ability to evaluate chronic disease mHealth apps.

1.7.3. Theoretical perspective – CHRONIQ framework

The CHRONIQ framework, as depicted in Figure 2.1, is a notable progression in evaluating chronic disease mHealth apps and was developed in response to the limitations identified in existing frameworks such as MARS, Enlight and AQUA (Guo & Lyu, 2023; O'Rourke et al., 2020). CHRONIQ integrates robust aspects of these models while introducing innovative constructs specifically designed to assess the nuanced demands of chronic disease mHealth apps (Charlie & Cilliers, 2024).

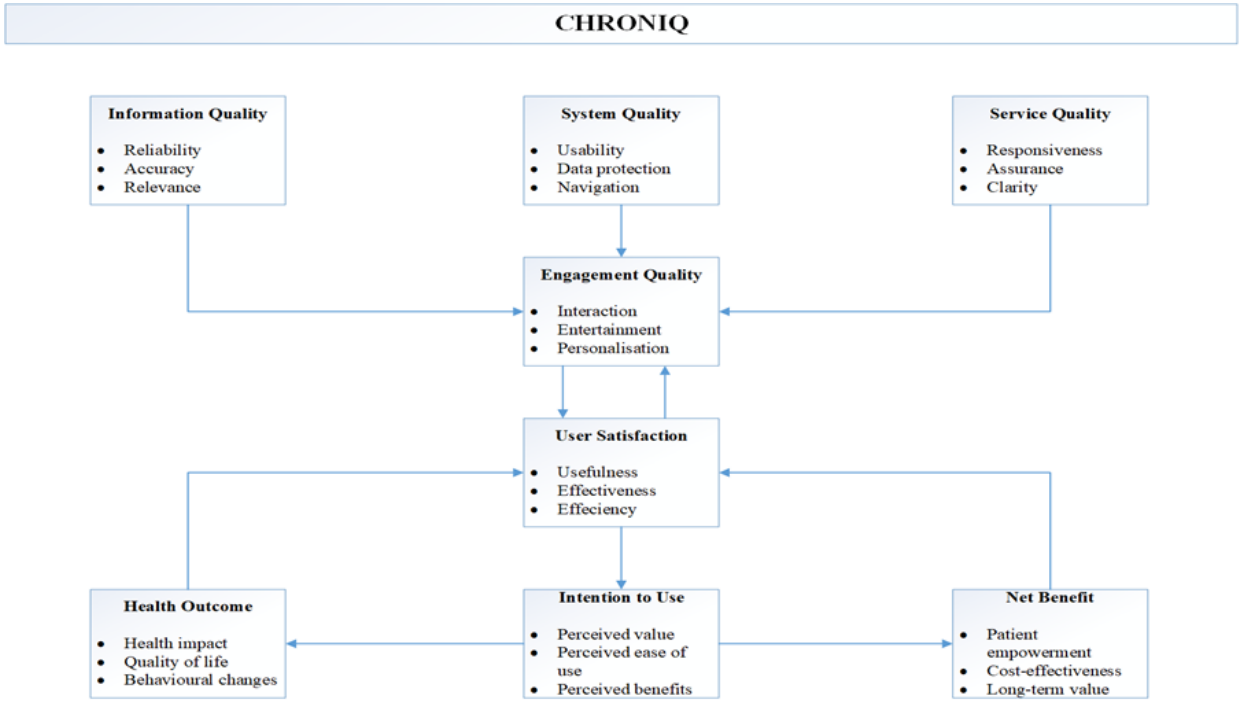

Figure 1.2: CHRONIQ framework

(Source: Charlie & Cilliers, 2024)

1.7.3.1. Development and innovations

The CHRONIQ framework synthesises the elements of existing evaluation tools, enhancing them with deeper insights into chronic disease management. For instance, while MARS provides a broad assessment of app quality (Stoyanov, et al., 2015), CHRONIQ extends this by focusing on aspects critical to chronic diseases, such as long-term user engagement and the precision of health information. Unique to CHRONIQ are constructs like engagement quality and health outcome, which directly address the interaction dynamics and the health improvements seen in users; areas often need to be explored in generic app evaluation tools. (Charlie & Cilliers, 2024).

1.7.3.2. Legislative perspective

The regulatory landscape surrounding mHealth apps is multifaceted and dynamic. Regional perspectives on mHealth regulation provide valuable insights into legislative approaches and challenges. Townsend (2015) offers a comprehensive analysis of mHealth regulation in African countries, emphasising the need for cohesive regulatory guidelines and collaboration to address legal gaps. For instance, Townsend (2015) emphasises that mHealth interventions in Africa have emerged mainly without dedicated legal frameworks, prompting a reassessment of current healthcare regulations to accommodate these interventions. Moreover, in the African landscape, the regulatory and legislative frameworks vary among nations, with notable differences, where mHealth policy components are sometimes integrated into broader health, e-government, or e-commerce regulations (Townsend, 2015).

In the context of South Africa, a report by Measure Evaluation (2016) outlines significant legislation, such as the Protection of Personal Information (POPI) Act of 2013 and the National Health Act No. 61 of 2003, in regulating mHealth. The POPI Act is crucial for mHealth projects to consider as the Act sets the minimum requirements for processing personal information. (Measure Evaluation, 2016). Moreover, the act grants individuals rights that mHealth projects or applications must not violate.

Concerning the National Health Act, Measure Evaluation (2016) underscores how the act emphasises confidentiality of all information concerning a user, including their health status and treatment. Additionally, amendments in 2014 added requirements from the National Health Normative Standards Framework for Interoperability in eHealth, which apply to mHealth interventions and apps handling user information (Measure Evaluation, 2016).

1.8. Research Methodology

A research methodology serves as a systematic framework that guides the execution of a study (Quinlan et al., 2019). The methodology delineates the specific research methods employed within the investigation and outlines the approaches through which the study aims to obtain its results (Saunders et al., 2019).

1.8.1. Research philosophy

According to Saunders, the research philosophy pertains to the development of knowledge and the nature of that knowledge (Muchanga, 2020). The philosophical approach adopted for this study was rooted in positivism, as this study has been designed for data collection to evaluate hypotheses based on an existing theory (Park et al., 2020). This philosophical approach aligns well with the study's objective of empirically validating the CHRONIQ framework through quantifiable data and objective analysis.

1.8.2. Research approach

Research approaches in academic studies are broadly categorised into three types: quantitative, qualitative, and mixed methods (Saunders et al., 2019). The quantitative approach, often called deductive, relies on systematic and cyclic data collection, where the data gathered are numerical and analysed through statistical methods. This approach utilises quantifiable indicators such as ratings, scores, and frequency counts to provide measurable and unbiased results (Naoko Taguchi, 2018; Al-Ababneh, 2020). Quantitative research allows the researcher to remain independent of the subject matter, facilitating the testing of variables to confirm or refute hypotheses related to the study's topic. The outcomes of this approach are statistically valid and reliable, ensuring objectivity in the findings (Ganesha & Aithal, 2022).

Using a quantitative approach was suitable for validating the CHRONIQ framework because the method allowed for empirical testing of predefined hypotheses concerning the effectiveness of mHealth apps in chronic disease management. This method facilitates examining relationships between variables and ensures the generalisability of findings (Saunders et al., 2019; Haydam & Steenkamp, 2020). By employing statistical techniques to analyse data collected via surveys, this approach supported rigorous validation of the framework's theoretical assumptions and practical applications in a structured manner.

1.8.3. Research design

The selection of an appropriate research design is crucial, serving as the framework for aligning the study's objectives with systematic data collection and analysis methodologies (Sileyew, 2019). This study employed a descriptive research design, recognised for its efficiency in describing the characteristics of a large sample pertinent to the research hypotheses (Siedlecki, 2020).

A survey design was deemed particularly suitable for this study as it facilitates the structured collection of quantitative data (Siedlecki, 2020), allowing for comprehensive statistical analysis to assess the CHRONIQ framework's reliability and effectiveness in evaluating mHealth applications. This approach was instrumental in capturing a wide array of user experiences with mHealth apps, providing quantitative insights into critical aspects of app quality such as usability, functionality, content accuracy, and user satisfaction as defined by the CHRONIQ framework (Saunders et al., 2019; Charlie & Cilliers, 2024). These dimensions were essential for testing hypotheses about the impact of quality on app effectiveness and user satisfaction (Van Holm, 2021).

Through this design, the survey served as the primary instrument for data collection, systematically gathering data to help determine how well the CHRONIQ framework performs against existing standards in real-world scenarios. This method ensured the findings were robust and generalisable across the diverse landscape of health app users.

1.8.4. Population and sampling

The target population for this study included South Africans of all age groups who were potential users of health apps for chronic disease management. The term 'population' refers to a defined group of individuals with shared characteristics pertinent to the research aim (Dudovskiy, 2018). In this context, the population comprised individuals in South Africa interested in utilising mobile health applications to manage chronic health conditions.

As defined by Rahi (2017), sampling involves the selection of a subset of the population to participate in the study. The target population for this study included a diverse array of individuals across South Africa, all living with chronic diseases—a significant public health concern in the region. Chronic diseases such as cardiovascular conditions and diabetes contribute to 51% of deaths in South Africa (World Health Organisation, 2023).

This study employed a convenience sampling strategy to facilitate the recruitment of participants, targeting adults with chronic diseases who use health apps. Andrade (2021) describes a convenience sample as one that is selected from sources that are readily accessible to the researcher. For this study, participants were recruited through emails containing a link to the survey. The first page of the survey served as a screening tool, presenting an informed consent form and a question verifying the presence of a chronic disease. Only those who confirmed having a chronic disease could proceed to the questionnaire, ensuring the relevance and appropriateness of the sample for the study's objectives. This method allowed for efficient data collection while aligning with the study's practical constraints and participants' availability.

Using the Raosoft calculator with a confidence level of 95% and a margin of error of 5%, a minimum of 250 individuals was deemed necessary to achieve generalisable results, ensuring comprehensive coverage and relevance of the findings to the targeted demographic group.

1.8.5. Data collection

The methodological approach critically informed data collection techniques and analytic procedures, significantly influencing the study's overall reliability and validity (Pathiranage et al., 2020). This study adopted a quantitative research approach, strategically employing a survey to gather data. Questionnaires, particularly self-administered ones, are highly effective for descriptive or explanatory research, as they allow for structured data collection aligned with specific research objectives. (Heath, 2023).

In this context, a questionnaire was particularly apt given its capacity to systematically capture data across predefined constructs. Table 1 below outlines the constructs foundational to the conceptual framework of this study. The questionnaire was developed to align with these constructs, ensuring that each question directly contributes to the empirical assessment of the framework's components. This alignment facilitates targeted data collection and enhances the precision and applicability of the resulting data analysis.

Table 1.1: Research project scale

Construct	**Cronbach alpha**	**Number of dimensions**	**Reference**
Information quality	0.956	3	(Umaroh & Barmawi, 2021)

System quality	0.959	3	(Umaroh & Barmawi, 2021)
Service quality	0.954	3	(Umaroh & Barmawi, 2021)
Engagement quality	0.890	3	(Barzegari et al., 2021)
User satisfaction	0.939	3	(Umaroh & Barmawi, 2021)
Intention to use	0.953	3	(Pérez Tijero & Delgadillo Ávila De Mauricio, 2019)
Net benefit	0.966	3	(Umaroh & Barmawi, 2021)
Health outcome	0.840	3	(Barzegari et al., 2021)

1.8.6. Data analysis

In alignment with the quantitative methodology employed in this study, data analysis was conducted using statistical methods. Initially, the data collected from participants was thoroughly reviewed to identify and correct any incorrect responses. Once the dataset had been cleaned and validated, it was analysed using advanced statistical tools. For this purpose, the research employed the Statistical Package for Social Sciences (SPSS) as the primary software tool for data analysis. This tool is well-suited for implementing descriptive and inferential statistical techniques, essential for validating the validity and reliability of the study's findings. (Lani, 2009).

Descriptive statistics summarised the data and provided a clear understanding of the trends and patterns within the dataset. On the other hand, inferential statistics allowed for a deeper exploration of the relationships between variables through correlation and regression analyses, as Shrestha (2020) recommended. Furthermore, structural equation modelling (SEM) was utilised to examine the interactions between dependent and independent variables, providing a comprehensive model of the relationships inherent in the study's hypotheses.

1.8.7. Delimitations

The study was geographically limited to South Africa to analyse health app usage within the country's unique healthcare context and sociocultural dynamics. The mHealth app focused on chronic diseases' significant impact on public health and management needs, emphasising digital solutions that enhance patient outcomes and management efficacy.

Only apps specifically designed for chronic disease management were included in the study to ensure a focused study on chronic disease management. This approach aligned with broader public health goals and underscores the critical importance of app quality in effective disease management.

1.8.9. Ethical approval

This study adhered to the ethical principles outlined in the Belmont Report (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1976), ensuring compliance with the guidelines and procedures established by the University Interfaculty Research Ethics Committee (IFREC). Ethical clearance was obtained from IFREC to protect the rights and well-being of participants throughout the research process (Appendix 1).

The principles of respect for persons, beneficence, and justice guided the study's ethical conduct, emphasising informed consent, risk minimisation, benefit maximisation, and equitable treatment of participants (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1976). The research team was committed to transparency, integrity, and responsible conduct, maintaining high ethical standards and professional courtesy. Confidentiality protocols were implemented to safeguard participant privacy and data security. Detailed explanations of the study's objectives, methods, potential risks, and benefits were provided to all participants, who were asked for their voluntary and informed consent. Any participant concerns were addressed promptly, and participants retained the right to withdraw from the study at any point without repercussions.

CHAPTER TWO - LITERATURE REVIEW PART I

2.1. Introduction

This chapter establishes the foundation for understanding the complexities of chronic disease management in South Africa, the role of mHealth technologies, and the quality assessment of health applications. By synthesising previous research and theoretical contributions, the literature review aims to identify the limitations of the current knowledge and justify the study's relevance and necessity.

The chapter begins by exploring the prevalence and impact of chronic diseases in South Africa, highlighting the significant burden these conditions place on the healthcare system. The author then delves into the potential of mHealth technologies as innovative solutions for enhancing chronic disease management, with a particular focus on mobile applications and their types and functionalities.

However, assessing the quality and effectiveness of mHealth apps remains a challenge due to the complexity and diversity of their functionalities. As such, the discussion shifts to the concept of app quality, examining existing evaluation criteria and frameworks such as the MARS, Enlight Suite, and AQUA. The limitations of these existing tools—especially in the context of chronic disease management—underscore the need for more comprehensive and context-specific assessment models.

To address this gap, the chapter introduces the DeLone and McLean Information Systems (IS) Success Model, a widely adopted framework for evaluating information systems, including mHealth apps. The model's development, key constructs, and applicability across domains such as education and healthcare are discussed, emphasising its adaptability. This leads to the introduction of the CHRONIQ framework, a novel tool developed to address the shortcomings of existing models by offering a holistic, evidence-based, and disease-specific evaluation approach for chronic disease mHealth apps.

By the end of this chapter, the reader will gain a deeper understanding of the evolving landscape of mHealth app evaluation, the theoretical underpinnings guiding quality assessments, and the need for contextually relevant frameworks like CHRONIQ to improve app quality and effectiveness in chronic disease management.

2.2. Chronic Disease in South Africa

Chronic diseases in South Africa represent a significant public health challenge, contributing substantially to morbidity and mortality rates (Samodien et al., 2021; Statistics South Africa, 2023a). Chronic diseases, such as cardiovascular diseases, diabetes, chronic respiratory diseases, and cancer, collectively account for nearly 60% of all deaths in the country (Statistics South Africa, 2023a; World Health Organisation, 2023a). Minja et al. (2022) underscore how cardiovascular diseases are particularly prevalent, responsible for approximately 38.3% of the total mortality in Africa. Diabetes is another widespread chronic disease in South Africa, with Sharman and Bachmann (2019) reporting how the disease affects around 14% of the adult population in Southern Africa, highlighting the extensive burden these diseases place on the healthcare system.

The impact of chronic diseases is not uniform across the population and varies significantly among different demographic groups. For instance, a report by Statistics South Africa (2023) revealed how black South Africans had the highest age-standardised mortality rates, with the white population having the lowest overall mortality rates. According to the report, some reasons for these findings may be a reflection of genetic predisposition to the disease, access to care, dietary or other behavioural practices.

Moreover, there is a marked disparity in chronic disease prevalence between urban and rural populations, influenced by a range of socioeconomic factors (Akindele & Useh, 2021; Temane et al., 2024). For instance, Akpa et al. (2020), Abdelatif et al. (2021), and Rudasingwa et al. (2024) indicate how urban residents often have higher rates of obesity and hypertension, potentially due to lifestyle factors such as sedentary behaviour and unhealthy dietary patterns. In contrast, Willie and Maqbool (2023) assert how rural populations frequently encounter challenges in accessing healthcare services, adversely affecting chronic conditions' management and treatment.

According to the World Health Organization (2023b), gender disparities are also evident, with women showing a higher prevalence of conditions like hypertension and obesity compared to men. For instance, in South Africa, a report by Simelane (2024) indicates that nearly 50% of the female adult population is overweight or obese. Similarly, the World Obesity Federation (2024) found how over 30% of South African men and over two-thirds of women are either overweight or obese. This difference underscores the need for gender-specific health interventions and public health strategies that address women's unique risk factors and

healthcare needs (Gizamba et al., 2023; Modjadji et al., 2022; Specialist Forum, 2023). The analysis of these trends highlights the urgent need for comprehensive public health policies and targeted interventions to manage the diverse and growing burden of chronic diseases in South Africa, ensuring that all demographic groups receive adequate care and support.

2.3. Burden on Health Care Services of Chronic Diseases

Chronic diseases substantially burden healthcare services globally, severely straining healthcare infrastructure and resources (Australian Institute of Health and Welfare, 2024; Mahumud et al., 2022). Mahumud et al. (2022) underscore that chronic disease costs are expected to reach $47 trillion worldwide by 2030, severely straining healthcare systems and resources. The increasing prevalence of non-communicable diseases (NCDs) requires significant medical resources, including specialised medical personnel, advanced diagnostic tools, and long-term treatment facilities (Ndumwa et al., 2023).

This growing demand for healthcare often leads to overcrowded hospitals, extended wait times for treatment, and overworked healthcare professionals, particularly in low- and middle-income countries (Soyemi & Aborode, 2022; Statistics South Africa, 2023a). Mahmoud et al. (2022) indicate how, in these regions above, healthcare systems are frequently under-resourced, exacerbating the challenges in managing chronic diseases and providing adequate patient care

In Africa, the burden of chronic diseases has been rising rapidly, compounded by limited healthcare infrastructure and financial constraints (Africa CDC, 2022; Freeman et al., 2020, 2020; Mahmoud et al., 2022). Moreover, Li et al. (2022) highlight how many African countries face a dual burden of disease, dealing with both infectious diseases and the increasing prevalence of NCDs. This dual burden stretches healthcare systems thin, often prioritising immediate infectious disease outbreaks over chronic disease management.

Additionally, the lack of widespread access to early diagnosis and ongoing care for chronic diseases in many African nations leads to advanced disease stages at presentation, increasing treatment complexity and cost (World Health Organisation, 2022). This scenario not only overwhelms healthcare facilities but also impacts the quality of care, with limited resources often leading to insufficient follow-up and management of chronic conditions (Hacker, 2024).

Ndlovu et al. (2023) indicate how the burden on healthcare services in South Africa, due to chronic diseases, is particularly pronounced. A report by the World Health Organization (2023b) details how the country has seen a significant rise in NCDs, which now account for

over half of all deaths, highlighting the urgent need for effective healthcare strategies and resources to manage these conditions.

The public healthcare system, already under strain from high rates of communicable diseases like HIV/AIDS, faces additional pressures from the growing number of chronic disease patients. This has led to a shortage of hospital beds, increased workloads for healthcare professionals, and longer waiting times for patients requiring chronic disease management (Department of GCIS South Africa, 2023; Mboweni & Risenga, 2023).

The economic impact of chronic diseases on South Africa's healthcare system and the broader economy is substantial. For instance, Botha and Vermund (2022), Kirigia et al. (2017), and Masuku et al. (2023) highlight how the cost of managing NCDs includes direct healthcare expenses, such as hospital admissions, medical treatments, and pharmaceuticals, as well as indirect costs related to lost productivity and long-term disability. Moreover, Masuku et al. (2023) indicate that chronic diseases often lead to prolonged illness, requiring ongoing medical attention and limiting individuals' ability to work, affecting economic productivity.

Freeman et al. (2020) underscore how the government and healthcare providers must allocate significant portions of their budgets to managing these diseases, diverting funds from other critical areas, including infrastructure development and educational services. This financial strain is particularly challenging when public healthcare is already underfunded, necessitating reforms and increased investment to ensure sustainable healthcare services.

2.4. Mobile Health Solutions for Addressing Healthcare Challenges

Peremore (2023) indicates how mHealth technologies, a subset of eHealth, leverage mobile devices to deliver healthcare services and information. This includes a broad range of applications, from simple text message reminders to sophisticated mobile apps that monitor chronic conditions, facilitate telehealth consultations, and provide access to electronic health records (EHRs) (Chan, 2021; Moss et al., 2019; Peremore, 2023). Moreover, Moss et al. (2019) underscore how mHealth has been recognised for its potential to revolutionise healthcare delivery by making it more accessible, efficient, and patient-centred.

One of the primary benefits of mHealth in chronic disease management is its ability to alleviate the pressures on healthcare systems (Sousa et al., 2023). Hacker (2024) highlights how chronic diseases require ongoing management and frequent monitoring, which traditionally burden

healthcare facilities and professionals. Consequently, Sousa et al. (2023) state that mHealth can mitigate these pressures by enabling remote monitoring and managing chronic conditions, reducing the need for frequent in-person visits.

For instance, Hartch et al. (2024) posit how mHealth apps can track vital signs, medication adherence, and lifestyle factors such as diet and exercise, providing real-time feedback and alerts to patients and healthcare providers. This continuous monitoring allows for timely interventions, potentially preventing complications and hospital admissions (Hartch et al., 2024; Jakob et al., 2022). Moreover, Sousa et al. (2023) assert that mHealth facilitates better patient engagement and self-management, empowering patients with tools and information to take control of their health.

Additionally, Aboye et al. (2024) point out how mHealth technologies can improve access to healthcare in underserved and remote areas where traditional healthcare infrastructure may be lacking. According to Shih et al. (2023), the ubiquitous nature of mobile devices can facilitate bridging the gap between patients and healthcare providers, offering consultations, support, and information that would otherwise be inaccessible. This is particularly relevant in Sub-Saharan Africa, where healthcare resources are often stretched thin, as discussed in Section 4 (Aboye et al., 2024).

2.5. Mobile Health Explained

Peremore (2023) defines mHealth as using mobile devices, wearables, and telehealth services to support healthcare delivery and management. mHealth encompasses a wide range of digital tools, including smartphone apps designed for health monitoring, wearable devices that track physiological parameters like heart rate and sleep patterns, and telehealth platforms that enable remote consultations between patients and healthcare providers (Chan, 2021; Moss et al., 2019; Peremore, 2023).

The scope of mHealth extends from basic short message service (SMS) reminders for medication adherence to complex, integrated systems that collect and analyse health data in real personalised-time, facilitating more personalised and proactive healthcare management (Chan, 2021; Peremore, 2023). Aboye et al. (2024) indicate how the adoption of mHealth is driven by the technology's ability to bridge gaps in healthcare access, particularly in regions with limited healthcare infrastructure, thus making mHealth a critical component of modern healthcare systems globally.

When considering South Africa, Van Der Pol et al. (2022) state that the mHealth market has seen significant growth, driven by the increasing penetration of mobile devices and the pressing need to address healthcare challenges, particularly in managing chronic diseases. Additionally, the adoption rates of mHealth apps have steadily risen as more individuals leverage these technologies for monitoring and managing their health conditions (Ojo, 2018). For instance, according to a report by Ferraci (2023), n 2020, sub-Saharan Africa counted 495 million unique mobile subscribers, expecting the number to reach 615 million in 2025, approximately 50% of the population.

However, despite this growth, challenges still need to be addressed, including disparities in access between urban and rural populations and data privacy and security issues (Aboye et al., 2024). The South African government and private sector stakeholders are increasingly recognising the transformative potential of mHealth in healthcare delivery, particularly as the country faces the dual burden of communicable and NCDs. A prime example of this recognition is the National Digital Health Strategy for South Africa, 2019-2024, which aligns with the broader goals of the National Health Insurance (NHI) implementation (National Department of Health, 2022). This strategy, developed under the leadership of the Ministerial Advisory Committee (MAC) on eHealth, emphasises the integration of digital health solutions as a critical driver of health system transformation.

2.6. Mobile Health Applications

Health apps, also known as mHealth applications, as posited by Esteves et al. (2019), are designed to improve healthcare delivery by providing services ranging from disease management to medication reminders. These digital tools integrate seamlessly with mobile platforms like Android and iOS, making healthcare more accessible to various user demographics (Deloitte, 2021). In South Africa, the availability of health-related apps has grown substantially, reflecting a global trend where over 350,000 health apps were recorded by 2021, highlighting their increasing role in healthcare management (Deloitte, 2021).

Vaghefi and Tulu (2019) underscore how these apps offer numerous benefits, including enhanced patient engagement, improved self-management of chronic conditions, and more efficient healthcare service delivery. They enable real-time monitoring and tailored interventions, which are especially beneficial for managing NCDs prevalent in South Africa (Wang et al., 2022). By reducing the need for in-person visits, mHealth apps alleviate pressure

on healthcare facilities and can significantly cut costs and improve the scalability of health services (Esteves et al., 2019; Santo & Redfern, 2019).

However, the proliferation of mHealth apps also raises significant concerns, particularly regarding data security and privacy. The vast amounts of sensitive health data collected by these apps pose risks if not adequately protected, leading to potential data breaches (O'Grady et al., 2020). Moreover, the quality and reliability of these apps can vary, with some lacking proper validation, which could lead to inaccurate health management or misdiagnoses (Akbar et al., 2020; Nouri et al., 2018).

2.7. Mobile Health Application Quality

The current discourse on mHealth app quality underscores its critical importance due to the lack of standardised and objective assessment tools for these applications (Deniz-Garcia et al., 2023; Diano et al., 2023; Vervier et al., 2019). Stoyanov et al. (2015) and Tan et al. (2022) have noted that the Apple App Store and Google Play Store rely primarily on user ratings, which are subjective and do not necessarily reflect an app's effectiveness or functionality.

To address these limitations, the MARS tool was developed, offering a structured approach to app quality evaluation through criteria like engagement, functionality, aesthetics, and information quality, each rated on a five-point scale (Stoyanov et al., 2015; Terhorst et al., 2020). Despite its broad application, the MARS tool has limitations, especially in the context of chronic disease apps, which require specific features like complex treatment regimens and personalised care plans not fully covered by the MARS criteria (Guo & Lyu, 2023; Terhorst et al., 2020).

Another tool, the Enlight Suite, introduced by Baumel et al. (2017), incorporates critical constructs like persuasive design and therapeutic alliance into its evaluation framework. While the Enlight Suit is comprehensive, it also lacks focus on specific aspects of service quality crucial for chronic disease management (Messner et al., 2019; O'Rourke et al., 2020).

The AQUA tool developed by O'Rourke et al. (2020) integrates aspects of both MARS and Enlight, adding dimensions like usability, security, and therapeutic effectiveness. The tool is designed to be used by both developers and end-users, making it a versatile tool in mHealth app evaluation (O'Rourke et al., 2020; Sedhom et al., 2021). However, the tool also has limitations in fully capturing all necessary dimensions for chronic disease apps, specifically in

areas such as evidence-based content and detailed security protocols necessary for handling sensitive health data (Caponnetto & Casu, 2022; Sedhom et al., 2021).

The limitations and specific challenges of the MARS tool, Enlight Suite, and AQUA tool in evaluating chronic disease mHealth apps are discussed in much more depth in Chapter 3, Section 3.4, where a detailed comparison of these frameworks and their applicability to chronic disease management is further elaborated on.

2.8. Determinants of mHealth App Quality in Chronic Disease Management

In the search for relevant determinants, previous studies on mHealth apps have underscored various factors influencing app quality. These factors encompass not only technical attributes such as functionality and usability but, as indicated by Isabirye et al. (2019), should also encompass clinical aspects, including the accuracy of health information and the app's ability to facilitate patient engagement and chronic disease self-management.

For instance, in a much more general study on digital health for the self-management of chronic diseases, Achieng and Ogundaini (2022) found that social determinants such as cultural values and societal practices are crucial to how these technologies are designed and developed for use in sub-Saharan African countries such as South Africa. Similarly, Jacobs-Basadien et al. (2022) posit how the culture of patients in South Africa contributes to the low acceptance and use of mHealth apps. These findings by Achieng and Ogundaini (2022) and Jacobs-Basadien et al. (2022) indicate how technical attributes influence app quality and how cultural dimensions significantly impact it.

When considering existing mHealth app evaluation tools and frameworks, Azad-Khaneghah et al. (2021) reviewed 25 quality rating scales, discovering that only a single quality rating scale was designed for non-expert users (i.e. patients and caregivers). Moreover, none of the studies used a theoretical framework for app evaluation to support the scales, with the validity of existing quality rating scales yet to be investigated. In a similar study, Muro-Culebras et al. (2021) sought to analyse the psychometric properties of mHealth app quality evaluation tools, that is, the validity and reliability of these tools.

Of the eight evaluation tools reviewed by Muro-Culebras et al. (2021), only the MARS tool showed a moderate number of validated psychometric properties, with the tool being validated in many mHealth apps and being widely used. However, Charlie and Cilliers (2024) posit how evaluation tools and frameworks most commonly referenced in existing literature, such as the

MARS tool, provide practical but incomplete approaches to evaluating mHealth apps in the specific context of chronic disease.

