The effect of smartwatches on patient-centered healthcare

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ABSTRACT

Patient-centered healthcare lies at the core of health and social services, where individuals are recognized and encouraged to take an active role in their own care. The literature suggests that technological advancements are contributing to achieving patient-centred care. As technology is advancing, it is important to keep abreast of how emerging technologies are affecting patient-centred healthcare. Thus, the purpose of this study was to investigate the effects of smartwatches on patient-centred healthcare.

To achieve this, this study assessed the effect of features of smartwatches on the Picker's 8 principles of patient-centred healthcare. The sample for this study was 141 participants who use smartwatches. These participants were all part of a running club based in Gauteng province of South Africa.

The findings revealed that the activity tracking feature of a smartwatch has a moderate impact on emotional comfort and coordination and integration of care. Similarly, the vital signs monitoring feature has a moderate effect on the continuity and transition of care, while the data management feature demonstrated a moderate effect on the coordination and integration of care. Moreover, the activity tracking feature of a smartwatch has the strongest effect on the coordination and integration of care, while vital signs monitoring has the strongest effect on the continuity and transition of care. The data management feature, on the other hand, has the strongest effect on the coordination and integration of care.

Findings from this study, albeit their limitations, can assist healthcare providers to make informed decisions on which features of smartwatches they should focus on when promoting the use of wearables to provide patient-centred care.

KEYWORDS

Smartwatches, wearables, healthcare, patient-centered healthcare, activity tracking, vital signs monitoring, data management, physical activity, digital health technology.

DECLARATION

I, Patson Ndhlovu, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Patson Ndhlovu Signature:

Signed at …Johannesburg…………………………………………………

On the 28th………………………. day of …June…………………… 2023

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LIST OF ACRONYMS

AHP- Australian Health Professionals

AI- Artificial Intelligence

AVE- Average Variance Extracted

CGA- Central Gauteng Athletics

CR- Composite Reliability

EHR- Electronic Health Records

GOF- Goodness of Fit

GSMA- Global System for Mobile Communications

HTMT- Heterotrait-monotrait

ICT- Information Communications and Technology

IOT- Internet of Things

NFI- Normed Fix Index

PCH: Patient-Centered Healthcare

PLS- Partial Least Squares

PLS-SEM- Partial Least Squares Structural Equation Modelling

PTSD- Post-traumatic stress disorder

SEM- Structural Equation Modelling

SPSS- Statistical Package for the Social Sciences

SRMR- Standardized Root Mean Square Residual

SSA- Sub-Saharan Africa

USA- United States of America

VIF- Variance Inflation Factor

WHO- World Health Organization

CHAPTER 1. INTRODUCTION AND BACKGROUND OF THE STUDY

This chapter introduces the study. Firstly, the chapter provides the background of the study. Secondly, the study articulates the research problem, research question and research objectives that guide the study. Lastly, the chapter discusses the limitations and delimitations of the study, and the dissertation structure.

1.1. Introduction

The current advances in technology have prompted many people around the world to adopt wearables for various purposes (such as fitness tracking, health goals tracking, to name a few). In South Africa, the prediction was, user penetration of digital fitness and well-being will be 5.75% in 2023 and is expected to hit 7.06% by 2027 (Statista, 2023). On the other hand, many healthcare organizations are placing a strong emphasis on patient-centered healthcare to improve patients' health outcomes (Kuipers et al., 2019). In the context of South Africa, the concept of patient-centered healthcare is gaining traction albeit some limitations related to the history of the country, infrastructure and limited resources (Jardien-Baboo et al., 2019). It is in this context that, this research seeks to establish the effect of smartwatches on patient-centered healthcare from a South African perspective. Furthermore, this research aims to theorize the contribution of smartwatches in achieving patient-centered healthcare.

1.2. Background of the study

Patient-centered healthcare focuses on the health needs of the individual patient (World Health Organization, 2007). Therefore, patient-centered healthcare emphasizes that healthcare decisions and healthcare quality measurements should be driven by the patient's individual needs, preferences and desired outcomes (Catalyst, 2017). To this end, healthcare providers must ensure that the patient's treatment is aligned with the patient's goals and desires (Kennedy et al., 2017). This implies that patient-centered healthcare must be collaborative, accessible to patients, and must respect patients' views and decisions at all times. One of the main benefits of patient-centered healthcare is that it ensures that healthcare systems and providers improve patient-tailored resource allocation, productivity and communication with patients (Catalyst, 2017).

Patient-centered healthcare is about putting the patient at the centre and focusing on their needs and preferences. There are healthcare issues when healthcare professionals are not focusing on patient-centered healthcare (Kwame & Petrucka, 2021). These issues include lack of proper diagnosis, lack of trust in healthcare, lack of patient satisfaction, unfair treatment and breakdown in communication between the patients and the healthcare professionals (Kwame & Petrucka, 2021).

Using accurate and reliable data from patients will enable healthcare providers to make decisions based on data provided to provide personalised care. Smartwatch data can help providing that health-related data (Giusti et al., 2020). Therefore, this study explores the relationship between smartwatch features and patient-centered healthcare aspects that address patient needs. For example, smartwatches can collect data on heart rate, sleep patterns, physical activity, and other health-related metrics that can be used to monitor patients' health status and inform treatment decisions (Giusti et al., 2020).

Technology plays a pivotal role in patient-centered healthcare through remote monitoring of patients' health, and diagnoses and possibly flagging any risks the patients might encounter. Data management is also pivotal when it comes to patient-centered care as it is collected from multiple Internet of Things (IoT) devices, wearables and mobile applications. Patient-centered healthcare technologies such as self-service portals, electronic health record (EHR) systems and wearable devices such as smartwatches are used in many contexts such as in the military, healthcare sector and for personal use (Wearables, 2022). In 2021, the global shipment of wearables was over 533 million, with wearable devices dominating with 35.1% of the market share while smartwatches came second with 30.5% of the market share (Wearables, 2022).

According to Sayeed (2022), about 4% of worldwide deaths are caused by physical inactivity. Physical inactivity may lead to heart diseases, type 2 diabetes, cancer and so on (Centers for Disease Control and Prevention, 2019). On the other hand, smartwatches can be used to monitor and potentially improve physical activities. Smartwatches have features that would provide healthcare professionals with personalized patient health information so that they can provide patient-centered healthcare. These features include blood pressure monitoring, activity tracking, monitoring sleeping patterns, medical-related reminders and fall detection (Lu et al., 2020). However, there is scanty research that focuses on the impact of smartwatches on patient-centered healthcare, especially in developing countries. Thus, this study provides insights on how smartwatches can contribute to patient-centered healthcare from a developing country's perspective.

1.3. Research problem

Patient-centered healthcare was introduced many years ago. Although patient-centered healthcare is still a priority within healthcare systems, there is still a gap to be filled. According to Picker Institute (2022), patient-centered healthcare is the heart of health and social services whereby individuals are recognized and encouraged to play an active role in their care. According to Barrett et al. (2019), patient-centered healthcare ensures better health outcomes, better chances of recovery, higher patient satisfaction and improves quality of life.

Digital health technology is regarded as an engine for innovation and universal health coverage. Digital technology offers opportunities to maximize health care delivery and embraces agile approaches to ensure organisations respond quickly to the constantly evolving technological advancements (Sharma et al., 2018).

The Philips Future Health Index (2019) states that the development of digital health technologies such as digital health records, telemedicine and artificial intelligence will help ensure better health outcomes and reduce healthcare costs. Digital medical records enable access to more accurate, up-to-date and complete information about patients. Technology advances also improve remote patient monitoring.

The evolution of ordinary watches into smart devices that monitor physical activities is new milestone in the healthcare industry. It is believed that this development will improve the quality of care and give patients access to data such as their physical activity progress. Smartwatches are very useful for monitoring physical activity, especially in epilepsy patients, for cardiology and research purposes (Sayeed, 2022). According to Reeder and David (2016), smartwatches support wellness, facilitate self-monitoring of personal activity, receive feedback on activities, and enable research to understand patient health patterns and behaviour. Smartwatches help improve patient’s health and lifestyle choices, however, there is shortage of literature providing insights on how smartwatch features can have an effect on patient-centered healthcare. Therefore, this study intended to identify features of smartwatches that would contribute to patient-centered healthcare, and understand the extent to which these features contribute to patient-centered healthcare. Lastly, the study investigated how to theorize the contribution of smartwatches to patient-centered healthcare.

1.4. Research questions

This study has three research questions which are listed below:

1. What features of smartwatches contribute to patient-centered healthcare?
2. To what extent do these features contribute to patient-centered healthcare?

3. How can the contribution of smartwatches to patient-centered healthcare be theorized?

1.5. Research objectives

The formulated research objectives are:

1. To identify features of smartwatches that contribute to patient-centered healthcare.
2. To understand the extent to which these features contribute to patient-centered healthcare.
3. To explain the contribution of smartwatches for patient-centered healthcare.

1.6. Summary of the methodology adopted in this study

This study adopted the positivist philosophy, a deductive approach and the quantitative research method. The study used convenient sampling (non-probability sampling) from a sample of 181 participants. Data was analysed using Partial Least Structural Equation Modelling with the aid of Statistical Package for the Social Sciences (SPSS) software version 28 and Smart-PLS version 4.

1.7. Delimitations of the study

The study only focuses on people (participants) who are using smartwatches. The selected sample for this study is a group of runners within a running club as most of these runners have smartwatches and know the features which might have an impact on patient-centered healthcare.

The inclusion criteria are as follows:

i. Individuals using smartwatches.
ii. Individuals between the ages of 18 years and 65 years.

iii. Individuals who can read and understand English.

The exclusion criteria are as follows:

i. Individuals who do not use smartwatches.
ii. Individuals below the ages of 18 years old or above 65 years old.
iii. Individuals who cannot speak, read or understand English.

1.8. Dissertation structure

Chapter 1: Introduction and Background of the study

This chapter introduces the study and provides the background, the research problem, research questions, a synopsis of the methodology adopted in this study as well as the limitations and delimitations of the study.

Chapter 2: Literature Review and Theoretical Framework

This chapter explores of the concept of patient-centered healthcare including the use of smartwatches in the patient-centered healthcare context. In addition, this chapter discusses digital health technologies followed by a discussion of the nexus between technology and patient-centered healthcare in developed and developing countries context. The last part of this chapter discusses hypotheses development and the conceptual framework adopted in this study.

Chapter 3: Research Methodology

This chapter discusses the research methodology underpinning this study which is anchored on the Saunders' research onion framework research onion.

Chapter 4: Findings

This chapter presents the findings of the study using a quantitative research approach. The chapter presents the general characteristics of the data and the participants demographics. The chapter then discusses the construct validity assessments which included measuring convergent and discriminant validity. The chapter also assessed the relationships between the independent variables (smartwatch features) and the dependent variables (Patient-centered healthcare constructs). as well the resulting PLS-SEM model fit.

Chapter 5: Discussion of Findings

This chapter discusses the findings of the study presented in Chapter 4 based on the research questions.

Chapter 6: Conclusions and Recommendations

The last Chapter concludes the study by providing a summary of the entire study and major findings, recommendations. The Chapter further outlines the contributions of the study, the limitations of the study and suggestions for further research.

1.9. Chapter summary

This chapter introduced the study and provided the background of the study which included a view of technology advances, smartwatch features and patient-centered healthcare. The research problems, research questions, research objectives and summary of adopted methodology were identified to understand the aim of this study. Lastly, this chapter discussed the delimitations and the structure of this study.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Introduction

This chapter presents the literature review. The chapter discusses the concept of patient-centered healthcare, the use of smartwatches within patient-centered healthcare and Picker's 8 principles of patient-centered in relation to patient-centered healthcare. Furthermore, the chapter discusses the various types of digital technologies within patient-centered healthcare and the nexus between technology and patient-centered healthcare, from developing and developed countries' perspectives.

2.2. Patient-centered healthcare

Patient-centered healthcare is defined by O'Neill (2022) as caring for patients and their families in a way that is meaningful and valuable to an individual. Reynolds (2009) defines patient-centered healthcare as the focus on the patient and individual's healthcare needs. Its goal is to empower patients by making them active participants in their healthcare. This involves listening, informing and involving patients in their care to improve their healthcare outcomes (O'Neill, 2022). According to Picker Institute (2022), patient-centered healthcare is the heart of health and social services whereby individuals are recognized and encouraged to play an active role in their care.

The doctor-patient relationship has developed beyond the traditional 'doctor-knows-best' approach and has developed towards engaging patients more in their care to present them with opportunities to be involved in decision-making and self-administering care (Barrett et al., 2019). According to Barrett et al. (2019), the following are the benefits of actively involving patients in their care: (1) improved patient's adherence, (2) improved patient's satisfaction, (3) reduction of direct patient's costs such as travel costs, (4) reduction of indirect patient's costs such as productive days missed making doctor's visits, (5) improvement in patient's outcomes. Patient-centered healthcare presents a paradigm shift in the diagnosis and treatment of patients.

2.2.1. The use of smartwatches in patient-centered healthcare context

Cutting-edge technological developments are reaching new milestones. The advancement of the normal wristwatch into a smart device that monitors physical activities such as heart rate, sleep patterns, blood pressure and exercises is a new milestone in the healthcare industry. This development is believed to improve the quality of healthcare and allow patients to have access to data about their physical activity progress, amongst others. A smartwatch is a wearable device with biosensors that can collect information such as heart rate and it initially was used for elderly and chronically ill patients (Lu et al., 2016). Figure 2.1 below shows that there has been a sharp increase in the number of connected wearables in the Middle East and Africa from 2015 to 2022.

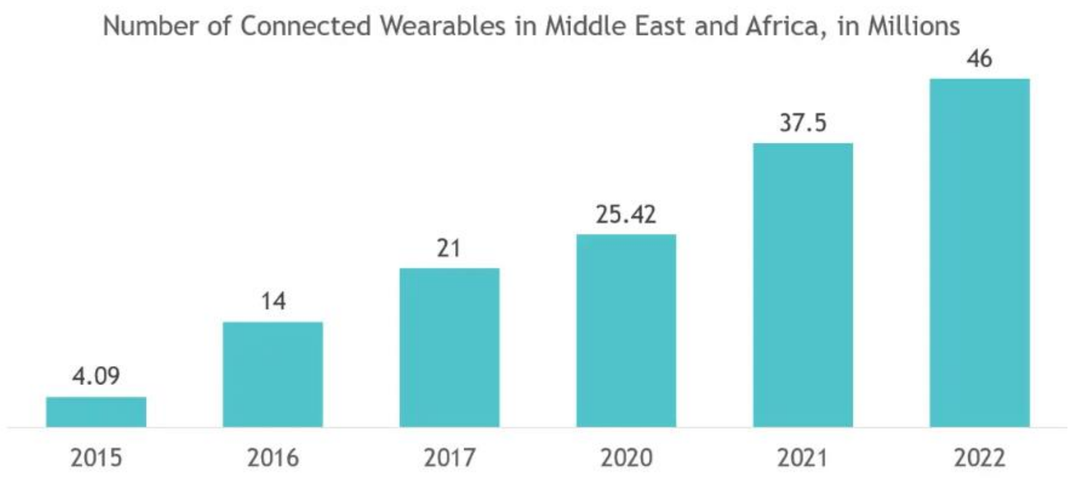

Figure 2. 1.Number of connected wearables in the Middle East and Africa
Source: Mordor Intelligence (2023)

Figure 2.1 shows that there has been an increase (a sharp increase) in the number of connected wearables in the Middle East and Africa from 2015 to 2022.

South Africa will be the biggest market for smartwatches in Africa as they are becoming affordable (Mordor Intelligence, 2023)

One of the main risks for mortality across the globe is low physical exercise. Smartwatches are very beneficial in monitoring physical exercises, especially for patients with epilepsy, in cardiology and for research purposes (Sayeed, 2022). According to Reeder and David (2016), smartwatches have a huge potential to support health and facilitate self-monitoring of personal activities, get feedback on activities and allow for research to be done to understand patients' health patterns and behaviours. Reeder and David (2016) further state that smartwatches can transform healthcare because they are familiar to most people and are increasingly available. They enable real-time monitoring of physical activities, have tailor-made messaging and notifications, and allow communication between friends and family.

Farivar et al. (2020) state that for the older generation, smartwatches are not as popular as they are with the younger generation. The reason is the complexity of operating them and the older generation's perception of technology. In the USA, 17% of smartwatch users are between 25-34 years of age and only 3.3% of users are 65 years and above (eMarketer, 2018; Farivar et al., 2020; Wurmser, 2019). This shows that wearable smart devices are more appealing to the young generation that is into high technology. Smartwatches can be beneficial to the elderly especially in cutting down the time spend making hospital visits (Alpert et al., 2020).

2.3. Digital healthcare in Africa

Sub-Saharan Africa (SSA) is still lagging when it comes to the quality of healthcare. It accounts for a quarter of disabilities and death caused by diseases worldwide yet it has 1% of the global health expenditure (World Bank, 2019). Health infrastructure in SSA is poor and patients have difficulties accessing basic healthcare (World Bank, 2019). On the other hand, with the increase in remote healthcare, SSA has also tapped into the trend of using wearable devices for health monitoring and fitness. Sub-Saharan Africa is also becoming a powerhouse in digital health innovations.

Digital healthcare has the potential to unlock opportunities in Africa’s health sector. According to GSMA (2021), SSA reached about 302 million smartphone connections in 2018 and this is expected to rise to 700 million in 2025. Smartphones have apps that promote remote healthcare and can also be linked to smartwatches. Health apps such as Hello Doctor in South Africa and Omomi for pregnant women in Nigeria are some examples of how smartphones are used for remote healthcare (GSMA, 2021).

Smartphones allow for remote patient monitoring by collecting data from patients to healthcare providers (Chebib, 2020). In Kenya where there are high rates of post-traumatic stress disorder (PTSD) due to domestic abuse, wearable devices have become helpful in monitoring patients with PTSD (Mwenda, 2022). Mental-related sicknesses like PTSD correlate with issues related to heart rate, blood pressure and respiratory rate (Hossain et al., 2021; Sadeghi et al., 2019). In SSA mental sicknesses such as dementia and other chronic conditions put a high demand on the quality and variety of healthcare services (Larson et al., 2013). Dementia is overwhelming for both patients and healthcare providers. The cost of dementia in SSA is estimated to be around US$6.2 billion per year (Dai et al., 2020). According to Alzheimer’s Association (2017), most caregivers are “sandwich generation” meaning that they take care of both the Alzheimer’s patient and a child or grandchild. Because the disease is characterized by memory loss, patients need the support of both caregivers and family. Wearable devices such as smartwatches make healthcare easier in this case by offering features such as fall and wandering detectors. Although smartwatches are useful in increasing the quality of patient healthcare, not much research on them has been done in SSA.