2.9. Regulatory Landscape of mHealth Apps in Sub-Saharan Africa and South Africa

When considering the regulatory landscape of mHealth apps in sub-Saharan Africa and South Africa, Bene et al. (2024) assessed the regulatory standards for health apps in sub-Saharan Africa. Still, of the 31 countries considered in the review, only three regulatory standards and guidance contained relevant information on the regulation of health apps. However, it is worth noting that none of the included regulatory standards were exclusively developed to regulate health apps for self-management.

Instead, the standards provide concepts and information relevant to regulating health apps (Bene et al., 2024). Nevertheless, Charlie and Cilliers (2024) posit exemplary initiatives such as the National Digital Health Strategy (NDHS) for South Africa (2019-2024), aimed at leveraging digital technologies to enhance the healthcare system and services, comprise a noteworthy policy supporting mHealth initiatives.

Similarly, the National Digital Plan (NDP) 2030 of South Africa, compiled by the National Planning Commission of South Africa (2012), emphasises the importance of digital health and mHealth interventions for improving the healthcare system. Moreover, Bene et al. (2024) point out how, although national policies such as the NDHS and NDP30 do not offer specific standards or guidance but rather outline the country's vision, policy directions, and strategies for using digital technologies in healthcare, they provide helpful information for identifying digital stakeholders who can play a role in regulating health apps for self-management.

2.10. The Delone and McLean Information Systems Success Model

Introduced by DeLone In 1992, the IS Success Model offers a holistic framework for defining IS success by integrating various perspectives (Delone & McLean, 1992). Urbach et al. (2009) explain that the model aligns with Shannon and Weaver's three levels of information, namely technical, semantic, and effectiveness, and Mason's (1978) concept of 'influence,' which describes the effects triggered by the receipt of information. The model articulates six success variables: system quality, information quality, use, user satisfaction, individual impact, and organisational impact. These variables are not isolated but interact to produce a composite picture of IS success, influencing personal and organisational outcomes (Angelina et al., 2019; Çelik & Ayaz, 2022). This structured approach allows for a nuanced assessment of IS outputs and their impacts, which is crucial for understanding the efficacy of mHealth applications within healthcare settings.

Delone and McLean's 1992 IS Success Model positions the infrastructure of the system within its foundational layer, suggesting that individual gains can influence organisational achievements (Çelik & Ayaz, 2022). However, this model faced critique for excluding certain variables and proposing that system usage alone should not equate to success. Critics such as Seddon and Kiew (1996) and Seddon (1997) argued for reevaluating how the benefits for individuals and organisations align with user satisfaction.

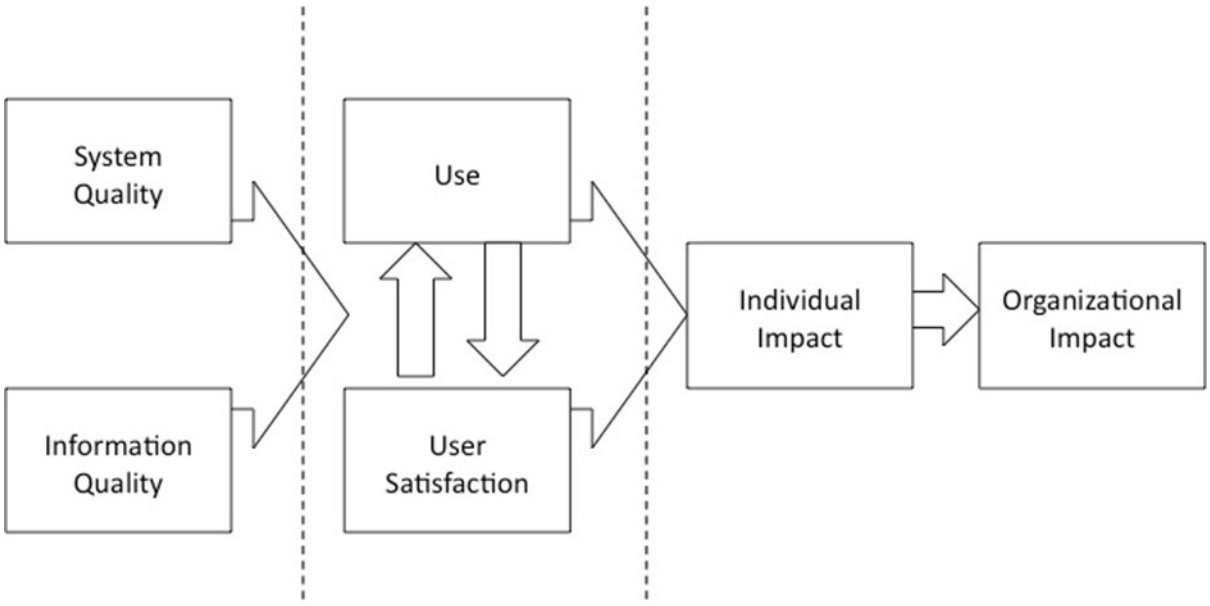

Figure 2.1: Information Systems Success Model

(Source: Delone and McLean's 1992)

In response to such feedback, Delone and McLean substantially updated their model in 2002, adding and removing elements to refine its analytical capability. This revision introduced 'service quality' as a crucial measure of IS implementation success. Th model shifted from 'use' to 'intention to use' as a metric for assessing user attitudes toward the system. Additionally, the concepts of individual and organisational impacts were merged into a single construct termed 'net benefits,' reflecting a more integrated approach to evaluating IS success (Alzahrani et al., 2019; Çelik & Ayaz, 2022).

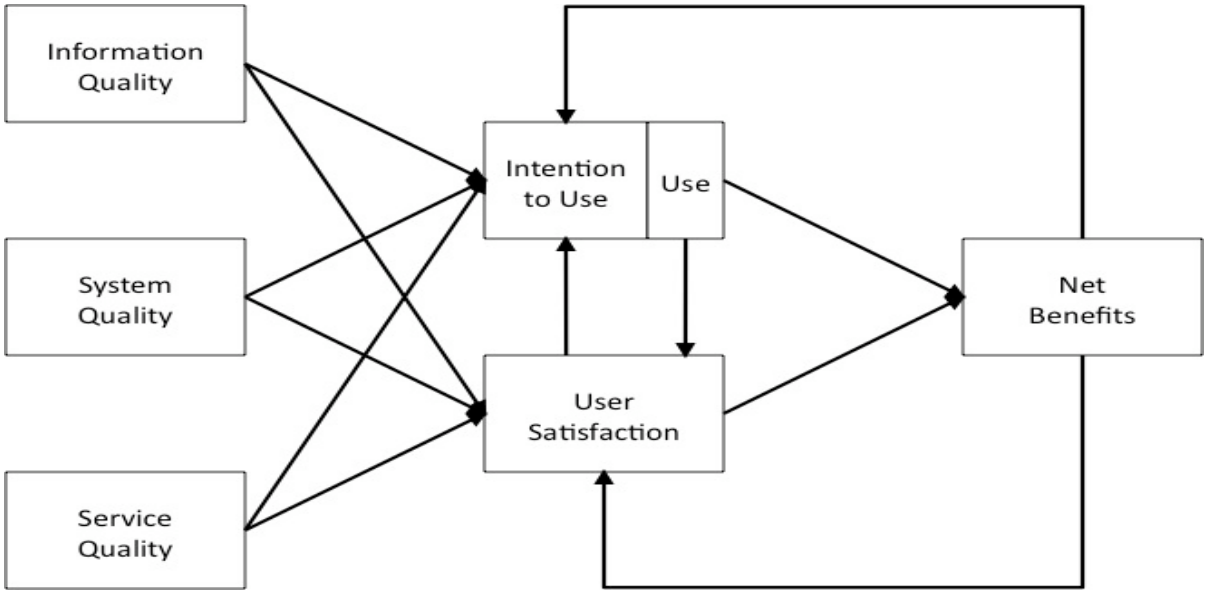

Figure 2.2: Updated Information Systems Success Model

(Source: Delone & McLean 2003)

The success of an IS is influenced by these six constructs, making the model comprehensive in its adoption (Delone & McLean, 2003). These six dimensions are summarised in Table 2.1, provided below on page 30. The table titled "Updated DeLone and McLean IS Success Model Construct Descriptions" overviews the six key constructs that form the foundation of the DeLone and McLean Information Systems Success Model. These constructs, information quality, system quality, service quality, intention to use/use, user satisfaction, and net benefits, serve as crucial indicators in evaluating the success of information systems, including mHealth apps.

The table outlines each construct's definition and the associated measuring variables. For example, information quality assesses the system's output, focusing on attributes like accuracy, completeness, and relevance. System quality centres on the system's performance and usability, while service quality highlights the level of support provided to users. Intention to use/use

measures user behaviour and motivation to engage with the system. User satisfaction reflects the users' overall contentment, and net benefits evaluates the system's overall impact on the stakeholders' goals.

Including studies like Alzahrani et al. (2019) and Delone and McLean (2003b) adds empirical support to each construct, ensuring that the framework is grounded in comprehensive research. Each construct's description is backed by examples from literature, reinforcing the significance of these factors in assessing an IS's success across various contexts, including education and mobile health applications.

2.11. The DeLone and McLean Information Systems Success Model in Various Contexts

The DeLone and McLean IS Success Model has proven to be a powerful tool for assessing the effectiveness of information systems across various sectors. Since its introduction in 1992, the model has been extensively applied not only in traditional fields such as commerce and e-learning (Alzahrani et al., 2019; Çelik & Ayaz, 2022; Delone & McLean, 2003a; Schnall et al., 2018) but also in healthcare, where its relevance continues to grow (Guo & Lyu, 2023; Keikhosrokiani et al., 2020; Ojo, 2018). These applications highlight the model's versatility and ability to adapt to different technological and organisational contexts, demonstrating its ongoing utility in evaluating IS effectiveness.

2.11.1. Education

Alzahrani et al. (2019) utilised the DeLone and McLean Information Systems Success Model to explore the determinants affecting the use of digital libraries in Saudi Arabia. Their research focused on the relationship between system, information, and service quality and their impact on user satisfaction and usage intentions. They found that these quality dimensions significantly influenced user satisfaction and behavioural intentions, particularly noting information quality as a critical predictor of user satisfaction that strongly affected users' intentions to engage with the system.

In a similar vein, Çelik and Ayaz (2022) applied the DeLone and McLean model to evaluate a Student Information System (SIS) that facilitated online access to academic and personal information for students, thereby enabling them to manage operations within a computerised environment. Analysing responses from 882 Turkish students, they discovered that while the quality constructs significantly affected system usage, they did not considerably impact user satisfaction. Additionally, their findings indicated that neither system usage nor user

satisfaction had a significant effect on the overall success of the SIS, contrasting with the results obtained by Alzahrani et al. (2019).

2.11.2. Electronic and mobile health

Keikhosrokiani et al. (2020) developed a theoretical model based on the DeLone and McLean Information Systems Success Model to evaluate the iHeart mHealth system in Iran, aimed at managing chronic diseases such as hypertension and arrhythmia. Their research involved surveying healthcare professionals to ascertain the human interaction factors that affect the system's success, focusing on ease of use, system performance, and responsiveness. The researchers discovered that information quality, privacy, trust, and mHealth literacy played significant roles in system usage, though user satisfaction and service quality did not impact as expected. The authors emphasized the importance of enhancing quality, trust, and user satisfaction while reducing errors and enhancing safety in mHealth interventions for chronic disease management.

Schnall et al. (2018) conducted a qualitative study using semi-structured interviews to evaluate the MyPEEPS mHealth app designed for HIV prevention in the United States, applying the DeLone and McLean model for their analysis. Their findings suggested that the app effectively provided practical and easily understandable information, achieving user satisfaction. However, the potential for future use could have been better due to insufficient app features, even though the app was well-received for its personalisation and user-friendliness. Service quality did not pose significant issues, and the app facilitated improved decision-making, better communication, healthier behaviours, and heightened HIV risk awareness among users.

Table 2.1: Updated DeLone and McLean IS Success Model Construct Descriptions

Constructs	Definition	Measuring variables	Studies
Information quality	This construct discusses the attributes of the system's output	Accuracy, completeness, consistency, ease of understanding, format, relevance	(Alzahrani et al., 2019; Delone & McLean, 2003a; Ekelund & Ekwall, 2021; Ratzos & Trzpis, 2022)
System quality	This construct centres around the perception of the system	Access, ease of use, navigation, reliability, efficiency, flexibility, performance	(Alzahrani et al., 2019; Delone & McLean, 2003a; Ekelund & Ekwall, 2021; Ratzos & Trzpis, 2022)
Service quality	Denotes the calibre of assistance and training provided to users within the system	Assurance, empathy, responsiveness	(Alzahrani et al., 2019; Delone & McLean, 2003a; Ekelund & Ekwall, 2021; Ratzos & Trzpis, 2022)
Intention to use/use	Refers to user behaviour during system interaction	The factors encompassing the users' motivation to utilise the system, their intentions for future system use, exploration of their preferences for alternative information systems,	(Alzahrani et al., 2019; Delone & McLean, 2003a; Ekelund & Ekwall, 2021; Ratzos & Trzpis, 2022)

		system reliability, and overall applicability	
User Satisfaction	Pertains to the level of satisfaction perceived by users of the system	Investigating users' overall contentment and disposition toward the information system, fulfilment of their expectations, sustained system usage, sufficiency, efficacy, and general satisfaction	(Alzahrani et al., 2019; Delone & McLean, 2003a; Ekelund & Ekwall, 2021; Ratzos & Trzpis, 2022)
Net benefits	Refer to how the system positively or negatively impacts the stakeholder's goals or objectives	By exploring users' perspectives on the benefits and drawbacks of system usage and analysing the impact of the system on users' behaviours and practices	(Alzahrani et al., 2019; Delone & McLean, 2003a; Ekelund & Ekwall, 2021; Ratzos & Trzpis, 2022)

(Own synthesis)

Guo and Lyu (2023) crafted a quality evaluation scale grounded in the DeLone and McLean IS Success Model, incorporating three quality factors, information, system, and service quality, and seven other metrics to assess mHealth apps for hypertension management in China. Their cross-sectional survey highlighted that information quality and service quality were pivotal in enhancing satisfaction among elderly users, with information timeliness being particularly crucial. Contrary to previous studies and the theoretical expectations of the IS Success Model, system quality did not significantly influence user satisfaction, underscoring a need for reevaluation of system attributes in the context of mHealth app effectiveness.

2.12. Existing Mobile Health Evaluation Frameworks

This section explores the evaluation tools and frameworks used to assess the quality of mHealth applications, particularly in chronic disease management. The MARS tool, the Enlight Suite, and the AQUA tool are examined to understand their strengths, limitations, and applicability to chronic disease mHealth apps. Each tool has contributed to improving app quality assessment. Still, their relevance in chronic disease contexts is scrutinised, revealing limitations such as the lack of disease-specific criteria, therapeutic alliance, and service quality measures.

2.12.1. Mobile Application Rating Scale

Stoyanov et al. (2015) introduced the MARS tool as a comprehensive tool designed to assess the quality of mHealth apps. This tool was developed through a detailed review of existing literature and criteria for assessing app and web quality. An expert panel refined these criteria, creating subscales within the MARS framework. The initial study evaluated 60 mental health-focused mHealth apps from the Apple App Store, where the first 10 were used for piloting purposes, and the remaining 50 were assessed for inter-rater reliability (Stoyanov et al., 2015; Terhorst et al., 2020; O'Rourke et al., 2020).

The MARS framework is structured around five key quality dimensions: engagement, functionality, aesthetics, information quality, and subjective quality. These dimensions encompass 23 specific items that rate the quality of each app on a five-point Likert scale, ranging from 1 (inadequate) to 5 (excellent). If an item did not apply to a specific app, a "Not applicable" option was available. However, mean scores were used in the evaluation to ensure consistency, especially in cases where specific dimensions were not applicable (Stoyanov et al., 2015). Notably, the "Not applicable" option was eliminated in the engagement category, as engagement is considered universally essential for app quality.

Despite its wide usage, particularly in evaluating mental health apps, the MARS tool has limitations when applied to chronic disease mHealth apps. Since it was initially developed using mental health apps, it may lack specificity for chronic disease apps, which often require more complex functionalities like personalised care plans, treatment regimens, and condition-specific features (Guo & Lyu, 2023). As a result, the MARS tool may need to fully capture the nuanced needs of chronic disease management apps, potentially limiting its effectiveness in this domain.

Additionally, studies show that chronic disease mHealth apps are underrepresented in validation studies of MARS. For example, Terhorst et al. (2020) found that out of 1,299 apps analysed across health domains, only a small number targeted chronic diseases like cancer, which reduces the scale's ability to assess these apps comprehensively. Moreover, the MARS tool lacks disease-specific evaluation criteria, which are crucial for effectively assessing apps designed for chronic conditions like hypertension, where multiple functions such as reminders, recording, and consultation are essential (Guo & Lyu, 2023).

The MARS also does not directly address therapeutic alliance and persuasiveness, which are critical in engaging users with chronic conditions. Research has shown that therapeutic alliance is a key predictor of success in various interventions (Klein et al., 2003). The MARS tool needs to incorporate this construct, which could limit its ability to assess apps aimed at chronic disease management (O'Rourke et al., 2020).

Another notable limitation of the MARS tool is its omission of service quality as a distinct evaluation criterion. Service quality, which includes responsiveness, reliability, and user support, is critical for assessing the overall experience of mHealth app users (DeLone & McLean, 2003). While the MARS tool assesses engagement and functionality, explicitly incorporating service quality into the evaluation would offer a more holistic assessment of app performance, particularly for chronic disease management apps (David et al., 2022). Incorporating these additional criteria would enhance the MARS tool's applicability and provide a more complete evaluation of chronic disease mHealth apps, addressing both the functional and relational aspects of the user experience.

2.12.2. Enlight Suite

Baumel, Faber, Mathur, Kane, and Muench (2017) developed a comprehensive evaluation framework known as the Enlight Suite, specifically designed to assess the quality and therapeutic potential of mobile and web-based eHealth interventions. The Enlight tool emerged

in response to the limitations of existing evaluation frameworks, which often needed more critical constructs for evaluating intervention outcomes such as persuasive design, behaviour change, and therapeutic alliance. These concepts were integral to the development of the Enlight tool, marking the first time they were systematically incorporated into a quality evaluation framework (Baumel, Faber, Mathur, Kane, & Muench, 2017).

The Enlight Suite is structured into three key sections: classification, quality assessment, and checklists. The classification section categorises eHealth programs based on their intended users, the clinical condition they address, and the program's primary aim (O'Rourke, Pryss, Schlee, & Probst, 2020; Baumel et al., 2017). The quality assessment section focuses on six core constructs: usability, visual design, user engagement, content, therapeutic persuasiveness, and therapeutic alliance. Each construct is rated on a scale of one to five, with several specific items under each construct. Additionally, the Suite includes a general subjective evaluation, which allows raters to provide an overall subjective assessment of the program after completing the structured rating process (Baumel et al., 2017; O'Rourke et al., 2020).

The checklist section addresses essential domains related to using eHealth interventions, including the program’s credibility, evidence-based nature, privacy protections, and basic security measures (Baumel et al., 2017). This component ensures that eHealth programs provide therapeutic benefits and adhere to essential ethical and security standards.

The researchers tested the Enlight Suite on 84 eHealth programs across various delivery platforms (mobile and web-based) and targeting different clinical aims, such as behavior changes related to chronic conditions like physical activity, diet, smoking cessation, and alcohol use (Baumel et al., 2017). The results demonstrated solid reliability and internal consistency across all quality constructs, indicating the Suite's robustness. The Suite was also deemed applicable across various clinical aims and delivery mediums. The study underscored the significance of persuasive design and therapeutic alliance as crucial factors in evaluating eHealth interventions, and it revealed meaningful correlations between the quality constructs and initial validity measures.

Despite its comprehensive framework, the Enlight Suite does have some limitations, mainly when applied to the context of chronic disease management apps (O'Rourke et al., 2020). One notable limitation is its lack of explicit focus on service quality. While the Enlight Suite excels at evaluating design and engagement factors, it does not fully account for broader service quality dimensions, such as reliability, responsiveness, and support services offered by the app.

These factors are critical for chronic disease management apps, where a reliable and supportive user experience is essential for ensuring long-term patient engagement and adherence to treatment plans (Guo & Lyu, 2023).

Another potential limitation of the Enlight Suite is its generalisability across different platforms and clinical conditions. The tool was primarily developed with certain conditions and delivery platforms in mind, meaning that further validation and investigation are necessary to confirm its applicability in other contexts. Additionally, while the Enlight Suite underwent systematic review and testing, its validity and reliability, specifically for chronic disease management apps, have yet to be extensively examined, indicating the need for further empirical studies to solidify its effectiveness in this area (O'Rourke et al., 2020).

2.12.3. Multidimensional App Quality Assessment Tool for Health-Related Apps

O'Rourke, Pryss, Schlee, and Probst (2020) developed the AQUA questionnaire as a comprehensive tool to evaluate mHealth application quality. This assessment framework builds upon existing models, such as the Mobile Application Rating Scale (MARS) tool and the Enlight Suite, while incorporating new criteria derived from literature reviews and certification guidelines. The AQUA tool aimed to overcome the challenges posed by its predecessors, particularly addressing issues such as inconsistent psychometric reliability in the MARS tool and the complex evaluation processes in the Enlight Suite (O'Rourke, Pryss, Schlee, & Probst, 2020).

The AQUA tool covers eight key dimensions of app quality: usability, user engagement, content, visual design, therapeutic quality, security, information, and impact. These dimensions comprehensively evaluate aspects such as app usability, design, therapeutic efficacy, data security, and user impact (Sedhom, McShea, Cohen, Webster, & Mathews, 2021; O'Rourke, Pryss, Schlee, & Probst, 2020).

The AQUA tool is available in two versions: one for developers (the expert version) and another for end-users (the user version). The expert version, containing 31 items across seven dimensions, focuses on usability, engagement, content, and security, offering developers insights into app quality throughout development (O'Rourke, Pryss, Schlee, & Probst, 2020). In contrast, the user version allows individuals to provide feedback on app quality from a user-centered perspective, adding an eighth dimension that captures subjective app effectiveness (Sedhom et al., 2021). Both versions use a five-point Likert scale for quantitative assessment,

and mean scores are calculated for each dimension to provide a comprehensive evaluation (O'Rourke et al., 2020).

While the AQUA tool offers a multidimensional approach to assessing mHealth app quality, particularly in terms of usability and therapeutic potential, it has some limitations. For instance, it only partially addresses all aspects of data protection and privacy, which are critical in health-related applications (Caponnetto & Casu, 2022; Sedhom et al., 2021). Additionally, while it assesses various app functionalities, the AQUA tool lacks in-depth evaluation of ethical issues such as informed consent and confidentiality which are critical in healthcare settings (O'Rourke et al., 2020).

Moreover, the tool may need to fully capture the scientific rigour and evidence-based content required for chronic disease apps (Sedhom et al., 2021). Although the AQUA tool assesses information quality, it only partially encompasses all key dimensions highlighted by the Delone and McLean model, such as accuracy, relevance, and comprehensiveness of information (DeLone & McLean, 2003). Additionally, in the context of system quality, the AQUA tool evaluates usability and performance. Still, it lacks the technical depth to measure reliability, availability, and interoperability, as emphasized in the Delone and McLean model.

Service quality, which is a vital aspect of user experience in mHealth apps, is also not comprehensively addressed by the AQUA tool. While the tool emphasizes user engagement and therapeutic quality, it does not fully incorporate key service quality constructs such as responsiveness, assurance, empathy, and tangibility, essential in evaluating user support and overall app service quality (DeLone & McLean, 2003).

2.13. Evolution of the CHRONIQ Framework

The CHRONIQ framework for evaluating mHealth apps, particularly those aimed at chronic disease management, was developed through a synthesis of three established tools discussed above: the MARS tool, the Enlight Suite, and the AQUA tool (Baumel et al., 2017; Charlie & Cilliers, 2024; O'Rourke et al., 2020; Stoyanov et al., 2015). This evolution was not a straightforward adoption but a carefully structured integration that combined key features from each model while addressing their limitations. The goal was to create a holistic, multidimensional evaluation tool explicitly tailored to chronic disease mHealth apps, addressing the gaps that other frameworks had left unresolved (Charlie & Cilliers, 2024).

The journey toward CHRONIQ began by evaluating each model independently. The MARS tool, developed by Stoyanov et al. (2015), was assessed for its core strengths, such as its focus on app engagement, functionality, aesthetics, and information quality. However, it was noted that the MARS tool lacked attention to chronic disease-specific needs like personalised care plans and long-term user engagement, which are critical in chronic disease management apps (Guo & Lyu, 2023). Despite this limitation, several of MARS's constructs, such as information quality, system quality, and user satisfaction, were identified as essential components of the CHRONIQ framework (Charlie & Cilliers, 2024).

Similarly, the Enlight Suite, created by Baumel et al. (2017), contributed valuable dimensions focused on persuasive design, behaviour change, and therapeutic alliance, all crucial for engaging users with chronic conditions. However, Enlight's Suite's broader application to general eHealth rather than chronic disease-specific contexts highlighted a gap that needed addressing (O'Rourke et al., 2020). Still, constructs such as therapeutic quality and user engagement were adapted from the Enlight Suite to enhance the CHRONIQ framework (Charlie & Cilliers, 2024).

The AQUA tool, developed by O'Rourke, Pryss, Schlee, and Probst (2020), offered a multidimensional approach, combining elements from the MARS tool and Enlight Suite and adding additional features like usability content quality and security. While the AQUA tool provided a comprehensive framework for app quality, it lacked the therapeutic elements necessary for managing chronic disease apps (Caponnetto & Casu, 2022; Sedhom et al., 2021). Nevertheless, dimensions such as usability, security, and content quality were incorporated into the CHRONIQ framework (Charlie & Cilliers, 2024).

The Delone and McLean Information Systems (IS) Success Model (1992, updated in 2003) provided a robust theoretical foundation for the CHRONIQ framework, guiding the integration of constructs from the other models. Delone and McLean's six constructs, information quality, system quality, service quality, use, user satisfaction, and net benefits, offered a conceptual framework that facilitated the incorporation of dimensions from the MARS tool, Enlight Suite, and the AQUA tool (Charlie & Cilliers, 2024; Delone & McLean, 1992, 2003a). This model helped structure the CHRONIQ framework as an interconnected system, where each quality measure contributed to the success and effectiveness of chronic disease management apps.

Table 2.2 outlines the comparative development of the CHRONIQ framework. The table presents how key constructs from three established tools, MARS, Enlight Suite, and AQUA, were integrated into the CHRONIQ framework. Additionally, the table shows how the Delone and McLean Information Systems Success Model provided the theoretical foundation to guide the synthesis of these constructs.

2.14. The Chronic Disease Mobile Health Application Quality Evaluation Framework (CHRONIQ)

The development of the CHRONIQ framework was influenced by the foundational guidance provided by the Delone and McLean IS Success Model (Charlie & Cilliers, 2024). This theoretical underpinning served as a guiding scaffold, facilitating the amalgamation of constructs within the framework. By integrating the fundamental principles of the Delone and McLean model, the CHRONIQ framework acquired a robust conceptual structure, which in turn supported the seamless incorporation of dimensions sourced from various existing models (Charlie & Cilliers, 2024).

Upon evaluating each existing model, namely the MARS tool, the Enlight Suite, and AQUA tool, their respective strengths were harmonised to formulate the comprehensive CHRONIQ framework. The synthesis of these strengths was conducted in light of the findings from the literature review, which underscored the exigency of a comprehensive evaluation approach for mHealth apps intended for the nuanced realm of chronic disease management (Charlie & Cilliers, 2024).

2.15. The CHRONIQ Framework

The CHRONIQ framework, as depicted in Figure 2.3, is a notable progression in evaluating chronic disease mHealth apps. The framework represents an integration of dimensions drawn from established models, thereby surmounting their inherent limitations (Charlie & Cilliers, 2024). This study segment elucidates the multifarious constructs encapsulated within the CHRONIQ framework, each holding a pivotal import in the comprehensive evaluation of chronic disease mHealth apps.

Table 2.2: Evolution of CHRONIQ from MARS, Enlight, AQUA, and Delone and McLean

Construct	MARS	Enlight	AQUA	D&M IS Model	Contribution to CHRONIQ	Source
Information quality	✓		✓	✓	Refined from MARS, AQUA, and Delone and McLean	(Charlie & Cilliers, 2024; Delone & McLean, 2003a; O'Rourke et al., 2020; Stoyanov et al., 2015)
System quality	✓		✓	✓	Adopted from MARS, AQUA, and Delone and McLean	(Charlie & Cilliers, 2024; Delone & McLean, 2003a; O'Rourke et al., 2020; Stoyanov et al., 2015)
Service quality		✓	✓	✓	Integrated from Enlight, AQUA,	(Baumel et al., 2017; Charlie &

					and Delone and McLean	Cilliers, 2024; Delone & McLean, 2003b; O'Rourke et al., 2020)
User satisfaction	✓		✓	✓	Combined insights from MARS, AQUA, and Delone and McLean	(Charlie & Cilliers, 2024; Delone & McLean, 2003a; O'Rourke et al., 2020; Stoyanov et al., 2015)
Engagement quality		✓			Developed from Enlight	(Baumel et al., 2017; Charlie & Cilliers, 2024)
Health outcomes				✓	Added as a novel CHRONIQ dimension	(Charlie & Cilliers, 2024; Delone & McLean, 2003a)

Intention to use				✓	Integrated from Delone and McLean	(Charlie & Cilliers, 2024; Delone & McLean, 2003b)
Net benefits				✓	Developed from Delone and McLean	(Charlie & Cilliers, 2024; Delone & McLean, 2003b)

(Own source)

The discussion encompasses the dimensions of information quality, system quality, service quality, engagement quality, user satisfaction, health outcome, intention to use, and net benefits, delving into their contextual relevance and role in the evaluation process. These constructs enhance the comprehensive evaluation process, aligning effectively with the principles of the Delone and McLean IS Success Model while strategically integrating elements from the MARS, Enlight Suite, and AQUA tools.

2.16.1. Information quality

The information quality construct within the CHRONIQ framework addresses the issue of unreliable and irrelevant information often encountered in chronic disease mHealth apps (Nouri, Kalhori, Ghazisaeedi, Marchand, & Yasini, 2018). In managing chronic conditions, patients rely heavily on accurate and dependable information from mHealth apps to make informed decisions about their health (Chen, Xhou, Li, Li, & Jiang, 2020). This construct evaluates three critical dimensions: reliability, accuracy, and relevance.

Reliability signifies the degree to which patients can depend on the app's information. The dimension ensures that the information is consistent, dependable, and free from inconsistencies or errors, essential for maintaining user trust and facilitating effective health management (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020). Reliable information supports patients in making stable and consistent health decisions, improving health outcomes (Vervier, Valdez, & Ziefle, 2019).

Accuracy pertains to the correctness and precision of the information the app offers. Accurate information is crucial to prevent factual errors or misleading content, significantly impacting a patient's health management decisions (Chen et al., 2020). Ensuring accuracy involves rigorous verification and validation processes to uphold the integrity of the information provided (Mahmood, Zaman, Azhar, & Talib, 2019).

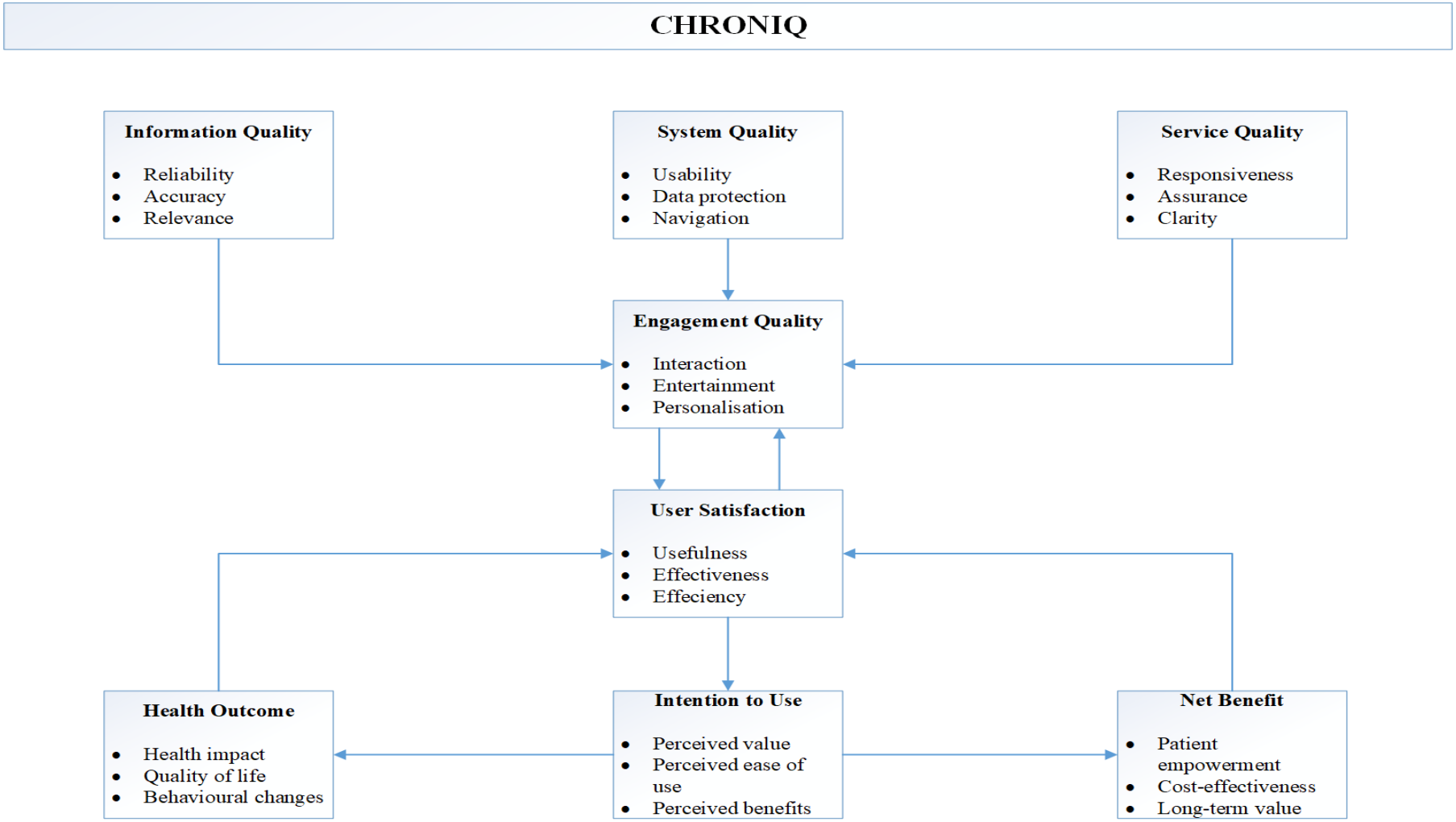

Figure 2.3: The CHRONIQ framework

(Source: Charlie & Cilliers 2024)

Relevance involves aligning the information with patients' needs and conditions and tailoring the content to address individual chronic health requirements. Relevant information ensures the content is meaningful and applicable to the users' health contexts, enhancing the app's utility and effectiveness (Ndayizigamiye, Kante, & Shingwenyana, 2020). By providing personalised information, mHealth apps can better support patients' self-management efforts and improve engagement (Anderson, Burford, & Emmerton, 2016).

2.16.2. System quality

The system quality construct in the CHRONIQ framework directly addresses issues related to usability, navigation, and data protection within chronic disease mHealth apps (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020). Usability problems often plague mHealth apps, hindering patients' ability to interact effectively with app features (Vaghefi & Tulu, 2019). Navigation issues can lead to user frustration, making it challenging for patients to access vital information and services (Wang & Qi, 2021). Data protection is a paramount concern in the digital healthcare landscape, as breaches can lead to severe consequences, eroding trust in the app (Vervier, Valdez, & Ziefle, 2019). The system quality construct assesses three fundamental elements: usability, navigation, and data protection.

Usability relates to the app's user-friendliness, ensuring patients can intuitively interact with its features. Practical usability is crucial for facilitating user engagement and ensuring patients can efficiently perform necessary tasks within the app (Baumel, Faber, Mathur, Kane, & Muench, 2017). High usability reduces the learning curve and enhances the overall user experience, which is significant for chronic disease management, where continuous use is essential (Celik & Ayaz, 2022).

Navigation focuses on the app's structural organisation, examining how well patients can navigate its various sections and functionalities. Good navigation design ensures users can effortlessly find and access the information and services they need (Esteves et al., 2019). Poor navigation can lead to frustration and abandonment of the app, undermining its effectiveness in supporting chronic disease management (Stoyanov et al., 2015).

Data protection encompasses security and privacy measures, ensuring user data remains safeguarded during interactions with the app. Robust data protection is critical to maintaining user trust and complying with legal and ethical standards (Mahmood et al., 2019). Ensuring the security and privacy of health data helps prevent breaches that could have severe consequences for patients (Van Haasteren et al., 2019). Effective data protection strategies are essential for

fostering trust and ensuring the long-term use of mHealth apps (Diano, Sica, & Ponticorvo, 2023).

2.16.3. Service quality

Service quality is instrumental in addressing the problem of inadequate support mechanisms within chronic disease mHealth apps (Diano, Sica, & Ponticorvo, 2023). This construct comprises three pivotal elements: responsiveness, assurance, and clarity.

Responsiveness pertains to the app's ability to promptly address patient inquiries and requests, offering timely assistance to enhance user satisfaction. Responsiveness is crucial for maintaining user engagement and ensuring patients feel supported in managing their chronic conditions (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020). Timely and effective responses to user queries can significantly improve the user experience and promote sustained app usage (Baumel, Faber, Mathur, Kane, & Muench, 2017).

Assurance encompasses the app's ability to inspire patient confidence and trust by providing accurate, reliable information and guidance. Assurance is vital for fostering trust, as patients must rely on the app for critical health information and management strategies (Mahmood, Zaman, Azhar, & Talib, 2019). Reliable and trustworthy information reassures patients, enhancing their confidence in the app’s capabilities and supporting effective chronic disease management (Vervier, Valdez, & Ziefle, 2019).

Clarity relates to how comprehensibly the app conveys information and instructions, employing clear language and intuitive design. Clear and understandable information is essential for ensuring patients can easily follow health guidance and use app features effectively (Chen, Xhou, Li, Li, & Jiang, 2020). An intuitive design that simplifies navigation and information retrieval can significantly enhance user satisfaction and adherence to health management protocols (Anderson, Burford, & Emmerton, 2016).

Service quality indirectly addresses the concept of therapeutic alliance, which refers to the collaborative and trusting relationship between a healthcare professional and a patient. In the context of mHealth apps for chronic disease management, service quality, with its elements of responsiveness, assurance, and clarity, contributes to fostering a sense of trust and collaboration between the patient and the app (Ndayizigamiye, Kante & Shingwenyana, 2020). When patients perceive the app as responsive, reliable, and transparent in its guidance, they are more likely to trust and engage with it, mirroring the therapeutic alliance's positive aspects (O'Grady et al., 2020).

2.16.4. Engagement quality

The engagement quality construct adopted from the Enlight framework (Baumel et al., 2017) addresses the challenge of low user engagement often observed in chronic disease mHealth apps. The construct recognises that actively motivating patients to participate in their care is critical to app success (Baumel, Faber, Mathur, Kane, & Muench, 2017; Stoyanov et al., 2015). Engagement quality encompasses three core elements: interaction, entertainment, and personalisation.

Interaction underscores the importance of user-friendly interfaces and two-way communication, allowing patients to engage with the app actively. Compelling interaction features ensure patients can easily navigate the app and communicate their needs or concerns, enhancing their overall experience and promoting sustained use (Esteves et al., 2019). Interaction is vital for creating a sense of involvement and responsiveness, significantly enhancing user engagement (Nouri, Kalhori, Ghazisaeedi, Marchand, & Yasini, 2018).

Entertainment focuses on integrating captivating content that maintains user interest and is a motivational tool. Incorporating elements of gamification, engaging visuals, and interactive content can make the app more enjoyable and encourage regular use (Baumel et al., 2017). Entertainment features can help to reduce the monotony often associated with chronic disease management, making the process more engaging and less burdensome for patients (Wang & Qi, 2021).

Personalisation tailors the app experience to suit individual user needs and preferences, ensuring the app remains relevant and resonates with patients. Personalised features can include customised health tips, reminders, and progress tracking that align with the patient's specific health conditions and goals (Chen, Xhou, Li, Li, & Jiang, 2020). Personalisation enhances the app's perceived value, encouraging continued use and adherence to health management plans (Mahmood, Zaman, Azhar, & Talib, 2019).

By addressing these dimensions, interaction, entertainment, and personalisation, the engagement quality construct aims to solve the problem of disengagement and non-compliance often encountered in chronic disease management apps. The CHRONIQ framework achieves therapeutic persuasiveness by fostering a highly engaging and persuasive environment, motivating patients to participate actively in their care and adhere to treatment plans (Ndayizigamiye, Kante, & Shingwenyana, 2020). Engaging and personalised app experiences

can improve health outcomes by encouraging consistent and proactive patient involvement (Anderson, Burford, & Emmerton, 2016).

2.16.5. User satisfaction

User satisfaction, encompassing usefulness, effectiveness, and efficiency, is pivotal in addressing user dissatisfaction with an app's performance (Diano, Sica, & Ponticorvo, 2023). This construct directly shapes the user experience of chronic disease mHealth apps.

Usefulness refers to how much patients perceive the app as valuable in supporting their health management journey. This dimension hinges on patients' assessment of the app's capacity to meet their needs and provide relevant information. An app perceived as applicable can significantly enhance patient engagement and adherence to health management plans (Chen, Xhou, Li, Li, & Jiang, 2020). The perceived usefulness of an app is crucial for its sustained use and effectiveness in managing chronic diseases (Anderson, Burford, & Emmerton, 2016).

Effectiveness gauges the app's ability to achieve desired health outcomes and improve the user's condition, encapsulating the app's impact on health and well-being. This dimension assesses whether the app can deliver tangible health benefits, such as better disease control, improved quality of life, and enhanced patient self-management (Ndayizigamiye, Kante, & Shingwenyana, 2020). Effective apps provide clear, actionable insights that help patients manage their conditions more effectively (Mahmood, Zaman, Azhar, & Talib, 2019).

Efficiency evaluates the app's performance in delivering information and support promptly and with minimal effort on the user's part. Efficient apps streamline the user experience, making it easy for patients to access information and support when needed (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020). Efficiency reduces the cognitive load on users, enhancing their overall satisfaction and likelihood of continued app use (Baumel, Faber, Mathur, Kane, & Muench, 2017).

By addressing these dimensions of usefulness, effectiveness, and efficiency, the user satisfaction construct ensures patients have a positive and fulfilling experience with the app. A high level of user satisfaction is crucial for the app's success, as it encourages ongoing engagement and adherence to health management protocols (Vervier, Valdez, & Ziefle, 2019). Ensuring user satisfaction helps mHealth apps achieve their intended health outcomes and support patients in managing their chronic conditions more effectively (Stoyanov et al., 2015).

2.16.6. Intention to use

The intention to use construct within the CHRONIQ framework addresses the problem of app abandonment and encourages long-term engagement (Larson, 2018). This construct assesses patients' inclination to continue using the app based on perceived value, ease of use, and anticipated benefits in chronic disease management, thus retaining patients' interest and commitment to using the app over an extended period.

Perceived value refers to the user's perception of the app's worth and how it meets their health management needs. When patients perceive high value in the app, they are more likely to use it consistently and rely on it to manage their chronic conditions (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020). This perception of value is influenced by the app's ability to provide relevant, accurate, and helpful information tailored to the user's specific health requirements (Chen, Xhou, Li, Li, & Jiang, 2020).

Perceived ease of use assesses patients' perceptions of the app's user-friendliness and how easily they can navigate its features. An app that is easy to use reduces the barriers to engagement, making it more likely that patients will incorporate it into their daily health management routines (Stoyanov et al., 2015). User-friendly interfaces and intuitive design are crucial for enhancing the overall user experience and encouraging regular app usage (Vaghefi & Tulu, 2019).

Perceived benefits assess patients' expectations of the advantages and outcomes they anticipate from using the app, such as improved health outcomes and enhanced quality of life. When patients believe the app will lead to tangible health benefits, they are more motivated to use it consistently (Mahmood, Zaman, Azhar, & Talib, 2019). Anticipated benefits include better disease management, increased patient empowerment, and improved health and well-being (Ndayizigamiye, Kante, & Shingwenyana, 2020).

By addressing these dimensions, perceived value, ease of use, and perceived benefits, the intention to use construct encourages patients to remain actively engaged with the app. This helps solve the problem of app abandonment and promotes long-term usage, which is essential for effective chronic disease management (Baumel, Faber, Mathur, Kane, & Muench, 2017). Sustained engagement with mHealth apps ensures that patients continue to benefit from the app's features and support, leading to better health outcomes over time (Anderson, Burford, & Emmerton, 2016).

2.16.7. Health outcome

The health outcome construct in the CHRONIQ framework directly addresses the problem of limited evidence regarding the effectiveness of mHealth apps in improving health outcomes for patients managing chronic conditions (Diano, Sica, & Ponticorvo, 2023; Nouri, Kalhori, Ghazisaeedi, Marchand, & Yasini, 2018). This construct evaluates the app's impact on a patient's health and overall well-being, encompassing three essential dimensions: health impact, quality of life, and behavioural changes.

Health impact delves into the app's tangible effects on patients' health, monitoring objective metrics and improvements in disease management. This dimension assesses how effectively the app helps control symptoms, manage medication, and monitor vital signs, which are crucial for chronic disease management (Chen, Xhou, Li, Li, & Jiang, 2020). Accurate tracking and management tools the app provides can significantly improve patient health outcomes (Vervier, Valdez, & Ziefle, 2019).

Quality of life explores enhancements in patients' psychological well-being, stress reduction, and improved coping mechanisms. Chronic disease management is not only about physical health but also about maintaining a good quality of life. This dimension evaluates how the app reduces patients' stress and anxiety, improving their mental health and overall life satisfaction (Mahmood, Zaman, Azhar, & Talib, 2019). Improved quality of life can result from better disease management, increased patient empowerment, and more effective self-care strategies (Ndayizigamiye, Kante, & Shingwenyana, 2020).

Behavioural changes assess whether the app promotes positive health-related actions. This dimension examines how the app influences patients' behaviour, encouraging them to adopt healthier lifestyles, adhere to medication schedules, and engage in regular physical activity (Baumel, Faber, Mathur, Kane, & Muench, 2017). Positive behavioural changes are essential for long-term health improvements and effective chronic disease management (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020).

By addressing these dimensions, health impact, quality of life, and behavioural changes, the health outcome construct provides a comprehensive understanding of how mHealth apps influence patients' overall well-being and their journey towards managing chronic conditions. This comprehensive evaluation helps solve the problem of limited evidence and uncertainty regarding the efficacy of mHealth apps, ensuring that these tools genuinely benefit patients (Stoyanov et al., 2015). A robust health outcome construct supports developing and deploying

more effective mHealth solutions for chronic disease management (Anderson, Burford, & Emmerton, 2016).

2.16.8. Net benefits

The net benefits construct within the CHRONIQ framework addresses the problem of app value and sustainability (Akbar, Coiera, & Magrabi, 2019). This construct reflects the holistic advantages of chronic disease mHealth apps by considering patient empowerment, cost-effectiveness, and long-term value.

Patient empowerment refers to the app's capacity to empower individuals in managing their chronic conditions, ensuring that patients feel informed, engaged, and capable of making informed decisions regarding their health. Empowering patients through mHealth apps can improve self-management and health outcomes (Chen, Xhou, Li, Li, & Jiang, 2020). Empowered patients are more likely to adhere to treatment plans and actively participate in their health management, which is crucial for managing chronic diseases (O'Grady, Melia, O'Sullivan, Young, & Duggan, 2020).

Cost-effectiveness pertains to the economic efficiency of using the app in chronic disease management. This dimension assesses whether the app provides a cost-effective solution by potentially reducing healthcare costs while maintaining or improving the quality of care (Mahmood, Zaman, Azhar, & Talib, 2019). Cost-effective mHealth apps can decrease the need for frequent doctor visits and hospitalisations, leading to significant savings for both patients and healthcare systems (Ndayizigamiye, Kante, & Shingwenyana, 2020). Evaluating cost-effectiveness ensures that the app offers economic benefits alongside health improvements (Baumel, Faber, Mathur, Kane, & Muench, 2017).

Long-term value evaluates the enduring advantages of using the app over an extended period. This dimension examines whether the app contributes to sustained positive health outcomes, reduced healthcare utilisation, and enhanced overall well-being (Vervier, Valdez, & Ziefle, 2019). Long-term value is critical for the sustainability of mHealth apps, as it ensures that the benefits provided are not short-lived but continue to support patients' health over time (Anderson, Burford, & Emmerton, 2016). Sustained usage and long-term benefits are indicators of an app's success in managing chronic diseases (Stoyanov et al., 2015).

The net benefits construct, by addressing patient empowerment, cost-effectiveness, and long-term value, ensures that the app delivers tangible and sustainable advantages. This approach solves the problem of app value and sustainability, ensuring that mHealth apps for chronic disease management provide meaningful and lasting benefits to users and healthcare systems (Nouri, Kalhori, Ghazisaeedi, Marchand, & Yasini, 2018). Ultimately, the net benefits construct supports the development of mHealth solutions that are effective and economically viable, promoting their widespread adoption and sustained use (Diano, Sica, & Ponticorvo, 2023).

2.17. Conclusion

This chapter has explored the landscape of chronic disease management in South Africa, the potential of mHealth technologies, and the challenges associated with evaluating the quality of mHealth apps. The growing burden of chronic diseases, especially in resource-limited settings, highlights the urgency of adopting innovative solutions that enhance healthcare access and patient self-management. mHealth apps offer promising avenues for addressing these challenges by facilitating remote monitoring, patient engagement, and continuous care delivery.

Despite their potential, the chapter has identified significant gaps in the current frameworks used to assess mHealth app quality. Existing tools such as the MARS, Enlight Suite, and AQUA, while valuable, fall short of addressing the specific needs associated with chronic disease management—such as long-term engagement, personalised care plans, and the complexity of treatment regimens. Similarly, although the DeLone and McLean IS Success Model provides a strong theoretical foundation for evaluating information systems, it requires contextual adaptation to meet the nuanced demands of healthcare applications.

To address these limitations, the CHRONIQ framework was introduced as a novel, contextually relevant solution for evaluating mHealth apps tailored to chronic disease management. Drawing from established models while integrating unique constructs such as engagement quality and health outcomes, the CHRONIQ framework offers a more comprehensive and disease-specific evaluation approach. The framework aims to support both app developers and healthcare professionals in designing and assessing applications that are not only technically sound but also effective in improving health outcomes.

In doing so, this chapter has laid the conceptual groundwork for the study, emphasising the importance of standardised and context-sensitive evaluation tools. The development of the

CHRONIQ framework marks a significant step toward improving the quality, relevance, and effectiveness of mHealth interventions in South Africa and contributes to the broader discourse on leveraging digital technologies to combat the global chronic disease epidemic.

CHAPTER THREE - METHODOLOGY

3.1. Introduction

A research methodology serves as a systematic framework that guides the execution of a study, ensuring that the investigation is conducted in a structured and coherent manner (Quinlan et al., 2019). The methodology delineates the specific research methods employed within the investigation and outlines the approaches through which the study aims to obtain its results (Saunders et al., 2019). This section discusses the philosophical underpinnings and approaches employed in the research process, providing a clear justification for the chosen methods.

This section also includes a detailed description of the research paradigm, approach, design, and instruments. The study employed a quantitative approach, leveraging structured data collection and statistical analysis to test the hypotheses. The primary research instrument used was a structured questionnaire designed to systematically collect data on various dimensions of mHealth app quality, such as usability, functionality, content accuracy, and user satisfaction. The data collection process involved distributing online questionnaires to adults with chronic diseases across South Africa, utilising networks from healthcare providers, patient advocacy groups, and community organisations. Ethical considerations were meticulously addressed, ensuring compliance with the Belmont Report's principles of respect for persons, beneficence, and justice.

3.2. Research Philosophy

Research philosophy pertains to the development of knowledge and the nature of that knowledge (Muchanga, 2020). The study adopted a positivism paradigm, which aligned to empirically validate the CHRONIQ framework through quantifiable data and objective analysis (Park et al., 2020). Positivism emphasises observable, objective realities and often involves statistical hypothesis testing (Maksimović & Evtimov, 2023). This philosophical approach was well-suited for this study as the approach sought to evaluate hypotheses based on an existing theory using structured methodologies and empirical data collection, central to positivist research (Park et al., 2019).

By employing positivist principles, the study could systematically collect and analyse data to draw valid and reliable conclusions about the framework's effectiveness in assessing and improving the quality of mHealth apps for chronic disease management in South Africa.

While positivism is the chosen paradigm, the author deemed it essential to briefly discuss other philosophical approaches, such as interpretivism and pragmatism, to contextualise the selection. Interpretivism focuses on understanding the meaning of human experiences and social contexts from the participants' perspectives (Denzin & Lincoln, 2017). The philosophy involves a subjective approach where the researcher interprets the data based on their understanding of the social world (Denzin & Lincoln, 2018). While interpretivism is valuable for exploring complex social phenomena and gaining deep insights into participants' experiences (Denzin & Lincoln, 2017), the paradigm was less suitable for this study, which aimed to test predefined hypotheses and assess the effectiveness of a theoretical framework using statistical analysis.

Pragmatism is a philosophical approach that prioritises practical outcomes and real-world applications of research findings (Elgeddawy & Abouraia, 2024). Pragmatism combines both positivism and interpretivism and focuses on the research questions and the consequences of the research (Elgeddawy & Abouraia, 2024; King, 2022; Creswell & Creswell, 2017). Pragmatism is flexible and allows for the use of mixed methods (King, 2022). However, the philosophy was not suitable for this study as the primary aim was to empirically validate the CHRONIQ framework through quantitative measures rather than exploring practical applications or integrating qualitative insights.

3.3. Research Approach

Research approaches in academic studies are broadly categorised into three types: quantitative, qualitative, and mixed methods (Saunders et al., 2019). The quantitative approach often relies on systematic and cyclic data collection, where the data gathered are numerical and analysed through statistical methods. This approach utilises quantifiable indicators such as ratings, scores, and frequency counts to provide measurable and unbiased results (Naoko Taguchi, 2018; Al-Ababneh, 2020). When considering deductive research, this approach begins with a general theory or hypothesis and then proceeds to test this theory by collecting and examining specific data. In comparison, inductive research begins with specific observations or actual examples of events, trends, or phenomena (Hassan, 2024).

Quantitative research allows the researcher to remain independent of the subject matter, facilitating the testing of variables to confirm or refute hypotheses related to the study's topic. The outcomes of this approach are statistically valid and reliable, ensuring objectivity in the findings (Ganesha & Aithal, 2022). As Streefkerk (2022) described, qualitative research

explores phenomena in-depth through non-numeric data to understand individuals' or groups' meanings, concepts, and experiences. Mixed-method research integrates quantitative and qualitative approaches within a single study to comprehensively analyse the research objective(s) (George, 2023).

Using a quantitative approach was suitable for validating the CHRONIQ framework because the method allows for empirical testing of predefined hypotheses concerning the effectiveness of mHealth apps in chronic disease management. This method facilitated examining relationships between variables and ensures the generalisability of findings (Saunders et al., 2019; Haydam & Steenkamp, 2020). By employing statistical techniques to analyse data collected via surveys, this approach supported rigorous validation of the framework's theoretical assumptions and practical applications in a structured manner

3.4. Research Design

The selection of an appropriate research design is crucial, serving as the framework for aligning the study's objectives with systematic data collection and analysis methodologies (Sileyew, 2019). This study employed a descriptive research design, recognised for its efficiency in describing the characteristics of a large sample pertinent to the research hypotheses (Siedlecki, 2020). Singh (2023) underscores how descriptive research design is a widely used method in various fields, particularly for the design’s effectiveness in accurately portraying a population or phenomenon. Moreover, the concept involves systematically observing and documenting aspects of a subject without influencing or manipulating variables, making the research design ideal for studies aiming to describe characteristics, frequencies, trends, and categories.

A survey design was particularly suitable for this study as it facilitated the structured collection of quantitative data (Siedlecki, 2020), allowing for comprehensive statistical analysis to assess the CHRONIQ framework's reliability and effectiveness in evaluating mHealth apps. This approach was instrumental in capturing a wide array of user experiences with mHealth apps (Charlie & Cilliers, 2024), providing quantitative insights into critical aspects of app quality such as usability, functionality, content accuracy, and user satisfaction as defined by the CHRONIQ framework (Saunders et al., 2019; Charlie & Cilliers, 2024). These dimensions were essential for testing hypotheses about the impact of quality on app effectiveness and user satisfaction (Van Holm, 2021).

3.5. Population and Sampling

The target population for this study included South Africans of all age groups who were potential users of health apps for chronic disease management. The term 'population' refers to a defined group of individuals with shared characteristics pertinent to the research aim (Dudovskiy, 2018). In this context, the population comprised individuals in South Africa interested in utilising mHealth apps to manage chronic health conditions.

As Rahi (2017) underscored, sampling involves the selection of a subset of the population to participate in the study. The target population for this study included a diverse array of individuals across South Africa, all living with chronic diseases, a significant public health concern in the country. Chronic diseases, such as cardiovascular conditions and diabetes, contribute to 51% of deaths in South Africa (World Health Organisation, 2023).

This study employed a convenience sampling strategy to recruit participants, focusing on adults with chronic diseases who use mHealth apps. According to Andrade (2021), a convenience sample consists of participants selected from sources readily accessible to the researcher. This study recruited participants through online platforms and direct contact with healthcare institutions.

The recruitment process involved sharing a survey link via WhatsApp, LinkedIn, Facebook, and Twitter. Posts on these platforms encouraged users to share the link within their networks, promoting a diverse and random selection of respondents across South Africa. This strategy ensured a broad and representative sample of mHealth app users managing chronic diseases.

Additionally, the researcher reached out to private and public health institutions across different provinces. Contact was made via telephone and email, targeting decision-makers who could authorise the distribution of the survey. These institutions received a QR code linked to the online survey, facilitating easy access for potential respondents (Appendix 2).

Locally, specialist physicians' practices were approached within the researcher's region for permission to collect data. Upon receiving consent, paper-based questionnaire versions were distributed at these practices. A QR code directing participants to the online survey was also provided (see Appendix 2), offering an alternative method for participation. This multifaceted approach ensured comprehensive coverage and inclusivity in the recruitment process, capturing a wide range of experiences and insights from mHealth app users managing chronic diseases.

Using the Raosoft calculator with a confidence level of 95% and a margin of error of 5%, a minimum of 250 individuals was determined necessary to achieve generalisable results, ensuring comprehensive coverage and relevance of the findings to the targeted demographic group.

3.6. Research Instrument

The primary research instrument for this study was a structured questionnaire designed to collect quantitative data to evaluate the CHRONIQ framework for assessing mHealth apps aimed at chronic disease management in South Africa. Taherdoost (2022) describes a questionnaire as an essential research instrument to assist the researcher in gathering relevant data concerning the research topic.

The questionnaire for this study was structured to ensure that it captured comprehensive and relevant data across various predefined constructs, aligning with the study's objectives. Moreover, the items used in the development of the questionnaire were based upon theoretically derived and previously validated frameworks and instruments such as the Delone and McLean IS Success Model, the MARS tool, Enlight Suite and AQUA tool (Baumel et al., 2017; Delone & McLean, 2003; O'Rourke et al., 2020; Stoyanov et al., 2015).