Palliative care is a cost-effective component of cancer services in SSA, but the coverage is still low in SSA. Digital healthcare can increase the quality of healthcare in palliative care (Okunade et al., 2019). Mobile phones can be utilized to track certain physical trends in a patient and this will reduce the cost of patient monitoring and improves communication between patient and healthcare provider (Beratarrechea et al., 2014).

Chidhau, Mutizwa and Muzama et al. (2021) state that digital health intervention played a crucial role in Zimbabwe's healthcare system during the Covid-19 pandemic. Digital health interventions such as social media, mobile health and telemedicine were highly utilized during the pandemic. Zimbabwe is still struggling with the implementation of digital health interventions due to reasons such as corruption, lack of funding, shortage of skilled workforce, and weak health infrastructure (Chidhau et al., 2021). In Rwanda, the Ministry of Health deployed five smart anti-epidemic robots to contain the spread of Covid-19 which they deployed to treatment centres (Mudzingwa, 2020).

Implementation of digital health has faced challenges such as short-lived projects and limited documentation of digital healthcare impact in Africa (Kipruto et al., 2022). As such, it is difficult to measure whether digital healthcare is efficient or not and draw some lessons from the findings. Digital health assists in addressing health challenges in SSA if the end-user is put at the centre of the policy implementation stage. It is also worth noting that digital health cannot replace the fundamental building blocks of healthcare which are service delivery, health workforce, health information systems, access to essential medicines, vaccines and technology, financing, and leadership/governance (World Health Organization, 2019).

2.3.1. Digital healthcare in South Africa

In South Africa, most of the wearable devices are used for fitness purposes (Le Roux, 2017). They are mostly used to track cycle rides, tracking runs and gym workouts. Mobile Ecosystem Forum (2015) states that South Africans are the biggest users of health and fitness apps with an average of 22% compared to the global average of 15%. Nigeria follows South Africa at 17% and they mostly use health apps to train and relax their minds and manage weight (Mobile Ecosystem Forum, 2015).

Muller (2020) states that in South Africa, 13% of households own a wearable device and the youth dominate the market with 33.7% of individuals ranging between 18-24 years of age, referred to as Generation Y. According to Markert (2004), Generation Y refers to millennials born between 1981 and 2005. This is the first generation that grew up in the era of computers, mobile phones, electronic devices, and the Internet (Muller, 2020). Generation Y makes up about 35.12% of South African consumers and they tend to associate themselves with higher social status trends (Hattingh, 2020). According to Muller (2020), the main reason for Generation Y’s use of wearable devices is to monitor heart rate and blood pressure.

Adoption of mobile health (mHealth) is also growing in Africa, especially in South Africa and Nigeria. There is general excitement about living a healthy lifestyle such that medical aid schemes offer incentives for people who use wearable devices. In South Africa, Discovery medical aid and life insurance link fitness devices to its vitality program where members can earn points through workouts, the number of steps taken and participating in races (Discovery, 2022; Le Roux, 2017). The vitality program also offers rewards of smoothies at local cafes and at times members get to win wearable devices that are funded by Discovery if they maintain health goals (Le Roux, 2017). All this is aimed at promoting healthier lifestyles. In its study, PwC (2015) states that more than three-quarters of the South African working-class wear wearable devices if the data they collect from these devices improve their work conditions. Benefits that attract workers to use wearable devices are flexible working hours, fitness incentives, lower health insurance premiums, free health screening and flexible working hours (Le Roux, 2017; PwC, 2015). It is clear that wearable devices are penetrating the workplace which encourages employees to live healthily. It also helps those with chronic illness to monitor their health status at the workplace.

2.4. Pillars of patient-centered healthcare

To improve healthcare, Picker's 8 principles of patient-centered healthcare was designed by O'Neill in 2022. This framework was adopted in this study to assess the effect of smartwatches in patient-centered healthcare. The patient-centered healthcare model could help governments and private organizations to play a crucial role in developing clearer policies and processes necessary for care providers to deliver quality healthcare (Santana et al., 2018).

Below is an illustration of Picker's framework:

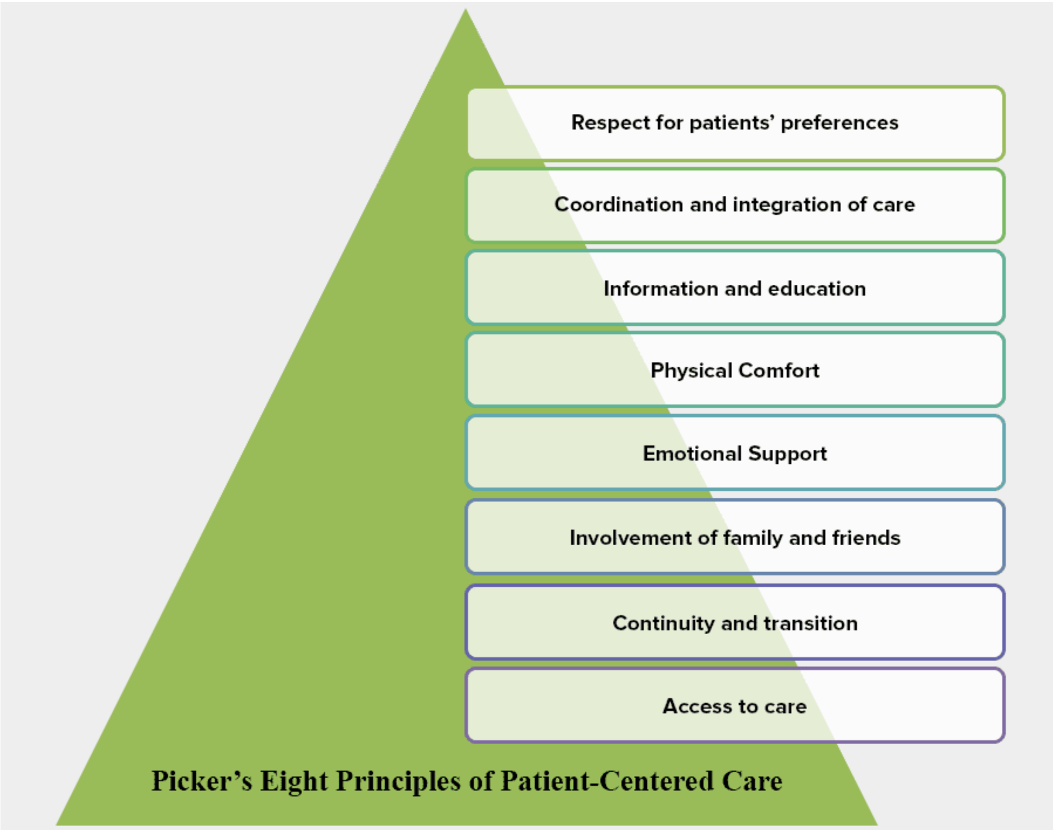

Figure 2. 2. Picker's Eight Principles of Patient-Centered Care
Source: O'Neill (2022)

Access to care - Patients have the right to access the right service at the right time and quality care that caters for their needs (Picker Institute, 2022). Access includes ease of scheduling appointments, reducing waiting time for treatments, and the availability of the right professionals and advice (O'Neill, 2022; Picker

Institute, 2022). Smartwatches can facilitate patients' access to their physical exercise data on their wrists which makes them active participants in their healthcare.

Continuity and Transition - It is important to have seamless transitions after a patient has been discharged from the hospital. Patients should have access to all the information they need after they get discharged. This information may include regular treatments, upcoming doctor visits and any other continued support they might need (Picker Institute, 2022). Some smartwatches achieve this by linking the device to the metabolic monitors that are used with patients in intensive care. If the smartwatch sensors detect an abnormality, the doctor on duty receives an alert anywhere in the hospital and can quickly attend to the patient. This allows for continuity of care in the sense that the patient does not have to wait for a particular doctor to be on duty to be attended to.

Involvement of Family and Friends - Healthcare staff need to understand and acknowledge the importance of family, caregivers, friends and support networks in the well-being of the patient. The involvement of such people has to be welcomed and supported because it addresses the emotional needs of the patient (Picker Institute, 2022). Smartwatches allow for communication between family and friends through sharing of physical data statistics via their wearable devices. It is also a quicker way of updating loved ones on how one is doing.

Information and Education - The key to successful patient-centered care is to educate patients on the clinical manifestations of their diseases, the effects of medicine and the lifestyle options (Barrett et al., 2019). People should always receive reliable, high quality and accessible information. This information should be provided in a manner that is understandable and helpful in making informed decisions about their health (Picker Institute, 2022). Smartwatches achieve this by having inbuilt applications that provide physical information without complicated medical jargon. The information is easy to read and also allows for research to be conducted to understand behaviours and patterns.

Respect for Patient's Preference - Every patient has a right to be involved and make decisions about their healthcare. There should be a reciprocal relationship between the patient and healthcare staff such that the choices and preferences of the patient are respected regardless of social or cultural values (Picker Institute, 2022). By using a smartwatch, a patient is directly involved in their healthcare in such a way that they have a choice to improve their physical wellness or not to. Smartwatches, therefore, offer patients an opportunity to move from being passive to active participants in healthcare.

Physical Comfort - Every person deserves to be treated in a safe environment that ensures dignity and privacy (Picker Institute, 2022). People's physical needs are of importance hence care providers need to be mindful of this, especially in pain management, physical activities, and personal care (Picker Institute, 2022). Having a smartwatch is like having an exercise companion. The patient does not need to visit the healthcare facility to have exercises and heart rate measures. They can do it in the comfort of their homes or in places they feel more comfortable. Some smartwatches with features such as the guided meditation rejuvenates the spirit. Something a patient may not easily have access to if they were to go to a clinic.

Emotional Support - Patient-centered care should be holistic in nature. This means that it should also place importance on an empathic and respectful approach to people's emotional needs (Picker Institute, 2022). Smartwatches support self-motivated personal activities. They also keep an eye on stress levels by measuring heart rate and offering meditation applications.

Coordination and Integration of Care - People should receive treatment that is appropriate and effective, and that also meets their needs and respects the patient's preferences (AHP, 2020; Barrett et al., 2019; Picker Institute, 2022). The AHP (2020), states that all treatments must be considered in terms of how they integrate with other treatments. With smartwatches, patients' readings can be monitored in real-time and stored on a central server, so that dangerous levels are detected immediately, and an alert is sent directly to a doctor's wrist. This allows the doctor to react quickly and precisely. Remote patient monitoring also allows healthcare staff to analyse health data quickly which improves doctor-patient relationship.

2.5. Patient-centered healthcare in the Covid-19 era

Covid-19 has had a huge impact on the way healthcare is provided. With social distancing regulations, virtual healthcare became a norm. The pandemic has challenged how healthcare is delivered and innovative ways to deliver healthcare services were devised and sometimes improvised. Digital healthcare has significantly increased since the advent of Covid-19 and has shown how much can be gained from digital healthcare processes (Maier et al., 2021). Although many countries moved to virtual healthcare models, the required infrastructure to enable such models such as electrical power, cellular services, and the internet is not equally distributed (Sutarsa et al., 2020).

Covid-19 pandemic made it possible for health systems to use digital healthcare systems, commonly known as eHealth systems. Hägglund et al. (2022) state that digitalization and eHealth's goals are to improve the efficiency and effectiveness of healthcare and strengthening self-care through empowering patients. Possible ways a patient could be empowered include allowing the patient to have access to medical data, participate in their care, and design and improve healthcare systems (Bärkås et al., 2021; Riggare et al., 2021; Wass & Vimarlund, 2018). This helps the patient with understanding what is going on with their health.

Covid-19 exposed the limitations of healthcare systems globally. It allowed care providers to care for patients from a distance and still be able to show empathy and gain patients' trust virtually. Covid-19 made it possible for cameras to be put on Intravenous (IV) poles so that doctors could respond quickly to patients from a distance (Gupta et al., 2021). This increases the efficiency of healthcare providers. Covid-19 has set in a fresh outlook for the future that is characterized by greater accessibility, better treatment, and more safety for patients (Bowman, 2021). Due to the Covid-19 pandemic, milestones in the use of technology in healthcare have been achieved in a short period. It has allowed the health sector to rethink ways to offer quality patient-centered healthcare virtually.

2.6. Digital health technologies

Digital health technology is defined as information and communication technology (ICT) for health (Olu et al., 2019). The World Health Organization (2022) defines digital health as a broad term including e-health and developing areas such as the use of computer science in strengthening health systems, public health, increasing equity in access to health services, and promotion of universal health coverage. Digital technology offers opportunities to maximize health care delivery and research regardless of the risk of data privacy and quality (Sharma et al., 2018). Digital health technology is regarded as an engine for innovation and universal health coverage.

Accenture (2021) states that healthcare organizations are faced with the reality that every business is a digital business and Covid-19 pandemic accelerates technological transformation across industries. However, for low-income countries, it is not easy to transition from traditional to digital health services. Olu et al. (2019) argue that in Africa, digital health technology is hampered by poor planning, weak health systems, lack of awareness and knowledge about digital health, poor infrastructure, and poor internet connection among other factors. For digital health technologies to be successfully implemented, there is a need for a strong health system backing them up. This is challenging for developing countries hence they are always lagging in technology solutions to healthcare.

2.6.1. Types of digital health technology

Health Apps - Mobile apps such as smartphones and wearable technology (smartwatches, Fitbit, shoes) are used for health solutions. These have in-built apps to promote healthy behaviours such as gentle reminders about long sedentary periods (Muammar et al., 2018). These offer fitness data tracking and they increase the level of transparency using detailed analytics that can be viewed on smartphones (Bowman, 2021).

Telehealth - This is a digital way of receiving healthcare by making it possible through devices that work on 5G networks (Bowman, 2021). This allows people to contact health professionals remotely and it has been very useful during the Covid-19 pandemic.

Patient Portals - This has become popular because of its ability to offer a user login where patients can schedule an appointment, communicate with care providers, and pay their medical bills (Bowman, 2021). It streamlines the management of medical information for both patients and providers.

Electronic Health Records (EHR) - This is a modern medical information storage system kept in private medical databases that are only accessible to care providers. They offer readable and organized information which reduces the risk of medical errors (Manca, 2015). EHRs can help improve patient-centered healthcare by improving communication, providing personalized treatment and increasing shared decision-making. However, electronic health records are prone to cyber-attacks.

Digital Signatures - They offer patients an easy and faster way of submitting documents and they are easily traceable to the signer.

Artificial Intelligence (AI) - AI is defined as the ability of computers to carry out tasks that are usually done by human intelligence and can impact millions of people by changing the way healthcare is provided (Richardson et al., 2021). Examples of AI include chatbots, and other AI-powered radiological image analysis and diagnostic tools. AI is expected to surpass human practitioners soon, especially in accuracy, reliability, and generating new knowledge (Bjerring & Busch, 2020).

2.7. The nexus between technology and patient-centered healthcare

Digital transformation is impacting people’s daily lives economically, politically, and socially. The World Health Organization (WHO) implemented a Global Strategy on Digital Health 2020-2025 with the aim of strengthening health systems and improving healthcare for everyone (World Health Organization, 2021). This move by WHO is also in line with United Nations’ Sustainable Development Goals which emphasize growth in information and communication technology that can interconnect the global systems and accelerate human progress (United Nations, 2022; World Health Organization, 2021). Healthcare systems have been striving to change. Part of this improvement has taken the digital route.

The Philips Future Health Index (2019) states that development in digital health technology such as digital health records, telehealth, and artificial intelligence is beneficial in ensuring better health outcomes and reducing the cost of healthcare. Digital health records allow access to more accurate information and up-to-date complete information about patients. In addition, telehealth allows for 24/7 care regardless of location. AI, on the other hand, helps in making clinical decisions support and personalized treatment (Philips Future Health Index, 2019). Figure 2.3 below shows a summary of the role technology plays in patient-centered healthcare.

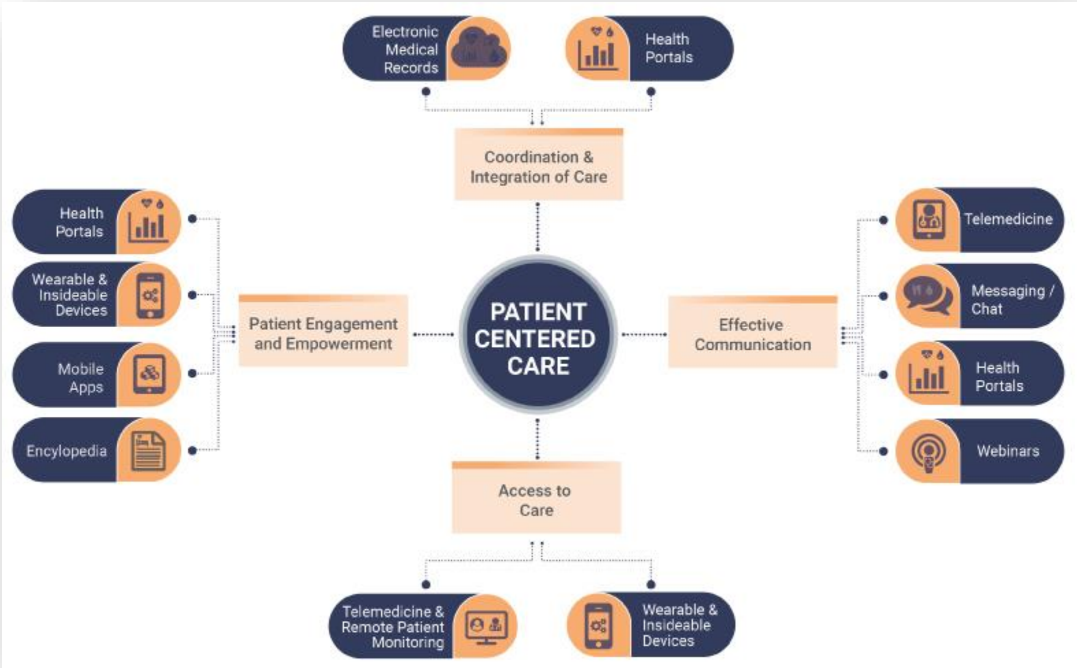

Figure 2. 3.Health technology tools that enhance patient-centered care
Source: Muammar et al. (2018)

2.7.1. Patient-centered healthcare in Developed Countries

Technological innovations in the health space are meant to empower patients. Developed countries have come up with alternatives and technology to improve healthcare but they still face challenges with the quality of healthcare services and the costs attached to them (Bali, 2018). eHealth in developed countries such as Sweden, the Netherlands, and Australia is used by more than half of the care providers, in the form of electronic health records (Furusa & Coleman, 2018). Japan also improved its healthcare systems to effectively manage patients' effects of Covid-19, avoid duplicates, and improve systems integration and product accurate data insights (Takeshita et al., 2022).

Most developed countries have invested in advanced healthcare systems that offer services of high quality to people. Germany developed a "smart card", which is a health care for patients covered by insurance (Gu et al., 2021). This card contains personal information such as insurance details and medical records (Gu et al., 2021; Muchangi & Nzuki, 2014). The United States of America (USA) previously invested US$1.2 billion towards the adoption of electronic health records across the country's hospitals (Gu et al., 2021). The Canadian government formed the Canada Health Infoway to encourage the use of electronic health records in exchanging medical information across federal districts (Gu et al., 2021).