3.7. Structure of the Questionnaire

This section provides a detailed breakdown of the organisation of the questionnaire used in this study. The questionnaire was divided into sections to collect comprehensive data on various aspects of the CHRONIQ framework (see Appendix 4). Each section was designed to capture specific information, including informed consent and demographic details, and to evaluate critical constructs such as information quality, system quality, service quality, engagement quality, user satisfaction, intention to use, net benefit, and health outcome. The structured format ensured that the questionnaire effectively gathered relevant data, facilitating a thorough analysis of the study's objectives.

3.7.1. Informed consent

This section ensured that participants provided informed consent before proceeding with the survey. The section included a key question to determine whether the respondent had a chronic disease. Importantly, all participants—regardless of whether they had a chronic disease or not—were allowed to complete the survey.

3.7.2. Demographic information

This section collected essential demographic data, such as age, gender, and type of chronic disease. Gathering this information was crucial for contextualising the survey results and ensured that the sample was representative of the target population (Keane et al., 2023; Taherdoost, 2022). The demographic data helped in understanding the diverse backgrounds of the respondents and how these factors might influence their use of mHealth apps.

3.7.3. Information quality

This section evaluated the quality of information provided by the mHealth app. The section focused on reliability, accuracy, relevance, comprehensiveness, and understandability (Delone & McLean, 2003; Stoyanov et al., 2015; Umaroh & Barmawi, 2021). These questions measured how well the app provides users with necessary and helpful information for managing their chronic conditions.

3.7.4. System quality

This section assessed the app's technical performance, including its usability, design, compatibility, and overall functionality (Delone & McLean, 2003; Stoyanov et al., 2015; Umaroh & Barmawi, 2021). The questions in this section aimed to understand how easy and effective it is for users to navigate and use the app, which is critical for ensuring sustained engagement.

3.7.5. Service quality

This section measured the quality of service features provided by the app, such as customer support, reminders, and educational resources (Delone & McLean, 2003; Stoyanov et al., 2015; Umaroh & Barmawi, 2021). The quality of these services can significantly impact user satisfaction and the overall effectiveness of the app in managing chronic diseases.

3.7.6. Engagement quality

This section examined the app's ability to engage and interact with users (Barzegari et al., 2021; Baumel et al., 2017; Delone & McLean, 2003a; O'Rourke et al., 2020). The section included features that motivate and involve users in managing chronic conditions. Engagement quality is crucial as it influences the user's continuous interaction with the app and adherence to its recommendations.

3.7.7. User satisfaction

This section gauged users' overall satisfaction with the app, focusing on its usefulness, effectiveness, and user experience (Baumel et al., 2017; Delone & McLean, 2003; Umaroh &

Barmawi, 2021). High user satisfaction indicates the app's success and ability to meet users' needs.

3.7.8. Intention to use

This section assessed the users' willingness and intention to continue using the app, reflecting its perceived value and ease of use (Delone & McLean, 2003a; Pérez Tijero & Delgadillo Ávila De Mauricio, 2019; Stoyanov et al., 2015). Understanding the intention to use helps predict long-term usage patterns and the app's potential impact.

3.7.9. Net benefit

This section evaluated the app's overall benefits, including health improvements and cost-effectiveness (Delone & McLean, 2003; Umaroh & Barmawi, 2021). The net benefit is a critical measure of the app's value to users and its effectiveness in managing chronic diseases.

3.7.10. Health outcome

This section measured the impact of the app on users' health outcomes, such as symptom management and quality of life (Barzegari et al., 2021, 2021; Baumel et al., 2017; Delone & McLean, 2003a; O'Rourke et al., 2020; Stoyanov et al., 2015). The ultimate goal of any mHealth app is to improve health outcomes, making this a vital part of the questionnaire.

3.7.11. Likert scale

The questionnaire employed a 4-point Likert scale to measure the degree of agreement or disagreement with various statements (Taherdoost, 2022). This scale provided a robust method for quantifying subjective data, allowing for nuanced insights into participant responses.

Cronbach's alpha measured the internal consistency or reliability of a set of items in a questionnaire (Alkhadim, 2022). The measurement indicated how well the items within a scale are correlated to one another (Yudhistir, 2022). A high Cronbach's alpha value suggested that the items consistently measure the same underlying construct, ensuring the reliability of the data collected (Alkhadim, 2022). Typically, a Cronbach's alpha value above 0.7 is considered acceptable, indicating good internal consistency, while values above 0.8 are considered more reliable (Alkhadim, 2022; Yudhistir, 2022). The values listed in the table below reflect that the scales used in this study met these criteria, confirming the reliability of the measured constructs.

Table 3.1: Research project scale

Construct	Cronbach alpha	Number of dimensions	Reference
Information quality	0.956	3	(Umaroh & Barmawi, 2021)
System quality	0.959	3	(Umaroh & Barmawi, 2021)
Service quality	0.954	3	(Umaroh & Barmawi, 2021)
Engagement quality	0.890	3	(Barzegari et al., 2021)
User satisfaction	0.939	3	(Umaroh & Barmawi, 2021)
Intention to use	0.953	3	(Pérez Tijero & Delgadillo Ávila De Mauricio, 2019)
Net benefit	0.966	3	(Umaroh & Barmawi, 2021)
Health outcome	0.840	3	(Barzegari et al., 2021)

(Own source)

3.8. Piloting the Questionnaire

Before the full-scale data collection, the questionnaire underwent a piloting phase to ensure its validity and reliability. The pilot study involved a smaller sample from the same population as the main study, including adults with chronic diseases using mHealth apps in South Africa. Thirty participants were selected using convenience sampling to test the questionnaire.

The piloting aimed to identify and resolve any ambiguities or issues in the questionnaire items. Participants were encouraged to provide feedback on the questions' clarity, relevance, and comprehensiveness. This feedback was crucial in refining the questionnaire to enhance its effectiveness and ensure the questions are understood.

Data collected from the pilot underwent preliminary analysis using SPSS to assess the internal consistency and reliability of the constructs, specifically through Cronbach’s alpha. Any items

with low reliability or problematic phrasing were revised or removed based on these findings. Additionally, the pilot study helped estimate the time required to complete the questionnaire, ensuring it is reasonable and considerate of respondents' time. This piloting phase is an essential step in the research process, as it allowed for fine-tuning the questionnaire to achieve more accurate and reliable results in the main study.

3.9. Data Collection

The methodological approach critically informs data collection techniques and analytic procedures, significantly influencing the study's overall reliability and validity (Pathiranage et al., 2020). This study adopted a quantitative research approach, strategically employing a survey to gather data. Questionnaires, particularly self-administered ones, are highly effective for descriptive or explanatory research, as they allow for structured data collection aligned with specific research objectives (Heath, 2023).

In this context, a questionnaire was particularly apt given its capacity to systematically capture data across predefined constructs. The data collection process for this study involved a systematic distribution of online questionnaires. The researcher sent email invitations to adults with chronic diseases across South Africa, utilising networks from healthcare providers, patient advocacy groups, and community organisations. Each email contained a link to the survey hosted on a secure platform, with a brief study overview, and an informed consent form.

Participants answered a screening question to confirm the presence of a chronic disease. Those who did not have a chronic disease were not be able to proceed with the survey. For those who qualified, the survey collected comprehensive data on various dimensions, such as app usability, functionality, content accuracy, and user satisfaction, using structured questions on a 4-point Likert scale. This method ensured that the data collection process was efficient and reached a broad and diverse sample, capturing relevant insights from both urban and rural areas in South Africa.

3.10. Reliability and Validity

Rozali et al. (2022) describe validity as the degree to which an instrument accurately measures what it is intended to measure. Validity is crucial in determining whether a questionnaire is appropriate for research, ensuring that the collected data accurately reflects the studied concepts. Taherdoost (2022) describes reliability as the consistency of the results obtained from the instrument. In surveys, reliability indicates the extent to which the instrument yields consistent results over repeated administrations.

Cronbach's alpha and factor analysis are the two most commonly used tests to assess the internal consistency of scales. Rozali et al. (2022) explain that Cronbach's alpha measures the internal consistency or reliability of a set of items within a questionnaire. A high Cronbach's alpha value suggests high reliability, indicating that the items consistently measure the same construct. Conversely, a low value may indicate low reliability, suggesting the items need to measure the intended construct more effectively (Alkhadim, 2022; Rozali et al., 2022; Yudhistir, 2022). Generally, a Cronbach alpha value of 0.80 or higher is acceptable (Alkhadim, 2022). Yudhistir (2022) asserts that alpha values in the range of 0.60 to 0.80 are adequate for internal consistency and reliability, while Rozali et al. (2022) highlight that satisfactory Cronbach alpha values are often greater than 0.71.

To ensure the validity of this study, a thorough review of the literature was conducted and discussed in various chapters. A relatively large sample of 250 individuals with chronic diseases voluntarily participated in self-administered questionnaires, allowing for a high response rate. The research instrument was evaluated with experts in information systems and statistics. Specifically, a statistician conducted statistical tests to assess the validity of the research instrument and interpret the results, ensuring both the reliability and validity of the data collected.

3.11. Data Analysis

The data analysis for this study was performed using descriptive and inferential statistical techniques. The analysis leveraged the capabilities of SPSS version 27.0 and SmartPLS 4.0 for structural equation modeling (SEM). Additionally, Microsoft Excel was used to organise and summarise the data visually.

3.11.1. Descriptive statistics

The initial stage of the analysis involved using descriptive statistics to summarise the sample's demographic characteristics and construct responses. Descriptive statistics involved summarising and organising data to describe the basic features of a dataset, providing simple summaries about the sample and the measures (Dong, 2023). Descriptive statistics was crucial for understanding the distribution and central tendencies of variables such as gender, age, and chronic disease status. This process helped describe respondents' general profile and engagement with health apps.

3.11.2. Factor analysis

Before moving to hypothesis testing, exploratory factor analysis (EFA) uncovered the latent structure of the measured variables without imposing a predetermined factor structure. EFA is an approach used to uncover the latent variables that explain the pattern of correlations within a set of observed variables, allowing researchers to explore the data without a predetermined structure (Omura et al., 2022). This technique was employed to ensure that the constructs being measured are aligned with the theoretical framework.

Following EFA, confirmatory factor analysis (CFA) was conducted to validate the measurement model. Unlike EFA, CFA required the researcher to specify the number of factors and which variables are associated with which factors beforehand (Baharum et al., 2023). CFA allowed the study to confirm the validity and reliability of the constructs identified, as measured by fit indices, Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE).

3.11.3. Structural equation modeling (SEM)

The relationships between the latent variables were analysed using partial least squares structural equation modeling (PLS-SEM). SEM is a multivariate statistical analysis technique that allows for the simultaneous examination of multiple dependent and independent variables, offering a holistic view of the data (Statistic Solutions, 2023) . SEM not only assesses direct relationships between variables but also considers indirect effects, making it ideal for testing complex theoretical models (Johnson & Wichern, 2007; Statistic Solutions, 2023).

PLS-SEM was chosen for its flexibility in handling non-normal data and small sample sizes, making it well-suited to this study. Through SEM, the study tested the relationships among the constructs identified in the CHRONIQ framework, such as information quality (IQ), system quality (SQ), service quality (SEQ), engagement quality (EQ), user satisfaction (US), health outcomes (HO), intention to use (IU), and net benefits (NB). In addition, path coefficients, t-statistics, and p-values were used to test the significance of the relationships between constructs.

3.12. Delimitations

The study was geographically limited to South Africa to analyse health app usage within its unique healthcare context and sociocultural dynamics. The study focused on chronic diseases' significant impact on public health and management needs, emphasising digital solutions that enhance patient outcomes and management efficacy.

Only apps designed for chronic disease management were included in the study. This approach aligned with broader public health goals and underscores the critical importance of app quality in effective disease management.

3.13. Ethical Consideration

This study adhered to the ethical principles outlined in the Belmont Report (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1976), ensuring compliance with the guidelines and procedures established by the University Interfaculty Research Ethics Committee (IFREC). IFREC had granted ethical clearance to protect the rights and well-being of participants throughout the research process (see Appendix 1).

The principles of respect for persons, beneficence, and justice guided the study's ethical conduct, emphasising informed consent, risk minimisation, benefit maximisation, and equitable treatment of participants (National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research, 1976). The research team was committed to transparency, integrity, and responsible conduct, maintaining high ethical standards and professional courtesy.

3.14. Confidentiality and Informed Consent

Confidentiality protocols were strictly implemented to safeguard participant privacy and data security. Participants received detailed explanations about the study's objectives, methods, potential risks, and benefits. Informed consent was obtained from all participants, who had the opportunity to ask questions and raise concerns. Participants were informed that their participation is voluntary and they could withdraw from the study without any negative consequences.

3.15. Data Collection Procedures

Data collection involved gathering personal and social information directly from participants through an online questionnaire. The nature of the questions ensured no physical or psychological harm to the participants, with the survey designed to be stress-free and respectful of the participants' time and condition. All responses were anonymous, and no identifiable personal information was collected.

3.16. Data Storage and Disposal

The research data was securely stored on a cloud drive with stringent security measures such as password protection. Physical documents, including signed consent forms, were stored in a

locked file cabinet. The data is being retained for at least five years, after which all hard copies will be shredded, and digital files will be permanently deleted. A disposal certificate will be issued to confirm the destruction of data.

3.17. Dissemination of Findings

The findings of this study were disseminated through academic publications, oral presentations, and the final thesis. Participants who wished to receive feedback on the study results were contacted, ensuring that all shared information is anonymised to protect their privacy. Measures such as encrypting computer-based files and removing personal identifiers from study documents were also implemented to maintain confidentiality.

CHAPTER FOUR - RESULTS AND ANALYSIS

4.1. Introduction

This chapter presents the study's findings in detail. The data was analysed using software tools, including SmartPLS 4.0, SPSS 27.0, and Microsoft Excel. Descriptive and inferential statistics were utilised to interpret the data, providing a complete understanding of the study. The chapter covers key aspects such as the participants' response rate, reliability analysis, descriptive statistics of the data, and hypothesis testing. Graphs and tables are employed to visually present and summarise the results, enhancing clarity and understanding of the findings.

4.2. Response Rate

The researcher issued 250 questionnaires manually and electronically. Table 4.1 shows the number of targeted surveys and the number of returned questionnaires.

Table 4.1: Response rate

Instrument	Distributed	Returned	Response rate (%)
Questionnaire	250	201	80

The data in Table 4.1 demonstrates a remarkable 80% response rate achieved through phone calls and email follow-ups. This research aimed to identify the determinants of mHealth App quality, specifically focusing on the CHRONIQ framework for managing chronic disease in South Africa. The high response rate achieved implies strong engagement and interest among participants, enhancing the credibility and reliability of the findings.

4.3. Demographic Statistics

Before exploring the results, it is essential to understand the demographic characteristics of the participants, as they provide crucial context for interpreting the findings. This section presents an overview of the respondents' gender, age, provincial distribution, chronic disease status, and use of health applications. The demographic statistics are presented in Table 4.2 as frequencies and percentages to provide a clear understanding of the demographic distribution of the respondents.

Table 4.2: Demographic statistics

Variables	**Frequency (N=201)**	**Percentage (%)**
Gender		
Male	116	57.7
Female	85	42.3
Age		
18-24 years	94	46.8
25-34 years	51	25.4
35-44 years	18	9
45-54 years	21	10.4
55-64 years	17	8.5
Province		
Eastern Cape	133	66.2
Free State	9	4.5
Gauteng	18	9
KwaZulu-Natal	10	5
Limpopo	3	1.5
Mpumalanga	4	2
North West	4	2
Western Cape	20	10
Chronic disease status		
Yes	165	82.1
No	36	17.9
Health application status		
Yes	185	92
No	16	8

The demographic statistics in Table 4.2 provide valuable insights into the participants in the study on the determinants of Health App quality, specifically the CHRONIQ framework for managing chronic diseases in South Africa. The gender distribution shows that 57.7% of the respondents were male. In comparison, 42.3% were female, indicating a fairly balanced gender

representation, allowing diverse perspectives on health app usage for chronic disease management.

In terms of age, nearly half of the respondents (46.8%) were between 18-24 years, followed by 25.4% in the 25-34 age group. This suggests that younger individuals form the majority of the sample, which could reflect their higher likelihood of using technology such as health apps to manage their chronic conditions. The representation of older participants (above 35 years) is smaller, which could indicate potential barriers or lower adoption of health apps among older age groups.

The provincial distribution reveals that most respondents (66.2%) were from the Eastern Cape, followed by smaller groups from Gauteng (9%) and the Western Cape (10%). This geographic concentration in the Eastern Cape may influence the generalisability of the findings across South Africa.

A significant 82.1% of participants reported being diagnosed with a chronic disease, reinforcing the relevance of this population to the study's focus. Additionally, 92% of respondents confirmed using health applications to monitor or manage their health (e.g. running app, food tracker, vital signs monitor). The high usage rate of health apps among chronic disease patients indicates that such technology plays a critical role in their daily health management, making the study's exploration of app quality highly relevant for improving healthcare outcomes in this demographic.

4.4. Construct Responses

The study employed a four-point Likert scale to assess the construct variables, with options ranging from "Strongly Disagree" (1) to "Strongly Agree" (4). This scale allowed participants to express their levels of agreement or disagreement with the statements in a structured manner. By limiting the response options, the scale aimed to reduce indecision and encourage more definitive responses. Ultimately, this approach enabled a precise quantification of attitudes and perceptions related to the constructs under investigation. All eight constructs that were tested in this study include information quality (IQ), engagement quality (EQ), system quality (SQ), service quality (SEQ), ser satisfaction (US), intention to use (IU), health outcomes (HO), and net benefits (NB).

4.4.1. Information quality (IQ)

Respondents were exposed to nine items designed to assess IQ. These items aimed to evaluate various aspects of the quality of information provided. Figure 4.1 summarises the responses gathered from participants regarding these IQ measures.

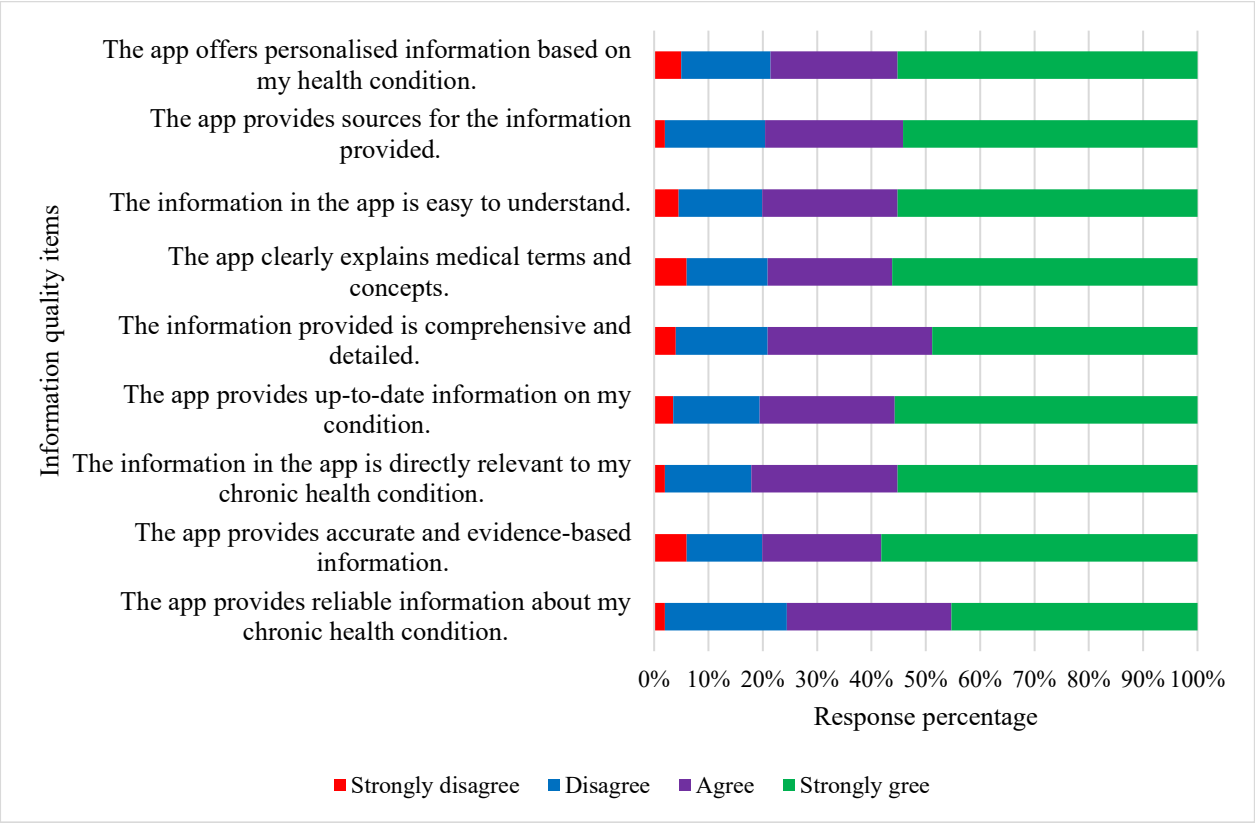

Figure 4.1: Information quality responses

Figure 4.1 illustrates that most respondents agreed or strongly agreed with the statements regarding the app's information quality. Most notably, over 80% felt that the app provides accurate, evidence-based, and up-to-date information. However, a smaller percentage showed concerns about the app providing comprehensive details and sources, as evidenced by higher disagreement levels.

4.4.2. System quality (SQ)

Nine questions were posed to evaluate SQ. The responses provided insights into various aspects of the system's performance. Figure 4.2 summarises the critical statistics of these responses.

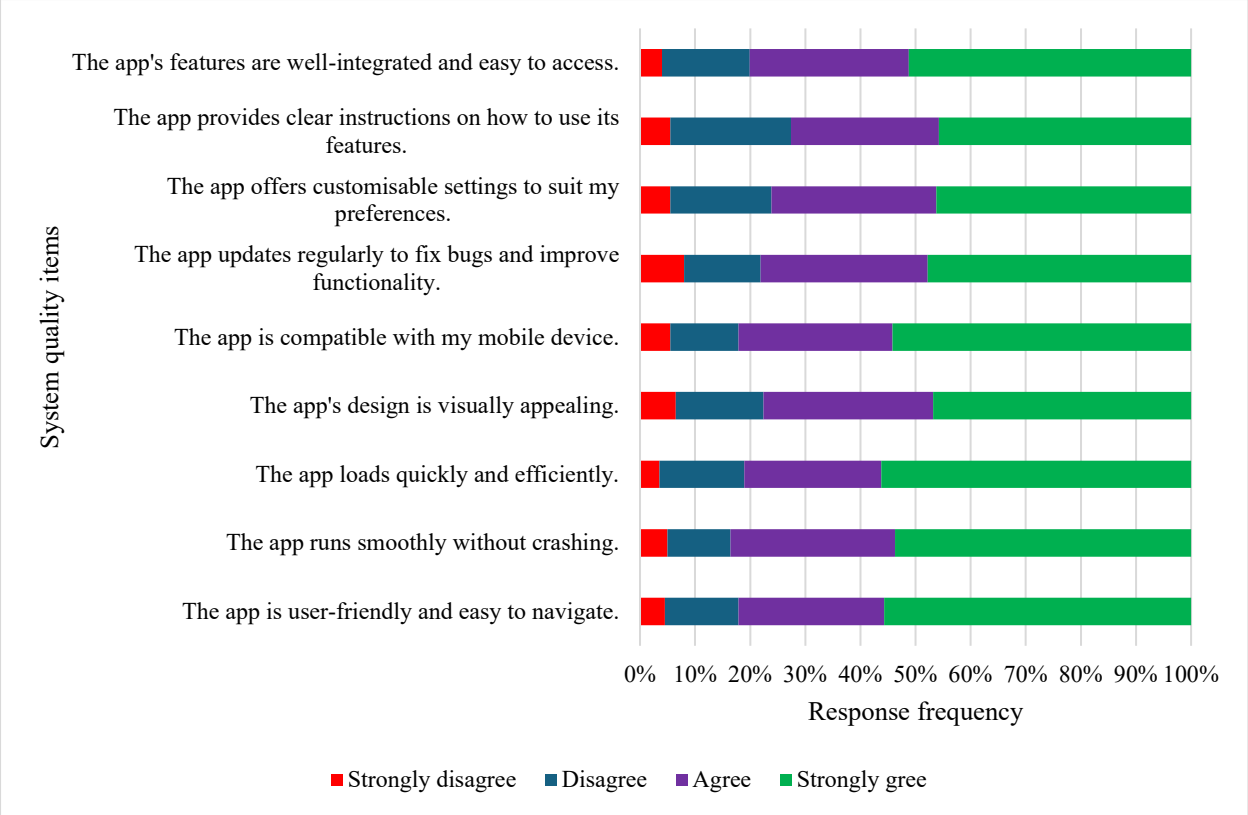

Figure 4.2: System quality responses

Figure 4.2 illustrates that most respondents expressed satisfaction with the app's SQ, particularly regarding user-friendliness, smooth operation, and quick loading times. Over 80% agreed or strongly agreed with these positive attributes. However, there were some concerns regarding the app's customisability and clarity of instructions, with more than 20% either disagreeing or strongly disagreeing in these areas. Additionally, many respondents had mixed opinions on the app's ability to update regularly to fix bugs and improve functionality.

4.4.3. Service quality (SEQ)

Service quality was assessed using nine specific items. These items evaluated the quality of support and services provided by the app. Figure 4.3 summarises the responses gathered from participants regarding SEQ.

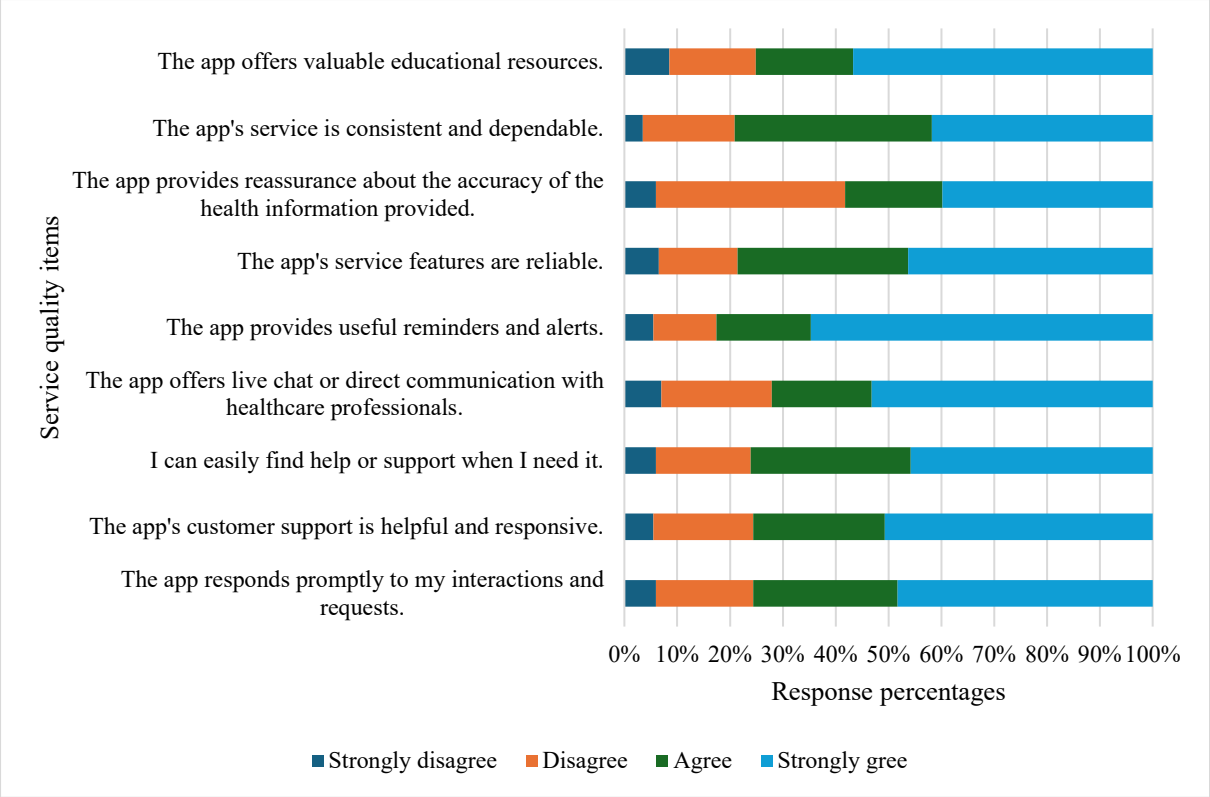

Figure 4.3: Service quality responses

Figure 4.3 illustrates that most respondents agreed or strongly agreed with the app's SEQ. Notably, over 60% of users appreciated the app's reminders, alerts, and direct communication with healthcare professionals. However, there were concerns about the app's ability to provide reassurance on the accuracy of health information, with over 35% expressing disagreement.

4.4.4. Engagement quality (EQ)

Several questions were posed to evaluate EQ. These questions aimed to assess how effectively the app engages with its users. Figure 4.4 presents the frequency distribution of the responses gathered.

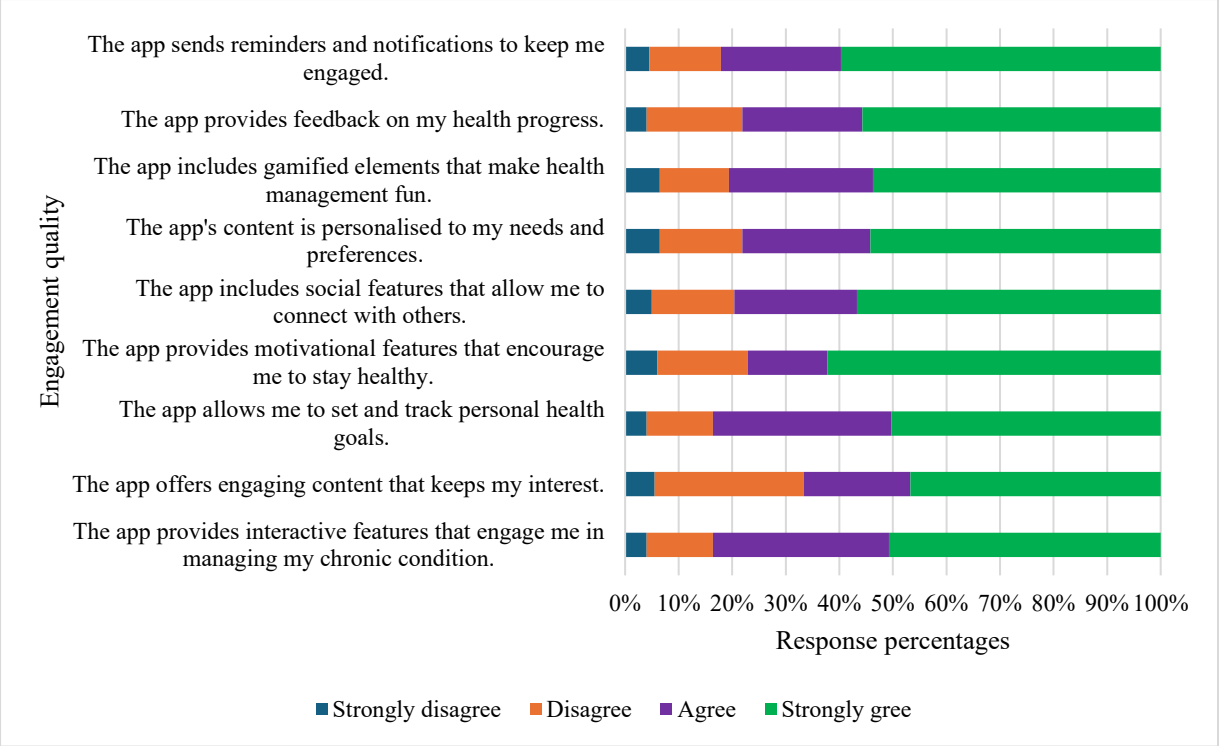

Figure 4.4: Engagement quality responses

Figure 4.4 illustrates that most respondents agreed or strongly agreed with the app's EQ. More than 80% appreciated the app's motivational features, reminders, and ability to help track personal health goals. However, there were mixed opinions regarding the app's engaging content and personalised features, with around 20% expressing disagreement.

4.4.5. User satisfaction (US)

Specific questions were asked to assess US with the app. These questions aimed to gauge overall satisfaction with the app's performance and features. Figure 4.5 provides a summary of the responses collected from participants.

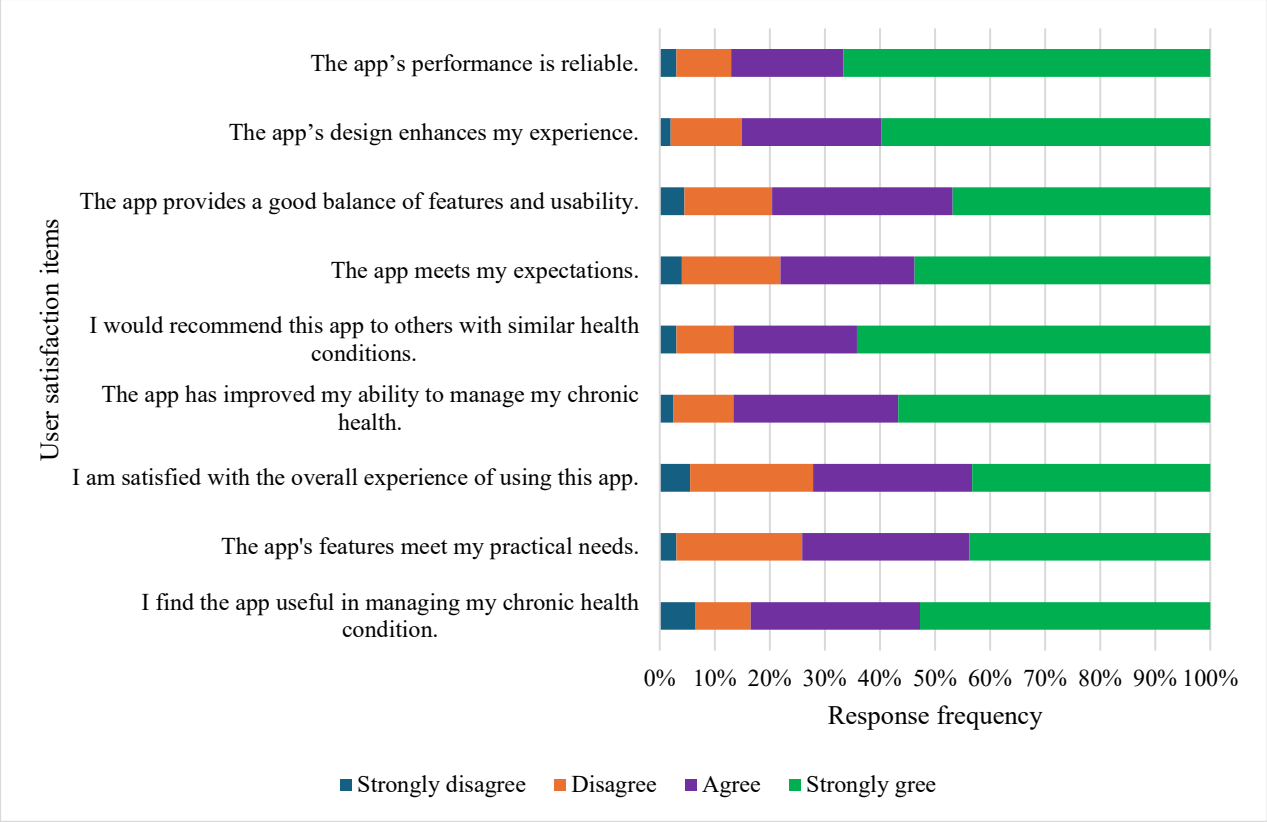

Figure 4.5: User satisfaction responses

The findings in Figure 4.5 indicate that most respondents were satisfied with the app's usefulness and performance in managing their chronic health condition. Over 80% agreed or strongly agreed that the app improved their ability to manage their condition and would recommend it to others. However, there were mixed opinions regarding whether the app's features fully meet practical needs, with around 26% expressing some disagreement.

4.4.6. Intention to use (IU)

Nine questions were asked to evaluate the app's IU and assess users' willingness to continue using it. Figure 4.6 summarises the responses collected from participants regarding their intention to use the app.

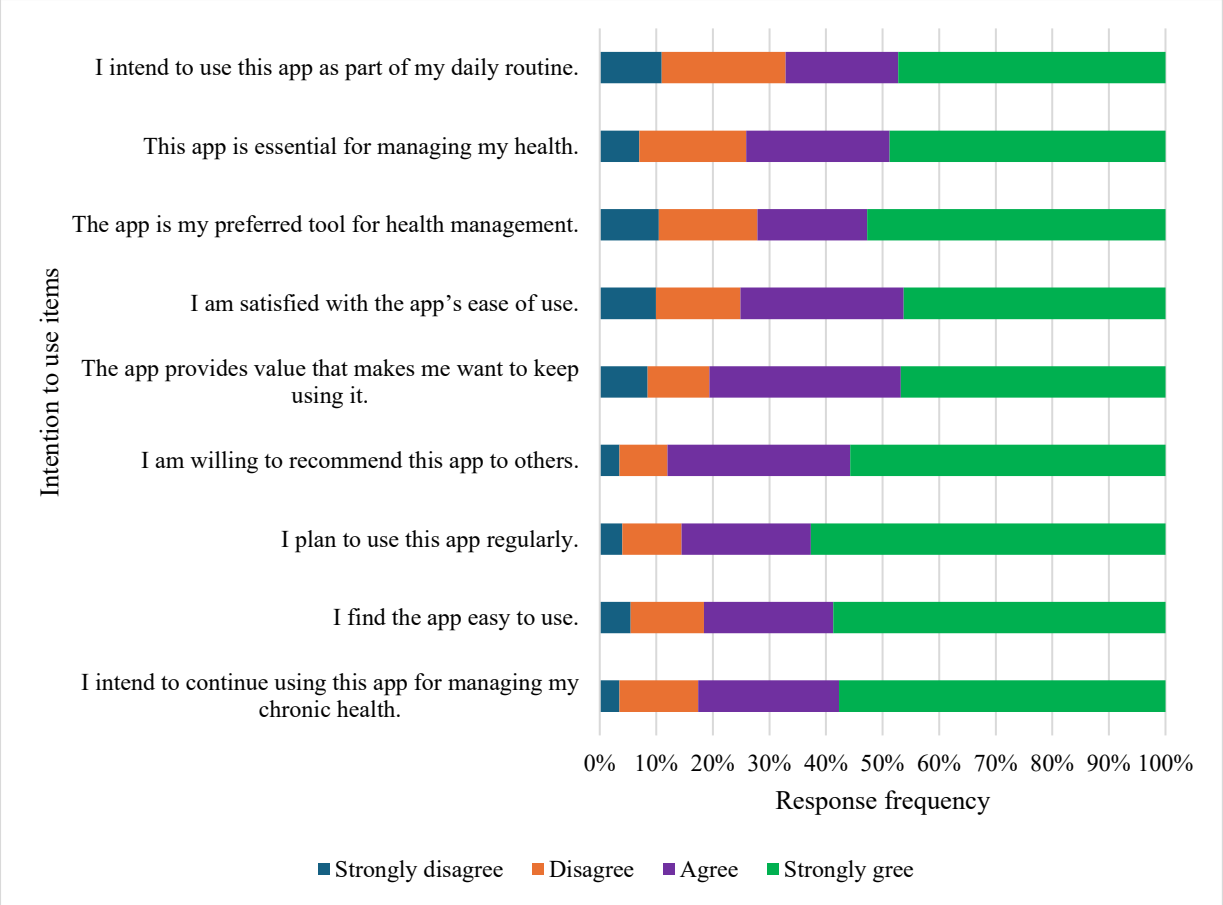

Figure 4.6: Intention to use responses

Figure 4.6 demonstrates that most respondents intend to continue using the app to manage their chronic health conditions, with around 82.6% expressing their commitment. Additionally, the app's ease of use received positive feedback, as 81.6% of users agreed or strongly agreed that they found it user-friendly. Furthermore, nearly 88.1% indicated they would recommend the app to others, suggesting a solid level of satisfaction and perceived value among users.

4.4.7. Health outcomes (HO)

The HO construct consists of nine items to assess the app's effectiveness on users' health. An item analysis was performed on all nine items to evaluate their contributions to the overall construct. Figure 4.7 presents the results of this analysis, highlighting each item's performance and relevance within the health outcomes construct.

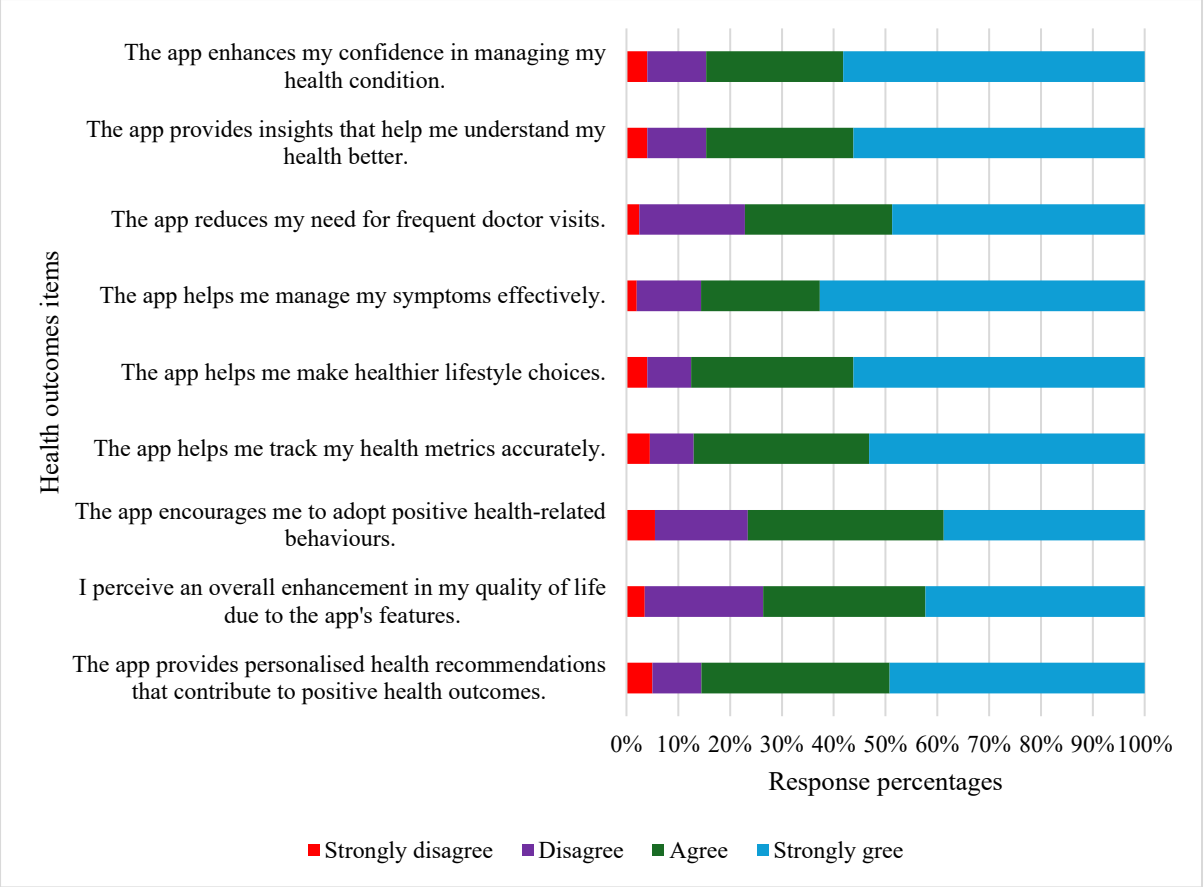

Figure 4.7: Health outcomes responses

According to Figure 4.7, most respondents perceived the app as a valuable tool for improving their health outcomes. Notably, 49.3% strongly agreed that the app provides personalised health recommendations, while 62.7% felt it effectively helps them manage their symptoms. Additionally, 58.2% of users reported increased confidence in managing their health conditions, highlighting the app's positive impact on users' overall well-being.

4.4.8. Net benefits (NB)

Net benefits were evaluated using nine items designed to capture the overall advantages users experience from the app. Figure 4.8 presents the results from the NB responses, illustrating user perceptions of the app's effectiveness. This analysis provides insights into how well the app meets its users' needs and the value it adds to their health management experience.

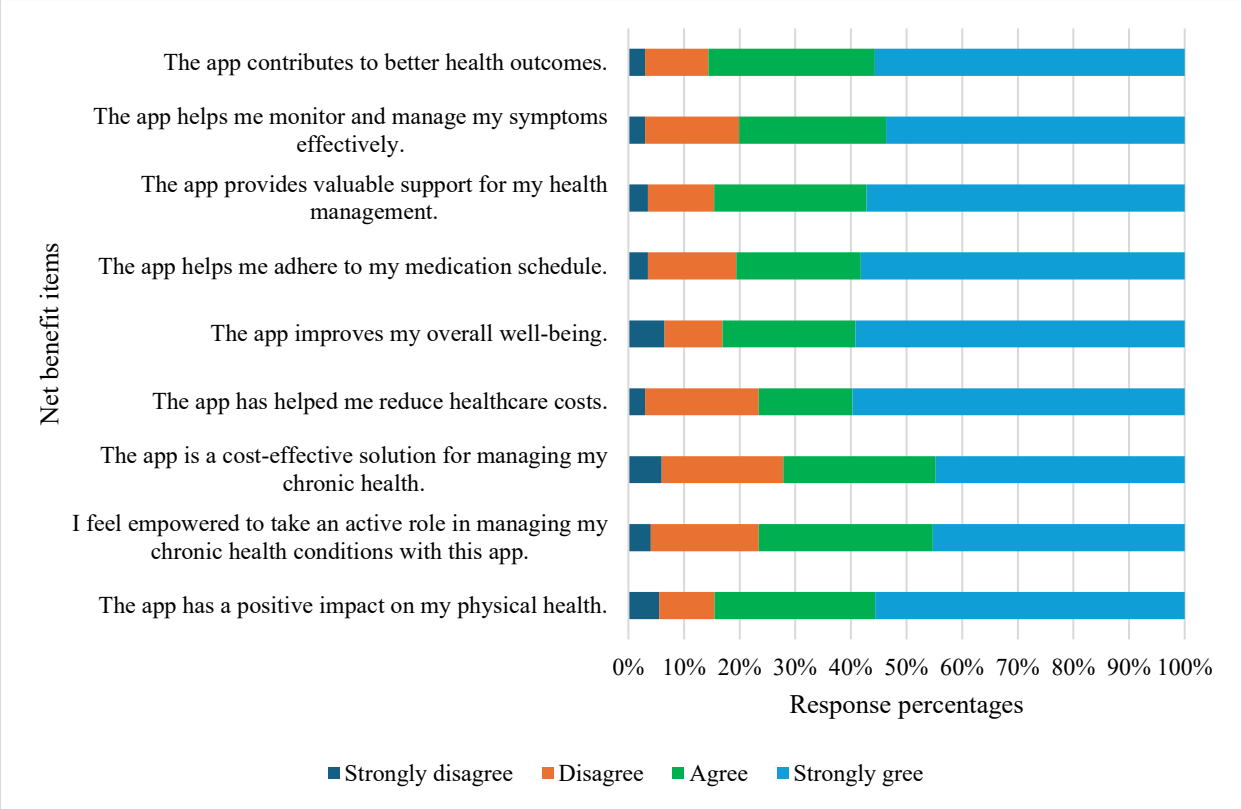

Figure 4.8: Net benefit responses

Net benefits was evaluated through nine items that assess the perceived advantages users gain from the app in managing their health. Figure 4.8 illustrates that most respondents agree that the app positively impacts their physical health, enhances their overall well-being, and provides valuable support for health management. These results indicate a strong perception among users that the app contributes to better health outcomes and empowers them to manage their chronic conditions actively.

4.5. Sample Adequacy

To assess the sample adequacy, the Kaiser-Meyer-Olkin (KMO) measure was applied, which evaluates the suitability of the data for factor analysis. A higher KMO value, typically above 0.70, suggests that the sample is adequate for such analysis. Additionally, Bartlett's test of sphericity was conducted to examine if the correlation matrix significantly deviates from an identity matrix, indicating that relationships exist between the variables. The variables analysed in this study include information quality, engagement quality, system quality, service quality, user satisfaction, intention to use, health outcomes, and net benefits. These variables were selected for their critical role in understanding the effectiveness and user experiences with mHealth apps, from the quality of information and services to their broader impact on user

satisfaction, usage intention, and health outcomes. Table 4.3 presents sample adequacy test results.

Table 4.3: Sample adequacy tests

Information quality (IQ) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.749
Bartlett's test of sphericity	Approx. Chi-square	240.529
	Df	10
	Sig.	<0.001
System quality (SQ) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.793
Bartlett's test of sphericity	Approx. Chi-square	203.068
	Df	10
	Sig.	<0.001
Service quality (SEQ) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.764
Bartlett's test of sphericity	Approx. Chi-square	226.911
	Df	10
	Sig.	<0.001
Engagement quality (EQ) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.875
Bartlett's test of sphericity	Approx. Chi-square	595.293
	Df	28
	Sig.	<0.001
User satisfaction (US) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.757
Bartlett's test of sphericity	Approx. Chi-square	260.35
	Df	10
	Sig.	<0.001
Intention to use (IU) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.731
Bartlett's test of sphericity	Approx. Chi-square	130.454
	Df	6

	Sig.	<0.001
Health outcomes (HO) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.886
Bartlett's test of sphericity	Approx. Chi-square	570.186
	Df	28
	Sig.	<0.001
Net Benefits (NB) KMO and Bartlett's test		
Kaiser-Meyer-Olkin measure of sampling adequacy		0.887
Bartlett's test of sphericity	Approx. Chi-square	611.312
	Df	28
	Sig.	<0.001

Table 4.3 displays the KMO values for all variables well above the 0.5 threshold, confirming that the sample size is adequate for conducting factor analysis. The KMO values are as follows: IQ = 0.749, SQ = 0.793, SEQ = 0.764, EQ = 0.875, US = 0.757, IU = 0.731, HO = 0.886, and NB = 0.887. Additionally, Bartlett's test of sphericity yielded significant p-values (Sig. = 0.000), further indicating that the inter-correlation matrix is not an identity matrix. This confirms adequate correlation among variables and supports factor analysis for the dataset.

4.6. Inferential Statistics

Partial least squares structural equation modelling (PLS-SEM) is employed for analysing quantitative data. Known for its flexibility, PLS-SEM is widely adopted in business and social science research, especially when dealing with smaller sample sizes or non-normal data (Hair et al., 2014). Confirmatory factor analysis (CFA) predetermines the entire measurement model, providing a robust test of the theoretical framework behind a measure (Williams et al., 2009). As a result, this study employs it before hypothesis testing. Under CFA, the Cronbach alpha (CA) coefficient and composite reliability (CR) are used to determine the scales' reliability. average variance extracted (AVE) is used to assess the convergent validity of a construct in a measurement model.

4.6.1. Reliability test

A reliability test confirms that the data accurately represents the intended concepts by assessing the consistency of the scale items used for the study variables. This research employed a 4-point Likert scale for all variables, and internal consistency was evaluated using CA. A

Cronbach's alpha value above 0.70 (Hair et al., 2019) is acceptable, indicating that the items reliably measure the same underlying concept.

4.6.1.1. Information auality (IQ) Reliability analysis

A reliability analysis was conducted on the IQ construct, which consisted of nine items. The Cronbach's alpha test was performed to assess the internal consistency of the construct, and the results are presented in Table 4.4. These findings demonstrate the reliability of the IQ construct, ensuring the items cohesively measure the underlying concept.

Table 4.4: Reliability results for information quality

Cronbach's alpha			**Number of items**	
0.763			5	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
IQ1	13.144	7.184	0.540	0.716
IQ2	13.010	6.870	0.544	0.714
IQ5	13.095	6.876	0.597	0.696
IQ6	13.040	7.258	0.447	0.749
IQ9	13.045	6.983	0.528	0.719

The results in Table 4.4 show a high level of internal consistency for the IQ construct, with a Cronbach's alpha value of 0.763, exceeding the recommended threshold of 0.70. This reliability was achieved after removing items with corrected item-total correlations below 0.30, as Pallant (2016) suggested. These adjustments ensured that only items contributing positively to the construct's consistency were retained.

4.6.1.2. System quality (SQ) reliability analysis

The nine-item SQ construct underwent a reliability test to assess its internal consistency. The results are presented in Table 4.5.

Table 4.5: Reliability results for system quality

Cronbach's alpha	Number of items

0.749			5	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
SQ4	12.881	6.696	0.581	0.680
SQ5	12.751	7.328	0.459	0.725
SQ7	12.891	7.238	0.457	0.726
SQ8	12.930	6.735	0.557	0.689
SQ9	12.786	7.149	0.521	0.704

The item-total statistics indicated that removing any of the presented items would not significantly improve the CA, which yielded an acceptable value of 0.749. The corrected item-total correlations ranged from 0.457 to 0.581, all exceeding the recommended threshold of 0.30. This suggests that the items consistently measured the same construct, ensuring reliable results. These findings align with Pallant's (2016) guidelines for internal consistency.

4.6.1.3. Service quality (SEQ) reliability analysis

A reliability test was performed on the SEQ variable, which consists of nine items. This was done to assess the internal consistency of the construct and determine whether the items consistently measured the same underlying concept. Cronbach's alpha value and corrected item-total correlations were examined to ensure the scale's reliability. The results are presented in Table 4.6.

Table 4.6: Reliability results for service quality

Cronbach's alpha			Number of items	
0.759			5	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
SEQ1	12.970	7.369	0.513	0.721
SEQ2	12.940	7.416	0.503	0.724
SEQ3	12.990	7.460	0.504	0.724

SEQ5	12.731	7.487	0.517	0.719
SEQ6	12.965	7.104	0.596	0.691

The results in Table 4.6 indicated a high level of internal consistency, as evidenced by aCA value of 0.759, which surpasses the recommended threshold of 0.7. The corrected item-total correlations ranged from 0.503 to 0.596, all exceeding the acceptable threshold of 0.30. This suggests that the items effectively measured the same construct, ensuring reliability. These findings align with Pallant's (2016) recommendations for evaluating scale reliability.

4.6.1.4. Engagement quality (EQ) reliability analysis

A reliability test on the EQ variable consisted of nine items. This assessment aimed to evaluate the items' reliability in the construct. The results are presented in Table 4.7, providing insights into the internal consistency of the EQ variable.

Table 4.7: Reliability results for engagement quality

Cronbach's alpha			Number of items	
0.861			8	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
EQ2	23.154	21.501	0.523	0.853
EQ3	22.935	21.381	0.665	0.837
EQ4	22.901	21.050	0.596	0.844
EQ5	22.920	20.824	0.673	0.835
EQ6	22.975	20.664	0.660	0.836
EQ7	22.955	21.473	0.573	0.847
EQ8	22.935	21.161	0.635	0.840
EQ9	22.861	22.070	0.530	0.851

The research findings presented in Table 4.7 showed a CA value of 0.861, which exceeds the recommended threshold of 0.7 (Hair et al., 2019), indicating a high level of internal consistency among the items. Additionally, the corrected item-total correlations ranged from 0.523 to

0.673, all surpassing the acceptable threshold of 0.30. This suggests that the items effectively measured the same construct, aligning with the findings of Pallant (2016).

4.6.1.5. User satisfaction (US) reliability analysis

A reliability test was conducted on the US variable, which comprised nine items. The results are detailed in Table 4.8. This assessment was performed to ensure the reliability and internal consistency of the items used in measuring user satisfaction.

Table 4.8: Reliability results for user satisfaction

Cronbach's alpha			Number of items	
0.777			5	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
US1	12.746	7.200	0.536	0.740
US2	12.896	7.014	0.601	0.719
US3	12.945	6.952	0.559	0.733
US6	12.766	7.210	0.532	0.742
US7	12.826	7.345	0.521	0.745

After removing four items, the CA value for the US construct was 0.777, indicating good internal consistency. The corrected item-total correlation values for all retained items exceeded the threshold of 0.30, demonstrating that these items effectively measured the same construct. The results further support the reliability of the user satisfaction variable.

4.6.1.6. Intent to use (IU) reliability analysis

The IU variable consisted of nine items, all included in the internal consistency test. Table 4.9 summarises the results of this reliability analysis. The findings provide essential insights into the IU construct's internal consistency, setting the stage for further discussion of its reliability.

Table 4.9: Reliability results for intent to use

Cronbach's alpha	Number of items
0.700	4
Item-total statistics	

Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
IU2	10.035	3.764	0.486	0.622
IU3	9.940	3.816	0.543	0.587
IU4	9.980	4.130	0.479	0.628
IU5	10.194	3.887	0.409	0.675

The reliability test results in Table 4.9 indicated a CA value of 0.700, demonstrating acceptable internal consistency for the IU variable. Additionally, the corrected item-total correlations for all retained items exceeded the recommended threshold of 0.30, reinforcing that the items effectively measure the same construct. These findings suggest that the IU variable is reliable for further analysis.

4.6.1.7. Health outcomes (HO) reliability analysis

The reliability test for the HO construct, which comprised nine items, was thoroughly conducted. The results are presented in Table 4.10. This analysis assesses the internal consistency of the items, ensuring that they effectively measure the same underlying construct.

Table 4.10: Reliability results for health outcomes

Cronbach's alpha			Number of items	
0.857			8	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
HO1	23.333	17.393	0.602	0.840
HO2	23.508	17.441	0.552	0.846
HO4	23.274	17.960	0.528	0.848
HO5	23.234	17.260	0.654	0.834
HO6	23.169	17.681	0.603	0.840
HO7	23.398	16.401	0.740	0.823
HO8	23.264	17.795	0.536	0.847
HO9	23.244	17.405	0.595	0.841

After removing certain items, the reliability analysis resulted in a substantial CA value of 0.857, exceeding the recommended threshold of 0.700, as indicated by Hair et al. (2019). Initially, the CA was 0.914, demonstrating an improvement in internal consistency. The corrected item-total correlations for the retained items ranged from 0.528 to 0.740, all surpassing the acceptable threshold of 0.30, indicating that the items effectively measured the same construct, as Pallant (2016) recommended.

4.6.1.8. Net benefits (NB) reliability analysis

A reliability test was conducted on the NB construct, which comprised nine items. Table 4.11 summarises the results of this analysis. The findings provide insights into the NB items' internal consistency and effectiveness in measuring the intended construct.

Table 4.11: Reliability results for net benefits

Cronbach's alpha			Number of items	
0.858			8	
Item-total statistics				
Items	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's alpha if item deleted
NB2	23.229	20.717	0.406	0.864
NB3	23.299	18.300	0.685	0.832
NB4	23.075	18.389	0.718	0.828
NB5	23.050	18.538	0.686	0.832
NB6	23.055	19.612	0.568	0.846
NB7	23.025	19.344	0.647	0.837
NB8	23.100	18.990	0.673	0.834
NB9	23.025	20.774	0.454	0.858

The results in Table 4.11 indicated a high level of internal consistency, with a CA value of 0.858, demonstrating strong reliability of the NB scale. The corrected item-total correlations for each retained item ranged from 0.406 to 0.718, all exceeding the recommended threshold of 0.30. This suggests that the items effectively measured the same construct, aligning with Pallant's (2016) recommendations.