According to Healthcare Automation and Digitalization Congress (2021), patient-centered healthcare is a necessity for patients who require individual attention. Deloitte Centre for Health Solutions (2020) states that healthcare systems in Europe are faced with pressure even though the quantity and quality of healthcare have improved. The complexity of healthcare needs in developed countries has grown and there is an increasing public expectation of quality healthcare (Deloitte Centre for Health Solutions, 2020). The gap between resource supply and healthcare demand is widening as many countries try to close this gap through digital health technology.

Many people in developed countries do not want to be passive patients; they want healthcare that is easily accessible and that allows them to have choices, and this has given rise to the increase of people using wearable devices that can track and store health data (Deloitte Centre for Health Solutions, 2020). This means that people can own their data and choose who to share it with. However, the varying responses to eHealth in developed countries is an indication that the adoption of technology in patient-centered healthcare is not informed by the availability of technology only. Factors such as trust and institutional support play a pivotal role as well.

2.7.2. Patient-centered healthcare in Developing Countries

Societies have high expectations of quality public services and to have such, there is a need of careful planning and implementation of healthcare policies. Developing countries are met with various challenges when they want to use technology to improve patient-centered healthcare. Makubalo et al. (2020) state that one of the major challenges faced is inconsistent electricity power supply which makes it difficult for African countries to successfully implement electronic health records (EHR) and to date, no country in Africa has done it.

Digital health technology has not been easily accessible to many people in need of it. Low-income countries such as those in Africa are prone to many diseases but they have limited access to health technology (Oloruntoba, 2019; Shahin et al., 2020). Manyazewal et al. (2021) argue that Africa carries a huge burden of diseases and its healthcare challenges are the greatest across the globe with a life expectancy of 60 years compared to the global average of 72 years. Africa does not have adequate access to healthcare technology that can improve patient-centered health services yet it bears 23% of the global disease burden and 16% of the world's population (Manyazewal et al., 2021). This means that it is currently difficult for Africa to deal with the health needs of its population, and this also points to gaps in the global health system. There was increased use of smartphones and other digital technologies during the pandemic, however, the challenges are high data costs, and lack of knowledge on how to navigate the healthcare systems (Fischer et al., 2021).

Electronic health records are very helpful in developing countries especially in integrating patient information but it is difficult to implement (Cilliers & Katurura, 2017; Makubalo et al., 2020). The major impediments to the successful implementation of digital health services are infrastructure, training, and access to better devices such as smartphones (Manyazewal et al., 2021). Makubalo et al. (2020) also state that electronic health records are difficult to implement in South Africa because of inconsistent electricity supply, lack of government support and required infrastructure. South Africa is in the process of implementing the National Health Insurance with plans to shift healthcare towards preventative care and health that is patient-centered but it keeps on being hampered by issues of power cuts, lack of funds, and lack of required infrastructure (Makubalo et al., 2020). This means that patients do not have access to their complete health information, and it tempers with the quality of patient-centered healthcare provided.

From the above, one may realize that there is a gap in the global health systems that hinders the delivery of quality healthcare systems. This gap is even bigger in developing countries where issues of affordability, accessibility and skills are lacking. This study, therefore, seeks to investigate the effect that smartwatches may have on patient-centered healthcare in a developing country's context of South Africa.

2.8. Hypothesis development and conceptual framework

Smartwatches have many features. The literature has revealed three smartwatch features that have an impact on patient-centered healthcare. These features are activity tracking (workout routine, sleeping patterns, sedentary reminders), vital signs monitoring, and data management (storage, integration, and reporting) (Reeder & David, 2016; Wang, 2017). The literature reveals that activity trackers have been adopted for collecting health data, monitoring fitness and health activities so that users can be proactive when it comes to taking good care of their health (Pingo & Narayan, 2019). Activity tracking helps users set fitness and health goals with the aim of improving them and staying healthy (Pingo & Narayan, 2019). Data can also be collected from multiple sources to provide insights for better decision making for both patients and healthcare providers. Users can also share their health and fitness data with friends and family.

A study by Purwanto (2022) explored the link between smartwatch features and patient-centered healthcare aspects that address patient needs. The study found that smartwatch features such as heart rate monitoring, sleep tracking, and physical activity tracking can provide valuable data that can be used to improve patient-centered care (Jat & Grønli, 2022). Activity tracking can play a role in patient-centered healthcare by providing valuable health data that can be used to personalize care and improve outcomes (Chiauzzi et al., 2015). For example, activity tracking can help patients monitor their physical activity levels and set goals for improvement. This can help patients become more involved in their care take care of themselves and make informed decisions about their health. Additionally, healthcare providers can use activity tracking data to monitor patient progress and tailor treatment plans to their individual needs (Chiauzzi et al., 2015).

Smartwatches can also be used to monitor blood pressure (He et al., 2022). Hypertension causes heart problems that may lead to death (World Health Organization, 2021). Monitoring blood pressure is pivotal to preventing hypertension. Therefore, blood pressure monitoring is a key smartwatch feature that enables a patient to have insights on this vital health sign and hence make informed decisions about their healthcare (He et al., 2022). Monitoring vital signs is an important part of patient-centered healthcare (Brekke et al., 2019).

Vital signs such as blood pressure, heart rate, respiratory rate and body temperature can provide valuable information about a patient's health status and help healthcare providers make informed decisions about patient care (Brekke et al., 2019). By monitoring vital signs, healthcare providers can quickly identify potential health problems and take the necessary steps to stop the progression of the disease or disorder. (Mok et al., 2015). Effective vital signs monitoring requires accurate and reliable data collection, storage, analysis, and sharing.

Although smartwatch data storage is usually limited, the data emanating from a smartwatch is usually synchronized with a smartphone or a computer (Wang, 2017). According to Reeder and David (2016), data retrieved from smartwatches can be integrated with Internet of Things (IoT) and Electronic Health Records (EHRs) to provide a comprehensive view/reports of an individual's health conditions and patterns. Data management in healthcare involves the collection, storage, analysis, and sharing of health-related data (Pastorino et al., 2019). Effective data management can help healthcare providers make informed decisions about patient care and improve patient outcomes (Jat & Grønli, 2022).

In the context of smartwatches, data management involves ensuring that the data collected from these devices is accurate, reliable, and secure.

Based on the above evidence from the literature pertaining to the contribution of smartwatches on patient-centered healthcare, the following hypotheses and sub-hypotheses were formulated:

- Hypothesis H1: Activity tracking feature of a smartwatch has a positive effect on pateint-centered healthcare
    - H1.1: Activity tracking feature of a smartwatch has a significant positive effect on continuity and transition.
    - H1.2: Activity tracking feature of a smartwatch has a significant positive effect on the involvement of family and friends.
    - H1.3: Activity tracking feature of a smartwatch has a significant positive effect on information and education.
    - H1.4: Activity tracking feature of a smartwatch has a significant positive effect on the respect for patients' preferences.
    - H1.5: Activity tracking feature of a smartwatch has a significant positive effect on physical comfort.
    - H1.6: Activity tracking feature of a smartwatch has a significant positive effect on emotional comfort.
    - H1.7: Activity tracking feature of a smartwatch has a significant positive effect on coordination and integration of care.
    - H1.8: Activity tracking feature of a smartwatch has a significant positive effect on access to care.
- Hypothesis H2: Vital signs monitoring feature of a smartwatch has a positive effect on patient-centered healthcare
    - H2.1: Vital signs monitoring feature of a smartwatch has a significant positive effect on continuity and transition.
    - H2.2: Vital signs monitoring feature of a smartwatch has a significant positive effect on the involvement of family and friends.

    - H2.3: Vital signs monitoring feature of a smartwatch has a significant positive effect on information and education.
    - H2.4: Vital signs monitoring feature of a smartwatch has a significant positive effect on the respect for patients' preferences.
    - H2.5: Vital signs monitoring feature of a smartwatch has a significant positive effect on physical comfort.
    - H2.6: Vital signs monitoring feature of a smartwatch has a significant positive effect on emotional comfort.
    - H2.7: Vital signs monitoring feature of a smartwatch has a significant positive effect on coordination and integration of care.
    - H2.8: Vital signs monitoring feature of a smartwatch has a significant positive effect on access to care.
- Hypothesis H3: Data management feature of a smartwatch has a positive effect on patient-centered healthcare
    - H3.1: Data management feature of a smartwatch has a significant positive effect on continuity and transition.
    - H3.2: Data management feature of a smartwatch has a significant positive effect on the involvement of family and friends.
    - H3.3: Data management feature of a smartwatch has a significant positive effect on information and education.
    - H3.4: Data management feature of a smartwatch has a significant positive effect on the respect for patients' preferences.
    - H3.5: Data management feature of a smartwatch has a significant positive effect on physical comfort.
    - H3.6: Data management feature of a smartwatch has a significant positive effect on emotional comfort.
    - H3.7: Data management feature of a smartwatch has a significant positive effect on coordination and integration of care.
    - H3.8: Data management feature of a smartwatch has a significant positive effect on access to care.

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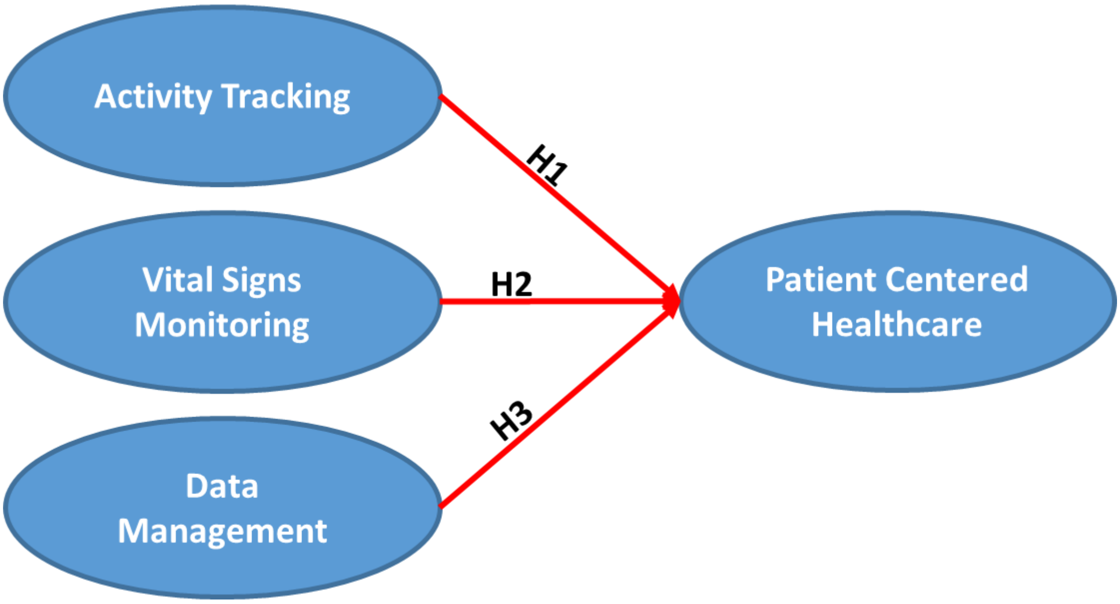


Figure 2. 4. *Conceptual Framework (Source: Authors' own)*

This study is anchored on three independent variables (constructs) and 1 dependent construct that depicts the 8 principles of patient-centered(O'Neill, 2022; Picker Institute, 2022) . The Picker's 8 principles are:

i. Access to care
ii. Continuity and Transition
iii. Involvement of Family and Friends
iv. Information and Education
v. Respect for Patient's Preference
vi. Physical Comfort
vii. Emotional Support
viii. Coordination and Integration of Care.

On the other hand, the items of the three independent variables (activity tracking, vital signs monitoring, data management) were formulated based on a literature review of features of a smartwatch. The items for the dependent and independent variables are reflected in the data collection instrument (questionnaire) presented in Appendix B.

2.9. Chapter summary

Digital health technology has brought a shift on how patient-centered healthcare is provided. It has brought faster and more efficient ways to attend to patients remotely. Wearable devices such as smartwatches have allowed patients to actively participate in their care and to have a sense of ownership of their wellbeing. This has been seen more during Covid-19 pandemic which became a catalyst for the implementation of digital health technologies. This study focuses on the effect of smartwatches in improving patient-centered healthcare therefore this chapter provided a detailed literature review to address the research questions and research objectives.

CHAPTER 3. RESEARCH METHODOLOGY

3.1. Introduction

This chapter describes the methodology adopted in this study. The chapter is anchored on the Saunders Research Onion (2019) to explain the research philosophy, approach, strategy, techniques, procedures and time horizon adopted in this study. Figure 3.1 below illustrates the layers of the research onion.

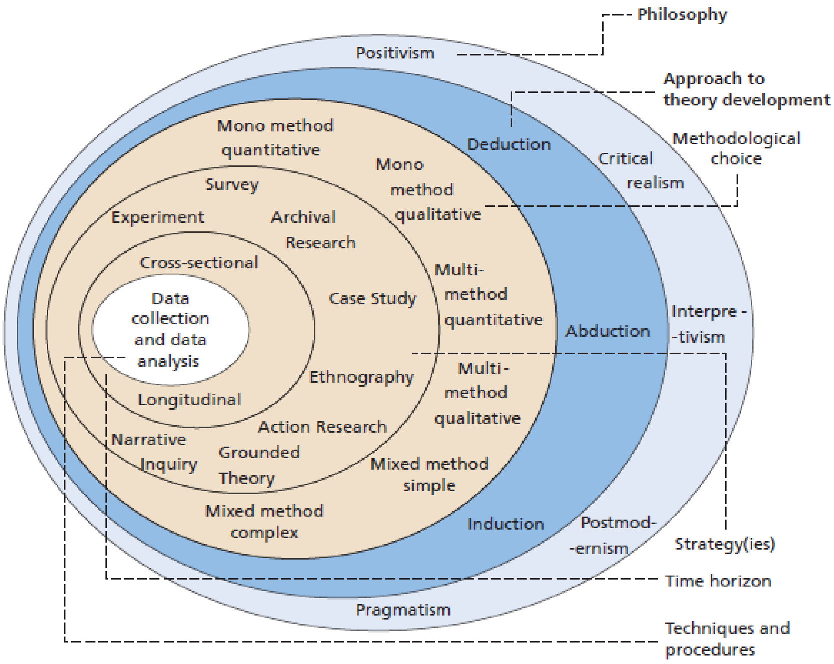


Figure 3. 1. The research onion
Source: Saunders, Lewis and Thornhill, (2019)

3.2. Nature of study

A research study can be categorized as either descriptive, exploratory, causal or explanatory research. Descriptive research describes the behaviour and occurrence of a phenomenon, how the sample population behaves and it is recommended if the aim of the research is to create a hypothesis and propose relationships (Dudovskiy, 2022). Descriptive research answers the "what" question instead of the “why” question, therefore, most descriptive studies would have suggestions for further research to understand the “why” that was not explored in the descriptive study (Dudovskiy, 2022). Exploratory research, on the other hand, draws new knowledge from events/situations and reveals insights. Exploratory research plays an important role in generating hypotheses, refining research questions, and guiding subsequent research (George, 2023). Explanatory research, also known as causal, aims to understand the relationships and cause-effect dynamics between variables that have not been investigated (Rahi, 2017). Unlike exploratory research, which focuses on uncovering new knowledge, explanatory research seeks to provide explanations and answers to specific research questions. It investigates why certain phenomena occur and attempts to establish causal connections by analysing existing data and employing quantitative methods such as experiments, surveys, and statistical analysis (Rahi, 2017). Explanatory research involves formulating hypotheses and testing them rigorously to determine the factors that influence or contribute to a particular outcome. Its findings contribute to theory development, decision-making processes, and the development of practical solutions to real-world problems (George & Merkus, 2023).

This study is explanatory in nature, as its main objective is to understand the effect of smartwatches on patient-centered healthcare and uncovers new knowledge related to the relationships between smartwatch features and patience-centered healthcare. The study further provides possible explanations on why the relationships may exist or why there may not be any relationships between the variables. The findings of this study could be used as the foundation for future research studies to further investigate the wearable technologies on patient-centered healthcare.

3.3. Research philosophy

Research philosophy is the lens through which knowledge is acquired within a specific subject or domain. This acquired knowledge can be applied to address specific issues or contribute to the generation of novel insights (Saunders, Lewis & Thornhill, 2019:130). The research philosophy acts as the underlying foundation that informs the development of knowledge, relying on a set of assumptions (Melnikovas, 2018: 33). These assumptions encompass ontological assumptions pertaining to the realities encountered during the research process, epistemological assumptions concerning acceptable and valid human knowledge, and axiological assumptions involving ethical values during the research (Saunders et al., 2019:130; Burrell & Morgan, 2017:1). These assumptions shape researchers' understanding of research questions, their selection of research techniques, and their interpretation of research outcomes. The subsequent section discusses the five primary research philosophies, namely positivism, critical realism, interpretivism, postmodernism, and pragmatism and an explanation of the research philosophy that guides this study.

Positivism

Positivist philosophy places emphasis on the existence of reality and asserts that the world and its surroundings are objectively real, allowing for the discovery and understanding of tangible factors (Walliman, 2010). This philosophical approach is typically structured, deductive and uses large samples and quantitative research methods (Saunders et al., 2019:130). Positivism only focuses on factual information and is not based on the researcher’s opinion (Dudovskiy, 2022). Positivists maintain minimal engagement with the study’s participants so that they may not influence participants’ responses (Wilson, 2010). This research adopted the positivism philosophy that focuses on scientific empirical methods to provide clear, accurate, precise, and unbiased information (Saunders et al., 2019:130). This philosophy was selected to test hypotheses pertaining to the relationships between the smartwatch features and patient-centered healthcare and make deductions based on factual and non-biased information.

Critical Realism

This philosophy is centered around clarifying what is seen and experienced. Critical realists see reality to be external and autonomous, yet not straightforwardly open through people's perceptions and information about the reality around them (Saunders et al., 2019:130). The essence of critical realism lies in figuring out what is unbiasedly genuine and what is emotionally acknowledged as the truth (Taylor, 2018).

Interpretivism

The interpretivism philosophy is centered on discovering new or more insights and translations of the social world and contexts. Researchers use the interpretivism paradigm to gain access to authentic (first hand) information, which enables them to gain deeper understanding, insights into the history of objects, human or events, and social context (Pham, 2018). Interpretivists may collect valuable information by conducting interactive interviews where they can probe and gain more understanding regarding their subject/area. However, researchers who adopt the interpretivism philosophy may be biased in their conclusions as they rely on their subjective interpretation. Interpretivists typically use the inductive research approach, small sample sizes and qualitative research methods (Saunders et al., 2019:130).

Postmodernism

Postmodernism is often used to explore the complexities of power dynamics and how they shape social relations, emphasizing the importance of context, historical contingencies, and social constructions in the production of knowledge (Saunders et al., 2019). Postmodernism researchers employ diverse methodological approaches, often emphasizing qualitative methods such as ethnography, textual analysis, and discourse analysis (Saunders et al., 2019). They engage in in-depth investigations of anomalies, silences, and within existing narratives and systems, questioning taken-for-granted assumptions and seeking to expose the limitations and biases inherent in traditional modes of inquiry (Saunders et al., 2019).

Pragmatism

Pragmatism research philosophy emphasizes the integration of theory and practice, considering knowledge as a tool for action and problem-solving (Saunders et al., 2019). Pragmatists often employ an iterative and adaptive approach, utilizing methods that are responsive to the specific research context and flexible enough to accommodate changes in real-world circumstances. This can include a combination of quantitative and qualitative methods, as well as participatory and action-oriented research approaches (Saunders et al., 2019).

3.4. Research approach

The second layer of the research onion entails choosing the research approaches to theory development. These approaches are deduction, abduction and induction (Saunders et al., 2019).

Deduction

This approach helps to test an existing theory or a set of hypotheses (Melnikovas, 2018:38). This approach tests the validity of specific assumptions and evaluates certain propositions. This study is based on a deduction research approach as it tests variables using hypotheses and is anchored on the Picker’s 8 principles of patient-centered healthcare (Picker Institute, 2022) and an extant literature on what constitutes smartwatch features.

Induction

This approach starts with observation, data collection, data analysis and then build a theory or a conceptual framework based on the information gathered (Saunders et al., 2019:155; Melnikovas, 2018:38).

Abduction

This theory development approach begins with pieces of information like signs or clues, which give the fundamental thoughts for further research (Melnikovas, 2018:38). Abduction often uses a combination of the deduction and induction approaches. Abduction is the most flexible approach and therefore researchers with different research philosophies can use it (Saunders et al., 2019:153).

3.5. Research methods

The third layer in the research onion is the research method, which includes qualitative, quantitative and mixed methods.

Qualitative Method

This method is based on an inductive approach to develop extensive knowledge by exploring and unpacking information related to events, situations and artefacts. This approach values people's subjective experiences and obtaining detailed information from a small sample (Leavy, 2017).

Quantitative Method

This study adopted the quantitative research method. The quantitative research method is usually used when researchers want to evaluate or explain a theory using quantitative measures (Leavy, 2017). In this study, the researcher aimed to identity the features of smartwatches that contribute to patient-centered healthcare and the extent to which these features contribute to patient-centered healthcare. This study adopted the quantitative research method as the researcher sought to evaluate the effect of the features of smartwatches (independent variables) on patient-centered healthcare (dependent variable). To achieve this, the researcher collected data using a pre-determined sample size and made inferences based on statistical analyses.

Mixed Method

This method is typically used when conducting social and behavioural science research (Leavy, 2017). Mixed method is required when a study needs both qualitative and quantitative research methods to answer research questions (Melnikovas, 2018). Mixed method can be useful as it integrates the benefits of both qualitative and quantitative (George, 2023). This method is used when the research questions cannot be answered using only qualitative or quantitative methods. In a mixed method the data collection needs to be systematic to ensure that the data is integrated accordingly and represented in a proper manner.

3.6. Research strategy

There are different types of research strategies namely: experiment, survey, archival research, case study, grounded theory, action research, ethnography and narrative inquiry (Saunders et al., 2019). Survey are used when a researcher wants to understand characteristics, opinions, preferences of a certain group. A survey is used when you cannot reach the entire population (McCombes, 2023).

This study used the survey research strategy to collect data from a sample of a population using predefined research questions. A survey was deemed appropriate as the researcher could not get hold of the entire population of runners and due to time constraints allocated to this study. The study was supposed to completed within a certain period.

The table below illustrates the advantages and disadvantages of surveys.

Table 3. 1. Advantages and disadvantages of surveys

Advantages	Disadvantages
• A cost-effective way of collecting data from a large population.	• Accuracy of the responses is dependent on the respondents' memory and/or knowledge of the topic.
• Data is usually standardized which enables ease of comparison with other studies.	• The sample should be representative in order for the findings and conclusion to be accurate.
• Easy to explain and understand.	
• The researcher can manage the research that is conducted alone.	

Source: Saunders (2009)

3.7. Time horizons

Time horizon refers to the timeframe of the research. Time horizon is divided into two namely, cross-sectional and longitudinal. This research was based on cross-sectional time horizon as the research timeline has already been established and the study had to be completed by 30th June 2023. The longitudinal time horizon is suitable for a study in which the data collection spans over an extended period (Saunders et al., 2019).

3.8. Study site

A study site refers to a place or area where the research takes place. This research was conducted through a runners' club based in Gauteng province in South Africa. This site was chosen because it has many members who are already using smartwatches. In addition, the researcher is also a member of the club which made it easier to recruit the study participants.

3.9. Techniques and procedures

Techniques and procedures are actions and tools used to collect and analyse data (Melnikovas, 2018). Techniques and procedures are essential to ensure that the researcher is well acquainted with how to collect data and how to design the research instrument (George, 2023).

3.9.1. *Research instrument design*

The design of a research instrument plays a crucial role in conducting research as it forms the foundation for drafting an effective questionnaire. According to Giesen, Meertens, Vis-Visschers and Beukenhorst (2012), the design of a research instrument consists of six steps highlighted in Figure 3.2 below. The following sections explain how this study's questionnaire (research instrument) was designed and developed using these six steps. The figure below indicates that an output from one step may be used as an input in the following step.

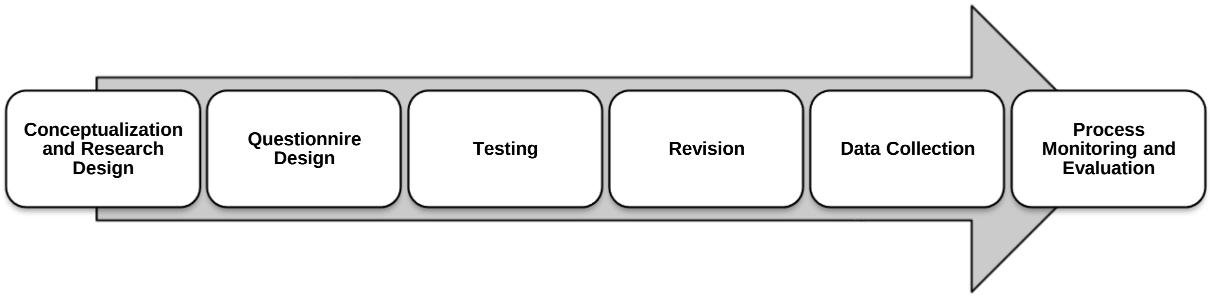


Figure 3. 2.Questionnaire development process
Source : Giesen et al. (2012)

The first step in research instrument design is identifying the variables that need to be measured (Giesen et al., 2012). The questions within the questionnaire were drafted based on the independent variables (smartwatch features) and the dependent variable (patient-centered healthcare). Based on extensive literature search, smartwatch features were divided into 3 constructs (activity tracking, vital signs monitoring and data management). The dependent variable was constructed based on the Picker's 8 principles of patient-centred healthcare which are access to care, continuity and transition, involvement of family and friends, information and education, respect for patient's preferences, physical comfort, emotional comfort and, coordination and integration of care.

Questionnaire design

The questions were written down, revised and formatted to ensure that they are easy to understand. The questionnaire comprised closed-ended questions. The first part of the questionnaire introduced the study followed by a consent form that each participant had to agree upon before filling the questionnaire. The questionnaire consisted of 3 sections that the participants had to answer:

Section A: This section aimed to collect participants' demographics information such as gender, level of education and age range of the participants. The last two questions in this section sought to find out if participants use smartwatches and how often do they use them.

***Section* B:** This section aimed at the insights on the participants' use of the smartwatch features including activity tracking, vital signs monitoring and data management features. The foundation for questions in these sections were based on smartwatch features.

Section C: This section aimed to gather information related to patient-centered healthcare based on Picker's 8 principles (O'Neill, 2022; Picker Institute, 2022)**.** This section investigated participants personal experiences and views related to patient-centered healthcare. Section B and C were based on a Likert scale of 1 (Strongly Disagree) to 5 (Strongly Agree). All respondents' answers are anonymized. The questions in this section were developed to address Picker's 8 principles that were identified in the literature. The researcher created those questions based on the abovementioned information.

3.9.2. Pilot Study

Prior to administering the questionnaire to the potential respondents, a pilot study was conducted to ensure that the questionnaire is error free, unambiguous and easily understood. In this study, ten participants were selected as part of the pilot study. The participants pointed out some grammar and spelling errors. Two of the participants could not understand the link between the topic and the questions, however, that was clarified. The appearance and formatting of the questionnaire were modified to make it more visually appealing.

3.10. Target population and sampling methods

3.10.1. Target population

The target population refers to participants selected based on specific selection criterion (Alvi, 2016). The selection of the target population is critical as the population must have the information required for the research. Since the study aims at identifying the features of smartwatches, the targeted population were individuals from the running club, who use smartwatches. The targeted population is approximately 400 club runners. Hence, the population's sample size for this study was 200 runners from a running club that is part of Central Gauteng Athletics (CGA) association. The selection of this sample was mainly based on the researcher's familiarity with the running community.

3.10.2. Sampling methods

There are two types of sampling methods, namely probability sampling (simple random, stratified random, cluster and systematic) and non-probability sampling (convenience, quota, snowballing and purposive) (Alvi, 2016). Probability sampling entails a random selection from a sample and it is considered to be costly and time-consuming (Alvi, 2016). Non-probability sampling can be based on multiple factors and does not include random sampling (Alvi, 2016). This study was based on non-probability sampling as not all members of the population have a chance to participate in the study. Additionally, the method is cost effective and time consuming. Convenient sampling is defined by the ease of access to participants amongst other factors. This study adopted the convenient sampling method (non-probability sampling) as it is cost-effective and less time-consuming.

The selected running club has more than 400 runners. According to sample size determination using Krejcie and Morgan table, if the population size is 400 then the sample size should be at least 196 (Krejcie & Morgan (1970). However, Hair et al., 2021) has indicated that, to enable meaningful statistical analysis, a sample size must have a minimum of 200 participants. Therefore, the targeted sample size for this study was a minimum of 200 respondents from the selected running club. Due to certain limitations mentioned in section 3.12 only 181 (90%) participants were able to complete the questionnaire.

3.11. Data collection

An online survey was designed using the Qualtrics online data collection tool. The link to the survey was shared through the running club's WhatsApp group, individual runners' WhatsApp and email. A reminder was sent on a weekly basis for participants to complete the survey. The participants were informed that they will receive no rewards for participating in the study. The participants were presented with a consent form that they had to accept prior to participating in this study. The consent form stipulated amongst other things that participants had the right to withdraw from the study at any time. The consent form also mentioned that their participation is voluntary and all the information they provided would remain confidential. The consent form can be found in Appendix A.

3.12. Data analysis

3.12.1. Data cleaning

Prior to conducting data analysis, the collected data was cleaned to ensure that the data is of good quality. Firstly, data extracted from Qualtrics was exported to IBM Statistical Package for the Social Sciences (SPSS) for data cleaning. The values captured in Qualtrics were adjusted in SPSS to ensure they correspond to numeric values initially assigned to them. However, this was only performed on the demographics section (sections A2 to A5). The rest of the values were kept as exported from Qualtrics. Secondly, as the study only targeted those who are currently using a smartwatch, all responses with a "No" answer to the question related to the use of smartwatches ("Do you use a smartwatch") were deleted. Thirdly, all the incomplete responses were deleted, that is, any instance whereby a respondent did not answer all the questions was deleted. At the end of the data cleaning process, only 141 records were kept for further analysis out of the 181 that were initially collected.

3.12.2. Data analysis

Data analysis is a process of structuring the data in such a way that provides a meaning. Data analysis was conducted using the Statistical Package for Social Science (SPSS) and SmartPLS 4.0 software. Data analysis for this study was conducted using Partial Least Squares- Structural Equation Modelling (PLS-SEM). Partial Least Squares Structural Equation Modelling (PLS-SEM) is a statistical analysis technique that is used to analyse complex cause-effect relationship models with latent variables as the most salient research methods across a variety of disciplines (Cepeda-Carrion et al., 2018). PLS-SEM has several benefits; it is useful when the sample size is small, that is, sample that is less than 200 (Hair et al. 2019, p. 5), in which is the case in this study. PLS-SEM is also useful when there is a complex structural model with multiple constructs or model indicators (Hair et al. (2019), p. 5), as such is the case for this study.

3.13. Measurement approaches

In the context of Smart PLS (Partial Least Squares) analysis, formative and reflective constructs or variables represent two distinct measurement approaches (Hanafiah, 2020). They have different characteristics and implications in terms of measurement and analysis. The key differences can be summed up as follows:

3.13.1. Nature of relationship

- Reflective Constructs: Reflective constructs are formed by indicators that are believed to measure the underlying latent construct. In this case, the construct is considered to be a cause of the indicators (Hanafiah, 2020). The indicators are expected to covary and share common variance due to the underlying construct.

- Formative Constructs: Formative constructs, on the other hand, are formed by indicators that are considered to be influenced by the latent construct. The indicators are seen as manifestations or determinants of the construct (Hanafiah, 2020). The construct is not assumed to cause the indicators, but rather the construct is defined by the indicators.

3.13.2. Measurement approach

- Reflective Constructs: Hanafiah (2020) states that reflective constructs use a reflective measurement approach, where the indicators are assumed to be interchangeable and provide consistent information about the construct. The observed variables are considered to be reflective of the underlying construct, and the construct is estimated based on the covariance structure of the indicators.

- Formative Constructs: Formative constructs use a formative measurement approach, where the indicators are seen as distinct and providing unique information about the construct. The observed variables are considered to form the construct, and the construct is estimated based on the relationships between the indicators and the construct (Hanafiah, 2020).

3.13.3. Indicator reliability

- Reflective Constructs: In reflective measurement, the focus is on the reliability of the indicators, as they are expected to measure the same underlying construct (Hanafiah, 2020). The reliability of the indicators is assessed using measures such as Cronbach's alpha or composite reliability.

- Formative Constructs: For formative measurement, the focus is on the validity of the indicators rather than their reliability (Hanafiah, 2020). The indicators should be reliable in terms of measuring the construct, but their intercorrelation is not necessary. The emphasis is on the uniqueness and contribution of each indicator to the construct.

3.13.4. Model assessment

- Reflective Constructs: Reflective models are typically evaluated using measures of model fit, such as the goodness-of-fit index (GoF) or the average variance extracted (AVE) (Hair et al., 2021). These measures assess the overall fit of the model and the amount of shared variance between the construct and its indicators.

- Formative Constructs: Formative models are evaluated based on the significance and relevance of the relationships between the indicators and the construct (Hair et al., 2021). The focus is on the predictive power of the construct rather than the model fit measures used in reflective measurement.

In this study, the assumption is that all the constructs are reflective and therefore, all the indicators (variables) for each construct are reflective. Therefore, a measurement model with reflective measurements, which include the cronbach's alpha, composite reliability, Average Variance Extracted, the heterotrait-monotrait ratio (HTMT) and the Variance inflation factor (VIF).

Table 3. 2. Measurement model assessment

Quality Criteria	**Criteria**	**Description**	**References**
Indicator Reliability	Cronbach's alpha >= 0.7	Cronbach’s alpha is a measure of internal consistency reliability.	(Purwanto, 2021)
Indicator Reliability	Composite Reliability rho_a >= 0.7	Measure of internal consistency reliability.	(Henseler et al., 2015)
Indicator Reliability	Composite Reliability rho_c >= 0.7	Measure of internal consistency reliability.	(Henseler et al., 2015)
Model Assessment	Average Variance Extracted (AVE) >= 0.5	The degree to which individual items reflecting a construct converge in comparison to items measuring different constructs. AVE assesses convergent validity	(Purwanto, 2021)

Discriminant Validity	Heterotrait-monotrait ratio (HTMT) <= 0.85	In information systems research, it is argued that discriminant validity should be assessed by the Heterotrait-Monotrait Ratio (HTMT).	(Henseler et al., 2015)
Collinearity	Variance Inflation Factor (VIF) <= 3	VIF is used to evaluate the formative collinearity of indicators.	(Purwanto, 2021)

To answer the first research question, this study established if there are significant positive relationships between smartwatch features and patient-centered healthcare. In the case where there are positive relationships between the independent and dependent constructs, the hypotheses pertaining to the research question were then supported. This analysis was done by examining the direction of the path coefficient (i.e. whether it is positive or negative) and the p values. To answer the second research question, a PLS-SEM model was derived from the relationship between the dependent and independent variables. Path coefficient values were analysed to indicate the effect sizes of the relationships. Research question three was analysed through an evaluation of the results obtained from research questions one and two in addition to determining the PLS-SEM coefficient of determination (R^2) and the model fit (through Standardized Root Mean Square Residual (SRMR)).

3.14. Limitations and challenges of the study

The planned sample size was 200 participants, however, only 181 participants managed to respond to the questionnaire due to certain limitations/challenges. The following were the challenges encountered:

- Low response rate because participants were busy, however, reminders were sent out to avoid this.

- The unwillingness of the potential respondents to participate.

3.15. Ethical clearance considerations

The researcher applied for and received ethical clearance from the university and permission to contact runners from Fat Cats Athletics Club (See ethical clearance in Appendix D and permission letter from the running club in Appendix C). The ethical clearance form ensured that data collection only began after clearance was received. The form confirmed that all the ethics related information was correct and maintained the ethical standards. This research had minimal risk as there were no sensitive questions asked and the questions were based on people's everyday lives/activities and opinions. The form provided high level description of research data including the instrument that was used to collect the data.

The participants (runners) received an online consent form that they had to accept prior to participating in this study. The consent form also mentioned that their participation is voluntary and all the information they provided would remain confidential and they could withdraw at any time. And also, that data/results of this study will only be used for this research purpose. The participants were also informed that all the data collected is stored in a password-protected file and the researcher is the only person who can access the data.

3.16. Chapter Summary

This chapter used the research onion to describe the research methods, approaches, and designs adopted in this study to address the research questions. A quantitative research design was followed and the research strategy used was a survey. A questionnaire was the research instrument used for this study. The chapter also provided the rationale of the research methodology choices. This chapter also highlighted the data collection, research instrument design, the data analysis process and the ethical considerations pertatining to this study.

CHAPTER 4. FINDINGS

4.1. Introduction

This chapter presents the findings of this study. Firstly, this chapter discusses the general charecteristics of the collected data. Then the chapter presents the descriptive analysis of the participants' demographics. Moreover, the chapter presents the findings of the study based on the partial least squares structural equation modelling (PLS-SEM) statistical analysis in relation to this study's guiding research questions.