4.6.2. Confirmatory factor analysis

Confirmatory factor analysis (CFA) is a statistical technique that serves as a framework for examining the relationships between observable and latent variables. Teo and Khine (2009) highlight its role in validating the underlying factor structure, ensuring that the observed variables align with the specified latent constructs. Additionally, Suhr (2006) describes CFA as a statistical tool to confirm the factor structure of a collection of observed variables. This method establishes the reliability and validity of measurement instruments, providing a rigorous basis for further analysis and interpretation of the data.

Reliability refers to how data-collecting techniques or analytic procedures produce consistent results (Saunders et al., 2009). This is the consistency with which a measuring device delivers consistent findings while measuring the same concept (Leedy and Ormrod 2015). The reliability metrics in the study were analysed using two separate computing methods: the CR test and the CA test. According to Memon et al. (2017), the internal consistency dependability of the measures is determined using the Cronbach alpha test. CA testing with a cut-off coefficient of 0.7 was utilised as per Hair et al. (2019) recommendations. A significant alpha value denotes reliability, while low ratings suggest an inability to rely on the instrument (Malhotra, 2010).

CR considers each underlying component's influence on each item and each item's omissions, providing a robust measure of dependability (Mkhatshwa, 2015; Starkweather, 2012). According to Malhotra (2010), the minimum recognised CR value should be 0.70, equivalent to CA. The AVE test is used to assess validity and dependability. According to Malhotra (2010), AVE is the variance in indicators or observable variables that the latent idea may explain. An excellent metric has a value of 0.50. A reliability analysis was performed, and Table 4.12 displays the scale validity and reliability examinations for the constructs of this research study.

Table 4.12: Validity and reliability results

Sub-construct	**Items**	**Factor loadings**	**CA**	**CR**	**AVE**
Information quality (IQ)	IQ1	0.708			
	IQ2	0.745			
	IQ5	0.743			
	IQ6	0.673			
	IQ9	0.710	0.763	0.840	0.513

System quality (SQ)	SQ4	0.739			
	SQ5	0.678			
	SQ7	0.643			
	SQ8	0.759			
	SQ9	0.710	0.749	0.833	0.500
Service quality (SEQ)	SEQ1	0.670			
	SEQ2	0.656			
	SEQ3	0.667			
	SEQ5	0.742			
	SEQ6	0.815	0.759	0.837	0.508
Engagement quality (EQ)	EQ2	0.664			
	EQ3	0.754			
	EQ4	0.695			
	EQ5	0.756			
	EQ6	0.748			
	EQ7	0.686			
	EQ8	0.747			
	EQ9	0.643	0.861	0.892	0.508
User satisfaction (US)	US1	0.750			
	US2	0.766			
	US3	0.718			
	US6	0.708			
	US7	0.689	0.777	0.848	0.528
Health outcome	HO1	0.701			
	HO2	0.667			
	HO4	0.662			
	HO5	0.755			
	HO6	0.711			
	HO7	0.820			
	HO8	0.634			
	HO9	0.705	0.857	0.889	0.503
Intention to use (IU)	IU2	0.737	0.700	0.815	0.524

	IU3	0.763			
	IU4	0.701			
	IU5	0.691			
Net benefit (NB)	NB2	0.545			
	NB3	0.771			
	NB4	0.810			
	NB5	0.772			
	NB6	0.661			
	NB7	0.749			
	NB8	0.768			
	NB9	0.586	0.858	0.891	0.509

Table 4.12 presents the results of the scale dependability test for (IQ). Items IQ3, IQ4, IQ7, and IQ8 were excluded from the measurement model due to factor loadings below the recommended threshold of 0.500 (Hair et al., 2018). The remaining standardised factor loadings for the IQ variable range from 0.673 to 0.745, all exceeding the cut-off value 0.500.

Consequently, the (CA) value was calculated at 0.763, which significantly surpasses the minimum criterion of 0.7, affirming the evaluated items' reliability. Additionally, the CR index stands at 0.841, exceeding the acceptable threshold of 0.70, indicating sufficient internal consistency, as Hair et al. (2010) noted. Furthermore, the AVE is 0.513, more significant than the recommended value of 0.500. These findings suggest that the IQ variable demonstrates strong reliability and validity.

A CA value of 0.749 and a CR value of 0.833 were obtained for the SQ variables, exceeding the threshold of 0.700. Additionally, the AVE of 0.500 meets the minimum requirement for convergent validity. These values were attained after excluding items SQ1, SQ2, SQ3, and SQ6 due to their factor loadings falling below the acceptable level of 0.500. The standardised factor loadings for the remaining SQ items range from 0.643 to 0.759, indicating satisfactory performance. These findings suggest that the SQ construct demonstrates good reliability and validity, reinforcing its adequacy for measuring the intended variable in the study.

The reliability and validity of the SEQ construct were evaluated, leading to the removal of items SEQ4, SEQ7, SEQ8, and SEQ9 from the measurement model due to their standardised factor loadings falling below the minimum recommended threshold of 0.500. This refinement

resulted in the SEQ construct comprising five items. The final CA value obtained was 0.759, which is acceptable as it exceeds the threshold of 0.700. At the same time, the CR value of 0.837 for the SEQ variable also meets the acceptable standard. Convergent validity is affirmed by an AVE value of 0.805, which surpasses the minimum requirement of 0.500 proposed by Hair et al. (2010). These findings underscore the robustness of the SEQ construct, indicating that it reliably measures the intended dimensions of service quality in the study.

The EQ variable initially comprised nine items, with only EQ1 being eliminated from the analysis. The standardised factor loadings for the remaining items ranged from 0.643 to 0.756, which was deemed acceptable. The CA and CR values obtained were 0.861 and 0.892, respectively, exceeding the recommended threshold of 0.700 as established by Hair et al. (2019). Additionally, the AVE value of 0.508 supports convergent validity within the EQ variable. These results indicate that the EQ construct is reliable and effectively captures the study's intended dimensions of engagement quality.

The US construct was measured using nine items, of which US4, US5, US8, and US9 were excluded from the model due to low factor loadings (below 0.500). The remaining US items achieved CA and CR values of 0.777 and 0.848, respectively, exceeding the recommended threshold of 0.700, indicating a solid level of reliability for the construct. Additionally, the AVE value of 0.528 is acceptable, surpassing the minimum recommended value of 0.500, suggesting that the retained items effectively capture the underlying construct of user satisfaction. These findings reinforce the validity and reliability of the US construct in measuring user satisfaction within the study.

The reliability results for the HO construct indicate a CA value of 0.857 and a CR value of 0.889, exceeding the acceptable threshold of 0.700 as suggested by Hair et al. (2019). Additionally, the AVE value of 0.503 confirms convergent validity, surpassing the minimum recommended value of 0.500. The removal of HO3 from the measurement model has led to these robust results, emphasising the strength and reliability of the remaining items in effectively capturing the construct of health outcomes.

The reliability of the IU construct was evaluated based on nine items. IU1, IU6, IU7, IU8, and IU9 were removed due to factor loadings falling below the acceptable threshold of 0.500. After these eliminations, the CA and CR values improved to 0.700 and 0.815, respectively, meeting the required reliability standards. Furthermore, convergent validity is confirmed, as indicated

by an AVE value of 0.524, highlighting the construct's robustness in measuring the intention to use the health application effectively.

The NB construct was evaluated for reliability and validity, with only one item, NB1, being removed from the analysis. This refinement resulted in strong CA and CR values of 0.858 and 0.891, respectively, confirming the reliability of the NB variable. Additionally, the AVE value of 0.509 indicates the presence of convergent validity for this construct. These findings suggest that the net benefit variable is a reliable and valid measure, effectively capturing the perceived advantages of the health application in question.

Table 4.13 presents the results of the discriminant validity analysis conducted using the Fornell-Larcker criterion. Discriminant validity is established when a latent variable demonstrates less shared variance with other constructs in the model while accounting for a greater portion of the variance in its associated indicator variables. A latent variable has discriminant validity when it shares less variance with other constructs in the model and explains more variance in its associated indicator variables (Fornell and Larcker, 1981).

Table 4.13: Fronell-Larcker criterion discriminant validity

	EQ	**HO**	**IQ**	**IU**	**NB**	**SEQ**	**SQ**	**US**
EQ	**0.713**							
HO	0.628	**0.709**						
IQ	0.608	0.701	**0.716**					
IU	0.695	0.706	0.594	**0.724**				
NB	0.603	0.685	0.707	0.651	**0.714**			
SEQ	0.701	0.648	0.658	0.712	0.673	**0.713**		
SQ	0.649	0.666	0.572	0.675	0.632	0.657	**0.707**	
US	0.707	0.612	0.597	0.699	0.598	0.709	0.674	**0.727**

Note: The number in bold is the square root of AVE.

The results presented in Table 4.13 indicate consistent confirmation of discriminant validity across all measurement items. This is supported by the observation that the square root of the AVE values, shown along the diagonal, exceeds the correlation coefficients with other latent

variables. According to Hair et al. (2019), this criterion establishes the discriminant validity of the constructs. Moreover, additional checks were conducted to reinforce these findings. The results suggest a robust distinction between the latent variables in the model.

Additionally, the Heterotrait-monotrait (HTMT) ratio, a contemporary method for assessing discriminant validity in measurement models, was employed to reinforce these findings. According to Kline (2011), an HTMT threshold of 0.85 or lower is recommended for confirming discriminant validity. The HTMT discriminant validity assessment results are in Table 4.14. This analysis further supports the differentiation between constructs within the model. Thus, the combined evidence from both methods underscores the validity of the measurement framework used in this study.

Table 4.14: Heterotrait-monotrait ratio of correlations results

	EQ	**HO**	**IQ**	**IU**	**NB**	**SEQ**	**SQ**	**US**
EQ								
HO	0.730							
IQ	0.742	0.849						
IU	0.849	0.822	0.809					
NB	0.698	0.885	0.882	0.831				
SEQ	0.803	0.817	0.881	0.897	0.855			
SQ	0.798	0.829	0.746	0.833	0.787	0.875		
US	0.804	0.738	0.766	0.847	0.722	0.819	0.881	

The HTMT ratio analysis presented in Table 4.14 offers robust evidence of discriminant validity, with all calculated values remaining below the recommended threshold of 0.90, as indicated by Gold et al. (2001) and Teo et al. (2008). This outcome reinforces the conclusion that the measures employed in the model effectively capture distinct constructs, demonstrating a lack of meaningful correlations between them. Consequently, these findings highlight the precision of the measurement framework in distinguishing among various constructs, thereby enhancing the credibility of the model's overall structure.

4.6.3. Common method bias (CMB)

A collinearity test assessed the model's potential CMB presence. The variance inflation factor (VIF) was used to gauge the level of multicollinearity among the predictor variables in the regression model. As noted by Cenfetelli and Bassellier (2009) and Kock (2014a), a VIF value above 3.3 is often considered a sign of significant multicollinearity, which could compromise the accuracy of a structural equation model (SEM). The complete collinearity statistics, including VIF values, are detailed in Table 4.15.

Table 4.15: Full collinearity statistics results

Relationships	**EQ -> US**	**IQ -> EQ**	**IU -> HO**	**IU -> NB**	**SEQ -> EQ**	**SQ -> EQ**	**US -> HO**	**US -> IU**	**US -> NB**
VIF	1.000	1.878	1.956	1.956	2.224	1.872	1.956	1.000	1.956

The collinearity statistics in Table 4.15 reveal that all VIF values are well below the more conservative threshold of 3.3, as Cenfetelli and Bassellier (2009) and Kock (2014a) recommended. The highest VIF observed is 2.224, indicating that multicollinearity is not a concern in this model. This suggests that the predictor variables are independent enough to ensure that the SEM results are robust and reliable, with no significant issues related to multicollinearity.

All reliability and validity requirements are met, ensuring the constructs are robust and accurate. Figure 4.9 presents the visualisation of the measurement model, confirming the results of the reliability and validity analyses. This visual representation further supports the strength of the model's constructs, providing a clear overview of how well the indicators reflect their respective latent variables.

In the blue circles, ORD indicates that the variables are measured using an ordinal scale. The measurement model demonstrates that all outer loadings are acceptable, above the 0.50 threshold, suggesting that the indicators sufficiently represent their respective latent constructs. The AVE values, displayed within the blue circles or nodes, are also acceptable, as they meet the minimum value of 0.500. This implies that the constructs capture at least 50% of the variance from their indicators, confirming good convergent validity.

4.6.4. Descriptive statistics and correlation analysis

Descriptive statistics were calculated to assess each variable's distribution, such as the mean and standard deviation, skewness, and kurtosis. Furthermore, correlation analysis was done. The results for all variables and the correlation findings are presented in Table 4.16.

The descriptive statistics presented in Table 4.16 indicate that the mean scores for all constructs range from 3.209 (SQ) to 3.346 (IU), suggesting a generally positive perception among respondents regarding the aspects of mHealth applications being measured. The standard deviations range from 0.590 to 0.659, indicating a relatively consistent response among participants. The skewness values for all constructs are below 3, with the most pronounced value being -1.017 for IU, which indicates a slight leftward skew. The kurtosis values are also below 10, with the highest being 0.706 for IU. These findings collectively suggest that the data conforms to the normality assumptions outlined by Kline (2011) and Tabachnick and Fidell (2013), thereby minimising the risk of significant deviations that could compromise the reliability of further analyses.

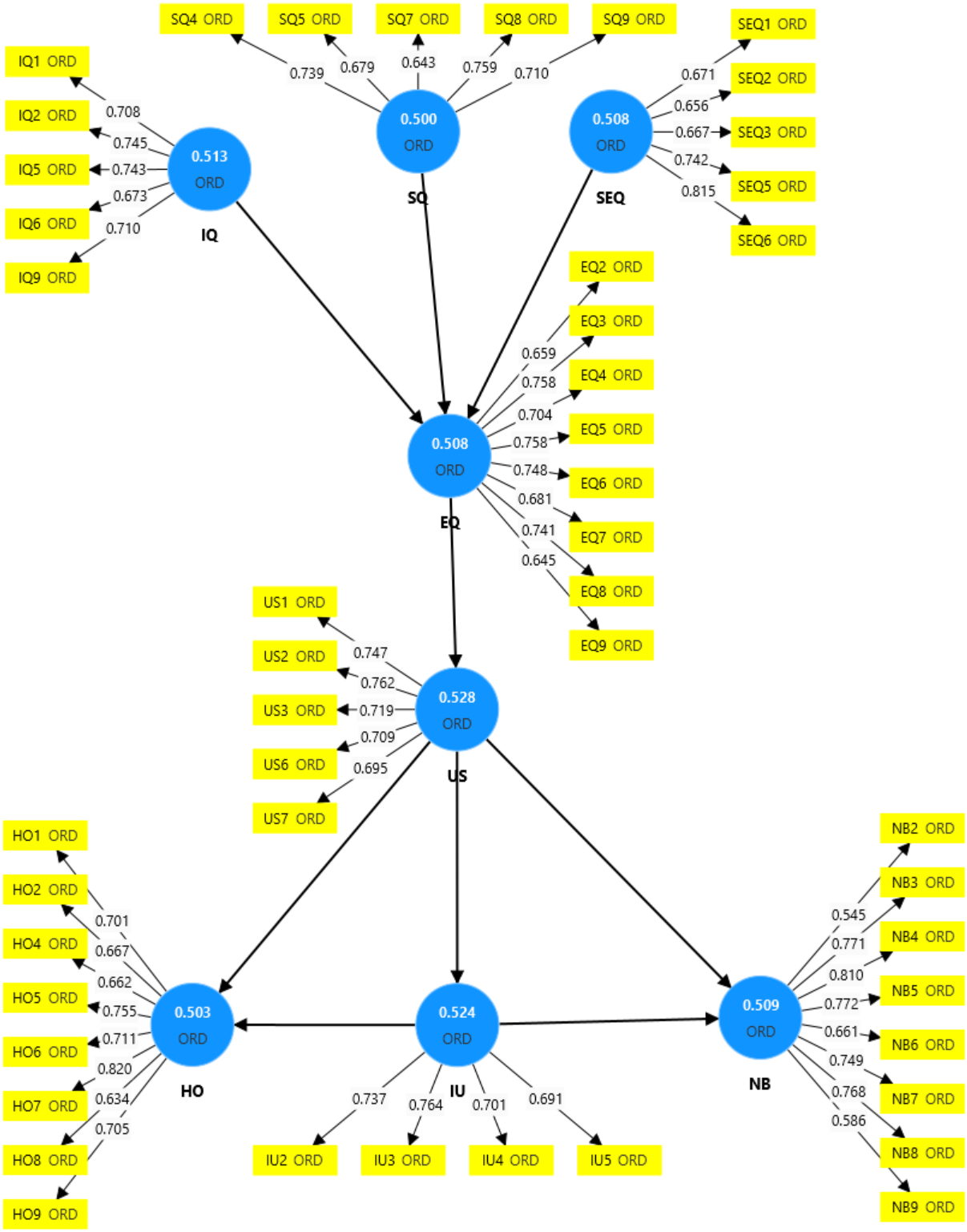

Figure 4.9: Measurement model

Table 4.16: Descriptive statistics and correlation results

Variables	**Mean**	**SD**	**Skewness**	**Kurtosis**	**IQ**	**SQ**	**SEQ**	**EQQ**	**US**	**HO**	**IU**	**NB**
IQ	3.267	0.644	-0.577	-0.518	1.000							
SQ	3.212	0.643	-0.536	-0.145	0.564**	1.000						
SEQ	3.230	0.659	-0.747	0.073	0.673**	0.659**	1.000					
EQQ	3.279	0.652	-0.810	0.064	0.604**	0.643**	0.730**	1.000				
US	3.209	0.650	-0.364	-0.511	0.591**	0.672**	0.706**	0.739**	1.000			
HO	3.329	0.590	-0.699	-0.253	0.769**	0.665**	0.659**	0.628**	0.602**	1.000		
IU	3.346	0.627	-1.017	0.706	0.595**	0.674**	0.726**	0.696**	0.696**	0.716**	1.000	
NB	3.301	0.622	-0.709	-0.130	0.746**	0.628**	0.691**	0.600**	0.589**	0.742**	0.646**	1.000

Note: *$=p<0.05$, **$=p<0.01$

Examining the correlation results reveals strong interrelationships among the constructs, with all correlations being significant at the 5% level. The correlation coefficient between IQ and HO is 0.769, indicating a robust positive relationship, which implies that as the perceived quality of information in mHealth apps increases, so does the positive impact on health outcomes. Similarly, other notable correlations include 0.746 between IQ and NB and 0.730 between SQ and EQ, reflecting the interconnected nature of these constructs. The correlation results show that all variables are positively and significantly related.

4.6.5. Structural equation modelling (SEM)

According to Fan et al. (2016), SEM is a type of causal analysis in which a model is verified against patterns of relationships among the data. Qureshi and Kang (2014) define SEM as a multivariate statistical tool for evaluating correlations among latent variables and observable factors in a model. Although related to regression analysis, SEM is more commonly used since it investigates the causal relationships among constructs while accounting for measurement bias. The SEM method does not require the availability of normal data to analyse latent variables and may be utilised in both exploratory and confirmatory studies.

4.6.6. Goodness-of-fit index

The normed-fit index (NFI) measures model fit, with values ranging from 0 to 1. According to Bentler and Bonnet (1980), an NFI value greater than 0.90 indicates a good fit. In addition, the standardized root mean square residual (SRMR) is another important statistic used to assess model fit, with values spanning from zero to 1.0. Hu and Bentler (1999) recommend a cutoff value of 0.08 (SRMR < 0.08) as a more suitable threshold for partial least squares (PLS) path modelling. The results concerning goodness-of-fit, obtained from SmartPLS during the analysis, are presented in Table 4.17.

Table 4.17: Goodness of fit results

SRMR	NFI
0.076	0.914

The findings in Table 4.17 demonstrate the adequacy of the fitted model, confirming its acceptability. The SRMR value of 0.076 highlights the model's strong fit, well below the recommended threshold of 0.08. Additionally, the NFI value of 0.914 exceeds the suggested cutoff of 0.90, indicating a solid alignment between the model and the data. These results affirm the model's effectiveness in capturing the complex relationships among the examined variables.

Hypothesis testing during the research could proceed next with the goodness-of-fit indices meeting the acceptable criteria.

4.6.7. Hypothesis testing

Hypothesis testing is a critical step in research that allows researchers to evaluate the validity of their proposed relationships between variables. Structural equation modeling uses SmartPLS 4.0 software to test the hypotheses. The following hypotheses were examined:

H1: Higher information quality (IQ) in mHealth apps will enhance user satisfaction (US).

H2: Higher system quality (SQ) in mHealth apps will lead to better app engagement quality (EQ).

H3: Higher service quality (SEQ) in mHealth apps will lead to higher app engagement quality (EQ).

H4: Enhanced engagement quality (EQ) in mHealth apps will positively affect user satisfaction (US).

H5: Enhanced user satisfaction (US) with mHealth apps will increase the intention to use these apps (IU).

H6: Greater intention to use (IU) mHealth apps will improve health outcomes (HO).

H7: Greater intention to use (IU) mHealth apps will increase perceived net benefits (NB).

H8: Enhanced user satisfaction (US) with mHealth apps will lead to better health outcomes (HO).

H9: Enhanced user satisfaction (US) with mHealth apps will increase perceived net benefits (NB).

The results of this analysis, including the path coefficients and significance levels, are presented in Table 4.18.

Table 4.18: SEM path coefficients

Hypothesis	**Relationship**	**Coefficient**	**SE**	**T statistic**	**P-values**	**Decision**
H1	IQ -> EQ	0.142	0.087	1.624	0.105	Not Supported
H2	SQ -> EQ	0.239	0.066	3.634	0.000	Supported

H3	SEQ -> EQ	0.501	0.090	5.569	0.000	Supported
H4	EQ -> US	0.747	0.040	18.583	0.000	Supported
H5	US -> IU	0.699	0.033	21.286	0.000	Supported
H6	IU -> HO	0.568	0.084	6.759	0.000	Supported
H7	IU -> NB	0.455	0.095	4.781	0.000	Supported
H8	US -> HO	0.215	0.075	2.859	0.004	Supported
H9	US -> NB	0.280	0.097	2.895	0.004	Supported

The findings presented in Table 4.18 suggest that the relationship between IQ and EQ still needs to be confirmed. The coefficient of 0.142 with a p-value of 0.105 suggests no statistically significant impact, meaning improvements in IQ do not necessarily lead to better engagement. This implies that more than enhancing information quality alone might be needed to improve users' engagement with mHealth apps. Therefore, the hypothesis is unsupported, and factors like service or system quality may play a more crucial role in user engagement.

The impact of SQ on EQ was confirmed, with a coefficient of 0.276 ($p < 0.001$). This indicates that better system quality, such as smoother app performance and functionality, significantly enhances user engagement. As system quality improves, users engage more actively with the app, improving overall experience. Thus, the hypothesis is supported, and improvements in system quality will likely increase engagement.

The relationship between SEQ and EQ was strongly confirmed, with a coefficient of 0.571 ($p < 0.001$). This suggests that improving service quality, such as providing timely support and user assistance, significantly boosts engagement. Users are more likely to interact positively with the app when they receive high-quality services, creating a more satisfying experience. Therefore, the hypothesis is supported, and enhancements in service quality lead to stronger engagement.

The hypothesis that higher EQ leads to improved US was confirmed, with a high coefficient of 0.606 ($p < 0.001$). As users engage more deeply with the app, their satisfaction increases significantly. Enhanced engagement makes users more likely to enjoy the app and feel positive about their experience. Hence, the hypothesis is supported, and improving engagement quality will directly lead to higher satisfaction levels.

The relationship between US and IU was strongly confirmed, with a coefficient of 0.698 ($p < 0.001$). This shows that greater user satisfaction leads to a higher intention to continue using the app. When satisfied with their experience, users are more motivated to use the app consistently, promoting long-term usage. Therefore, the hypothesis is supported, and increasing satisfaction encourages users to use the app.

The hypothesis that IU mHealth apps positively affect HO was confirmed, with a coefficient of 0.567 ($p < 0.001$). This suggests that as users intend to use the app more frequently, their health outcomes improve significantly. Regular usage contributes to better health management, underlining the value of sustained engagement with the app. Hence, the hypothesis is supported, and increasing usage intention will likely lead to improved health outcomes.

The relationship between IU and perceived NB was confirmed, with a coefficient of 0.454 ($p < 0.001$). This indicates that greater intention to use the app results in users perceiving more benefits, such as convenience and improved health; as users plan to engage more frequently, their perceived value of the app increases. Thus, the hypothesis is supported: higher usage intention leads to more significant perceived net benefits.

The hypothesis that US affects HO was confirmed, with a coefficient of 0.217 ($p = 0.004$). While the relationship is positive, the effect is moderate, meaning that while satisfaction contributes to better health outcomes, other factors, such as usage frequency, play a larger role. Satisfied users experience some improvements in health, but satisfaction alone is not enough for substantial health benefits. Therefore, the hypothesis is supported, and improvements in satisfaction modestly improve health outcomes.

The relationship between US and perceived NB was confirmed, with a coefficient of 0.283 ($p = 0.004$). This suggests that as users become more satisfied, they perceive more significant benefits from using the app, such as improved health and convenience. Satisfaction enhances the overall value users derive from the app, reinforcing their positive perception of its utility. Thus, the hypothesis is supported: higher satisfaction leads to greater perceived net benefits.

The analysis results confirm that hypotheses H2, H3, H4, H5, H6, H7, H8, and H9 are statistically significant at the 5% level, supporting these relationships. On the other hand, hypothesis H1 does not show statistical significance and is therefore not supported. These findings highlight the key factors that drive user engagement and outcomes in mHealth apps. For a clear visualization of these relationships, including the path coefficients and p-values, refer to Figure 4.10, which summarizes the overall model.

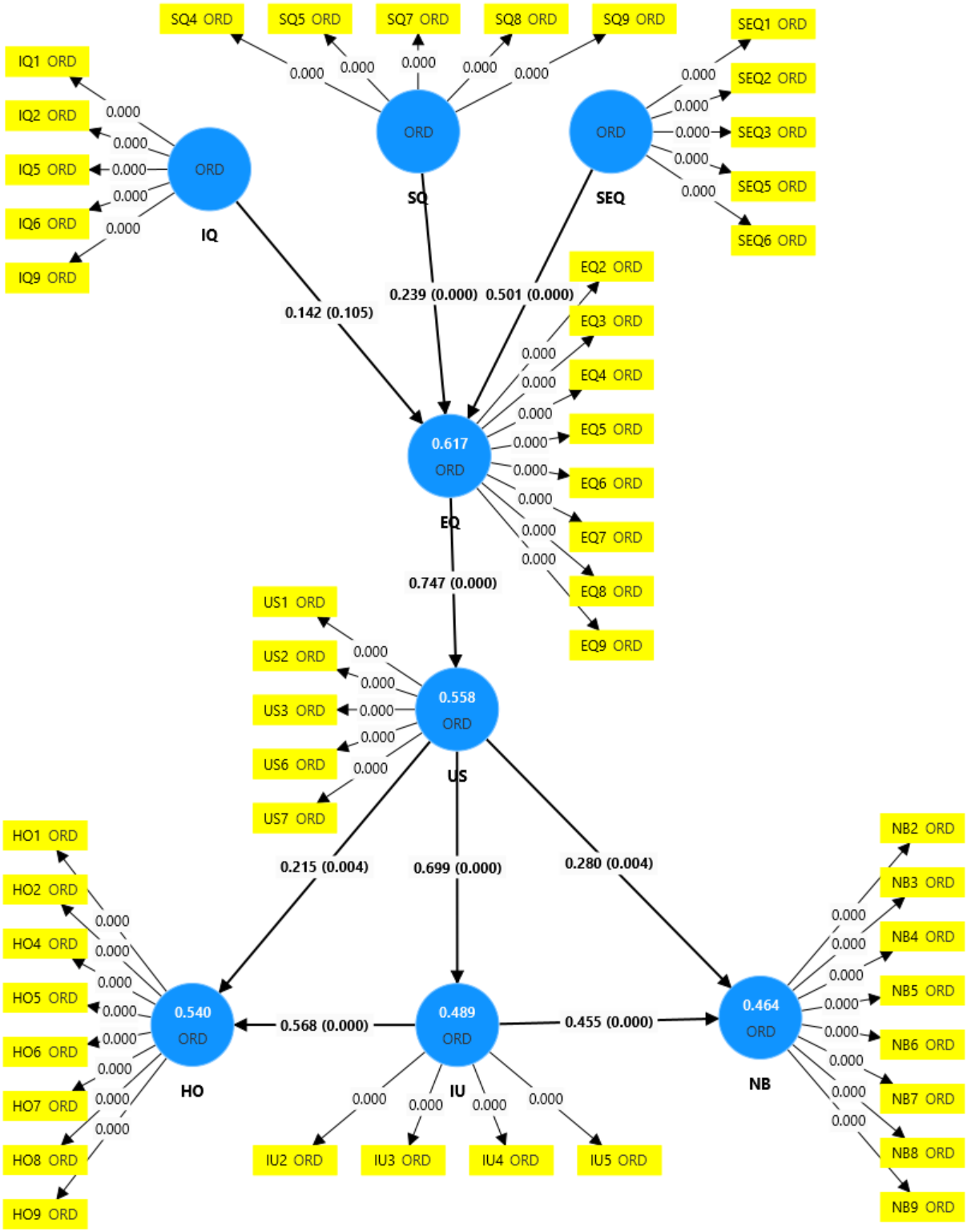

Figure 4.10: SEM with model parameters

All outer loadings exceeding the 0.50 threshold demonstrate the model's robustness, confirming its validity in measuring the constructs. Notably, all nine paths in the model are statistically significant at the 5% level, underscoring the relevance of these relationships. This

strong performance enhances the reliability of the model's findings and its implications for the study.