4.2. Descriptive analysis

4.2.1. General characteristics of the data

Table 4.1 was generated from SmartPLS 4 to confirm that there were no missing values and to get a sense of the general characteristics of the data. The first column in the table shows the variables that belong to the same constructs (A6 to A16). If two variables share the same first two values, then they belong to the same construct. For example, variables A6_1 to A6_4 fall under the same construct, that is, "activity tracking". As depicted in column 2, the first four variables had various data types as they captured various demographics of the participants. On the other hand, variables pertaining to independent constructs (A6 to A8) and the dependent constructs (A9 to A16) were on "Ordinal" scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) as depicted in the "scale min" and "scale max" columns. The table also indicates that there were no missing values (column 3) meaning that the data cleaning process outlined in section 3.10.1 was applied succesfully. The table reports on the mean (the average value within a set of options in a single variable), median (the most frequently chosen option within a set of options in a single variable). The skewness coeffcient presented in column 10 depicts the extent to which a variable’s distribution is symmetrical. Regarding the skewness of the data, Hair et al. 2022 (p. 66) indicated that an excellent value for skewness is between -1 and +1. Values which fall beyond the range of -2 and +2 generarlly despicts that the data is not normally distributed. In the context of this study, one may conclude that the data is normally distributed as all the skewness values fall within the acceptable range of between -2 and +2.

Table 4. 1. General characteristics of the data

Variables	**Type of data**	**Missing values**	**Mean**	**Median**	**Scale min**	**Scale max**	**Skewness**
A1	MET	0	2.674	3.000	1.000	5.000	0.11
A2	CAT	0	1.532	2.000	1.000	4.000	0.988
A3	CAT	0	3.894	3.000	1.000	7.000	0.738
A4	0|1	0	1.000	1.000	1.000	2.000	NaN
A5	ORD	0	3.411	4.000	1.000	4.000	-0.766
A6_1	ORD	0	4.064	4.000	1.000	5.000	-1.226
A6_2	ORD	0	3.957	4.000	1.000	5.000	-0.957
A6_3	ORD	0	4.383	5.000	1.000	5.000	-1.940
A6_4	ORD	0	3.270	3.000	1.000	5.000	-0.040
A7_1	ORD	0	3.404	4.000	1.000	5.000	-0.325
A7_2	ORD	0	2.865	3.000	1.000	5.000	0.153
A7_3	ORD	0	3.858	4.000	1.000	5.000	-0.834
A7_4	ORD	0	4.191	4.000	1.000	5.000	-1.312
A7_5	ORD	0	2.319	2.000	1.000	5.000	0.595
A7_6	ORD	0	2.348	2.000	1.000	5.000	0.806
A7_7	ORD	0	2.404	2.000	1.000	5.000	0.738
A8_1	ORD	0	3.532	4.000	1.000	5.000	-0.488
A8_2	ORD	0	3.596	4.000	1.000	5.000	-0.430
A8_3	ORD	0	2.667	2.000	1.000	5.000	0.290
A8_4	ORD	0	2.688	2.000	1.000	5.000	0.270
A8_5	ORD	0	2.823	3.000	1.000	5.000	0.079
A8_6	ORD	0	2.865	3.000	1.000	5.000	0.094
A9_1	ORD	0	3.560	4.000	1.000	5.000	-0.574
A9_2	ORD	0	3.426	4.000	1.000	5.000	-0.431
A9_3	ORD	0	3.021	3.000	1.000	5.000	-0.131
A10_1	ORD	0	3.248	3.000	1.000	5.000	-0.273
A10_2	ORD	0	3.234	3.000	1.000	5.000	-0.413

A10_3	ORD	0	3.191	3.000	1.000	5.000	-0.228
A11_1	ORD	0	3.972	4.000	1.000	5.000	-1.244
A11_2	ORD	0	3.794	4.000	1.000	5.000	-1.034
A12_1	ORD	0	3.851	4.000	1.000	5.000	-1.182
A12_2	ORD	0	3.603	4.000	1.000	5.000	-0.678
A12_3	ORD	0	3.660	4.000	1.000	5.000	-0.640
A13_1	ORD	0	3.887	4.000	1.000	5.000	-0.576
A13_2	ORD	0	3.858	4.000	1.000	5.000	-0.774
A13_3	ORD	0	3.872	4.000	1.000	5.000	-0.746
A14_1	ORD	0	4.163	4.000	1.000	5.000	-1.087
A14_2	ORD	0	4.199	4.000	1.000	5.000	-1.148
A14_3	ORD	0	3.986	4.000	1.000	5.000	-0.816
A15_1	ORD	0	4.191	4.000	1.000	5.000	-0.957
A15_2	ORD	0	3.993	4.000	1.000	5.000	-1.090
A15_3	ORD	0	3.603	4.000	1.000	5.000	-0.443
A15_4	ORD	0	4.099	4.000	1.000	5.000	-1.026
A16_1	ORD	0	3.624	4.000	1.000	5.000	-0.575
A16_2	ORD	0	3.667	4.000	1.000	5.000	-0.624

4.2.2. Demographics of the participants

This section analyses the demographics of the participants. This includes the age, gender, level of education of the participants, and their frequency of using smartwatches.

Table 4.2 depicts that 48.9% (N=69) of the participants were between the ages of 36 and 45 followed by 34.0% (N=48) of the respondents who were between 26 and 35 years (N=48), then 9.9% who were between 46 and 54 years (N=14), and 5.7% who were bewteen the age of 18 and 25 years (N=8). Only 2 respondents (1.4%) were 55 years of age or above.

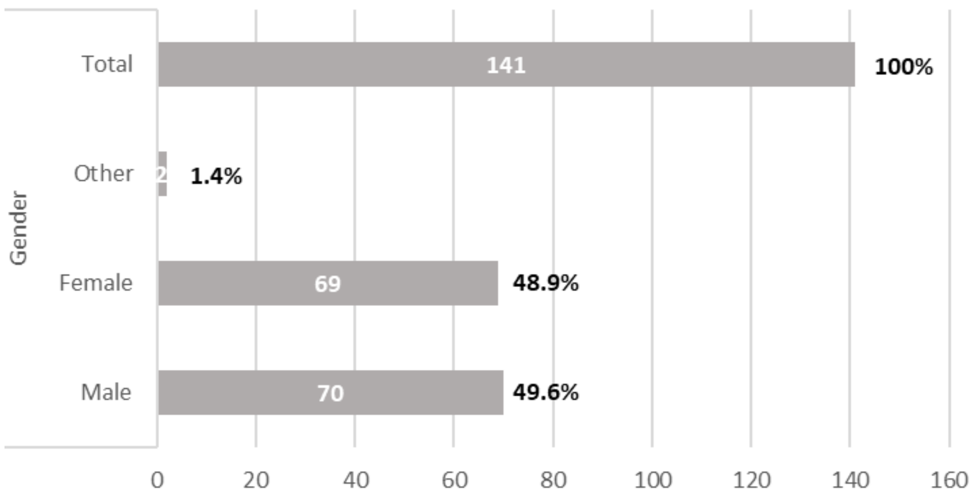
Table 4. 2. Demographics: Age Group

Which age group do you belong to?					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Age Group	**18 - 25 Years**	8	5.7	5.7	5.7
	26 - 35 Years	48	34.0	34.0	39.7

	36 – 45 Years	69	48.9	48.9	88.7
	46 - 54 Years	14	9.9	9.9	98.6
	55 Years and Above	2	1.4	1.4	100.0
	Total	141	100.0	100.0	

Figure 4.2 below illustrates that male participants accounted for 49.6% (N=70) of the participants while female participants accounted for 48.9% (N= 69) of the participants. Only 2 participants specified their gender as other. This means that both genders (“male” or “female”) were almost equally represented.

Figure 4. 2. Demographics: Gender



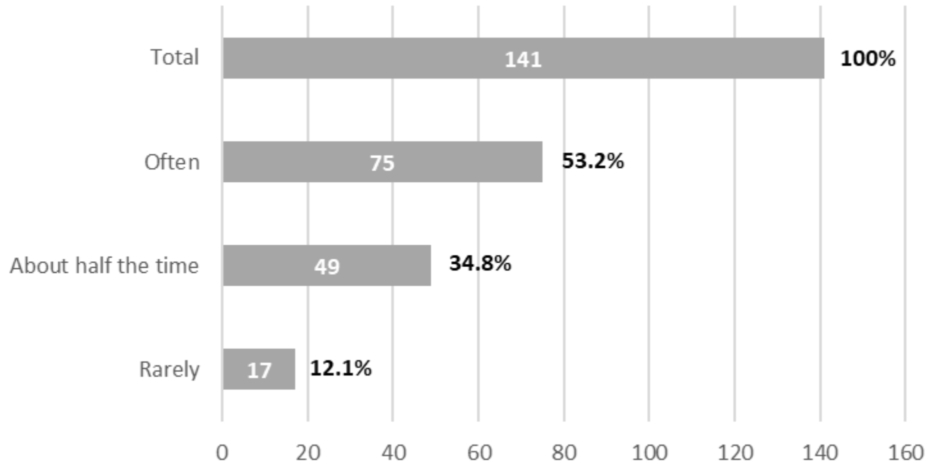
The participants had various qualifications. Table 4.4 below depicts that 36.2% (N=51) of participants had a Bachelor’s degree or equivalent. Honours degree or equivalent was the second highest qualification which 24.1% of the participants held (N=34). Participants who held a High School Diploma or equivalent accounted for 19.9% of the participants (N=28). Twenty-two participants (15.6%) held a Master’s degree or equivalent. Only 2.8% (N=4) participants had less than a high school diploma and the remaining 1.4% (N=2) held a Doctorate or equivalent.

Table 4. 3. Demographics: Highest formal level of education

What is your highest formal level of education?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	**Less than a high school diploma**	4	2.8	2.8	2.8
	High School Diploma or equivalent	28	19.9	19.9	22.7
	Bachelor's degree or equivalent	51	36.2	36.2	58.9
	Master's degree or equivalent	22	15.6	15.6	74.5
	Doctorate or equivalent	2	1.4	1.4	75.9
	Honours degree or equivalent	34	24.1	24.1	100.0
	Total	141	100.0	100.0	

Table 4.3 depicts that 53.2% (N=75) of the participants use smartwatches often. Only 34.8% (N=49) of the participants use smartwatches about half of the time. Only 12.1% (N=17) of the participants rarely use smartwatches. This is not suprising as the participants were athletes and hence are more likely to use smartwatches often.

Figure 4. 3. Demographics: Frequency of Use



The gender of the particpants was crosstabulated with the age group to determine the prevailing age category for each gender. Table 4.6 shows that 51% (N=35) of females and 47% (N=33) males were between the ages of 36 and 45 years. Only 3% (N=2) of males were 55 years and above and, there were no females who were 55 years and above. These results indicate that most participants (either female or male) were between 36 and 45 years old, followed by the age range of between 26 and 35. There were very few participants above 55 years in both genders combined.

Table 4. 4. Cross tabulation between age group and gender

Crosstabulation between age group and gender					
		What is your gender?			**Total**
		Male	**Female**	**Other**	
Which age group do you belong to?	**18 - 25 Years**	3	5	0	8
	26 - 35 Years	25	22	1	48
	36 – 45 Years	33	35	1	69
	46 - 54 Years	7	7	0	14
	55 Years and Above	2	0	0	2
Total		70	69	2	141

In addtion, as shown in Table 4.7, there are more females (64%, N=44) who use smartwatches often compared to males (41%, N=29). On the other hand, 41% of males (N=30) use smartwatches about half of the time. Only 16% (N=11) of males and 9% (N=6) of female respondents rarerly use their smartwatch. But it is important to note that this may vary depending on the specific demographic being studied, and that individual usage patterns can vary widely. Bärebring et al. (2020) stated that women are more health conscious (regarding their body shape and diet) and have more interest in health related matters. Therefore, this might be the reason why the finidngs suggest that more women use smartwatches perhaps to track their health related activities compared to men. However, more research is needed to make definitive conclusions on this matter.

Table 4. 5. Cross tabulation between gender and frequency

Crosstabulation between gender and frequency of use					
		What is your gender?			Total
		Male	Female	Other	
How often do you use your smartwatch?	Rarely	11	6	0	17
	About half the time	30	19	0	49
	Often	29	44	2	75
Total		70	69	2	141

4.3. Construct reliability and validity

Hair et al. (2021) state that construct validity assessment includes measuring convergent validity and discriminant validity. These assessments indicate whether constructs should be added in the subsequent PLS-SEM analysis or not.

4.3.1. Convergent validity

Convergent validity measures the cross-correlation between variables of the same structure, that is, of the same construct. The moderate or high correlation is evidence of convergent validity (Chin & Yao, 2014). PLS-SEM uses various measures to assess the convergent validity . These are Cronbach's alpha coefficient, Composite Reliability (CR), and Average Variance Extracted (AVE).

4.3.2. Cronbach's alpha

Cronbach's alpha is a coefficient that determines how well variables in a construct are correlated with each other (Johnson, 2013). A Cronbach alpha score of 0.70 or higher indicates good internal reliability/consistency of the variables within the same construct (Nunnally, 1978).

4.3.3. Composite reliability (CR)

Hamid et al. (2017) stated that the composite reliability (CR) calculates the internal consistency of the scaled terms. Composite reliability is a measure of common variance among variables used as a measure of latent construct (Fornell & Larker, 1981). Cronbach's alpha indicators are not assumed to be equally reliable. Acceptable variables require a convergent validity test and require a composite reliability score of 0.60 or higher (Nunnally and Bernstein, 1994).

4.3.4. Average Variance Extracted (AVE)

AVE calculates the variance of each construct (Gefen et al., 2000). It expresses the sum of the variances for each construct as a ratio and indicates whether the variance within a construct was actually caused by variations in the construct or by measurement error. An acceptable model should have an AVE value that is greater than 0.50 (Malhotra, 2010). If AVE is less than 0.50, variations in constructs may be primarily due to errors.

4.3.5. Results from construct reliability and validity tests

Construct reliability and validity were established for all constructs (Cronbach's alpha>=0.7, composite reliability (rho_a and rho_c)>=0.7, AVE>0.5) except for activity tracking and vital signs monitoring where AVE is 0.473 and 0.431 respectively. However, Fornell Larcker (1981) indicated that if AVE is less than 0.5, but composite reliability is higher than 0.6, the convergent validity of the construct can be adequate. Therefore activity tracking vital signs monitoring constructs of smartwatch features were not removed from the study.

Table 4. 6. Construct reliability and validity for all the constructs

	Cronbach's alpha	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
A6_Activity tracking	**0.630**	**0.622**	0.782	**0.473**
A7_Vital signs monitoring	0.774	0.778	0.838	**0.431**
A8_Data Management	0.873	0.890	0.904	0.612
A9_Access to care	0.846	0.880	0.907	0.767
A10_Continuity	0.884	0.905	0.928	0.810
A11_Involvement of family and friends	0.773	0.789	0.897	0.814
A12_Information and education	0.865	0.909	0.916	0.784
A13_Respect for patients' preferences	0.934	0.939	0.958	0.883
A14_Physical comfort	0.839	1.098	0.892	0.735

A15_Emotional comfort	0.880	0.939	0.914	0.727
A16_Coordination and integration of care	0.749	0.750	0.889	0.799

4.3.6. Collinearity between latent variables

The variance inflation factor (VIF) calculates the strength of the association between the independent variables. This association is also called multicollinearity, which can cause issues for regression models. Although multicollinearity does not reduce the explanatory power of the model, it does reduce the statistical significance of the independent variables, so detection of multicollinearity is essential.

According to Young (2018), a general rule of thumb is:

- Variables are not correlated if the VIF value equals to 1.
- Variables are moderately correlated if the VIF value is between 1 and 5.
- There is a high correlation if the VIF value is greater than 5.

There is significant multicollinearity if the VIF value is greater than 10 therefore it needs to be corrected (Kim, 2019)

As depicted in Table 4.9 below, none of the latent variables has a VIF greater than 5. This means that there is no collinearity issue which may significantly influence the results of PLS model.

Table 4. 7. Collinearity between latent (independent) variables

Variables	**VIF**
A6_1	**1.143**
A6_2	**1.456**

A6_3	1.273
A6_4	1.191
A7_1	1.362
A7_2	1.715
A7_3	1.362
A7_4	1.500
A7_5	2.136
A7_6	3.661
A7_7	3.623
A8_1	2.230
A8_2	1.892
A8_3	4.388
A8_4	4.580
A8_5	2.466
A8_6	2.259
A9_1	3.055
A9_2	3.474
A9_3	1.571
A10_1	2.230
A10_2	2.926
A10_3	2.595
A11_1	1.659
A11_2	1.659

A12_1	**2.159**
A12_2	**2.141**
A12_3	**2.488**
A13_1	**4.265**
A13_2	**4.597**
A13_3	**3.381**
A14_1	**1.873**
A14_2	**2.366**
A14_3	**1.918**
A15_1	**2.983**
A15_2	**2.302**
A15_3	**1.885**
A15_4	**3.162**
A16_1	**1.560**
A16_2	**1.560**

4.3.7. Discriminant validity

Hamid et al. (2017) state that discriminant validity measures the extent to which the constructs differ empiricaly from one another. Hamid et al. (2017) state that discriminant validity can be measured using Fornell-Lacker criterion, Heterotrait-monotrait (HTMT) ratio of correlation and cross-loading of indicator. HTMT can achieve higher specificity and sensitivity rates compared to the cross-loading criterion and his Fornell-Lacker criterion. Henseler et al. (2015) also recommend HTMT to assess discriminant validity, hence this study used HTMT to measure discriminant validity. Gold et al. (2001) state that the value should be less than

0.90 while Henseler et al. (2015) state that the value should be less than 0.85. For discriminant validity to be established between two reflective constructs, the HTMT value should be less than 0.90 (Hair et al., 2021).

Table 4.10 indicates that the HTMT for every construct related used in this study is less than 0.90. Thus, the discriminant validity was established for all the constructs.