4.6.8. Model explanatory power and predictive relevance

All endogenous constructs' explained variance (R-square) was analysed to assess the model's explanatory power. As per Hair et al. (2017), R-square values can be classified as substantial (0.75), medium (0.50), or weak (0.25). In addition, the model's predictive relevance was examined using Stone-Geisser's Q-square value for the endogenous constructs (Stone, 1974). According to Hair et al. (2013), Q^2 values of 0.02, 0.15, and 0.35 represent weak, moderate, and strong predictive relevance, respectively. The R-square and Q^2 values are summarised in Table 4.18 for further insight into the model's performance.

Table 4.18: R-square and Q-square

Construct	R-square	Q^2predict
EQ	0.617	0.582
HO	0.540	0.410
IU	0.489	0.459
NB	0.464	0.404
US	0.558	0.540

The results in Table 4.19 provide key insights into the model's explanatory power and predictive relevance. EQ shows a solid R-square value of 0.617, indicating that 61.7% of its variance is explained by the predictors, while its high Q^2 value of 0.582 highlights robust predictive relevance. HO has an R-square of 0.540, explaining 54% of its variance, and a Q^2 value of 0.410, showing moderate prediction accuracy. The IU and NB exhibit similar patterns, with R-square values of 0.489 and 0.464, respectively, and Q^2 values of 0.459 and 0.404, indicating solid predictive relevance. Lastly, US reflects strong explanatory power with an R-square of 0.558 and significant predictive relevance with a Q^2 value of 0.540. These results suggest that the model effectively captures and predicts the relationships within the constructs.

4.6.9. Effects sizes for path coefficients (f^2)

The effect size of each predictor was evaluated using Cohen's f^2 formula, which helps determine the impact of each independent variable on the dependent variables. According to Cohen (2013), the effect sizes can be categorised as large (0.35), medium (0.15), or small (0.02). This classification provides a benchmark for understanding the relative importance of each predictor in the model. The detailed results for the effect sizes are presented in Table 4.19 for further interpretation.

Table 4.19: The effect size (F2 values)

Links	**EQ -> US**	**IQ -> US**	**IU -> HO**	**IU -> NB**	**SEQ -> EQ**	**SQ -> EQ**	**US -> HO**	**US -> IU**	**US -> NB**
f^2	1.264	0.028	0.359	0.198	0.295	0.08	0.051	0.956	0.075

Table 4.20 displays the effect sizes (f^2 values) for the relationships among the constructs in the model. Notably, the effect size from Engagement Quality (EQ) to User Satisfaction (US) is substantial at 1.264, indicating a strong influence. The paths from Intention to Use (IU) to Health Outcomes (HO) and Perceived Net Benefits (NB) also show medium effect sizes of 0.359 and 0.198, respectively. Additionally, User Satisfaction (US) has a high effect size of 0.956 on Intention to Use (IU), further underscoring its importance in driving user engagement and outcomes. Other paths, such as System Quality (SQ) to Engagement Quality (EQ) and User Satisfaction (US) to Health Outcomes (HO), exhibit small to negligible effects, suggesting that these relationships may be less impactful.

4.7. Conclusion

This chapter began by outlining the respondents' profiles, followed by an analysis of the descriptive statistics for each variable. The study's validity and reliability were assessed using confirmatory factor analysis, which included measures such as Cronbach's alpha, composite reliability, and average variance extracted to test reliability. Convergent and discriminant validity were examined to ensure the tool's accuracy. Model fit was confirmed using established thresholds and indices to verify that the data aligned with the proposed model. Finally, hypothesis testing was conducted using structural equation modelling. The discussion of these findings is presented in the next chapter.

CHAPTER FIVE – DISCUSSION AND CONCLUSION

5.1. Introduction

The previous chapters presented the foundation for this study by defining the research problem, reviewing relevant literature on mHealth apps, and presenting the research methodology, results, and analysis. This chapter builds on that groundwork by examining the findings about the research objectives, hypotheses, and existing theoretical frameworks. This discussion chapter presents the results, as interpreted and contextualised by the researcher, linking them to the study's central hypotheses and the development of the CHRONIQ framework.

The hypotheses are discussed, highlighting areas where the findings support or challenge existing literature and theoretical models. Key insights are drawn regarding the practical implications of the results for healthcare providers, app developers, and the broader domain of chronic disease management using mHealth apps. Additionally, rejected hypotheses are analysed to explore potential reasons for rejection, including comparisons with existing research. Finally, the chapter addresses the study's limitations, proposes recommendations for future research, and provides concluding remarks on how the research objectives have been met.

5.2. High-level Overview of the Research Problem

Chronic diseases, such as cancer, cardiovascular diseases, and diabetes, represent a significant global health burden, accounting for approximately 74% of global mortality, with low- and middle-income countries like South Africa disproportionately affected (Statistics South Africa, 2023b; World Health Organisation, 2023a). As healthcare systems face increasing pressure to manage these diseases effectively, mHealth apps have emerged as promising tools for enhancing patient engagement and self-management of chronic conditions. These apps offer capabilities such as monitoring vital signs, medication adherence, and promoting lifestyle changes, which are critical for chronic disease management (Debon et al., 2019; Gong et al., 2020).

Despite the potential benefits, mHealth apps often face significant issues regarding the quality and reliability of their content. Many lack evidence-based features, scientific validation, and oversight from healthcare professionals, which raises concerns about their safety and effectiveness (Nouri et al., 2018; Charbonneau et al., 2020). Moreover, Charlie and Cilliers (2024) indicate how the absence of standardised, rigorous evaluation frameworks for mHealth

apps has led to significant variability in app quality and user trust. Existing evaluation tools like MARS, Enlight Suite, and AQUA, while valuable, have been critiqued for not addressing the unique requirements of apps designed for chronic disease management (Charlie & Cilliers, 2024; Guo & Lyu, 2023; O'Rourke et al., 2020).

In response to these challenges, Charlie and Cilliers (2024) developed the CHRONIQ framework to provide a comprehensive and standardised approach to assessing the quality of mHealth apps tailored explicitly for chronic disease management. Grounded in the Delone and McLean Information Systems Success Model (Delone & McLean, 2003b), CHRONIQ integrates multiple dimensions, such as system quality, information quality, service quality, and user satisfaction, to provide a more holistic evaluation (Charlie & Cilliers, 2024). However, while theoretically robust, CHRONIQ has yet to be validated empirically. This study aimed to fill that gap by validating and refining the CHRONIQ framework to ensure that it can reliably assess and improve the quality of mHealth apps, particularly in resource-constrained settings like South Africa.

5.3. Validation of the CHRONIQ Framework

The validation of the CHRONIQ framework is a crucial step in establishing its robustness and reliability as a tool for evaluating the quality of mHealth apps tailored for chronic disease management. This section presents the assessment of model fit, focusing on two critical components: measurement validation and structural model fit. Structural Equation Modeling (SEM) was utilised through SmartPLS 4.0 to validate the framework, emphasising the measurement model's reliability and validity and the overall structural relationships between constructs within the framework.

5.3.1. Measurement

The measurement model assessment focuses on validating the observed variables' ability to represent the latent constructs within the CHRONIQ framework accurately. A rigorous validation process was employed, utilising several critical statistical approaches to ensure the robustness of the constructs, namely construct validity, convergent validity, discriminant validity, and reliability. These steps were crucial in establishing the theoretical and empirical soundness of the framework.

First, Construct validity was rigorously assessed using Confirmatory Factor Analysis (CFA). This statistical technique evaluates how well the observed variables represent the underlying latent constructs they are intended to measure. CFA was employed to verify the relationships

between the observable indicators and their corresponding latent constructs, ensuring that each item reliably measures the concept it is supposed to capture. As outlined in Table 4.12, most factor loadings surpassed the acceptable threshold of 0.50, as Hair et al. (2019) recommended, indicating that most of the measured variables adequately represented their respective constructs.

Items that failed to meet this threshold, such as IQ3, IQ4, and other similar low-loading items were excluded from the final model to enhance the overall construct validity. This elimination process ensures that only the most reliable indicators are retained, thus improving the precision and robustness of the measurement model. By refining the model to exclude poorly performing items, the overall accuracy of the CFA was strengthened, affirming that the observed variables effectively represent the constructs in the CHRONIQ framework. This contributes to the model's validity, ensuring that the retained items provide a reliable basis for evaluating key dimensions such as Information Quality, System Quality, and User Satisfaction.

Next, Convergent validity was assessed using the Average Variance Extracted (AVE), a crucial metric that quantifies the degree to which a construct explains the variance of its indicators. AVE values for all constructs within the CHRONIQ framework surpassed the widely accepted threshold of 0.50 (Hair et al., 2019), indicating that the observed variables explain more than 50% of the variance in the construct. This means that the items within each construct, Information Quality, System Quality, and User Satisfaction, are sufficiently correlated and aligned with the underlying theoretical concept they are designed to measure

For instance, the AVE for Information Quality (IQ) was calculated at 0.515, which indicates that the majority of the variance in IQ is accounted for by its respective indicators, ensuring a solid representation of the construct. The high AVE scores across all constructs provide a solid foundation for further analyses, such as testing the structural relationships between constructs. This strong convergent validity supports the reliability of the CHRONIQ framework, as it confirms that the indicators chosen for each construct appropriately measure the underlying latent variables and are suitable for a comprehensive evaluation in this context.

Discriminant validity was rigorously assessed using the Fornell-Larcker criterion, a widely accepted method to ensure that each construct in the model is distinct from the others. The Fornell-Larcker criterion requires that each construct's square root of the Average Variance Extracted (AVE) exceeds its correlation with other constructs in the model. In this study, the results displayed in Table 4.13 show that the square root of the AVE for each construct is

indeed more significant than the correlations with any other constructs. This indicates that each construct, such as Information Quality (IQ), System Quality (SQ), Service Quality (SEQ), and User Satisfaction (US), measures a unique concept, confirming the discriminant validity of the CHRONIQ framework.

Additional checks on discriminant validity were performed to reinforce the findings further. The results consistently showed a robust distinction between the latent variables, validating the measurement model's structure and confirming that each construct is adequately differentiated. This validation is critical as it ensures the constructs in the CHRONIQ framework are conceptually distinct, supporting the model's theoretical integrity.

In addition to discriminant validity, the reliability of each construct was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR). Cronbach's Alpha evaluates the internal consistency of the items, while CR offers a more nuanced measure by considering the loadings of each item in the model. Both CA and CR values for all constructs surpassed the recommended threshold of 0.70 (Hair et al., 2019), suggesting high internal consistency. For example, the Information Quality construct yielded a CA value of 0.763 and a CR value of 0.841. At the same time, System Quality demonstrated a CA value of 0.749 and a CR value of 0.833, indicating strong reliability. These high levels of internal consistency reinforce the robustness of the CHRONIQ framework's measurement properties, ensuring that the items reliably capture the intended constructs.

5.3.2. Structural fit

The structural model fit assesses the relationships between the latent variables within the CHRONIQ framework. The evaluation focused on key metrics such as path coefficients, R^2 values, predictive relevance (Q^2), and the overall goodness-of-fit (GoF).

The path coefficients, which indicate the strength and direction of relationships between constructs, were broadly significant, with most hypotheses supported. For instance, the path from System Quality to Engagement Quality was significant, with a coefficient of 0.239 ($p < 0.001$), demonstrating that better system quality positively impacts user engagement. Similarly, User Satisfaction strongly predicted Health Outcomes (coefficient = 0.215, $p = 0.004$), affirming that satisfaction with the app contributes to improved health outcomes.

The R^2 values provide insights into the variance explained by the independent variables in the model. High R^2 values were observed for critical constructs, such as User Satisfaction ($R^2 = 0.747$), indicating that the CHRONIQ framework accounts for a substantial portion of the

variance in satisfaction. This highlights the model's explanatory power in predicting user satisfaction based on the quality of the mHealth app.

The predictive relevance (Q^2) was calculated using the Stone-Geisser criterion, where values greater than zero indicate the model has predictive power. The Q^2 values for User Satisfaction, Engagement Quality, and Health Outcomes all exceeded zero, confirming the model has predictive solid relevance for these critical constructs.

Lastly, the Goodness-of-Fit (GoF) index assessed the model's overall fit. Although GoF is not widely adopted in PLS-SEM, the GoF for the CHRONIQ framework was within acceptable ranges, further reinforcing the robustness of the model fit. These findings demonstrate that the CHRONIQ framework fits the data well and provides valuable insights into the relationships between app quality, user satisfaction, engagement, and health outcomes.

5.4. Discussion of Results to Hypotheses

This section discusses the results of hypothesis testing to assess the relationships between key constructs in the study and evaluates their implications for the mHealth app ecosystem.

H1: Higher information quality (IQ) in mHealth apps will lead to more excellent engagement quality (EQ)

The hypothesis that higher information quality (IQ) in mHealth apps will lead to greater engagement quality (EQ) was formulated on the premise indicated by Charlie and Cilliers (2024) that users would naturally engage more with apps that provide accurate, relevant, and comprehensive health information. As Larson (2018) and Nouri et al. (2018) indicate, IQ is often seen as critical in health-related apps, especially those designed for chronic disease management, where the reliability of health data can directly influence a user's decisions. However, the results of this study did not support this hypothesis.

The coefficient for the relationship between IQ and EQ was 0.142, with a p-value of 0.105, indicating no statistically significant relationship between the two variables. This lack of significance suggests that simply improving the quality of information within the app does not necessarily translate into higher levels of engagement.

The initial rationale for the hypothesis was drawn from the widely held belief that information quality is crucial for fostering user trust and engagement in health apps (Charlie & Cilliers, 2024; Larson, 2018; Nouri et al., 2018). In healthcare, particularly for chronic disease management, users rely heavily on accurate, credible, and up-to-date information to manage

their conditions effectively (Vaitkienė et al., 2022). For instance, Adjekum et al. (2018) posit that high-quality information can improve users' trust in digital health tools and encourage sustained use. Moreover, Delone and McLean (2003) highlight that regarding IS success IQ is a critical determinant of system success, influencing user satisfaction and system use. Similarly, Stoyanov et al. (2015) argued that IQ in mHealth apps directly impacts overall app quality and user engagement by providing users with trustworthy and actionable health data. Similar conclusions were drawn by Ojo (2018) and Venter et al. (2019), who found that evidence-based content plays a pivotal role in fostering trust and credibility among users, particularly in health apps where misinformation can have severe consequences, as further highlighted by Albrecht (2016) and Nouri et al. (2018)

Therefore, based on the aforementioned literature Charlie and Cilliers (2024) concluded that the same logic would apply in the context of mHealth apps used for chronic disease management. The expectation was that users would be more inclined to engage with an app that provides accurate information about their condition, treatment options, and lifestyle adjustments, all essential in managing chronic diseases such as diabetes, hypertension, and cardiovascular conditions.

The results, however, showed that IQ did not significantly impact EQ, contradicting the original assumption. One possible explanation for this finding is that IQ is just one of several factors contributing to user engagement. For instance study by Pham et al. (2019) highlights that engagement in mHealth apps is a multi-dimensional construct influenced by various factors, including system usability, personalisation, and the availability of interactive features such as real-time health tracking and notifications

Indeed, users might find even the most accurate and comprehensive information ineffective if the app is difficult to navigate or lacks essential interactive features that foster active involvement in managing their health. For instance, an app might offer high-quality medical information, but if users struggle to find that information or lack immediate feedback on their health activities, they may disengage from the app (Kao & Liebovitz, 2017). The Technology Acceptance Model (TAM) also supports this view, suggesting that Perceived Ease of Use often has a stronger influence on technology adoption and sustained use than the quality of the content alone (Ma & Liu, 2005).

H2: Higher system quality (SQ) in mHealth apps will lead to greater engagement quality (EQ)

The study results support the hypothesis that superior system quality (SQ) positively influences engagement quality (EQ). With a significant path coefficient of 0.239 and a p-value of less than 0.001, the data confirms that higher system performance in mHealth apps contributes to enhanced user engagement. This finding underscores the importance of smooth operation, quick loading times, reliability, and user-friendly navigation in driving user interaction with health applications.

The hypothesis was formulated based on the notion that the overall performance and usability of mHealth apps play a critical role in user engagement (Charlie & Cilliers, 2024). System quality refers to the technical functionality of an app, including factors such as reliability, ease of use, system performance, and interface design (Charlie & Cilliers, 2024; Delone & McLean, 2003b; Ratzos & Trzpis, 2022). In the context of mHealth apps, users expect seamless functionality, mainly since these apps are often used to monitor health conditions, track medications, and provide real-time health insights. Any technical shortcomings, such as bugs, slow response times, or crashes, could significantly deter users from engaging with the app.

The Delone and McLean IS Success Model (2003) emphasises the importance of system quality as a crucial determinant of overall system success. The model shows that superior system performance influences user satisfaction and promotes higher system use levels. In the case of mHealth apps, particularly those used for chronic disease management, the smooth functioning of the app is vital for encouraging users to engage regularly. This view is supported by Stoyanov et al. (2015), who noted that the usability of health apps, which includes performance metrics such as fast loading times and minimal downtime, is directly linked to higher engagement rates.

The significant relationship between system quality and engagement quality, as demonstrated by the path coefficient of 0.239 ($p < 0.001$), validates the importance of system functionality in maintaining user engagement. This finding suggests that users are more likely to engage with an app that operates reliably and is easy to navigate. The Cronbach's alpha value of 0.749 for system quality further highlights the construct's internal consistency and reliability, reinforcing the relationship's robustness.

Moreover, the positive impact of system quality on user engagement aligns with the literature in the field. In an attempt to examine the challenges and potential solutions for the

implementation and evaluation of digital health technologies, Mumtaz et al. (2023) identified various technical issues related to these interventions, such as technological usability, evidence standards, and data privacy concerns, are among the top reasons for user disengagement in digital health platforms. When apps function as expected, users experience fewer disruptions, which promotes sustained engagement.

The Delone and McLean (2003) the model supports the relationship highlighted by the hypothesis by asserting that a robust, well-performing system encourages users to engage more with the technology. This is particularly critical for mHealth apps, where users expect seamless interaction due to the sensitive nature of health data and the need for real-time functionality. As underscored by Davies (1989) and Ma and Liu (2005), the TAM also highlights the importance of ease of use in influencing the adoption and continuous use of technology, further supporting the notion that superior system quality directly impacts engagement. Both models highlight that system quality ensures users continue interacting with the system, ultimately enhancing engagement and long-term app usage.

H3: Higher service quality (SEQ) in mHealth apps will lead to higher engagement quality (EQ)

The results from the study strongly support the hypothesis that superior service quality (SEQ) leads to enhanced engagement quality (EQ), as evidenced by a significant path coefficient of 0.501 ($p < 0.001$). This suggests that users are more likely to engage with an mHealth app when they perceive its service components, such as support, timely feedback, and healthcare communication, as reliable and responsive. As indicated by Charlie and Cilliers (2024), high-quality service is crucial for fostering trust and ongoing interaction with health apps, where support systems and user assistance directly impact the user experience and engagement levels.

The rationale for this hypothesis stems from the growing recognition of the importance of service quality in user engagement within healthcare and digital health platforms (Charlie & Cilliers, 2024; Fatima et al., 2019). In mHealth apps, service quality refers to aspects like responsiveness, assurance, and clarity of the intervention. These elements are essential for chronic disease management, where users require continuous support to monitor health conditions and adhere to treatment plans (Charlie & Cilliers, 2024).

The Delone and McLean IS Success Model (2003) emphasises service quality as a core dimension influencing user satisfaction and system use. In the context of mHealth apps, timely and reliable service, such as providing real-time feedback, can significantly improve user

engagement. The model suggests that service quality enhances the user experience and encourages users to interact more frequently with the app, thus contributing to the system's overall success.

The path coefficient of 0.501 for the relationship between SEQ and EQ underscores that service quality strongly influences engagement quality among the constructs studied. This finding highlights that providing high-quality, responsive, and reliable support is more critical to user engagement than other factors, such as information or system quality. Cronbach's alpha for service quality was also high (0.759), indicating strong internal consistency and further validating the importance of this construct in driving engagement.

This result aligns with previous studies, such as those by Baumel et al. (2017), which emphasise the role of service quality in building a "therapeutic alliance" between the app and its users. When users perceive that they are receiving consistent and transparent guidance, they are more likely to trust the app and engage more frequently, similar to views by Brennan et al. (2013) and Varga et al. (2023) on how trust in a healthcare provider enhances patient compliance in conventional settings. High service quality can mirror the supportive relationships in face-to-face healthcare, fostering a sense of trust and reliability that encourages continuous engagement with mHealth apps.

The TAM highlights that perceived usefulness and perceived ease of use are critical to technology adoption and sustained engagement (Ma & Liu, 2005). Service quality directly influences these dimensions by providing users with timely, relevant, and easy-to-access support, which enhances their overall perception of the app's usefulness (Charlie & Cilliers, 2024). Users are more likely to engage with an app that they find reliable and helpful in managing their health needs, as these qualities reduce uncertainties and increase the app's perceived value.

H4: Enhanced engagement quality (EQ) in mHealth apps will positively affect user satisfaction (US)

The hypothesis that higher engagement quality (EQ) leads to greater user satisfaction (US) is strongly supported by the results of this study, with a coefficient of 0.747 ($p < 0.001$), indicating a significant and positive relationship between the two constructs. This suggests that users' overall satisfaction increases as they engage more deeply with an mHealth app through meaningful interactions and positive experiences. The finding aligns with the foundational premise that user satisfaction is primarily driven by how effectively users can

engage with the app (Charlie & Cilliers, 2024; Stoyanov et al., 2015), highlighting the importance of engagement dimensions such as interaction, interactivity, and personalisation.

The hypothesis was grounded in the belief that engagement quality is a critical determinant of user satisfaction, particularly in the context of mHealth apps designed for chronic disease management (Charlie & Cilliers, 2024). Engagement in this context, as described by Charlie and Cilliers (2024) refers to how users interact with various app features, including ease of use, the interactivity of the interface, and the degree to which the app offers personalised experiences. These factors are central to users' long-term satisfaction, as they determine whether users find the app enjoyable, helpful, and relevant to their healthcare needs.

The Delone and McLean IS Success Model (2003) emphasises that engagement (often linked to system use) is a precursor to user satisfaction, similar to findings by Charlie and Cilliers (2024) and Stoyanov et al. (2015). Users who find the app engaging, through personalised notifications, interactive health tracking, and intuitive design, are more likely to perceive it positively, leading to higher satisfaction.

The study's findings are consistent with previous literature. Charlie and Cilliers (2024) and Stoyanov et al. (2015) emphasised that high engagement quality, driven by factors like interactivity and personalisation, is essential for improving user satisfaction in mHealth apps. Apps that offer smooth navigation, personalised health insights, and effective feedback loops provide users with an enjoyable experience, making them more likely to engage with the app consistently and feel satisfied with its functionality (Hyzy et al., 2022).

Baumel et al. (2017) further validated this concept by demonstrating that interventions with higher engagement scores also scored well in content quality, therapeutic persuasiveness, and therapeutic alliance, contributing to higher user satisfaction. Their research suggests that the emotional and psychological connection users develop with the app, facilitated through engaging features, can lead to greater satisfaction, especially in health-related contexts. For instance, when users feel the app provides timely and relevant feedback on their health status, they are more likely to perceive it as trustworthy and helpful, enhancing their overall satisfaction.

H5: Enhanced user satisfaction (US) with mHealth apps will increase the intention to use (IU) these apps

The hypothesis that enhanced user satisfaction (US) will increase the intention to use (IU) mHealth apps was strongly supported by the study results, with a high coefficient of 0.699 (p

< 0.001). This significant relationship confirms that satisfied users are more likely to continue using the app in the future (Charlie & Cilliers, 2024), which is critical for the long-term success of mHealth applications. When users have positive experiences and feel satisfied with the app's usability, functionality, and ability to meet their healthcare needs, they are more inclined to develop a stronger intention to reuse the app consistently. This highlights the critical role of user experience in fostering app retention and engagement.

This relationship reflects broader research findings, where satisfied users are more likely to perceive an app as beneficial and reliable, leading them to use it regularly. Satisfaction promotes repeated use and strengthens users' trust in the app, ensuring they return to it as a reliable tool for managing chronic conditions. For example, a study by Stoyanov et al. (2015) highlights that user satisfaction with app features such as interactivity, functionality, and engagement quality significantly promotes long-term usage.

This hypothesis was developed based on the assumption that user satisfaction is a crucial determinant of sustained app usage (Charlie & Cilliers, 2024). In mHealth apps, satisfaction typically results from an app's ability to meet users' expectations regarding ease of use, reliability, usefulness, and personalised healthcare support. The CHRONIQ framework emphasises this connection between user satisfaction and continued use. It draws on models such as the Delone and McLean IS Success Model (2003), which suggests that satisfied users of an information system are more likely to continue using it. The TAM also reinforces this relationship, where perceived satisfaction often leads to higher behavioural intention to use a system (Ma & Liu, 2005). Specifically, when users feel that the app delivers value by improving their health management, they are more likely to engage with it in the long run, leading to repeated use and more robust engagement.

H6: Greater intention to use (IU) mHealth apps will improve health outcomes (HO)
The results confirm a significant relationship between intention to use (IU) mHealth apps and improved health outcomes (HO), supported by a strong coefficient of 0.568 ($p < 0.001$). This indicates that users with a higher intention to engage with mHealth apps consistently experience better health outcomes. The more users intend to use the app, the more likely they are to follow health-related recommendations and behaviours promoted by the app, such as adhering to medication schedules, tracking physical activity, and maintaining communication with healthcare providers (Charlie & Cilliers, 2024). This positive relationship highlights how

sustained usage of mHealth apps leads to improved self-management of chronic conditions and overall health.

The hypothesis aligns with various theoretical models, including the Health Belief Model (HBM), initially developed by Rosenstock (1974), which posits that individuals are more likely to adopt health-related behaviours when they perceive tangible benefits. The HBM suggests that if individuals believe that using an mHealth app will improve their health outcomes, they are more likely to develop a stronger intention to engage with the app, reinforcing the notion that perceived benefits drive usage behaviours. In the context of mHealth apps, features such as medication reminders, exercise tracking, and direct communication with healthcare providers provide users with tangible benefits that motivate continued app usage.

The Delone and McLean IS Success Model (2003) further supports this theoretical alignment, highlighting that the intention to use a system significantly impacts user outcomes and overall system success. In this case, as users form a stronger intention to use the app, they are more likely to engage regularly with its health-related features, leading to improved health outcomes. These models collectively explain how an individual's intention to use mHealth apps directly influences their health behaviours, leading to better management of chronic conditions.

Furthermore, studies have shown that greater engagement with health technologies often correlates with improved health metrics. Charlie and Cilliers (2024) underscore this by emphasising that users who maintain a solid intention to use an mHealth app over time are more likely to stay engaged with the app's features, leading to more effective management of chronic diseases. This is particularly relevant for chronic condition management, where sustained engagement is necessary for long-term health improvements.

H7: Greater intention to use (IU) mHealth apps will increase perceived net benefits (NB)
The data supported the hypothesis with a coefficient of 0.455 ($p < 0.001$), indicating a statistically significant positive relationship between users' intention to use an mHealth app and their perception of net benefits. This means that users who plan to use the app more frequently will likely perceive more excellent value over time. The findings align with the Delone and McLean IS Success Model (2003), which suggests that a higher intention to use an information system, such as an mHealth app, directly enhances the perceived net benefits. This is because regular usage increases familiarity with the app's features, and users are more likely to experience its full benefits, including improved health outcomes, convenience, or potential financial savings.

The theoretical underpinning of this hypothesis is further reinforced by studies like those by Charlie and Cilliers (2024) and Ratzos and Trzpis (2022) who argued that consistent system use fosters tangible advantages for the user. In the context of mHealth apps, the perceived benefits may include better health management, adherence to treatment plans, or even reducing the need for frequent in-person consultations, thus saving time and money. Additionally, users who recognise these long-term benefits are more likely to report a positive overall experience with the app, which can, in turn, encourage further usage, creating a cycle of continued engagement and benefit realisation.

This hypothesis also finds support in behavioural models such as the TAM, which emphasises that perceived usefulness is a crucial driver of intention to use technology (Ma & Liu, 2005). Users who see value in an app are more likely to use it consistently.

H8: Higher Health Outcomes (HO) will increase User Satisfaction (US)
In the initial hypothesis, it was proposed that improvements in health outcomes would directly lead to greater user satisfaction with mHealth apps. This assumption is grounded in the belief that users would feel more satisfied with the app's functionality, performance, and value if they noticed tangible improvements in their health (Charlie & Cilliers, 2024). The reasoning behind this hypothesis aligns with traditional healthcare satisfaction models, where patient satisfaction is often a byproduct of successful health interventions (Ferreira et al., 2023; Kagura et al., 2023).

However, the results of this study reveal a different relationship. As evidenced by the statistical analysis (coefficient: 0.215, $p = 0.004$), the direction of influence runs from user satisfaction (US) to health outcomes (HO) rather than the reverse. This finding suggests that users' satisfaction with the app, rooted in their experience with its usability, content, and engagement quality, is more critical in driving positive health outcomes than initially anticipated.

This result contradicts the original hypothesis and aligns more closely with existing research in digital health technologies, where user satisfaction is recognised as a crucial predictor of sustained engagement and health improvement (Cavacece et al., 2024). For instance, in a review by Oakley-Girvan et al. (2022), research shows that satisfied users are more likely to adhere to health interventions and engage more actively with the app, improving health outcomes over time. The authors posit that greater patient activation in their health care, which includes satisfaction with digital health tools, leads to improved adherence to treatment prescriptions and better health outcomes. Similarly, Okolo et al. (2024) indicate how engaged

patients are more likely to adhere to treatment plans, adopt healthy behaviours, and achieve better health outcomes.

The moderate effect size (coefficient of 0.215) further indicates that while satisfaction contributes to better health outcomes, it may not be the sole determinant. Health outcomes are influenced by various factors, including app usage frequency, the severity of the health condition, and the comprehensiveness of the mHealth intervention.

H9: Higher perceived net benefits (NB) will increase user satisfaction (US)
The initial hypothesis, based on the theoretical framework of DeLone and McLean (2003), postulates that higher perceived net benefits (NB) from mHealth apps will lead to greater user satisfaction (US). This is grounded in the idea that users will be more satisfied with an app when they perceive tangible benefits, such as improved health management, convenience, and cost savings (Charlie & Cilliers, 2024). According to Delone and McLean's (2003) model, the perception of net benefits is crucial in influencing user satisfaction. Users continuously evaluate the utility they derive from an app, and a positive evaluation leads to sustained use and satisfaction.

However, the results of this study provide a different perspective. The analysis reveals that the relationship runs in the opposite direction: user satisfaction (US) enhances perceived net benefits (NB), as indicated by the path coefficient of 0.280 ($p = 0.004$). This finding suggests that user satisfaction drives the perception of net benefits rather than net benefits leading to satisfaction.

The supported hypothesis—"Enhanced user satisfaction (US) with mHealth apps will increase perceived net benefits (NB)"—reveals that when users are satisfied with the app's performance, ease of use, and the quality of engagement it offers, they are more likely to perceive higher net benefits. This outcome aligns with the theoretical underpinnings of the CHRONIQ framework, wherein Delone and McLean (2003) underscore how high user satisfaction typically leads to greater net benefits derived from the IS. In digital health contexts, satisfied users are more likely to perceive the app as effective in providing them with the intended outcomes, such as improved health or convenience (Charlie & Cilliers, 2024; Schnall et al., 2018). Satisfaction leads to a positive outlook on the app's value, increasing their perception of the net benefits they receive.

This result contrasts the original hypothesis, suggesting that users first perceive the net benefits and then become satisfied, as mentioned by Charlie and Cilliers (2024). In the DeLone and

McLean model, net benefits are typically seen as one of the final constructs in the chain of IS success, influencing the user's intention to continue using the system (Delone & McLean, 2003b). The literature emphasises a feedback loop where the realisation of net benefits reinforces user satisfaction and continued usage. However, the findings suggest that satisfaction with the app—rooted in usefulness, effectiveness, and efficiency—plays a more immediate role in shaping users' perceptions of the net benefits.

This raises an important consideration: perhaps user satisfaction in the context of mHealth apps is more immediate and experiential, meaning that users need first to feel content with how the app functions and engages with them before fully appreciating its broader benefits. This flips the expected relationship and emphasises that an app's ability to satisfy users on a functional level is foundational to their recognition of long-term benefits.

H10: Higher user satisfaction will further reinforce user engagement with the mHealth apps, creating a feedback loop that sustains continued app usage

The original hypothesis, H10, sought to evaluate the reciprocal relationship between user satisfaction and user engagement with mHealth apps, proposing that increased satisfaction would reinforce engagement, thereby creating a feedback loop that sustains continued app usage. This concept aligns with the theoretical underpinning of the CHRONIQ framework and the Delone and McLean IS Success Model (2003), which suggests that positive user experiences promote continuous usage and further engagement. However, despite the relevance of this hypothesis, it still needs to be evaluated due to methodological limitations associated with testing reciprocal relationships within SEM.

Three key challenges prevented the testing of H10. First, the Identifiability Problem arose because SEM requires each parameter to be identified with a unique solution. (Wang & Miao, 2017). In the case of reciprocal relationships, such as the one proposed between user satisfaction and engagement, the direction of causality becomes ambiguous. It is difficult to determine whether user satisfaction drives engagement or vice versa, creating an under-identified structure that renders it infeasible to estimate parameters.

Second, the Violation of Recursive Structure posed a challenge. As Bongers et al. (2016) indicated, SEM generally operates under the assumption of a recursive structure, where causality flows in one direction. The feedback loop hypothesised in H10 would require a non-recursive structure, where causality could flow bidirectionally between satisfaction and engagement. SEM's assumptions do not easily accommodate such reciprocal relationships,

leading to complications in parameter estimation and model stability (Madhanagopal & Amrhein, 2019).

Lastly, the non-convergence of the algorithm further complicates the testing process. SEM algorithms, such as Maximum Likelihood Estimation, depend on a well-defined covariance structure to estimate parameters (Bollen & Pearl, 2013). Reciprocal relationships complicate the covariance structure, often leading to algorithmic failure and non-convergence (Bollen & Pearl, 2013; Madhanagopal & Amrhein, 2019), as was the case when testing H10.

Given these technical and methodological challenges, H10 was excluded from the final analysis. Despite this, the feedback loop between user satisfaction and engagement remains valuable for future research. Alternative statistical techniques, as postulated by Wang et al. (2024), including dynamic modelling or time-series analysis, may be better suited to explore this reciprocal relationship and should be considered in future studies. This approach would provide deeper insights into the cyclical relationship between satisfaction and engagement in the context of mHealth apps.

Figure 5.1 below is the final CHRONIQ framework that was developed for this study. The green arrows indicate hypotheses that were accepted, while the red arrows are those that were not accepted. The blue arrows represent the reversed relationships. The dotted line indicates the inverted relationship that was found during the analysis of the data as discussed in the previous chapter.

5.5. Implications of the CHRONIQ Framework

The CHRONIQ framework presents significant practical and healthcare implications, especially in chronic disease management through mHealth apps. This framework provides a structured and comprehensive approach to evaluating the quality of mHealth apps, addressing the gaps left by existing frameworks. The CHRONIQ framework's implications extend across various stakeholders, including app developers, healthcare providers, and patients, while aligning with healthcare policy objectives nationally and globally.

5.5.1. Practical implications

The CHRONIQ framework offers a practical tool for mHealth app developers, healthcare providers, and patients by introducing a multidimensional approach to evaluating app quality. For app developers, as indicated by Charlie and Cilliers (2024), the CHRONIQ framework provides a roadmap for creating more effective and reliable apps for chronic disease management. The framework integrates dimensions such as system quality, service quality,

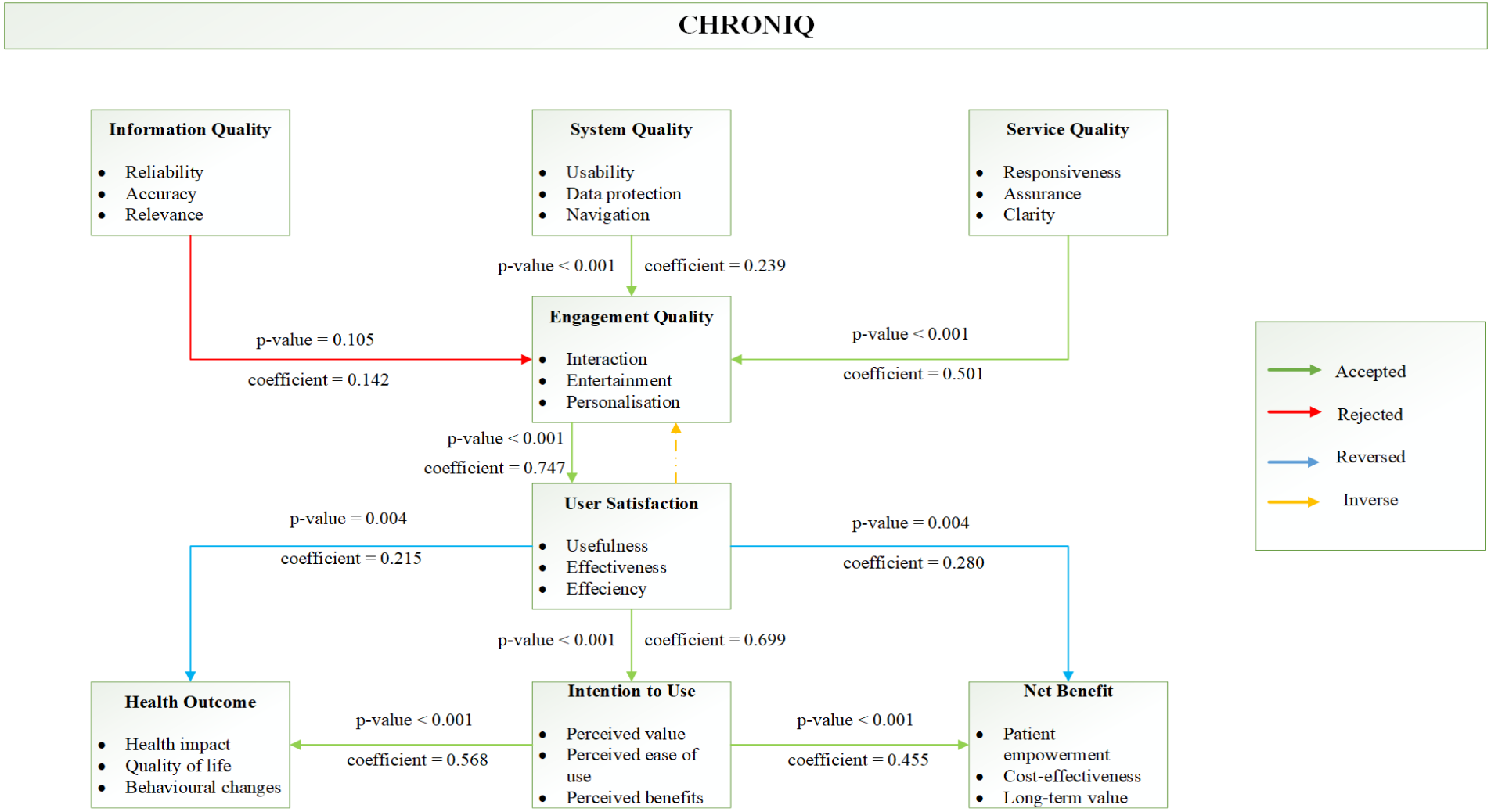

Figure 5.1 Final CHRONIQ framework

(Own source)

engagement quality, and user satisfaction, helping developers focus on essential app functionality aspects. Developers can enhance usability, increase user engagement, and improve health outcomes by ensuring that apps meet these standards. This approach ensures that developers build apps that function well and engage users through interactive features such as personalised notifications, health tracking, and feedback mechanisms, which are critical for chronic disease management.

For healthcare providers, the CHRONIQ framework offers a reliable tool for recommending high-quality mHealth apps to patients. Providers can use the framework to assess the effectiveness, usability, and safety of mHealth apps, ensuring that only the most reliable apps are used in patient care. This is particularly relevant for chronic disease management, where mHealth apps are often used to monitor medication adherence and promote healthy behaviours. The CHRONIQ framework focuses on constructs like health outcomes and net benefits, which ensures that healthcare providers recommend apps that have a measurable impact on patient health and well-being, thereby improving the overall quality of care.

Patients, in turn, benefit from the CHRONIQ framework because it ensures that the apps they use for managing chronic diseases are evidence-based, user-friendly, and effective. The framework's emphasis on user satisfaction and intention to use ensures that the selected apps provide accurate information and offer a positive user experience that encourages sustained engagement. This is crucial in chronic disease management, where long-term use of health apps can lead to better self-management of diabetes or cardiovascular disease.

5.5.2. Healthcare policy implications

From a healthcare policy perspective, the CHRONIQ framework aligns with crucial national and global health objectives, particularly in integrating digital technologies in healthcare delivery. In South Africa, the framework aligns with the National Digital Health Strategy (2019–2024), emphasising using digital health tools to improve healthcare access and quality. By providing a standardised evaluation framework, CHRONIQ ensures that mHealth apps are safe, reliable, and practical, enhancing healthcare services in resource-constrained settings. The framework's focus on service quality and system quality ensures that digital health interventions meet the national strategy's goal of leveraging technology to enhance healthcare delivery and reduce disparities in access.

Furthermore, CHRONIQ supports the objectives of South Africa's National Development Plan 2030, which seeks to reduce health inequalities and improve healthcare quality. By promoting mHealth apps that improve patient outcomes and self-management, CHRONIQ aligns to reduce the burden of chronic diseases in low-resource settings. For example, through CHRONIQ's focus on health outcomes, healthcare policymakers can assess the long-term impact of mHealth apps on managing chronic diseases, ensuring that digital tools contribute to reducing the country's overall disease burden.

5.6. Limitations of the Study

Although the study successfully validated the CHRONIQ framework and provided meaningful insights into using mHealth apps for chronic disease management, several limitations must be acknowledged. First, the study needed to be more focused on self-reported data. Participants' perceptions of app quality and health outcomes were collected through surveys, which may introduce biases such as social desirability or recall bias. These subjective measures may not fully capture the effectiveness of the mHealth apps in practice.

Second, the study was conducted within a specific geographical context, which is South Africa. While this provided valuable insights for the region, the generalisability of the findings to other contexts, particularly high-income countries, may be limited. The healthcare systems, user expectations, and technology infrastructures in different countries vary widely, meaning that the results may not be universally applicable without further validation in diverse settings.

Another limitation involves the technological diversity of the mHealth apps used in the study. The evaluation was based on a selection of apps for chronic disease management, but the diversity of mHealth apps in functionality, target conditions, and user interfaces is vast. Some apps may have unique features that could affect user engagement and satisfaction, and research needs to explore these nuances fully.

The sample size and specificity of the population studied may also present limitations. While the sample size was sufficient for structural equation modeling, larger sample sizes could provide more robust results. Furthermore, the study primarily focused on users with chronic conditions, which may limit the applicability of the findings to broader populations, including those using mHealth apps for preventive health measures.

5.7. Recommendations for Future Research

Given the limitations identified, several directions for future research are suggested. First, future studies should consider using objective data and self-reported measures. Integrating data

from app usage logs, health metrics, and clinical outcomes can provide a more accurate and holistic evaluation of mHealth apps' impact on health outcomes. This could help mitigate biases associated with self-reporting and give a clearer picture of app efficacy.

Second, expanding the geographical scope of the research is crucial. Future studies should evaluate the CHRONIQ framework in a broader range of contexts, including low-, middle-and high-income countries, to test its applicability across different healthcare systems and populations. This would provide a more comprehensive understanding of how the framework performs globally and how cultural and systemic factors influence mHealth app effectiveness.

Additionally, future research could explore customisations to the CHRONIQ framework to accommodate the diversity of mHealth apps. Different types of health apps—such as those targeting mental health, preventive care, or acute conditions—may require tailored evaluation metrics to account for their unique functionalities and user needs.

Finally, exploring qualitative research methods, such as interviews or focus groups, could provide richer insights into the user experience with mHealth apps. Understanding users' motivations, barriers, and expectations could further refine the framework to address the most critical factors influencing user engagement and health outcomes.

5.8. Conclusion

This study validated the CHRONIQ framework as an effective tool for evaluating the quality of mHealth apps, particularly those designed for chronic disease management. The framework provides a comprehensive and holistic assessment strategy by incorporating multiple dimensions—such as information quality, system quality, engagement quality, and health outcomes. The study demonstrated that higher system performance, service quality, and user satisfaction significantly improve user engagement and health outcomes, supporting the applicability of the CHRONIQ framework in real-world healthcare settings.

While the findings offer valuable insights, the study also highlights several areas for further refinement and research, especially in expanding the framework's applicability and integrating more objective data. The practical and policy contributions of the CHRONIQ framework are evident, particularly in addressing the healthcare needs of populations with chronic diseases. As mHealth apps continue to grow in importance, particularly in low- and middle-income countries like South Africa, the CHRONIQ framework can serve as a vital tool for ensuring that these digital health interventions are high quality, safe, and effective.

The study validated a novel framework and contributed to the growing field of mHealth by offering a robust evaluation method that can enhance both app development and healthcare delivery, ultimately improving the management of chronic diseases in underserved populations.

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APPENDICES

Appendix 1: Ethics Certificate

University of Fort Hare
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INTER-FACULTY HUMAN RESEARCH ETHICS COMMITTEE (IFHREC)
ETHICS CLEARANCE

Ethics Clearance ref. number:	CIL031SCHA01
Project title:	Determinants of mHealth App Quality: A Case Study of CHRONIQ Framework to Manage Chronic Disease in South Africa
Qualification registered for:	Master of Commerce: Information System
Student name:	Chumani Charlie
Student registration number:	202001174
Supervisor:	Prof L Cilliers
Department:	Information System
Co-supervisor:	N/A

On behalf of the University of Fort Hare Inter-Faculty Human Research Ethics Committee (IFHREC) I hereby grant ethics approval for CIL031SCHA01. This approval is valid for 12 months from the date of approval. Renewal of approval must be applied for BEFORE termination of this approval period. Renewal is subject to receipt of a satisfactory progress report. The approval covers the undertakings contained in the above-mentioned project and research instrument(s). The research may commence as from the 05/07/24, using the reference number indicated above.

Note that should any other instruments be required, or amendments become necessary, these require separate authorisation.
Please note that IFHREC must be informed immediately of

- Any material changes in the conditions or undertakings mentioned in the document;
- Any material breaches of ethical undertakings or events that impact upon the ethical conduct of the research.

The student must report to the IFHREC in the prescribed format, where applicable, annually, and at the end of the project, in respect of ethical compliance.

IFHREC retains the right to

- Withdraw or amend this approval if
    - Any unethical principal or practices are revealed or suspected;
    - Relevant information has been withheld or misrepresented;
    - Regulatory changes of whatsoever nature so require;
    - The conditions contained in the Certificate have not been adhered to.

- Request access to any information or data at any time during the course or after completion of the project.

Your compliance with Department of Health 2015 guidelines and any other applicable regulatory instruments and with IFHREC ethics requirements as contained in relevant policies and standard operating procedures, is implied.

IFHREC wishes you well in your research.

Yours Sincerely,

Dr Aceme Nyika
Chairperson: University of Fort Hare Inter-Faculty Human Research Ethics Committee (IFHREC)
05 July 2024

Appendix 2: Online Survey QR Code

Appendix 3: Informed Consent

University of Fort Hare
Together in Excellence

Dear Respondent,

You are invited to participate in this research on **the determinants of mHealth App Quality: A Case Study of the CHRONIQ Framework for Managing Chronic Disease in South Africa**. This study is conducted as part of the requirements for the award of a **Master of Commerce in Information Systems (IS)**. The research focuses on assessing and improving the quality of mHealth apps designed for chronic disease management using the CHRONIQ framework. The findings may also contribute to any publications arising from this research.

Participation in this study is voluntary. All responses will be completely anonymous, and completing and returning the questionnaire reflects consent to participate. You are greatly appreciated.

Answering the questionnaire will only require less than **10 – 20 minutes**. Your cooperation is highly appreciated. Feel free to reach me through my student email: 202001174@ufh.ac.za or mobile: **079 294 9804** for any clarification or concern.

By proceeding, I confirm that I have read and understood the information and agree to participate in the study under the stated conditions.

Your support will be greatly valued.

Appendix 4: Questionnaire Sample

Section A: Demographic Information

Please indicate your Gender:

Male	**Female**	**Other**

Please indicate your age: `

18-24	**25-34**	**35-44**	**45-54**	**55-64**	**65 and above**

Please indicate your province of residence:

EC	**FS**	**GP**	**KZN**	**L**	**MP**	**NC**	**NW**	**WC**

Have you been diagnosed with or suffer from a chronic disease (e.g., diabetes, obesity, hypertension)?

Yes	**No**

Did you use a health application to manage or monitor your health (e.g., running app, food tracker, vital signs monitor)?

Yes	**No**

If yes, please specify the type of application(s) you used: _____

1

Section B

For each of the statements below, please mark with an X the number that best describes how much you agree or disagree with the statement: Strongly Disagree (SD) Disagree (D) Agree (A) Strongly Agree (SA)

I strongly disagree	I disagree	I agree	I strongly agree
1	2	3	4

Code	Question	SD	D	A	SA
IQ1	The app provides reliable information about my chronic health condition.	1	2	3	4
IQ2	The app provides accurate and evidence-based information.	1	2	3	4
IQ3	The information in the app is directly relevant to my chronic health condition.	1	2	3	4
IQ4	The app provides up-to-date information on my condition.	1	2	3	4
IQ5	The information provided is comprehensive and detailed.	1	2	3	4
IQ6	The app clearly explains medical terms and concepts.	1	2	3	4
IQ7	The information in the app is easy to understand.	1	2	3	4
IQ8	The app provides sources for the information provided.	1	2	3	4
IQ9	The app offers personalised information based on my health condition.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
SQ1	The app is user-friendly and easy to navigate.	1	2	3	4
SQ2	The app runs smoothly without crashing.	1	2	3	4
SQ3	The app loads quickly and efficiently.	1	2	3	4
SQ4	The app's design is visually appealing.	1	2	3	4
SQ5	The app is compatible with my mobile device.	1	2	3	4
SQ6	The app updates regularly to fix bugs and improve functionality.	1	2	3	4
SQ7	The app offers customisable settings to suit my preferences.	1	2	3	4
SQ8	The app provides clear instructions on how to use its features.	1	2	3	4
SQ9	The app's features are well-integrated and easy to access.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
SEQ1	The app responds promptly to my interactions and requests.	1	2	3	4
SEQ2	The app's customer support is helpful and responsive.	1	2	3	4
SEQ3	I can easily find help or support when I need it.	1	2	3	4
SEQ4	The app offers live chat or direct communication with healthcare professionals.	1	2	3	4
SEQ5	The app provides useful reminders and alerts.	1	2	3	4
SEQ6	The app's service features are reliable.	1	2	3	4

SEQ7	The app provides reassurance about the accuracy of the health information provided.	1	2	3	4
SEQ8	The app's service is consistent and dependable.	1	2	3	4
SEQ9	The app offers valuable educational resources.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
EQ1	The app provides interactive features that engage me in managing my chronic condition.	1	2	3	4
EQ2	The app offers engaging content that keeps my interest.	1	2	3	4
EQ3	The app allows me to set and track personal health goals.	1	2	3	4
EQ4	The app provides motivational features that encourage me to stay healthy.	1	2	3	4
EQ5	The app includes social features that allow me to connect with others.	1	2	3	4
EQ6	The app's content is personalised to my needs and preferences.	1	2	3	4
EQ7	The app includes gamified elements that make health management fun.	1	2	3	4
EQ8	The app provides feedback on my health progress.	1	2	3	4
EQ9	The app sends reminders and notifications to keep me engaged.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
US1	I find the app useful in managing my chronic health condition.	1	2	3	4
US2	The app's features meet my practical needs.	1	2	3	4
US3	I am satisfied with the overall experience of using this app.	1	2	3	4
US4	The app has improved my ability to manage my chronic health.	1	2	3	4
US5	I would recommend this app to others with similar health conditions.	1	2	3	4
US6	The app meets my expectations.	1	2	3	4
US7	The app provides a good balance of features and usability.	1	2	3	4
US8	The app’s design enhances my experience.	1	2	3	4
US9	The app’s performance is reliable.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
IU1	I intend to continue using this app for managing my chronic health.	1	2	3	4
IU2	I find the app easy to use.	1	2	3	4
IU3	I plan to use this app regularly.	1	2	3	4
IU4	I am willing to recommend this app to others.	1	2	3	4
IU5	The app provides value that makes me want to keep using it.	1	2	3	4
IU6	I am satisfied with the app’s ease of use.	1	2	3	4
IU7	The app is my preferred tool for health management.	1	2	3	4
IU8	This app is essential for managing my health.	1	2	3	4
IU9	I intend to use this app as part of my daily routine.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
NB1	The app has a positive impact on my physical health.	1	2	3	4
NB2	I feel empowered to take an active role in managing my chronic health conditions with this app.	1	2	3	4
NB3	The app is a cost-effective solution for managing my chronic health.	1	2	3	4
NB4	The app has helped me reduce healthcare costs.	1	2	3	4

NB5	The app improves my overall well-being.	1	2	3	4
NB6	The app helps me adhere to my medication schedule.	1	2	3	4
NB7	The app provides valuable support for my health management.	1	2	3	4
NB8	The app helps me monitor and manage my symptoms effectively.	1	2	3	4
NB9	The app contributes to better health outcomes.	1	2	3	4
Code	**Question**	**SD**	**D**	**A**	**SA**
HO1	The app provides personalised health recommendations that contribute to positive health outcomes.	1	2	3	4
HO2	I perceive an overall enhancement in my quality of life due to the app's features.	1	2	3	4
HO3	The app encourages me to adopt positive health-related behaviours.	1	2	3	4
HO4	The app helps me track my health metrics accurately.	1	2	3	4
HO5	The app helps me make healthier lifestyle choices.	1	2	3	4
HO6	The app helps me manage my symptoms effectively.	1	2	3	4
HO7	The app reduces my need for frequent doctor visits.	1	2	3	4
HO8	The app provides insights that help me understand my health better.	1	2	3	4
HO9	The app enhances my confidence in managing my health condition.	1	2	3	4

Thank you for completing the questionnaire.

Appendix 5: CHRONIQ framework conference paper sample

2024 Conference on Information Communications Technology and Society

Introducing the Chronic Disease mHealth App Quality Evaluation Framework (CHRONIQ)

Mr. Chumani Charlie
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2024 Conference on Information Communications Technology and Society (ICTAS) | 979-8-3503-1491-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICTAS59620.2024.10507109

***Abstract*—The increase in mobile devices and mobile health applications (mHealth apps) has revolutionised healthcare, especially chronic disease management. Yet, concerns about app quality and evidence-based practices have emerged, crucial in addressing the significant global mortality caused by chronic diseases. This study aims to introduce the Chronic Disease mHealth App Quality Evaluation Framework (CHRONIQ). The framework was developed through a structured Literature Review that investigated current mHealth app evaluation literature and tools, such as MARS, Enlight Suite and AQUA, in the context of chronic disease management challenges. A total of 25 articles were included in the final thematic analysis. This result is CHRONIQ, a tailored evaluation framework for South African healthcare, addressing chronic disease management needs and enhancing healthcare delivery. The CHRONIQ framework consists of eight dimensions: Information, System, Service, Engagement, User Satisfaction, Health Impact, Intention to Use, and Net Benefits. These dimensions comprehensively assess app quality, user satisfaction, and health impact, aligning with the Delone and McLean Information Systems Success Model as the study's theoretical foundation. CHRONIQ is a valuable tool for healthcare professionals, policymakers, and researchers in South Africa and beyond. The framework's application can facilitate evidence-based decision-making, enhance user satisfaction, and ultimately improve healthcare outcomes in chronic disease management.**

Keywords— mHealth apps; chronic disease management; app quality evaluation; CHRONIQ framework; healthcare delivery

I. INTRODUCTION

In 2023, the global smartphone user count reached a staggering 6.8 billion [1]. The year 2023 also saw 4.8 million mobile applications (mobile apps) downloaded from the Apple App Store and Google Play Store [2]. Within this vast digital landscape, a noteworthy subset comprises health apps, which, according to Deloitte's 2021 report [3], surpasses 350,000 in number.

The extensive proliferation of mobile devices and the corresponding rise of mobile applications have fundamentally transformed how individuals access information and services, with profound implications for improving the quality of life.

The potential of health apps to enhance healthcare outcomes is exemplified by studies such as [4], demonstrating their ability to empower patients to monitor and manage health conditions. Moreover, this digital transformation extends its reach to healthcare delivery in urban and rural areas, particularly in developing countries [5].

Mobile health (mHealth) is referred to by the World Health Organization (2023) as encompassing wireless devices like cellphones and personal digital assistants (PDAs) for tracking patients' health and supporting medical and public health practices and health apps fall under the purview of mHealth interventions. Within the realm of mHealth, mobile health applications (mHealth apps) emerge as transformative tools that hold the potential to engage patients effectively, especially in managing chronic diseases [6].

Chronic diseases, including cancer, cardiovascular diseases, chronic pain, diabetes, kidney diseases, and respiratory diseases [7], are the leading cause of global mortality, contributing to 71% of all deaths, as reported by the World Health Organization (2018). South Africa is particularly burdened by these non-communicable diseases (NCDs), which account for more than 51% of all deaths, with a staggering 526,000 fatalities attributed to these diseases each year [8]. These statistics underscore the severity of chronic diseases as a global and South African public health concern.

Mobile apps have demonstrated moderate effectiveness in the short-term self-management of chronic medical conditions [9], with success stories in managing chronic diseases like diabetes [10]. mHealth apps offer various services, including information gathering, clinical support, education, communication, and health record management [11]. mHealth apps offer diverse functionalities that promote healthy behaviours, empower users, and improve clinical outcomes across various domains. Users can monitor their vital signs and emotions and practice mindfulness. However, the vast landscape of available mHealth apps poses challenges for users in selecting the most suitable app for their chronic condition management [12]. Additionally, the inconsistency in evidence regarding the effectiveness of these apps [13][14] and the prevalence of low-quality, non-evidence-based apps [13] compounds the issue.

Appendix 6: Proofreader certificate

JEANNE ENSLIN
FREELANCE LANGUAGE PRACTITIONER

Editing certificate

TO WHOM IT MAY CONCERN

I, Jeanne Enslin, acknowledge that I did the language editing of **Chumani Charlie's** dissertation submitted in fulfilment of the requirements for the degree Master of Commerce in Information Systems at Fort Hare University.

The title of the dissertation is:

Determinants of mHealth App Quality: A Case Study of CHRONIQ Framework to Manage Chronic Disease in South Africa

All language corrections and changes are evident in the version of the thesis in track changes/revision marking and with several important comments for the student's attention.
The quality of the final document, in terms of language, formatting and references remains the student's responsibility.

Jeanne Enslin
Language editor
jeanneenlsin@gmail.com

30 October 2024.

BA English and History (University of Stellenbosch)
Senior Teaching Diploma (University of Stellenbosch)
Honours in Translation Studies, cum laude (Unisa)
Post-graduate diploma in Editing, cum laude (University of Stellenbosch)

Appendix 7: Turnitin report

C, Charlie - 202001174_Dissertation.docx

ORIGINALITY REPORT

20%	16%	12%	7%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to University of Fort Hare Student Paper	1%
2	etd.uum.edu.my Internet Source	<1%
3	lup.lub.lu.se Internet Source	<1%
4	www.mdpi.com Internet Source	<1%
5	stmlportal.net Internet Source	<1%
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