Table 4. 8. Discriminant validity - Heterotrait-monotrait ratio (HTMT)

	A10_Continuity	A11_Involvement of family and friends	A12_Information and education	A13_Respect for patients preferences	A14_Physical comfort	A15_Emotional comfort	A16_Coordination and integration of care	A6_Activity tracking	A9_Access to care
A11_Involvement of family and friends	0.207								
A12_Information and education	0.485	0.509							
A13_Respect for patients preferences	0.300	0.332	0.677						
A14_Physical comfort	0.310	0.253	0.541	0.671					
A15_Emotional comfort	0.213	0.324	0.478	0.626	0.866				
A16_Coordination and integration of care	0.182	0.431	0.540	0.646	0.531	0.795			
A6_Activity tracking	0.297	0.244	0.296	0.294	0.377	0.420	0.509		
A9_Access to care	0.752	0.279	0.452	0.263	0.398	0.368	0.285	0.161	
A11_Involvement of family and friends	0.207								
A12_Information and education	0.485	0.509							
A13_Respect for patients preferences	0.300	0.332	0.677						
A14_Physical comfort	0.310	0.253	0.541	0.671					
A15_Emotional comfort	0.213	0.324	0.478	0.626	0.866				

A16_Coordination and integration of care	0.182	0.431	0.540	0.646	0.531	0.795			
A7_Vital signs monitoring	0.417	0.245	0.315	0.282	0.299	0.289	0.316		
A9_Access to care	0.752	0.279	0.452	0.263	0.398	0.368	0.285	0.251	
A11_Involvement of family and friends	0.207								
A12_Information and education	0.485	0.509							
A13_Respect for patients preferences	0.300	0.332	0.677						
A14_Physical comfort	0.310	0.253	0.541	0.671					
A15_Emotional comfort	0.213	0.324	0.478	0.626	0.866				
A16_Coordination and integration of care	0.182	0.431	0.540	0.646	0.531	0.795			
A8_Data Management	0.277	0.313	0.321	0.318	0.149	0.211	0.393		
A9_Access to care	0.752	0.279	0.452	0.263	0.398	0.368	0.285	0.159	

4.4. Assessing the relationships between the independent variables and dependent variables

Bootstrapping was run in SmartPLS 4 to establish path coefficients and the significance of the relationship between the independent variable (activity tracking) and the 8 principles of patient-centered healthcare (dependent variables). The bootstrapping method was run using the parameters depicted in Figure 4.1 below. These same parameters were applied when running bootstrapping to test the relationship between vital signs monitoring and data management features of a smartwatch and patient-centered healthcare.

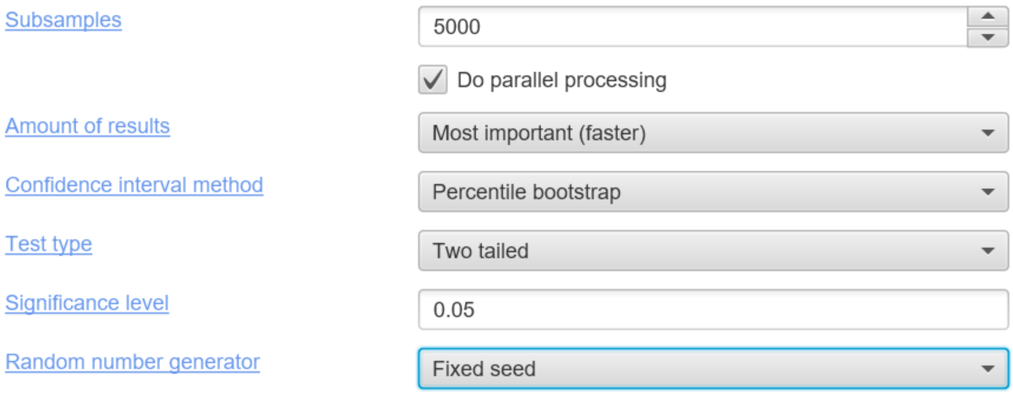


Figure 4. 1. Bootstrapping Configuration

The results depicted in Table 4.11 below show that there is a significant positive relationship (**$p<0.05$**) between activity tracking feature of a smartwatch and all the 8 principles of patient-centered healthcare except the *involvement of family and friends* (**$p=0.075$**) and *access to care* (**$p=0.374$**). Table 4.11 further depicts that the relationship between activity tracking, and *coordination and integration of care* has the highest path coefficient ($\beta=0.351$) and hence the activity tracking of a smartwatch has the strongest effect on the *coordination and integration of care* principle of patient-centered healthcare followed by *emotional comfort* ($\beta=0.319$). Table 4.11 further depicts that the relationship between activity tracking and *continuity and transition* has the lowest path coefficient ($\beta=0.229$) and hence activity tracking has the least effect on the *continuity and transition* principle of patient-centered healthcare.

Table 4. 9. Path coefficients (β) and significance of the relationships between activity tracking feature of a smartwatch and patient-centered healthcare

Latent Variables	Path Coefficients (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
A6_Activity tracking -> A10_Continuity and Transition	**0.229**	0.239	0.083	2.764	**0.006**
A6_Activity tracking -> A11_Involvement of family and friends	**0.179**	**0.197**	**0.101**	**1.782**	**0.075**
A6_Activity tracking -> A12_Information and education	**0.241**	0.265	0.070	3.446	**0.001**
A6_Activity tracking -> A13_Respect for patients' preferences	**0.238**	0.251	0.079	3.017	**0.003**
A6_Activity tracking -> A14_Physical comfort	**0.280**	'0.297	0.085	3.287	**0.001**
A6_Activity tracking -> A15_Emotional comfort	**0.319**	0.338	0.077	4.123	**0.000**
A6_Activity tracking -> A16_Coordination and integration of care	**0.351**	0.363	0.071	4.957	**0.000**
A6_Activity tracking -> A9_Access to care	**0.105**	**0.110**	**0.118**	**0.890**	**0.374**

The results depicted in Table 4.12 below indicate that there is a significant positive relationship (**$p<0.05$**) between vital signs monitoring feature of a smartwatch and all the 8 principles of patient-centered healthcare except the *involvement of family and friends* (**$p=0.063$**), *physical comfort* (**$p=0.0195$**) and *emotional comfort* (**$p=0.067$**). Table 4.12 further depicts that the relationship between vital signs monitoring and *continuity and transition* has the highest path coefficient (β=0.369) and hence the vital signs monitoring of a smartwatch has the strongest effect on *the continuity and transition* principle of patient-centered healthcare followed by *information and education* (β=0.293). Table 4.12 further depicts that the relationship between vital signs monitoring and *access to care* has the lowest path coefficient (β=0.223), hence vital signs monitoring has the least effect on the "*access to care*" principle of patient-centered healthcare.

Table 4. 10. Path coefficients (β) and significance of the relationships between vital signs monitoring feature of a smartwatch and patient-centered healthcare

Latent Variables	**Path Coefficients (β)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
A7_Vital signs monitoring -> A10_Continuity and Transition	**0.369**	0.381	0.082	4.483	0.000
A7_Vital signs monitoring -> A11_Involvement of family and friends	**0.198**	0.212	0.106	1.859	**0.063**
A7_Vital signs monitoring -> A12_Information and education	**0.293**	0.318	0.072	4.055	0.000
A7_Vital signs monitoring -> A13_Respect for patients' preferences	**0.242**	0.254	0.094	2.587	0.010
A7_Vital signs monitoring -> A14_Physical comfort	**0.190**	**0.208**	**0.147**	**1.297**	**0.195**
A7_Vital signs monitoring -> A15_Emotional comfort	**0.222**	**0.253**	**0.121**	**1.832**	**0.067**
A7_Vital signs monitoring -> A16_Coordination and integration of care	**0.246**	0.251	0.099	2.484	0.013
A7_Vital signs monitoring -> A9_Access to care	**0.223**	0.237	0.099	2.252	0.024

The results depicted in Table 4.13 below show that there is a significant positive relationship (**p<0.05**) between the data management feature of a smartwatch and all the 8 principles of patient-centered healthcare except the *physical comfort* (**p=0.0199**) and *access to care* (**p=0.162**). Table 4.13 further depicts that the relationship between data management and *coordination and integration of care* has the highest path coefficient (β=0.327), hence the data management feature of a smartwatch has the strongest effect on the *coordination and integration of care* principle of patient-centered healthcare followed by *information and education* (β=0.295). Table 4.13 further depicts that the relationship between data management and *emotional support* has the lowest path coefficient (β=0.205), hence data management has the least effect on the *emotional support* principle of patient-centered healthcare.

Table 4. 11. Path coefficients (β) and significance of the relationships between data management feature of a smartwatch and patient-centered healthcare

Latent variables	**Path coefficient**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
A8_Data Management -> A10_Continuity	0.261	0.269	0.083	3.154	**0.002**
A8_Data Management -> A11_Involvement of family and friends	**0.275**	0.285	0.088	3.111	**0.002**
A8_Data Management -> A12_Information and education	**0.295**	0.312	0.070	4.199	**0.000**
A8_Data Management -> A13_Respect for patients' preferences	**0.290**	0.297	0.077	3.789	**0.000**
A8_Data Management -> A14_Physical comfort	**0.127**	**0.142**	**0.099**	**1.285**	**0.199**
A8_Data Management -> A15_Emotional comfort	**0.205**	0.223	0.085	2.424	**0.015**
A8_Data Management -> A16_Coordination and integration of care	**0.327**	0.334	0.075	4.354	**0.000**

A8_Data Management -> A9_Access to care	**0.144**	**0.159**	**0.103**	**1.399**	**0.162**

4.4.1. Coefficient of determination -R^2- (R Square)

According to Urbach and Ahlemann (2010), coefficient of determination (R2) measures the goodness of fit for linear regression models. It measures the extent to which the variations within a dependent variable are caused by the independent variable(s). The R^2 value needs to be between 0 and 1.

Figure 4.2 depicted below shows the final model that depicts the relationship between activity tracking and patient-centered healthcare. As depicted in Figure 4.2 below, the R^2 (shown within the blue circles) for the *coordination and integration of care* is the highest (0.123). The R^2 value means that activity tracking explains 12.3% of the variation within the *coordination and integration of care* construct. This is not surprising as “activity tracking” has the highest effect on *coordination and integration of care* construct with a **β=0.351.**

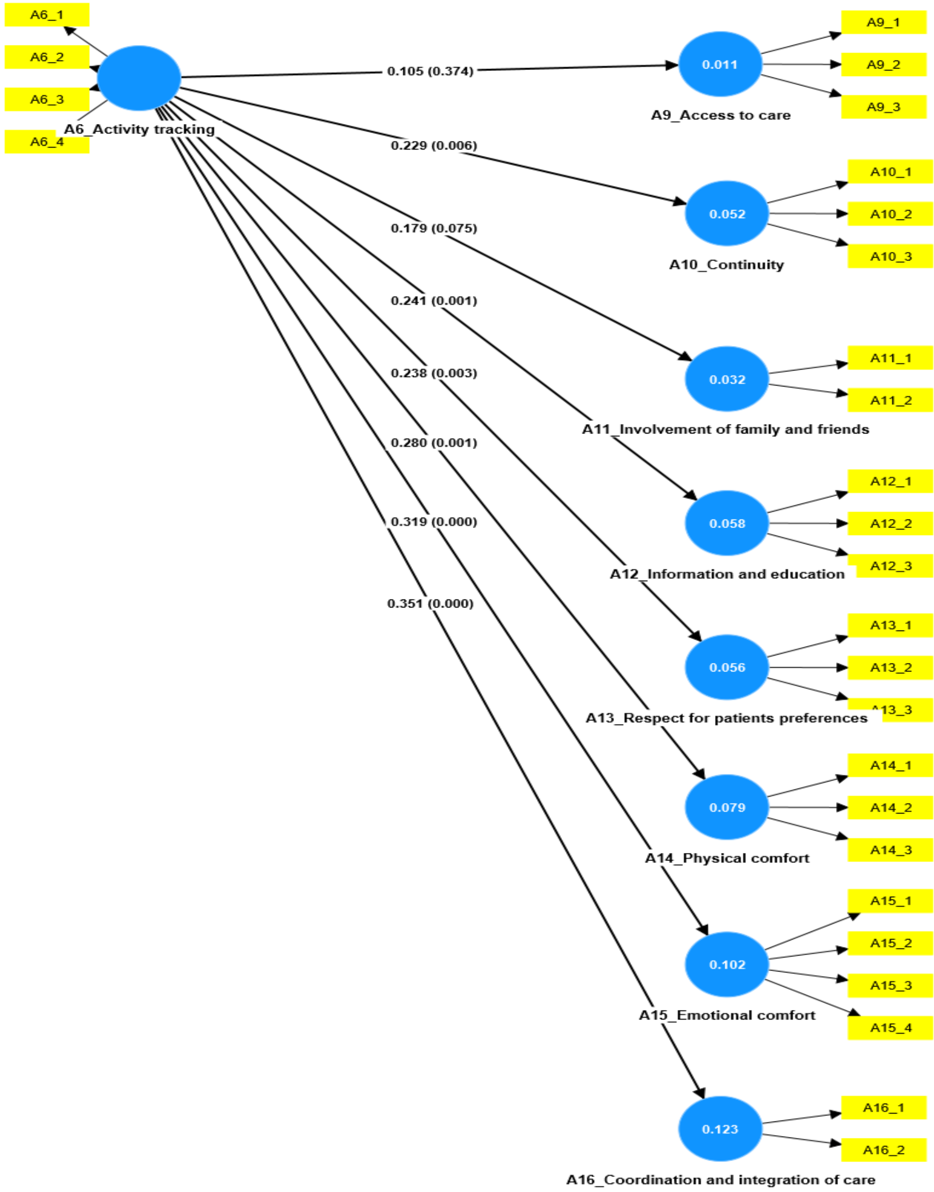


Figure 4. 2. Model depicting the relationship between the activity tracking feature of smartwatch with patient-centered care

Figure 4.3 depicted below shows the final model that depicts the relationship between vital signs monitoring and patient-centered healthcare. As depicted in Figure 4.3 below, the R^2 for the “Continuity” is the highest (0.136). The R^2 value means that vital signs monitoring explains 13.6% of the variation within the “continuity” construct. This is not surprising as “vital signs monitoring” has the highest effect on the “continuity” construct with a **β=0.369.**

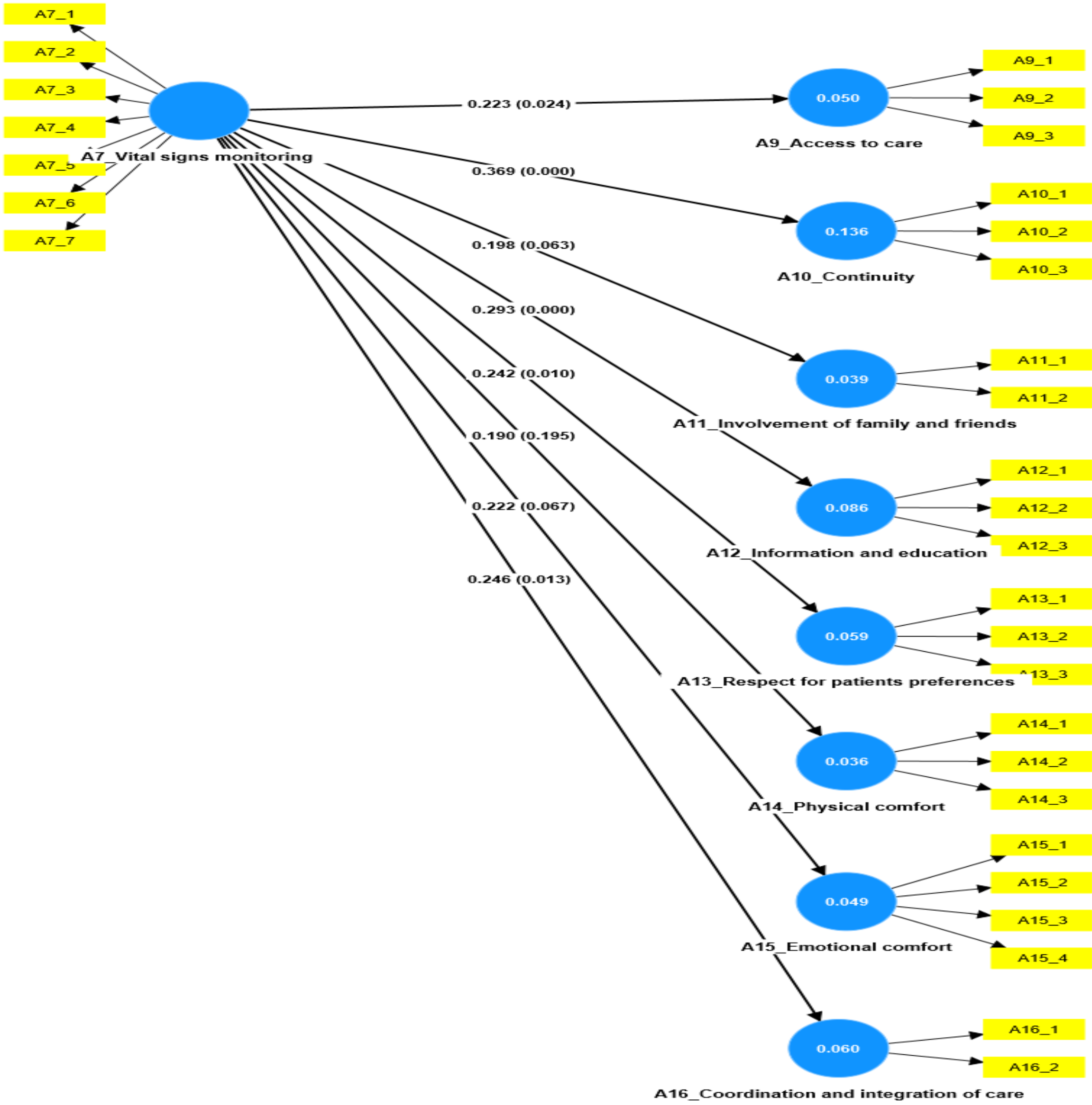


Figure 4. 3. Model depicting the relationship between the vital signs monitoring feature of smartwatch with patient-centered care

Figure 4.4 depicted below shows the final model that depicts the relationship between data management and patient-centered healthcare. The R^2 for the "Coordination and integration of care" is the highest (0.107). The R^2 value means that data management explains 10.7% of the variation within the "coordination and integration of care" construct. This is not surprising as "data management" has the highest effect on the "coordination and integration of care" construct with a **β=0.327.**

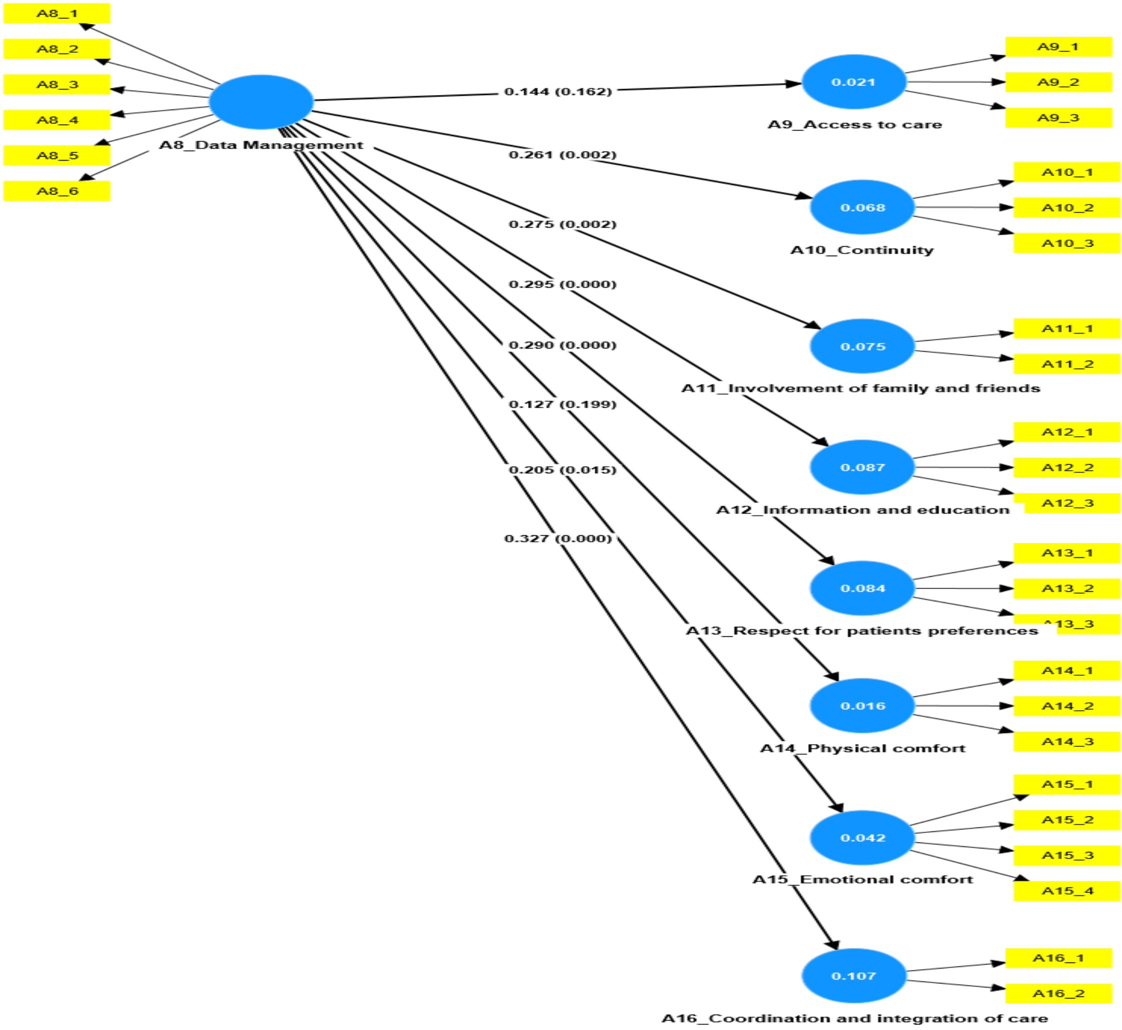


Figure 4. 4. Model depicting the relationship between the data management feature of smartwatch with patient-centered care

4.4.2. Model fit (SRMR)

Henseler et al. (2015) introduce the SRMR as a goodness of fit measure for PLS-SEM that can be used to avoid model misspecification. Model fit measures if the model will be fit for the data and be able to reproduce the necessary data. The model was analysed using Standardised Root Means Squared Residual (SRMR) and Normed Fix Index (NFI) using Smartpls V4. An acceptable SRMR value for a proposed model needs to be less than 0.10 (Ringle et al., 2022). Hu and Bentler (1999) also stated that an acceptable SRMR value needs to be less than 0.08. In addition, the NFI values are between 0 and 1. The closer the NFI to 1, the better the fit. NFI values greater than 0.9 typically represent an acceptable level of fit. (Ringle et al., 2022).

Table 4.14 below indicates the model fit for the relationship between the activity tracking feature of a smartwatch and patient-centered care. The SRMR value is 0.067 which is a good fit and therefore the proposed model is accepted.

Table 4. 12. Model Fit for Activity Tracking

	Saturated model	Estimated model
SRMR	0.067	0.241
d_ULS	1.722	21.926
d_G	0.956	1.732
Chi-square	801.350	1199.338
NFI	0.703	0.556

Table 4.15 indicates the model fit for the vital signs monitoring feature of a smartwatch and patient-centered care. The SRMR value is 0.088 which is a good fit therefore the proposed model is also accepted.

Table 4. 13. Model Fit for Vital Signs Monitoring

	Saturated model	Estimated model
SRMR	0.088	0.227
d_ULS	3.592	23.959
d_G	1.404	2.185
Chi-square	1098.440	1508.537
NFI	0.652	0.522

Table 4.16 indicates the model fit for the activity tracking feature of smartwatches. The SRMR value is 0.066 which is a good fit, therefore the proposed model is accepted.

Table 4. 14. Model Fit for Data Management

	Saturated model	Estimated model
SRMR	0.066	0.229
d_ULS	1.918	22.880

d_G	1.292	2.098
Chi-square	1017.764	1430.849
NFI	0.683	0.555

4.5. Chapter summary

This chapter presented the study's findings and the resulting PLS-SEM model that depicts the effect of smartwatches on patient-centered healthcare. Firstly, this chapter presented the general characteristics of the data followed by a description of the demographics of the participants. The chapter also presented the construct validity testing which included the convergent validity, cronbach's alpha, composite reliability, average variance extracted, discriminant validity.and the collinearity between latent variables The chapter further assessed the relationships between the independent variables and dependent variables followed by a description of the model fit The next chapter will discuss the findings in the light of the research questions.

CHAPTER 5. DISCUSSION OF FINDINGS

5.1. Introduction

This chapter discusses the findings depicted on the previous section. The chapter discusses the the findings in the light of the research questions that guide this study.

5.2. Discussion of findings

Research Question 1: What features of smartwatches contribute to patient-centered healthcare?

As indicated in Chapter 1, to answer this research question, the folowing hypotheses and sub-hypotheses were formulated:

- Hypothesis H1: Activity tracking feature of a smartwatch has a positive effect on pateint-centered healthcare
    - H1.1: Activity tracking feature of a smartwatch has a significant positive effect on continuity and transition.
    - H1.2: Activity tracking feature of a smartwatch has a significant positive effect on the involvement of family and friends.
    - H1.3: Activity tracking feature of a smartwatch has a significant positive effect on information and education.
    - H1.4: Activity tracking feature of a smartwatch has a significant positive effect on the respect for patients' preferences.
    - H1.5: Activity tracking feature of a smartwatch has a significant positive effect on physical comfort.
    - H1.6: Activity tracking feature of a smartwatch has a significant positive effect on emotional comfort.
    - H1.7: Activity tracking feature of a smartwatch has a significant positive effect on coordination and integration of care.

    - H1.8: Activity tracking feature of a smartwatch has a significant positive effect on access to care.
- Hypothesis H2: Vital signs monitoring feature of a smartwatch has a positive effect on patient-centered healthcare
    - H2.1: Vital signs monitoring feature of a smartwatch has a significant positive effect on continuity and transition.
    - H2.2: Vital signs monitoring feature of a smartwatch has a significant positive effect on the involvement of family and friends.
    - H2.3: Vital signs monitoring feature of a smartwatch has a significant positive effect on information and education.
    - H2.4: Vital signs monitoring feature of a smartwatch has a significant positive effect on the respect for patients' preferences.
    - H2.5: Vital signs monitoring feature of a smartwatch has a significant positive effect on physical comfort.
    - H2.6: Vital signs monitoring feature of a smartwatch has a significant positive effect on emotional comfort.
    - H2.7: Vital signs monitoring feature of a smartwatch has a significant positive effect on coordination and integration of care.
    - H2.8: Vital signs monitoring feature of a smartwatch has a significant positive effect on access to care.
- Hypothesis H3: Data management feature of a smartwatch has a positive effect on patient-centered healthcare
    - H3.1: Data management feature of a smartwatch has a significant positive effect on continuity and transition.
    - H3.2: Data management feature of a smartwatch has a significant positive effect on the involvement of family and friends.
    - H3.3: Data management feature of a smartwatch has a significant positive effect on information and education.
    - H3.4: Data management feature of a smartwatch has a significant positive effect on the respect for patients' preferences.

- H3.5: Data management feature of a smartwatch has a significant positive effect on physical comfort.
- H3.6: Data management feature of a smartwatch has a significant positive effect on emotional comfort.
- H3.7: Data management feature of a smartwatch has a significant positive effect on coordination and integration of care.
- H3.8: Data management feature of a smartwatch has a significant positive effect on access to care.

Table 5.1 below depicts that all hypotheses were supported except for H1.2 and H1.8 as the p values are greater than 0.05, that is beyond the threshold of $p<0.05$. As depicted in Table 5.1, it was established that activity tracking has a positive effect on continuity and transition ($p=0.006$), therefore H1.1 is supported. H1.3 and H1.5 are also supported as they have p values of 0.01. H1.4 is supported ($p=0.003$). Lastly H1.7 and H1.8 are also supported as they have p values of 0.000.

Hypothesis H1: Activity tracking feature of a smartwatch has a positive effect on pateint-centered healthcare

The activity tracking feature of a smartwatch or other wearable devices are widely used to ease the transition from clinics to outpatient care (Ferguson et al., 2022). This feature helps analyze whether the patient's condition has improved or not. This allows for tracking rehabilitation (workout reminders and other routine rehabilitation tasks) outside the ambulatory environment (Vijayan et al., 2021). In addition, activity tracking within smartwatches uses various sensors that collect data from the human body and present the data to the user to make informed decisions. Smartwatches can help chronically ill patients by providing sufficiently detailed data to monitor disease progression (Vijayan et al., 2021). Smartwatches also encourage people to be more physically active (Vijayan et al., 2021). Activity tracking supports spontaneous personal activity, which can lead to psychosocial improvements in depression and anxiety, and increase physical activity, which has antidepressant and anti-anxiety effects. This aspect helps people achieve emotional and physical well-being (Ferguson et al., 2022).

Table 5. 1. Hypotheses validation for research question 1

Sub-Hypothesis	Path Coefficients (β)	P values	Comments
H1.1 Activity tracking feature of a smartwatch has a significant positive effect on continuity and transition.	**0.229**	0.006	**Supported**
H1.2 Activity tracking feature of a smartwatch has a significant positive effect on the involvement of family and friends.	**0.179**	**0.075**	**Not supported**
H1.3 Activity tracking feature of a smartwatch has a significant positive effect on information and education.	**0.241**	**0.001**	**Supported**
H1.4 Activity tracking feature of a smartwatch has a significant positive effect on the respect for patients' preferences.	**0.238**	**0.003**	**Supported**
H1.5 Activity tracking feature of a smartwatch has a significant positive effect on physical comfort.	**0.280**	**0.001**	**Supported**
H1.6 Activity tracking feature of a smartwatch has a significant positive effect on emotional comfort.	**0.319**	**0.000**	**Supported**

H1.7 Activity tracking feature of a smartwatch has a significant positive effect on coordination and integration of care.	**0.351**	**0.000**	**Supported**
H1.8 Activity tracking feature of a smartwatch has a significant positive effect on access to care.	**0.105**	**0.374**	**Not supported**

Hypothesis H2: Vital signs monitoring feature of a smartwatch has a positive effect on patient-centered healthcare

Table 5.2 depicts that all hypotheses related to the effect vital signs monitoring feature of a smartwatch on patient-centered healthacre were supported except for H2.2, H2.5 and H2.6 as the p values are greater than 0.05. As depicted in Table 5.2, it was established that vital signs monitoring has a positive effect on continuity and transition (p=0.000), therefore H2.1 is supported. H2.3 (p=0.000), H2.4 (p=0.010), H2.7 (p=0.013) and H2.8 (p=0.024) are all supported as their p values are also less than 0.05.

Hypertension causes heart problems that may lead to death (World Health Organization, 2021). Monitoring blood pressure is pivotal to preventing hypertension. Smartwatches can be used to monitor blood pressure and presenting data from pulse reading in an understandable format (He et al., 2022). Therefore, blood pressure monitoring is a key smartwatch feature that enables a patient to have insights on this vital health sign and hence make informed decisions about their healthcare (He et al., 2022). Vital signs monitoring can encourage patients to be active participants in their healthcare. Vital signs monitoring can also assist with patients' transition and integration of care by remotely monitoring and virtually coaching patients to complete their rehabilitation activities outside the clinical centre (Vijayan et al., 2021).

Table 5. 2. Hypotheses validation for research question 2

Sub-Hypothesis	Path Coefficients (β)	P values	Comments
H2.1 Vital signs monitoring feature of a smartwatch has a significant positive effect on continuity and transition.	0.369	0.000	Supported
H2.2 Vital signs monitoring feature of a smartwatch has a significant positive effect on the involvement of family and friends.	0.198	0.063	Not Supported
H2.3 Vital signs monitoring feature of a smartwatch has a significant positive effect on information and education.	0.293	0.000	Supported
H2.4 Vital signs monitoring feature of a smartwatch has a significant positive effect on the respect for patients' preferences.	0.242	0.010	Supported
H2.5 Vital signs monitoring feature of a smartwatch has a significant positive effect on physical comfort.	0.190	0.195	Not Supported
H2.6 Vital signs monitoring feature of a smartwatch has a significant positive effect on emotional comfort.	0.222	0.067	Not Supported
H2.7 Vital signs monitoring feature of a smartwatch has a significant	0.246	0.013	Supported

positive effect on coordination and integration of care.			
H2.8 Vital signs monitoring feature of a smartwatch has a significant positive effect on access to care.	0.223	0.024	Supported

Hypothesis H3: Data management feature of a smartwatch has a positive effect on patient-centered healthcare

Table 5.3 depicts that all hypotheses were supported except for H3.5 and H3.8 as the p values are greater than 0.05. As depicted in Table 5.3, it was established that data management has a positive effect on continuity and transition (p=0.002), therefore H1.1 is supported. H3.2 (p=0.002), H3.3 (p=0.000), H3.4 (p=0.000), H3.6 (p=0.015) and H3.7 (p=0.020) are all supported as their p values are also less than 0.05. These findings and literature evidence below also indicate that there is a good correlation between activity tracking and patient centered healthcare.

Although smartwatch data storage is usually limited, the data emanating from a smartwatch is usually synchronized with a smartphone or a computer (Wang, 2017). This also enables the user to also easily view healthcare information at any time. According to Reeder and David (2016), data retrieved from smartwatches can be integrated with Internet of Things (IoT) and electronic health records (EHR) to provide a comprehensive view/reports of an individual's health conditions and patterns. The integration and secure storage of this data ensure efficient transition and coordination for patients who have already been discharged. Those patients can be monitored remotely by retrieving data that is stored in a central location and presenting it to the doctor. The doctor can also receive notifications if there are any issues with a patient’s health. Data and analytics that are stored in a central cloud repository can be viewed by friends and family and they can provide support to improve physical activities. All the data is managed according to the patient's preferences and the patient may decide to be an active participant to use the data in improving their health. Using data and analytics, meditation and depression management applications can be recommended to the patient based on their medical history.

Table 5. 3. Hypotheses validation for research question 3

Sub-Hypothesis	Path coefficient	P values	Comments
H3.1 Data management feature of a smartwatch has a significant positive effect on continuity and transition.	**0.261**	**0.002**	**Supported**
H3.2 Data management feature of a smartwatch has a significant positive effect on the involvement of family and friends.	**0.275**	**0.002**	**Supported**
H3.3 Data management feature of a smartwatch has a significant positive effect on information and education.	**0.295**	**0.000**	**Supported**
H3.4 Data management feature of a smartwatch has a significant positive effect on the respect for patients' preferences.	**0.290**	**0.000**	**Supported**
H3.5 Data management feature of a smartwatch has a significant positive effect on physical comfort.	**0.127**	**0.199**	**Not Supported**
H3.6 Data management feature of a smartwatch has a significant positive effect on emotional comfort.	**0.205**	**0.015**	**Supported**

H3.7 Data management feature of a smartwatch has a significant positive effect on coordination and integration of care.	**0.327**	**0.000**	**Supported**
H3.8 Data management feature of a smartwatch has a significant positive effect on access to care.	**0.144**	**0.162**	**Not Supported**

Research Question 2: To what extent do these features contribute to patient-centered healthcare?

This research question reports only on the hypotheses that were supported in research question 1. To answer this question, only hypotheses with a positive β and p values that are less than 0.05 were considered. This means that H1.2, H1.8, H2.2, H2.5, H2.6, H3.5 and H3.5 were excluded when answering this question. Path coefficient with values of 0.6 and above indicate large effect sizes whereas values between 0.3 and 0.5 are considered medium effect sizes and values below 0.2 are considered small effect sizes (Becker, 2000).

The first hypothesis (Activity tracking feature of a smartwatch has a positive effect on pateint-centered healthcare) has different effect sizes. H1.1, H1.3 and H1.4 have small effect sizes whereas H1.5 has a small effect size, however it is close to medium as its value is 0.280. H1.6 and H1.7 have medium effect sizes. The second hypothesis' (Vital signs monitoring feature of a smartwatch has a positive effect on pateint-centered healthcare) effect sizes range from small to medium. H2.1 has medium effect sizes whereas H2.3 has small effect sizes, however its closer to medium as the value is 0.293. H2.4, H2.7 and H2.8 have small effect sizes. The last hypothesis (Data management feature of a smartwatch has a positive effect on pateint-centered healthcare) also ranges from small to medium effect sizes. H3.1, H3.2, H3.3 and H3.4 have small effect sizes, however they are close to medium effect sizes. H3.6 has small effect size as it has a value of 0.205. Only H3.7 has a medium effect size with a value of 0.327.

All the hypotheses have values between 0.1 and 0.4. This means that the considered independent variables are considered to have small and medium effect on patient-centered healthcare. Smartwatch activity tracking increases daily steps with an average effect size of 0.6 which is considered to have a medium effect size (Ferguson et al., 2022).

Research Question 3: How can the contribution of smartwatches to patient-centered healthcare be theorized?

This section explains the contribution of smartwatch features to patient-centered healthcare based on the findings for research questions 1 and 2.

Activity Tracking

Activity tracking has a positive effect on continuity and transition, this could mean the activity tracking feature helps one to monitor their healthy/unhealthy behaviour which could then be shared with a physician for the sake of providing personalized healthcare. For example, logs from activity tracking could tell a physician whether the smartwatch user is adhering to preventive or curative healthy behaviour such as exercising. This will then inform the physician about the kind of personalized care to prescribe to the smartwatch user who in this case is the patient. The literature also attests that activity tracking feature of a smartwatch is effective in increasing physical activities and improving weight loss (Ferguson et al., 2022). Activity tracking also has positive effect on information and education. In this case, the information provided to the smartwatch user regarding their healthy/unhealthy behaviour should be reliable, high quality, understandable and helpful in making informed decisions about their health.

Activity tracking has a positive effect on respect for patient’s preferences which could mean that a smartwatch user can be directly involved in their healthcare such that they have a choice to improve their physical wellness by setting up and monitoring physical activities (such as walking or running routines).

Activity tracking has a positive effect on physical comfort which could mean that the users (especially the ones with physical needs) can track their physical activities from the comfort of their own home without having to go to the healthcare centre. For example, a user can complete rehabilitation tasks from the comfort of their home as the smartwatch will have activity tracking and recommendations.

Activity tracking has a positive effect on emotional comfort by recognising a user's emotional needs and providing recommendations. For example, a smartwatch user may use the activity tracking feature of smartphone to monitor and recommend sleeping patterns to reduce stress and improve mood and health. To cater for the user's emotional needs, activity tracking can also provide reminders for user to do some meditation using meditation apps.

According to the findings from the previous chapter, activity tracking has a positive effect on the involvement of friends and family. One can share one's smartwatch activity tracking stats with friends and family to keep one motivated and accountable. For example, Garmin has an app called Garmin Connect that allows friends, family and fellow athletes to share their fitness activities (Fitness Watches | Sport Watches | Smartwatches | Garmin, 2022). Smartwatch users can create groups or cheer each other on with likes and comments. When friends and family work together to compete and encourage each other, this would lead to improved physical activity and health. Another key feature within activity tracking is a fall detection that identifies when a user falls and calls the emergency contact in case it is a serious injury. According to Reeder and David (2016), activity tracking within smartwatches enables remote monitoring and can improve bi-directional communication between healthcare providers and smartwatch users. This will improve coordination and integration within healthcare.

Vital Signs Monitoring

Vital signs monitoring has a positive effect to access to care which could mean that patients can monitor vital signs such as heart rate, skin temperature, oxygen levels or blood pressure. Should the vital signs be at an abnormal rate, the patient can then schedule an appointment with the relevant healthcare professional. Vital signs monitoring has a positive effect on continuity and transition as the patients can gain access to healthcare information post getting discharged. The patient can view information on how to maintain good heart rate level or reduce blood pressure from their smartwatch. A notification can also be sent to the doctor if a patient's heart rate is at an alarming rate. According to Reeder and David (2016), smartwatches can provide continuous vital signs monitoring, provide recommendations based on activity measures and identify patterns of behaviour.

Vital signs monitoring has a positive effect on access to information and education. Smartwatches can provide easily understood information/tips on how to maintain good health (includes dietary plans) and what lifestyle options can improve vital signs such as blood pressure and heart rate. Vital signs monitoring has a positive effect on respect for patient's preferences. Smartwatches provide recommendations based on current vital signs stats. Those recommendations are to improve a patient's health conditions; therefore, the patient is involved in their own decision making in improving health. This includes using those recommendations to become more physically active, eating healthy food and improving their lifestyle.

Vital signs monitoring has a positive effect on coordination and integration to care which could mean that smartwatch readings for vital signs can be monitored in real-time so that a doctor is alerted when they reach an alarming level. The doctor can do remote monitoring by quickly analyzing the data.

Data Management

Data management feature of a smartwatch has a positive effect on continuity and transition which could mean that a patient can gain access to information anytime and anywhere from the smartwatch. Smartwatch healthcare data/information can be synced to a smart phone and stored on the cloud for easy access. Data management is the key as it enables smartwatch users to view detailed healthcare statistics. Such data can also integrate to other systems or third-party vendors for multi purposes, for example, Discovery Vitality can access smartwatch information and reward smartwatch users for being physically active and living a healthy lifestyle (Discovery Vitality, 2023.). Data management has a positive effect on the involvement of family and friends which could mean that smartwatch users can share physical data statistics with family and friends, and they can even compete on who has been more physically active during a particular period. Sharing of this information is easier and available immediately as it is stored in the cloud.

Effective management of data has a significant impact on improving information and education in healthcare. Nowadays, there is an enormous amount of healthcare data stored across multiple databases, including cloud-based systems. This data is then presented to users of smartwatches in a format that is easy to comprehend and interpret. The information displayed on smartwatches can include valuable recommendations for medications, lifestyle choices, and even updates on virus outbreaks. To make this possible, data from smartwatches seamlessly integrates with smartphone apps, allowing for the transmission of data for analysis and display (Deloitte, 2021)

When it comes to respecting patient's preferences, data management plays a crucial role. By collecting and securely storing patient preference data, smartwatches can provide personalized information and guidance based on individual goals. This empowers patients to actively participate in their own healthcare journey and make progress towards achieving their specific health objectives. Furthermore, data management also contributes to emotional support. Smartwatches can leverage stored data and advanced analytics to offer tailored plans and activities that help individuals manage stress, anxiety, and depression.

Data management also facilitates better coordination and integration of care. With comprehensive patients’ history securely stored, healthcare professionals can analyse health data to provide more targeted and suitable treatments that align with patients' specific needs and preferences. Additionally, the integration of smartwatch data with smartphone apps allows doctors to access vital patient’s health records for accurate diagnosis and continuous monitoring.

Smartwatch activity tracking, vital signs monitoring and data management are part of the broader digital transformation of the healthcare industry. Digital transformation includes utilizing data from multiple sources (smartwatches, healthcare information systems) for making informed decisions and personalizing patients’ experiences. The integration of technologies in all aspects of healthcare from patient care to administration processes strengthens patient-centered healthcare and ensures that everything is centered around the patient (Iyawa et al., 2020). The goal of digital transformation in healthcare is to improve quality of care, reduce costs and easier access to healthcare services (Chiauzzi et al., 2015). Smartwatch activity tracking and vital signs monitoring can contribute to digital transformation by providing valuable health-related data that can be utilized to personalize care and improve patient outcomes.

5.3. Chapter summary

This chapter discussed the findings and provided literature that supports some of the findings. The findings were discussed based on the research questions. Hypothesis validations were conducted to address all research questions. The chapter explained the extent to which smartwatch features contribute to patient-centered healthcare. It also explained how we can theorise the smartwatches features of patient-centered healthcare. This section emphasized on the linkage between dependent and independent variables and provided real-life example supported by some literature. It is concluded that some smartwatch features can contribute to patient-centered healthcare.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

This chapter concludes the study by summarising all the chapters and providing a summary of major findings. The chapter also articulates the contributions of and limitations to the study. It further provides recommendations based on the study's findings.

6.2. Summary of the study

The purpose of this study was to investigate the effect of smartwatches on patient-centered healthcare. To this end, the following three research questions were formulated:

- What features of smartwatches contribute to patient-centered healthcare?
- To what extent do these features contribute to patient-centered healthcare?
- How can the contribution of smartwatches to patient-centered healthcare be theorized?

The study was divided into six chapters. The first chapter introduced the study by providing the background, the research problem, research questions and limitations of the study. The second chapter presented the literature review. This chapter discussed the concept of patient-centered healthcare and the use of smartwatches in the patient-centered healthcare context. In addition, the chapter discussed digital health technologies and the nexus between technology and patient-centered healthcare in the context of developed and developing countries. The last part of this chapter discussed the study's hypotheses development and the conceptual framework that guides this study.

The third chapter discussed the research methodology through the lens of the research onion framework (Saunders et al., 2019). The study adopted the positivism philosophy and the deductive research approach. The quantitative research method was adopted and a survey was used to collect data. The chapter then discussed the techniques and procedures used to collect and analyze data. The study was conducted in Gauteng province of South Africa and the target population involved runners within a running club that is part of Central Gauteng Athletics (CGA) association. Furthermore, this study adopted the convenient sampling method and the target sample size was 200 participants. The chapter further discussed how data was analyzed, the measurement approaches used, the limitations of the study and concluded by providing ethical considerations of the study.

The fourth chapter discussed the findings of the study. Firstly, the chapter presented the general characteristics of the data and the participants' demographics. The chapter then discussed the construct validity assessments which included measuring convergent validity and discriminant validity. The chapter also assessed the relationships between the independent variables and dependent variables. The last sections discussed the coefficient of determination and model fit. The fifth chapter further discussed the findings in detail by discussing the research questions in the light of the findings and literature.

6.3. Summary of major findings

The major findings are presented below:

- Post administering the data, the total sample that was used was 141 responses. The findings indicated that most participants were male (49.6%) and females accounted for 48.9%. Most participants (either female or male) were between 36 years and 45 years old. There are more females (64%) who use smartwatches often compared to males (41%).

- Findings also indicated that smartwatch features have positive effects on patient-centered healthcare. More specifically, the activity tracking feature of a smartwatch has a medium effect size on emotional comfort and coordination and integration of care. The vital signs monitoring feature of a smartwatch also has a medium effect size on continuity and transition. The data management feature of a smartwatch also has a medium effect size on coordination and integration of care. The findings indicated that the activity tracking has the strongest effect on coordination and integration of care while vital signs monitoring feature of a smartwatch has the strongest effect on continuity and transition whereas data management has the strongest effect on coordination and integration of care.
- Furthermore, the findings reveal that activity tracking feature of a smartwatch explains 12.3% of the variation within the “coordination and integration of care” construct of patient-centered healthcare whereas vital signs monitoring explains 13.6% of the variation within the “continuity” construct. Data management explains 10.7% of the variation within the “coordination and integration of care” construct. The SRMR revealed that the PLS-SEM model derived from the study is a good fit for the data used in this study.

6.4. Conclusion of the study

6.5. Contribution of the study

Based on literature review, it is apparent that there are limited studies on the effects of smartwatches on patient-centered healthcare, globally and in South Africa. Hence, this study provided insights on the topic from a South African perspective. Through construct validity, this study established the latent variables that could be used to measure the tested constructs. Thus, this provides a foundation for future studies that may seek to explore further the constructs pertaining to patient-centered healthcare of smartwatch features. Moreover, the study generated a PLS-SEM model that could be used to compare the effect sizes derived from the study with other findings through, for example, meta-analysis studies.

6.6. Limitations of the study

Below are the key study's limitations:

- The study did not cover all the features of a smartwatch and therefore future studies can expand on the results derived from this study.
- The study did not delve into complex modelling due to the nature and scope of the dissertation. Further investigation, through a follow-up study, could unveil more useful insights into the nexus between smartwatch features and patient-centered care.
- The study did not consider the control variables therefore future studies will look at the relationships between smartwatch features and patient-centered healthcare.

6.7. Recommendations

Based on the above findings, the following recommendations are made:

- Based on the results from this study, it is recommended that stakeholders in the provision of patient-centered care, in their quest to promote the use of smartwatches to foster patient-centered care should consider activity tracking and data management if they want to promote coordination and integration of care as the study found that activity tracking and data management features of smartwatch have the strongest effect on coordination and integration of care.
- Based on the results from this study, it is recommended that stakeholders in the provision of patient-centered care, in their quest to promote the use

of smartwatches to foster patient-centered care should consider vital signs monitoring if they want to promote continuity and transtion as the study found that vital signs monitoring features of smartwatch have the strongest effect on continuity and transition.

- This study considered three features of a smartwatch i.e. activity tracking, vital signs monitoring and data management, hence, the researcher acknowledges that not all the features of a smartwatch were covered in this study. Therefore, it is recommended that future studies should look into other features of smartwatches that were not explored also considering that smartwatch technology is always evolving.
- This study assessed the effect of smartwatch features and patient-centered care. The researcher acknowledges that there could be unexplored moderating variables. Therefore, it is recommended that further research is conducted to establish the effect of potential moderating variables on the relationship between smartwatch features and patient-centered care.
- This study was conducted using a sample size of 141 participants. It is recommended that further studies that seek to explore further the relationship between smartwatch features and patient-centered care should use a larger sample size.

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APPENDIX A: PARTICIPANT INFORMATION SHEET

Title of Project: The effect of smartwatches on patient-centered healthcare

<u>Please read carefully through all the information before making a decision on your participation</u>

My name is Patson Ndhlovu and I am a Masters of Management: Digital Business student at Wits Business School student. I am conducting a piece of research on the effect of smartwatches on patient centered healthcare

If you agree to take part in this research, I will ask you to answer the questionnaire. It should take approximately 10 minutes.

Your participation in this research is completely voluntary. If at any point you wish to no longer take part in the research you have the right to withdraw at anytime and there will be no pressure to stay.

All the information you give **will be anonymous and confidential** and only used for the purposes of this research and will only be accessible to me. No third parties will have access to any of the information you provide.

The data will be collected and stored in accordance with Wits University Data Policies and will be disposed of in a secure manner. The information will be used in a way that will not allow you to be identified individually.

You will have the opportunity to discuss your participation and be debriefed on the research once it has been conducted and analysed.

If you are not sure about anything mentioned above please do not hesitate to ask me.

If you agree to take part you will be asked to sign a consent form. The consent form will not be used to identify you. It will be filed separately from all other information.

Thank you very much for your time and help!

Kind regards

Patson Ndhlovu

INTERVIEW CONSENT FORM

I,………………………………………., agree to participate in this questionnaire.

I have been informed about my involvement in the research, and what is required of me. I understand that:

- My participation in the research study is voluntary;
- I may withdraw from the research at any time with no negative consequences for myself.
- My answers will be kept confidential and the anonymised data will be safely stored on password protected computers and folders;
- I have received the contact details of the researchers on the participant information sheet;
- All my questions about the research have been answered and I agree that my responses from the questionnaires can be used for the research;
- I have read the abovementioned information and agree to participate as per the above conditions.

If you have any concerns or questions related to the study in general, or the items in the questionnaire, please contact the project leader, Dr. Patrick Ndayizigamiye, ndayizigamiyep@uj.ac.za, 0115591223.

Name of Participant: ___________________

Signature: ______________________________

Date: __________________________________

APPENDIX B: QUESTIONNAIRE

THE EFFECT OF SMARTWATCHES ON PATIENT-CENTERED HEALTHCARE

<u>Please Note</u>: Patient-Centered healthcare focuses on the patient and individual's healthcare needs. Its goal is to empower patients by making them active participants in their healthcare. This involves listening, informing and involving patients in their care to improve their healthcare outcomes.

We are interested in understanding the effects of smartwatches features on patient-centered healthcare. Please answer the questions below. There are no right or wrong answers to these questions so please be as honest and thoughtful as possible in your responses. All responses will be kept strictly confidential. Thank you for your cooperation!

SECTION A: DEMOGRAPHIC INFORMATION

Please indicate your response to the question by ticking in the appropriate box.

1. Which age group do you belong to?

18 – 25 Years	26 -35 Years	36 -45 Years	46 – 54 Years	50 Years and Above

2. What is your gender?

Male	Female	Other	Prefer not to say

3. What is your highest formal level of education?

Less than a high school diploma	High School diploma or equivalent	Batchelor's or equivalent	Honours or equivalent	Masters or equivalent	Doctorate or equivalent

4. Do you own a smartwatch?

Yes	No

5. How often do you use the following your smartwatch?

Rarely	**About half the time**	**Often**	**Very Often**

SECTION B: SMARTWATCH FEATURES

6. **Activity Tracking** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
6.1. I use a smartwatch to track my steps daily.					

6.2. I use a smartwatch to enable me to create workout activities.					
6.3. I use a smartwatch to enable me to track my workout activities.					
6.4. I use a smartwatch to provide me with workout recommendations.					

7. **Vital Signs Monitoring** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
7.1. I use a smartwatch to track my sleep quality.					
7.2. I use a smartwatch to monitor my blood pressure.					
7.3. I use a smartwatch to monitor calories burnt on a daily basis.					
7.4. I use a smartwatch to monitor my heart rate.					

7.5. I use a smartwatch to track my diet.					
7.6. I use a smartwatch to remind me to take medication.					
7.7. I use a smartwatch to remind me of doctor's appointment.					

8. **Data Management** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
8.1. I use a smartwatch to securely store my health data (blood pressure, fitness, heart rate and weight).					
8.2. I use a smartwatch to sync my health data (blood pressure, fitness, heart rate and weight) in real-time.					
8.3. I use a smartwatch to share my health information with other health institutions.					

8.4. I use a smartwatch to share my health information with other third-party institutions.					
8.5. I use a smartwatch to generate detailed reports regarding my health using visual representation.					
8.6. I use a smartwatch to use my historical health data for predictive analysis (e.g. predict if I would get stressed, sick, etc.).					

SECTION C: PATIENT-CENTERED HEALTHCARE PRINCIPLES

9. **Access to Care** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
9.1. It is easy to schedule my appointments with healthcare providers.					
9.2. It is easy to access healthcare ins titutions to get my medication.					

9.3. I find that the healthcare referral process has a minimal waiting period.					

10. **Continuity and Transition** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
10.1. It is easy to access my health information after a doctor's visit.					
10.2. It is easy to access information related to my ongoing medical treatment.					
10.3. It is easy to access information related to my upcoming doctor's visits					

11. **Involvement of Family and Friends** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
11.1. My family supports me in improving my health.					
11.2. My friends support me in improving my health					

12. **Information and Education** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
12.1. Healthcare professionals I have consulted provided me with reliable information regarding diseases.					
12.2. Healthcare professionals I have consulted provided me with most recent information regarding the effects of medication.					
12.3. Healthcare professionals I have consulted provided me with most recent information regarding healthy lifestyle options.					

13. **Respect for Patient's Preferences** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
13.1. Healthcare professionals I have consulted respected my					

choices regardless of my social background.					
13.2. Healthcare professionals I have consulted respected my views regardless of my social background.					
13.3. Healthcare professionals I have consulted respected my preferences regardless of my social background.					

14. **Physical Comfort** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
14.1. Healthcare professionals I have consulted ensured my privacy in caring for my physical needs.					
14.2. Patient areas in the healthcare facility that I visit the most are kept clean.					
14.3. Patient areas in the healthcare facility that I visit the most are comfortable.					

15. **Emotional Comfort** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
15.1. Healthcare professionals I have consulted are respectful.					
15.2. Healthcare professionals I have consulted are empathetic.					
15.3. Healthcare professionals I have consulted provided me with emotional assistance					
15.4. Healthcare professionals I have consulted ensured my dignity.					

16. **Coordination and Integration of Care** (Please indicate the extent to which you agree or disagree with the following statements):

	Strongly Disagree	**Disagree**	**Neutral**	**Agree**	**Strongly Agree**
16.1. Healthcare professionals I have consulted always informed me on how my treatment affects other treatments that I've taken in the past.					

16.2. My transition between multiple healthcare professionals has been seamless.					

THANK YOU FOR YOUR PARTCIPATION....

APPENDIX C: PERMISSION LETTER

Permissions Letter

I Vongani Mashile in my capacity as Chairman of Fat Cats Athletic Club hereby give permission to **Patson Ndodana Ndhlovu, Student No.: 2440655** to conduct research at Fat Cats Athletic Club.

The student may approach individual runners to participate in this research. The student may send out questionnaire to individuals for the purpose of this research. This should be conducted within the 1st quarter of 2023.

Regards,

Vongani Mashile

Fat Cats Athletic Club Chairperson

Signature of Chairperson: Vmashile

Date: 20/01/2023

Fat Cats Athletic Club
www.fatcats.africa

APPENDIX D: ETHICS CLEARANCE CERTIFICATE

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB2440655/442
This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The effect of smartwatches on patient centered healthcare
Investigator / Researcher	Mr Patson Ndhlovu
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed anonymity and confidentiality.
Issue Date of Certificate	2023-01-23
Expiry date	Date of submission of the project / research report
Chairperson	Prof Anthony Stacey +27 11 717 3587 +27 82 880 4531 anthony.stacey@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

23/01/2023
Date: