Undergraduate Thesis

SMARTWATCH DATA MONITORING

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SMARTWATCH DATA MONITORING: ENHANCING HEALTH MANAGEMENT FOR OLDER ADULTS THROUGH USER-CENTERED MOBILE APPLICATIONS

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Abstract

Physical activity and regular health monitoring are crucial for maintaining functional independence and quality of life among individuals. The rise of smart wearable devices plays a significant role in promoting a healthier lifestyle, marking an evolution from when wearable computing consisted of heavy and complex equipment to modern, lightweight devices, making everyday self-tracking far more accessible. However, older adults often face challenges staying active due to physical limitations, health-related limitations, and reduced motivation. While technology offers potential solutions, the effectiveness of wearable devices and mobile applications among the elderly depends on the clarity and accessibility of the software that presents this data.

This thesis aims to investigate the integration of wearable devices with mobile applications for monitoring physical activity among individuals, with an emphasis on producing an interface that remains usable for older adults. Specifically, the research involves developing a mobile application that integrates with a smartwatch to display personalized health information. By analyzing the usability of existing devices and tailoring the design to meet user needs, the study aims to enhance engagement and usability.

A user-centered design approach will be employed, focusing on the participants' usability and feedback to improve the user experience further. Through this work, the thesis demonstrates that these solutions can empower individuals to actively manage their health. The findings offer design guidelines for accessible smartwatch-based monitoring, influencing future development in promoting health-related strategies.

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Introduction

1.1 Background

The global population is aging at an unprecedented rate. According to the United Nations, the number of individuals aged 65 and above is projected to reach 2 billion people by 2050 [1]. Another study found that of these age groups, by 2050, approximately 1.2 billion people will require continuous monitoring [17]. In the European Union, according to Eurostat [13], more than one-fifth of the population was aged 65 years and over as of January 2024, and this proportion is projected to rise to 32.5% by 2100, highlighting the growing need for continuous health monitoring among older adults.

Concurrently, technological advancements have significantly transformed healthcare delivery, allowing remote monitoring and personalized patient care [4]. Wearable devices, particularly smartwatches, have become essential tools for health monitoring.

This demographic shift represents a fundamental transformation of society, as life expectancy increases while fertility rates decline to historically low levels [2], with older adults making up an increasingly larger portion of the total population. Such a substantial change presents many challenges worldwide, particularly in healthcare, social services, and technological adaptation.

This shift intensifies demands on healthcare systems, especially as age-related chronic conditions like heart disease, diabetes, and arthritis become more prevalent, creating a greater need for ongoing care and support services. For instance, wearable technology has been increasingly adopted to monitor various health parameters, which has been shown to improve patient outcomes [4].

1.2 Problem

With the steady improvements in US healthcare, the life expectancy of individuals is also improving. While this phenomenon is great for the lives of people, it is an imposing issue in the healthcare system [16]. The challenge with a growing population creates significant challenges for healthcare systems worldwide. The frequent hospital visits and the need for continuous care place a substantial burden on medical facilities and healthcare providers. Additionally, healthcare costs have risen significantly in recent years, making it increasingly difficult for families to manage the constant supervision of older adults at home [5]. The frequent hospital visits are often the result of chronic conditions that become more common with age, such as cardiovascular disease and diabetes, which requires continuous monitoring and treatment.

Furthermore, the rising cost of healthcare further increases the issue. Treating elderly patients is typically more expensive due to the complexity of their needs, often involving multiple medications, regular diagnostics, and specialized services like home nursing or physiotherapy [5].

Therefore, there is a pressing need for alternative, affordable, and accessible solutions that enable elderly individuals to monitor their own health. Self-monitoring is crucial as it can help detect early signs of potential health issues, maintain an acceptable quality of life, and support proactive management of chronic conditions. Such solutions could not only reduce the burden on healthcare systems but also encourage the older adults to take a more active role in managing their health.

1.3 Solution

A promising solution involves the use of smart monitoring devices, particularly smartwatches. Smartwatches enable continuous health monitoring, helping to reduce hospital visits, and to encourage physical activity. Smartwatches in particular can track key metrics such as respiratory rate, blood oxygen levels, steps, exercise/workout tracking, stress, and sleep patterns. Additionally, smartwatches can provide timely reminders to users for medication intake and to engage in physical activities, empowering older adults to maintain a healthier lifestyle [3].

This thesis aims to develop a mobile application that seamlessly integrates with smartwatch-collected data, providing users with accessible and meaningful health insights. A key focus of this work will be on ensuring the application's ease of use and overall user-friendliness, focusing on the needs and preferences of the users. The findings are expected to contribute valuable insights into how smartwatch data can be effectively collected, presented, and utilized to empower individuals in proactively managing their health, while potentially reducing the burden on healthcare systems.

1.4 Thesis Structure

The structure of the thesis is as follows:

Chapter 2 – Literature review:

Chapter 2 provides an overview of the key concepts and research related to wearable technology and digital health. It begins with the introduction and evolution of wearable devices, followed by a breakdown of the main categories of smart devices. The chapter also explores market trends and the rapid growth of the wearable tech industry. A section is dedicated to the role of wearable devices in healthcare, including their connection to telemedicine and the Internet of Things (IoT). Finally, the chapter addresses critical issues surrounding data collection, such as user safety, privacy, and concerns over the accuracy and reliability of health-related data.

Chapter 3 – Methodology:

This chapter describes the implementation and features of the mobile application. It includes an overview of the apparatus used, a comparison of popular smart devices, and the technologies applied, such as React Native. It also presents the system architecture, explains the application's structure and core functionalities, and showcases key interface elements with screenshots.

Chapter 4 - Pilot study and evaluation:

This chapter presents the results of the pilot study, focusing on the evaluation of the smartwatch data monitoring application. It provides an analysis of the participants' backgrounds and expectations through the pre-questionnaire, assesses usability and user satisfaction through the post-questionnaire, and discusses additional qualitative insights gathered from participant interviews. A correlation analysis is included to explore relationships among various usability and functionality metrics, helping to identify consistent patterns in user perception.

Chapter 5 - Discussion and future work:

This chapter looks at what the pilot study results mean for the smartwatch data monitoring application and how it can be improved going forward. It begins by discussing the main usability results, then looks at how user background influenced the feedback. Next, it highlights the app's strengths based on both the questionnaire scores and what participants said. The chapter also points out the current limitations of the app and the pilot study. Finally, it offers suggestions for how the app could be improved in future versions, including new features, better design, and integration with other systems.

Chapter 6 – Conclusion:

Chapter 6 provides a final summary and evaluation of the thesis, reflecting on the app's development, effectiveness, and user feedback. The chapter discusses how the app can help improve everyday health management and supports the growing need for remote healthcare solutions. It also points out areas for improvement and suggests future work

Chapter 2

Literature Review

2.1 Introduction to Wearable Technology

Wearable technology refers to any electronic device designed to be worn by an individual that offers a variety of tools, such as communication, monitoring vital signs, and data collection [18]. These devices come in various forms, from a head-mounted display to smart clothing and jewellery to a wearable wrist-worn smart device [12], and can improve the quality of life through real-time feedback. These devices are typically worn as accessories or part of clothing, allowing seamless interaction with the users' daily life. Other categories of wearable technology can be implantable and patchable. Wearables can include smartwatches, fitness trackers, smart glasses, and even smart fabrics embedded with sensors.

2.1.1 Evolution of wearable technology

Wearable technology has undergone significant evolution from its early beginnings in the 1970s to the present day, transforming the way we interact with technology and the benefits provided to us [6]. This progression can be traced through improvements and miniaturization in sensor technologies, increased battery life, and improved wireless connectivity, all of which have helped shift wearable technology from research prototypes to mainstream consumer products [6]. Steve Mann is widely regarded as the pioneer of wearable computing. He created what is often described as the world's first wearable device: a bulky computer backpack and headgear with a camera attached to it [10]. He was also among the first to experiment with integrating wireless communications into wearable platforms, demonstrating real-time video streaming and personal imaging capabilities [6]. Even in these early stages, Mann was exploring the possibility of capturing and transmitting data, a concept central to modern wearable technology. As shown in Figure 2.1 [7], although looking quite different from modern devices, Mann's early work laid the foundation for the miniaturization and integration we see today.

Figure 2.1 Evolution of Steve Mann's Wearable Computing Prototypes [7]

As the technology keeps improving, the components of a smart device are becoming increasingly smaller and more efficient. The physiological sensors play a very important role in the collection of health data and have been greatly improved by this trend of miniaturization. The majority of these sensors have been miniaturized using methods like micro-electro-mechanical systems (MEMS), allowing them to be accommodated in small-sized wearable devices [19]. This technology has paved the way for wearables to provide a variety of features, such as GPS navigation, contactless payment, and even augmented reality features. These advancements have not only improved the functionality of wearables but have also broadened their applicability.

As a result, wearable devices have found broader uses in the military, healthcare, and entertainment. By the early 2000s, commercially available wearable smart devices and fitness trackers began to appear, paving the way for more commercially successful devices, such as Fitbit and the Apple Watch [10]. These new devices have set new standards for how users interact by seamlessly connecting to smartphones [11]. Today, wearable devices are equipped with advanced sensor technologies, are integrated with Artificial Intelligence (AI), and are capable of cloud-based analytics to deliver personalized health insights, recommendations, and early signs of health-related conditions [7]. AI algorithms analyze the vast amounts of data collected by wearables to identify patterns and trends. At the same time, cloud-based analytics platforms provide the infrastructure for storing and processing this data, enabling personalized health recommendations and early detection of potential health issues. In military applications, wearables are used for soldier movement tracking, vital sign monitoring, and even augmented reality training simulations [28-29]. In healthcare, wearable sensors enable remote patient monitoring, early detection of health issues, and personalized treatment plans [30]. In the entertainment industry, wearables enhance experiences through motion tracking and haptic feedback and create immersive virtual reality environments [31].

This progression highlights how wearable technologies have moved from experimental and research projects to essential tools of our everyday lives. However, as the technology advances, it also faces challenges. Issues such as data accuracy, security, device interoperability, and ethical considerations related to privacy need to be addressed, which we will discuss more later in this chapter. Despite these challenges, the potential of wearable technology to enhance healthcare delivery and improve personal productivity remains significant.

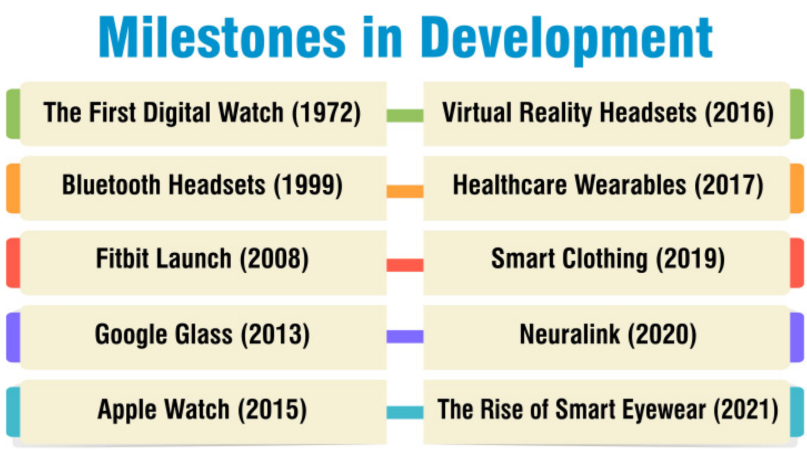

Figure 2.2 Milestones in wearable technology [11]

2.1.2 Categories of smart devices

Wearable technology encompasses a wide range of devices, each offering innovative solutions

And targeting various aspects of our daily lives. Regardless of their type, the technology shares certain common features and attributes.

Figure 2.3 shows the different range of devices designed to be positioned on different parts of the human body. These devices can be utilized for serving different purposes, including fitness tracking and health monitoring, communication, and augmented reality. For example, head-mounted devices like glasses and headsets can offer visual or audio feedback, while wrist-worn devices like smartwatches typically measure physiological signals like heart rate and activity. Rings and belt-like devices offer monitoring parameters such as sleep or posture, and smart clothes integrate sensors in fabrics so that body-wide data can be collected continuously.

Figure 2.3 Devices for different parts of the body [9]

More specifically, these can be broadly categorized into several types:

Wrist-worn Devices:

Wrist-worn devices, such as fitness trackers and smartwatches, are the most widely adopted category of wearables and will be the main focus of this research. Wrist-worn wearables transformed from simple step counters to advanced communication and health tools that monitor multiple health parameters such as heart rate, sleep patterns, and physical activity.

Popular examples include the Apple Watch [58] and Fitbit trackers [59]. High-end variants now include features such as ECG and fall detection, in addition to monitoring blood oxygen levels, increasing their use in personal health management. Moreover, with the constant evolution of Artificial Intelligence (AI), wearables have also become more proactive, with examples of better recognition of fall detection [36]. Their integration of wrist-worn devices with smartphones has expanded their functionalities, enabling users to receive notifications, make calls, and even make contactless payments.

Head-mounted devices

Head-mounted devices (HMD), such as Virtual Reality (VR) and Augmented Reality (AR) headsets, are leading the trend for immersive technology. These devices can simulate computer-generated environments or overlay digital information in the real world, offering new technologies in gaming, education, and professional training [32].

VR headsets such as the Meta Quest [28] and the Apple Vision Pro [29] offer fully immersive experiences, while AR devices like the Microsoft HoloLens [52] and Google Glasses [72] overlay digital content with the real world, enhancing the user's perception and interaction with their surroundings. In healthcare, VR headsets are used for pain management and mental health treatment, demonstrating the versatility of this technology outside entertainment [33]. AR devices, specifically smart glasses, can also be used in healthcare by providing surgical and clinical assistance [34].

The potential of HMD extends beyond the above fields, with AR headsets finding applications in agriculture and manufacturing by providing workers with real-time information, instructions, and remote assistance [9]. As technology advances, VR and AR capabilities are expected to converge, enabling seamless mixed-reality (MR) experiences that further connect the virtual with the physical world [35].

Smart clothing

Smart clothes represent a category of wearable technology in which electronic components and sensors are built directly into fabrics known as e-textiles [12]. This technology enables continuous monitoring of physiological metrics without requiring externally worn devices like a smartwatch and it was made possible mainly because of advancements in wireless communication, Artificial Intelligence (AI), and the Internet of Things (IoT).

Researchers have developed smart clothing capable of tracking electrocardiogram (ECG) signal monitoring, respiratory rate, and body temperature, offering noninvasive, continuous health monitoring. In a workplace, smart textiles integrated with sensors can support posture monitoring and correction, which is helpful for people with prolonged awkward postures during work [37]. Additionally, advanced smart fabrics incorporate thermoregulatory materials that adjust body temperature based on environmental conditions, enhancing comfort and lowering the risk of injury [38].

Some examples are smart shirts that monitor heart rate and respiration, smart socks for runners that analyze gait, and smart jackets with integrated heating elements or touch-sensitive controls. In healthcare, smart clothing is being explored for uses like monitoring patients with chronic conditions, while in athletics, it offers real-time performance tracking to optimize training and reduce injury risks. As research advances, smart garments are expected to play a growing role in both personal health management and professional applications.

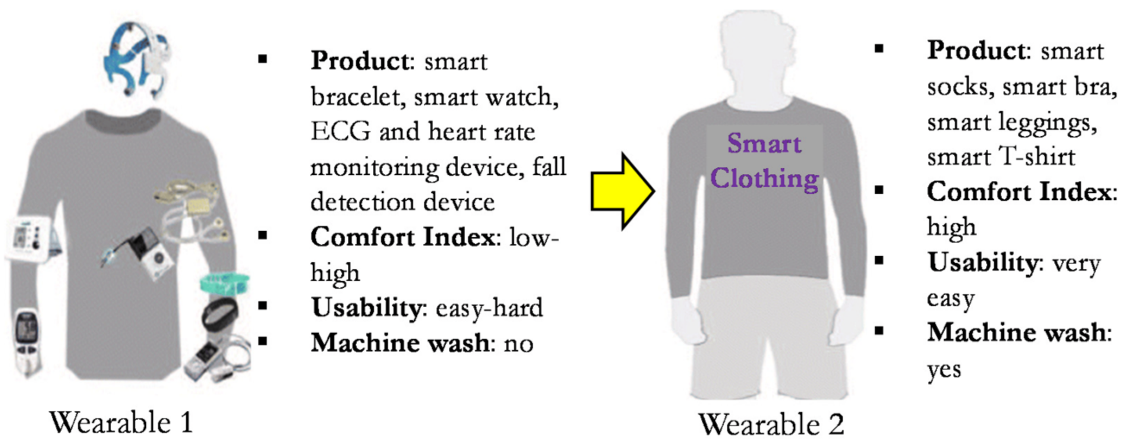

Figure 2.4 Comparison between Multiple Wearable Devices and Smart Clothing [12]

Smart Rings

Smart rings represent a category of wearable technology designed to provide continuous biometric monitoring without compromising any comfort or aesthetics [68] by embedding miniaturized sensors, including photoplethysmography (PPG), temperature sensors, accelerometers, and gyroscopes, to enable 24/7 tracking. Inside the ring, these devices can capture a broad spectrum of physiological data such as heart rate, skin temperature, respiratory rate, and sleep-related metrics, and send that information to a paired smartphone to display and analyze the data [68]. Smart rings are designed for simplicity and ease of use, requiring minimal user interaction. Once worn, they operate passively in the background, automatically recording and synchronizing biometric information throughout the day, which encourages sustained use by requiring almost no deliberate user interaction [68].

Figure 2.5 Samsung Galaxy Ring [71]

Figure 2.6 Oura Ring [70]

2.1.3 Market Growth and Trends

The global smartwatch market has experienced considerable growth and is anticipated to increase steadily in the future as well. According to Fortune Business Insights, the market was valued at USD 33.58 billion in 2024 and is projected to reach USD 105.20 billion by 2032 [21]. This growth is mainly driven by the growing awareness of consumers regarding the effectiveness of these devices in health and fitness, and their technological advancements, which allow these devices to connect with smartphones and other devices [14]. Additionally, COVID-19 has played a massive role in accelerating the adoption of wearable devices [21], as consumers seek tools for remote healthcare monitoring and tracking their daily health.

2.1.4 An Overview of Digital health and Wearable health Technology.

Wearable technologies are becoming essential tools in modern healthcare. These devices are revolutionizing healthcare by shifting from traditional, centralized clinical care to more personalized and continuous health monitoring [36]. A variety of these devices used in healthcare consists of smartwatches, fitness bands, smart clothing, and even implantable sensors, which provide real-time insight into key health metrics such as heart rate, blood pressure, sleep patterns, and activity tracking [11].

This transition from periodic visits to a clinic toward continuous monitoring enables a more proactive and personalized approach to healthcare [9]. As shown in Figure 2.7, instead of relying only on scheduled doctor visits to assess a patient's condition, wearable devices can continuously track vital signs and detect anomalies that may indicate potential health issues. For instance, irregular heart rhythms detected by a smartwatch could alert users to potential arrhythmias, prompting early medical intervention before symptoms become severe. Similarly, long-term tracking of sleep patterns could help detect conditions such as sleep apnea, which often goes undiagnosed in traditional healthcare settings.

Research has shown the positive impact of wearable technologies on patient outcomes. For example, continuous glucose monitoring (CGM) systems have been shown to improve glycemic control in patients with diabetes through the provision of real-time blood glucose data, enabling adjustments in therapy and lifestyle [41].

Moreover, the integration of Artificial Intelligence (AI) and Machine Learning (ML) with wearable technology has significantly enhanced the value of collected data. AI algorithms can efficiently identify patterns and anomalies in health data, often outperforming traditional clinical methods in predicting patient prognosis [39]. In some cases, these AI-powered analytics have been shown to outperform human doctors in detecting early signs of diseases [39]. By recognizing risk factors and deviations in health metrics before symptoms develop, wearables contribute to a preventive healthcare model rather than a purely reactive one. This topic will be further explored in the following section on data collection.

Smartphones play a crucial role in the wearable technology ecosystem as they can reduce patient costs and serve as excellent tools that sync, store, and analyze data collected from the wearable [14]. The ability to transmit real-time health data to cloud platforms or electronic health records (EHRs) allows for seamless communication between patients and healthcare providers, making telemedicine and remote consultations more effective than ever. However, while the convenience and accessibility of smartphone-integrated wearables enhance patient engagement, this approach also raises important concerns about data privacy and security, which will be explored later in this chapter.

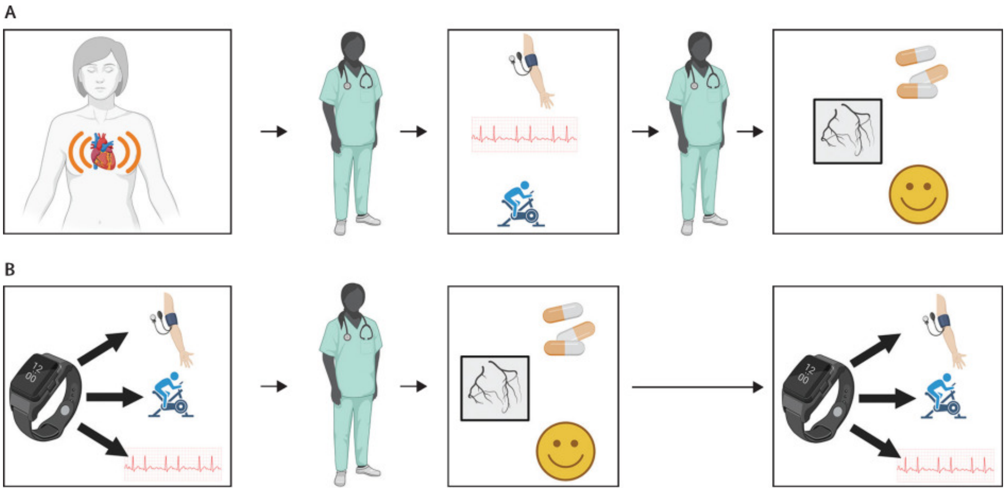

Figure 2.7 Patient-doctor interactions with and without wearable devices [15]

2.2 Mobile Health in the Context of Smartwatch Data Collection

Mobile health (mHealth) is the use of mobile devices such as smartphones and wearables to deliver healthcare services and manage health-related information [42]. It is a part of the broader concept of digital health, which emphasizes the use of mobile and other technologies in healthcare for wireless communication and data transmission. mHealth leveraging smartwatch data collection has emerged as a transformative approach in healthcare. It is a revolutionary approach as it enables continuous, real-time monitoring of vital signs such as heart rate, blood oxygen levels (SpO2), physical activity, and sleep patterns. This constant data stream offers a granularity of information previously unavailable in traditional healthcare settings.

Mobile health is an emerging field that continuously grows, with numbers showing that in June 2021, there were more than 350,000 health-related mobile apps worldwide, with that number increasing every day [20]. This growth is further fueled by the rising adoption of smartwatches as well as the COVID-19 pandemic, which has significantly accelerated the adoption of mHealth technologies due to the increased need for remote care and monitoring [20]. It offers cost savings, better clinical outcomes, and improved access to healthcare [42]. This growth reflects a fundamental shift towards remote monitoring and personalized healthcare. The increasing availability of affordable smartwatches with advanced sensors further fuels this expansion.

The persistent monitoring provided by mHealth technologies not only helps patient care but is also important in pharmaceutical and research. The constant stream of information makes researchers capable of detecting digital biomarkers and monitoring treatment responses in near real-time [15]. By integrating mHealth data in research trials, researchers can observe patient responses continuously, which may lead to more efficient trials and earlier identification of undesirable drug reactions [20].

Mobile health, particularly when combined with telemonitoring, is particularly useful for people living in isolated areas with limited access to clinics, elderly people, patients with chronic diseases such as diabetes and dementia, and disabled persons who may have difficulty arriving at clinics. In developing countries where medical care is not accessible, mHealth is a viable solution in closing the healthcare gap [42].

Beyond patient care, mHealth can also be used as an educational tool, as A project in South Africa called “Cellphones4HIV” is described as sending messages that act as reminders for medication or to inform about HIV-related topics. Text messages, in particular, have become a great and cost-efficient way to remind patients about their medical appointments, significantly reducing patient nonattendance to their scheduled meetings [43]. Beyond text messaging, mHealth apps can also provide educational videos, interactive tools, and personalized health information [77].

Some notable concerns of mHealth are that its methods must be regulated. There are large safety and reliability concerns that largely affect the doctor–patient relationship that needs to be addressed [44], will be discussed in more detail in the sections that follow.

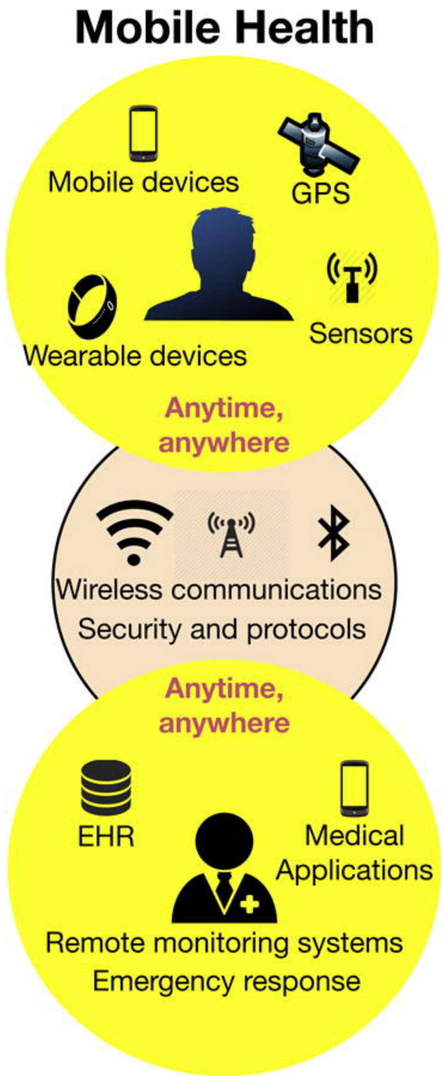

Figure 2.8 Components and Flow of mHealth System [42]

Figure 2.8 shows the core architecture of mHealth systems, emphasizing the interconnected ecosystem of mobile devices, wearable sensors, and wireless communication technologies. At its foundation, mHealth relies on real-time data collection from wearable and mobile devices, which is transmitted via wireless protocols. This data can include vital signs, location, or activity levels. The integration with electronic health records (EHRs) and specialized medical applications enables healthcare providers to monitor patients and respond to emergencies when needed remotely.

2.3 Telemedicine & Internet of Things

Integrating Internet of Things (IoT) and telemedicine technologies into mobile health (mHealth) represents a transformative shift in healthcare delivery. Telemedicine refers to the delivery of healthcare services from a distance through the use of digital communication technologies, which facilitates consultations, diagnosis, and treatments without requiring patients to be physically in a healthcare facility [75]. The Internet of Things (IoT) is a network of devices capable of communicating and sharing data to enable automation, monitoring, and decision-making [55]. IoT significantly improves medical care by introducing new technologies and improving existing ones. The concept of Internet of Medical Things (IoMT) is a concept of merging IoT with medicine. With the large technological advancements in the network and communication, mainly affected by the emergence of the 5G network, medical technology has greatly improved people's living standards [53]. Breakthroughs in Artificial Intelligence (AI) and sensor technologies have greatly accelerated IoMT adoption, equipping healthcare professionals with smart devices capable of real-time patient monitoring and more precise clinical decision-making.

The Internet of Medical Things (IoMT) can be particularly useful for tracking and monitoring hospital equipment inventories as well as any other medical aids [53]. Moreover, it can be particularly useful for equipment maintenance, as IoMT solutions enable healthcare professionals to detect potential problems early and provide timely and effective solutions. This proactive approach minimizes downtime, optimizes resource allocation, and ultimately enhances patient care in healthcare facilities.

IoMT can also be used for ambulance emergencies. It can track the patient's vitals, telemonitor him, and send vital information to the hospital to help it prearrange the stuff that they will need to save his life. Using a GPS tracker in the ambulance can help open the road by changing the red traffic lights [54].

The Internet of Things has experienced significant growth because of the recent advancements in sensor technologies and Artificial Intelligence, accelerating its adoption in healthcare. A smart device equipped with the latest technologies in the Internet of Things field can help healthcare providers monitor a patient's vital signs more efficiently and make more accurate decisions.

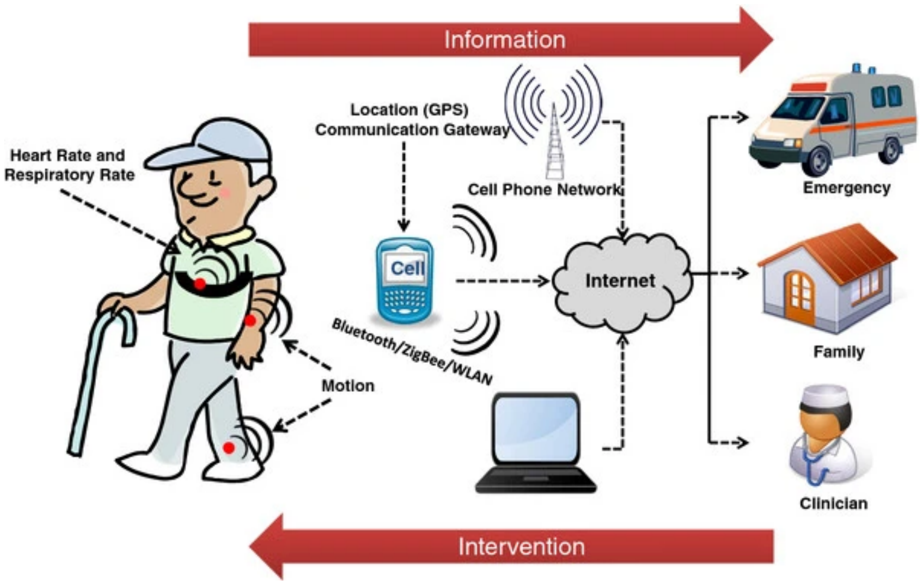

Figure 2.9 Remote Patient Monitoring Workflow [19]

Figure 2.9 shows the flow of data and intervention in a remote patient monitoring system. Wearable sensors collect physiological parameters and transmit this information through communication gateways (e.g., mobile networks) to cloud-based systems via the internet. This data is made accessible to clinicians, family members, or emergency services in real time. The system enables continuous observation of patient status outside traditional clinical settings, allows timely interventions, and improves the quality of care, especially for elderly or chronically ill individuals.

2.3.1 Challenges

One of the main challenges facing these technologies is battery life, given that users have to rely on them continuously throughout the day [16]. Consequently, more efficient charging solutions and energy management strategies are needed to keep these devices active and to maintain a seamless user experience.

Beyond battery life concerns, network reliability and coverage limitations are also significant challenges that need to be addressed, which are affecting majorly the effectiveness of IoT-based telemedicine systems. These systems heavily rely on consistent, high-speed internet connectivity, which is often lacking in remote regions. This lack of infrastructure can have an impact on the real-time transmission of critical patient data, therefore compromising the quality of care. Even in urban areas, network outages or bandwidth constraints can have an impact on data flow, delaying essential medical interventions. While advancements like 5G-IoT aim to enhance reliability, their uneven deployment means that many areas still face connectivity challenges, limiting the widespread adoption of telemedicine services.

Another challenge is user acceptance and ease of use, which are also crucial in influencing the success and long-term adoption of IoT-based telemedicine platforms. The ease of use and usefulness of these technologies significantly affect their adoption among healthcare professionals [55]. Also, ease of use is a key factor that directly impacts how easily healthcare providers use and adopt these platforms, with intuitive systems being easier and more likely to be integrated into their workflow. User acceptance also plays a crucial role, reflecting how healthcare providers view the benefits and effectiveness of these technologies in improving their work and patient outcomes.

2.4 Data collection in Smartwatches

Modern smartwatches have become sophisticated data-collection devices equipped with a variety of sensors capable of collecting data and continuously monitoring health and activity metrics. These devices have seen significant improvement due to advancements in Micro-Electro-Mechanical Systems (MEMS) sensors, which have made it possible to reduce the cost, power consumption, and size of sensors used in wearables [45]. Previously, most biometric sensors were large, expensive, and energy-intensive, limiting their application in consumer-grade wearables. However, MEMS technology has enabled the miniaturization of these components, making smartwatches more efficient and accessible for real-time health monitoring. Apart from this, due to these advancements, these devices can be equipped with wireless communication technologies that are capable of efficiently transmitting data, such as Wi-Fi and Bluetooth Low Energy (BLE), which is crucial for the development of remote monitoring. The miniaturization of these technologies has also enabled the development of devices like the peacemaker and cochlear implants, which significantly improve the quality of life of patients [48].

When collecting data from smartwatches, it is important to ensure user consent and privacy. Users must be properly informed about how their data will be used and stored, which includes providing clear and concise information about data processing practices. However, detailed discussions on data privacy, encryption, and compliance with regulations will be further elaborated in the subsequent safety concerns section.

Machine learning and AI have the potential to transform healthcare by providing diagnostics and predicting any health-related issue. These technologies can filter the raw data collected from a smart device into meaningful information and accurately pinpoint any abnormalities from these metrics [40]. For example, machine learning algorithms can analyze patterns in heart rate variability, sleep quality, and physical activity levels to identify early signs of conditions such as cardiovascular disease or diabetes. However, challenges related to accuracy, reliability, and ensuring the validity of these insights remain crucial areas and will be examined in more detail in sections 2.3.1 and 2.3.2.

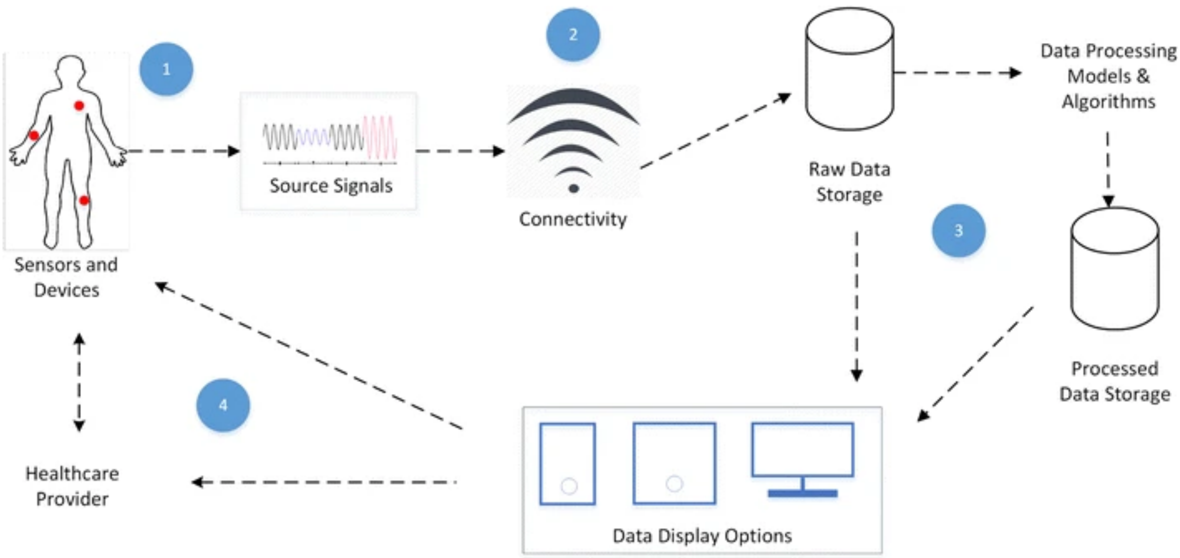

Figure 2.10 Wearable Health Data Workflow [40]

Figure 2.10 illustrates the end-to-end flow of wearable health monitoring systems. It begins with sensors and wearable devices capturing physiological signals, which are then transmitted to remote servers for raw data storage. This is processed employing advanced algorithms and models, which generate clinically useful information that is stored separately. These results are then made available through various display interfaces, such as mobile phones, tablets, or desktop dashboards, in a way that allows healthcare professionals to interpret the data and make informed decisions.

The following sections outline a more detailed approach to the primary data metrics typically collected by a modern smartwatch:

Physical Activity Metrics

One of the most fundamental data metrics collected by smartwatches is related to physical activity. Smartwatches utilize accelerometers to quantify user activity by measuring parameters such as step count, intensity of movement, and sedentary time. More advanced smartwatches integrate GPS sensors to gather sophisticated data, including speed, precise location coordinates, distance traveled, altitude, and terrain variations. This comprehensive data set enables accurate tracking of user movements over extended periods, facilitating the analysis of patterns in user activity and behavior, as well as goal tracking and fitness assessments [15].

Heart Rate and Cardiovascular Metrics

Heart rate monitoring is an important metric often collected through optical photoplethysmography (PPG) sensors, which measure blood volume changes in capillaries at the wrist to measure heart rate, resting heart rate, and heart rate variability (HRV) continuously. Smartwatches with enhanced capabilities also feature ECG sensors, which are capable of capturing electrical activity of the heart for a detailed insight into heart rhythms. ECG sensors can detect irregularities like atrial fibrillation (AFib), a major stroke risk factor, and enable proactive heart health management, particularly for older adults [49]. These metrics provide useful information in assessing cardiovascular well-being, detecting arrhythmias, monitoring stress levels, and determining overall fitness levels. Continuous heart rate data are valuable in the early detection of potential cardiovascular risks and conditions.

Sleep monitoring metrics

Sleep monitoring is another significant data collected by smartwatches, enabled mainly by motion sensors (accelerometers and gyroscopes) and optical heart rate sensors. These devices monitor user sleeping habits, distinguishing between different sleep phases such as deep sleep, REM sleep, and light sleep. Smartwatches can recognize disruptions in sleep, interruptions, and overall sleep duration and efficiency. Sleep-tracking capabilities in wearable devices have an important application in diagnosing sleep disorders, assessing sleep quality, and determining relationships between sleep and overall health.

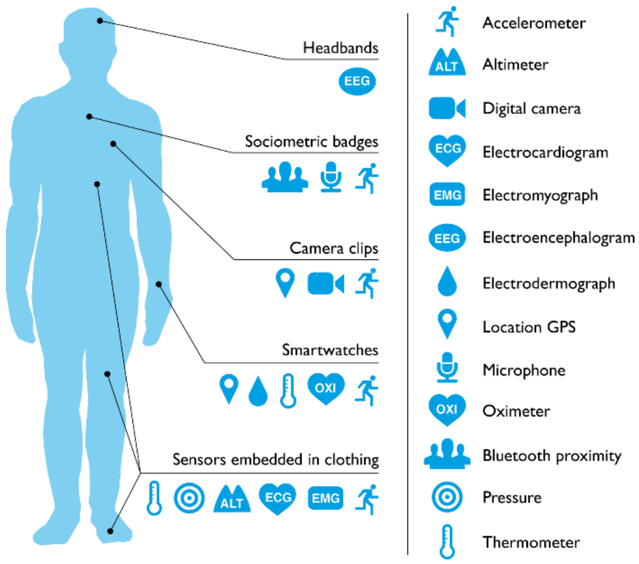

Figure 2.11 Body-Worn Sensors and Their Data Types [4]

2.4.1 Safety concerns about data collection

Despite their numerous health and lifestyle benefits, smart devices pose considerable safety concerns and have been subject to numerous high-profile privacy breaches and misuse cases primarily related to data collection and data security. In spite of the rapid adoption of wearable devices, this has been significant as the extensive collection, storage and analysis of personal data create vulnerabilities that could be easily exploited for unauthorized access and misuses, raising serious ethical and privacy concerns.

A critical issue revolves around the control and ownership of personal data generated by wearable devices. Although users physically own their devices, the collected data is often controlled by device manufacturers or third-party services, which raises concerns about user autonomy and data ownership [4]. Moreover, there is an increasing concern about wearable technology companies selling anonymized user data to third-party entities, often without transparent disclosure or explicit consent from users, creating significant ethical and privacy issues [4]. Wearable devices gather a lot of user data, including sensitive data such as biometric data and GPS location. The lack of clarity from technology companies can lead to highly targeted and oftentimes intrusive advertisements [51]. Therefore, there is a need for strong privacy frameworks and strict regulations to reduce these risks.

Privacy has always been an important part of any individual. While the human movement data collected from smart devices may seem anonymized, there's a concern about the ability to identify individuals through this data [50]. Sensor-generated data, seemingly anonymous, can reveal user identities by examining unique movement patterns and behaviors. This uniqueness means that even coarse or seemingly anonymized datasets can be re-identified using minimal external information, such as home or work addresses, leading to unauthorized profiling and misuse of personal information [50]. The widespread collection and sharing of mobility data by various entities, including mobile carriers and app developers, further intensifies these privacy concerns, highlighting the urgent need for effective privacy measures to protect sensitive personal information.

Companies are responsible for being discreet, transparent, and specific about the data they collect, their methods of collection, and how data will be used. They should explicitly ask for user consent before collecting data. Data security and privacy must be prioritized through robust security measures such as AES encryption, end-to-end encryption, and secure authentication protocols like TLS to protect against unauthorized access. Many cases show data being stored without adequate security measures, highlighting the necessity for these stringent security practices [51].

Compliance with privacy regulations like the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States is crucial [41]. GDPR emphasizes the rights of individuals to control their personal data, including the right to access and erase their data. Similarly, HIPAA sets standards for protecting sensitive patient health information, ensuring that any data collected from smartwatches is handled in accordance with these strict regulations. These regulations highlight the importance of handling smartwatch-generated data responsibly and securely.

2.4.2 Smart device data accuracy concerns

Smart device accuracy can be essential for people who want their devices to display as accurate metrics as possible. While manufacturers market these devices under the premise that they help with health and fitness, many fail to back up their statements with empirical evidence supporting their product's reliability, with studies revealing error margins of up to 25% for tracking physical activity [4]. This disparity between marketing claims and scientific validation raises concerns about the effectiveness of these devices in real-world applications [22].

As the market for wearable technology continues to expand rapidly, with projections reaching 138.7 billion USD by 2028 [23], it becomes increasingly crucial to establish standardized accuracy and reliability benchmarks in wearable technology. This is particularly important as these devices are increasingly used for health monitoring and medical purposes. While there are also some devices that are medically approved, there must be a way to easily differentiate these from consumer-grade smart devices. Several studies have highlighted the variability in accuracy across different wearable devices and metrics [23]. For instance, a 2020 study found that wrist-worn devices showed mean absolute percentage errors ranging from 2% to 13% in heart rate measurements during moderate exercise [76].

The distinction between medically approved and consumer-grade devices is primarily based on their intended use and regulatory classification [24]. Medically approved devices undergo rigorous testing and must comply with specific regulations to ensure lower error margins. To differentiate between these categories, consumers and healthcare professionals should consider the following:

1. Intended use: Devices marketed for specific medical purposes, such as diagnosis or treatment, are likely to be medically approved.
2. Data accuracy claim: Medically approved devices typically provide more precise accuracy claims and have undergone clinical validation studies.
3. Marketing language: Consumer-grade devices often use general wellness terms, while medical devices make specific health-related claims.

The distinction between medically approved and consumer-grade devices is crucial for consumers and healthcare professionals. Medically approved devices must comply with specific regulations, such as those set by the FDA in the United States or the European Medicines Agency in Europe [25]. Understanding these differences between medically approved and consumer-grade devices is crucial as the wearable technology market continues to evolve, ensuring their proper and intended use.

Furthermore, developing a standard protocol for data integration from wearable devices into healthcare systems is essential. This would simplify the process of incorporating device data into clinical decision-making. Healthcare providers would not need to learn multiple systems or data formats, improving efficiency and reducing the likelihood of errors. A standardized protocol would facilitate interoperability between different devices and healthcare systems, potentially leading to more comprehensive and accurate health monitoring [26-27].

The development of tools like the Wearables for Health (W4H) Toolkit demonstrates progress in this direction, providing a unified framework for data acquisition, storage, analysis, and visualization from various wearable devices [27]. Similarly, the design of FHIR (Fast Healthcare Interoperable Resources) interfaces for wearable healthcare devices aims to establish a standard clinical data exchange format, further supporting the integration of wearables into remote medical services [26].

As wearable technology continues to advance, addressing these challenges will be crucial for maximizing its potential in healthcare and ensuring its proper and intended use. By establishing clear standards and protocols, the industry can foster innovation while maintaining the trust and safety of consumers and healthcare professionals alike.

Chapter 3

Methodology

3.1 Introduction

This chapter of the thesis provides an overview of the methodology used in the development of the smartwatch application. Specifically, it details the design architecture, and the technologies and tools used during the development. Additionally, it addresses and explains the reasons behind selecting these technologies and how they align with the project's goal. It also explains about the apparatus used and compares it with other apparatuses.

3.2 Apparatus

Garmin Vivoactive 5: Overview and Features

The Garmin Vivoactive 5 [57], developed by Garmin, is a GPS-enabled smartwatch designed to provide accurate health and activity monitoring metrics. This watch was selected because of its reliability and for its tracking capabilities, as it features advanced biometric sensors that are capable of tracking steps, heart rate, blood oxygen saturation levels, stress, and intensity levels. It also features a high-resolution AMOLED touchscreen display, offering excellent visibility in outdoor environments. Its reliable sensor accuracy, battery life, and robust data collection capabilities make it suitable for conducting research in wearable technology and health monitoring.

Figure 3.1 Garmin Vivoactive 5 [57]

Table 3.1 Specifications of Garmin vivoactive 5

Garmin Vivoactive 5 specifications [57]	
Display Type	AMOLED, 1.2-inch (30.4mm)
Battery Life	Up to 11 days (smartwatch mode), up to 5 days with always on display
Screen resolution	390 x 390 pixels
Weight	36g
Water Resistance	5 ATM (50 m)

Sensors	GPS, GLONASS, Galileo, heart rate monitor, Pulse Ox, accelerometer, compass
Connectivity	Bluetooth, Wi-Fi, NFC (Garmin Pay)
Storage	4GB
Dimensions	42.2 x 42.2 x 11.1 mm

3.2.1 Comparison to other smart devices

To determine the most suitable device for this study, a comparison was conducted among some popular and widely recognized smart health devices, such as the FitBit Sense [59], Biobeat [60], Medtronic Guardian Connect [61], Omron HeartGuide [62], and Apple Watch [58]. These devices were evaluated and compared based on features, accuracy, ease of use, and cost:

The Apple Watch [58], which debuted in 2025, is among the most popular smartwatches globally and offers robust fitness tracking capabilities, including ECG monitoring on their higher end smartwatches, and fall detection. However, its high cost and shorter battery life compared to its competitors limits its suitability for and convenience of having continuous data collection over multiple days.

The Fitbit Sense [59] is a more budget-friendly option that includes heart rate monitoring, skin temperature sensing, and stress tracking, but it lacks the medical-grade certifications of some of its competitors. Biobeat [60] and Medtronic Guardian Connect [61] are more clinically oriented, offering FDA-approved data quality suitable for hospital use. However, their usability and cost may not align with the needs of studies outside controlled environments (like labs and hospitals) due to their focus on specific conditions like hypertension or diabetes. The Omron HeartGuide [62], designed primarily for blood pressure monitoring, is an excellent device in terms of accuracy but falls short in other, more general-purpose tracking capabilities such as sleep or stress levels monitoring.

In contrast, the Garmin Vivoactive 5 offers a strong balance between performance, usability, and affordability. It includes all the essential features and capabilities within a consumer-accessible form factor. Additionally, Garmin's robust ecosystem allows it to reliably synchronize and extract data, making it a practical choice.

Considering all the factors above, the Garmin Vivoactive 5 was chosen for this study due to its well-rounded feature set, user-friendly interface, reliable sensor accuracy, and practical battery life. While it may not have the medical-grade precision of specialized clinical devices, it provided sufficient reliability for general health monitoring to an average consumer.

3.2.2 Smartphone

For this study, a generic Android smartphone was used to test and operate the smartwatch application. No specific brand or model was required, as the application is designed to run effectively on any modern Android device that supports standard connectivity and app functionality. The focus was placed on ensuring the application performed consistently and reliably across typical consumer hardware, making it broadly accessible and practical for everyday use.

In addition to physical device testing, An Android emulator was also used during development to speed up testing and debugging. It allowed for quick iteration of the user interface and core features without needing to deploy to a physical device each time. This streamlined the development process and ensured early issues could be identified and resolved efficiently.

3.3 Technologies used

This section highlights the key technologies used in the development of the mobile application. These technologies were mainly used for their flexibility, performance as well as compatibility with cross-platform development needs.

3.3.1 React Native

React Native is an open-source framework that was developed by Meta Platforms [73] that allows developers to build mobile applications for both iOS and Android platforms using

JavaScript [63] and React components. React Native was first introduced in 2015 and has since become one of the most popular choices for mobile development. React Native is also useful as it lets developers create mobile apps using familiar tools used in web development.

React Native works by allowing developers to write JavaScript code that is executed on both iOS and Android platforms. This process involves several key steps:

1. **JavaScript:** The JavaScript code written by developers is executed by a JavaScript engine, such as Hermes on Android or JavaScriptCore on iOS. This engine runs the code and manages the application's state.

2. **Communication with Native Modules:** When the application needs to access device-specific features like the camera or GPS, React Native communicates with native modules written in languages like Java, Kotlin, Swift, or Objective-C. These modules provide the necessary interfaces to interact with the device's hardware.

3. **Rendering UI Components**: React Native uses a set of pre-built native UI components that are rendered on the device. These components are designed to mimic the native look and feel of each platform, which ensures that the application appears consistent along with other applications on the device.

4. React Native optimizes performance by batching updates and minimizing unnecessary re-renders. This is similar to how React works in web development. In React Native, this means that multiple state updates are processed together, reducing the number of times the app needs to re-render, which helps maintain a smooth and responsive user experience.

One of the advantages of React Native is its ability to support cross-platform development, which allows developers to write a single codebase that is executed on both iOS and Android platforms, helping to reduce development time and costs. React Native also supports hot reloading, allowing developers to immediately see the results of code changes without rebuilding the entire application. Additionally, it offers a native-like performance by leveraging native components and APIs [65], resulting in high-performance mobile applications. The framework's large and active community also contributes to its ecosystem with a wide range of libraries and tools, making it easier for developers to access resources and find solutions.

Brief overview of other technologies:

- **API (Application Programming Interface) [65]:** is a set of rules and protocols that allow different software systems to communicate with each other. It acts as a bridge between applications, enabling them to exchange data or services. APIs are commonly used to integrate functionalities from external services into applications, such as payment processing or weather data retrieval. Nowadays, APIs often return data in JSON format, which is a common method for exchanging data between systems.

- **JSON (JavaScript Object Notation) [66]:** is a lightweight, text-based data interchange format used to exchange data between web servers and clients. Because of its ease of use and readability, it quickly became one of the most popular choices for web development. JSON represents data in key-value pairs and arrays, and it is language-independent, allowing it to be used across various programming languages.

3.3.2 Garmin Health API

The Garmin Health API [64] is a technology developed by Garmin that allows developers to access health and activity data collected by Garmin wearable devices. This technology allows developers to securely integrate this data into their applications, and it is primarily used in healthcare, fitness, and research applications to monitor individual health data. By integrating the Garmin Health API into applications, developers can build personalized tools that promote health and well-being. Access to the API is free for approved developers, although commercial use requires a licensing fee.

3.3.2.1 Garmin Integration via 3ahealth Platform

To connect the user's smartwatch with the mobile application, the integration of Garmin Connect is achieved using a third-party bridge provided by 3ahealth. This platform acts as a middleman that enables secure access to health and activity data collected by the Garmin device.

Figure 3.2 3ahealth Bridge Interface for Garmin Integration

This connection can be done by using the OAuth 2.0 authorization framework, a technology that is widely used and is an industry standard for secure access delegation. When users choose to sync their Garmin device, they are redirected to the official Garmin Connect login page (Figure 3.3). After successfully authenticating with their credentials, the application receives permissions in the form of an access token, so that the application can access the user's activity data.

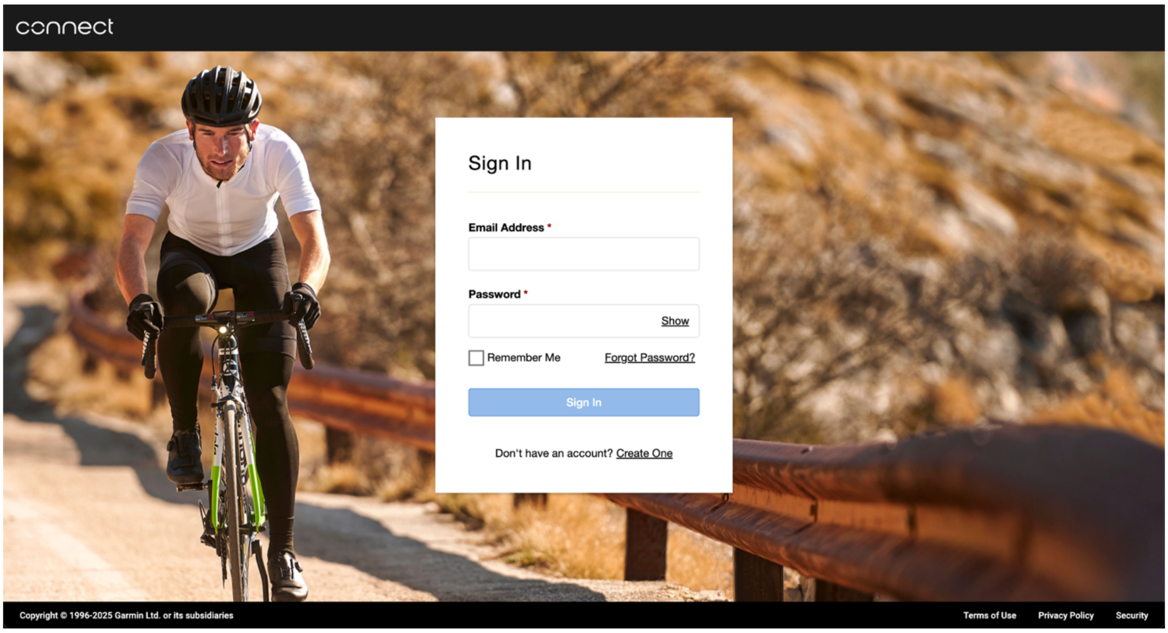

Figure 3.3 Garmin Connect Login Page

Once the user is authenticated, the application communicates with a secure API endpoint that is provided by 3ahealth, which returns a JSON response containing the user's Garmin data. Specifically, the application accesses the */garmin/dailies* endpoint, which delivers structured health metrics such as daily step count, floors climbed, active kilocalories, heart rate metrics, stress levels, and intensity duration. This data is then parsed and used by the application to properly display and visualize these summaries of the user's health activity within the mobile interface.

3.3.3 Webstorm IDE

Webstorm [74] is an integrated development environment (IDE) developed by JetBrains, and it was used throughout the implementation of the mobile application. It is provided with the necessary tools and a feature-rich environment for writing, testing, and debugging the React Native codebase. One of the most helpful features of WebStorm during the development was its seamless integration with the Android Emulator. This allowed for writing code and testing the results of the application without having to switch to external tools. The built-in terminal and version control also contributed to a smoother workflow, allowing the project to be managed and updated in a single development interface. WebStorm's support for React Native development made it a very effective tool to build and maintain the application.

3.3.4 Libraries used

The following libraries were utilized in the development of the smartwatch section of the PATHeD mobile application:

Table 3.2 React Native Libraries and Their Core Function

Library:	**Description:**
react-native-webview	Provides a WebView component for embedding web content in React Native apps.
react-native-progress & react-native-svg	Enables customizable progress indicators like bars, circles, and pies using SVG rendering.
react-native-gifted-charts	Offers rich chart types (bar, line, pie, donut) with animations and gradient effects.
react-native-segmented-control	Provides a WebView component for embedding web content in React Native apps.
moment	Simplifies date parsing, validation, and formatting with support for internationalization.
react-native-vector-icons	Offers vector icons from popular sets like FontAwesome.
react-native-calendars	Customizable calendar component supporting date marking, range selection, and localization.
react-native-async-storage	Persistent key-value storage for offline data management in React Native apps.
react-native-html-to-pdf	Converts HTML strings to PDF documents for exporting data.
react-native-view-shot	Captures React Native views as images (PNG/JPG) for embedding in PDFs or other uses.

react-native-fs	Provides access to the device's file system for saving and retrieving files.

3.4 System Architecture

This section provides a high-level overview of the mobile application's architecture. It describes the application's core functionalities, explains how users interact with it, and outlines how various technologies and components are used to provide a seamless experience.

FIGURE FLOWCHART

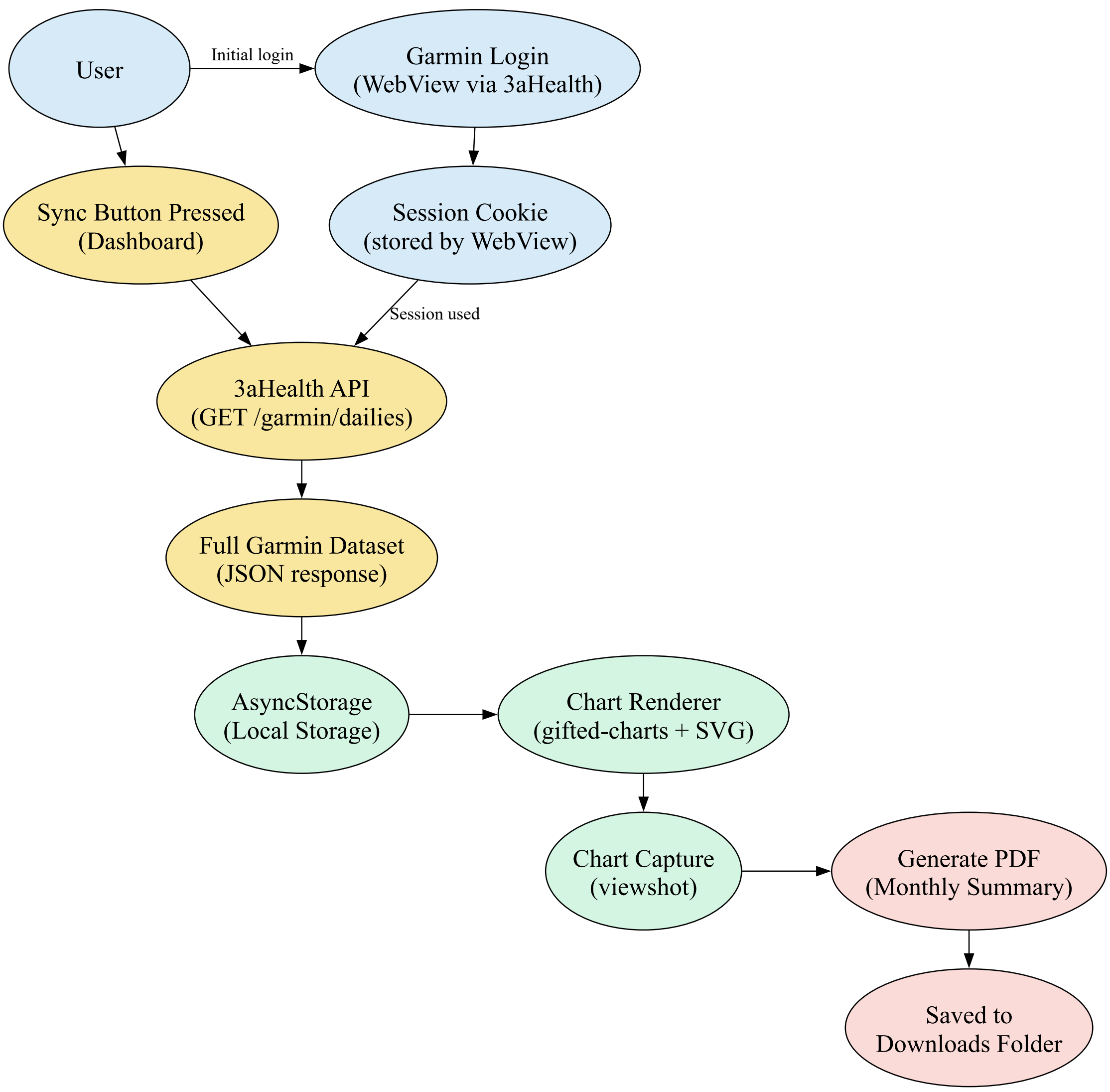

Figure 3.4 Smartwatch Sync and Report Generation Architecture

Figure 3.4 illustrates the architecture of the smartwatch synchronization and report generation process within the mobile application. The flow begins when the user initiates synchronization from the dashboard. If the user is not logged in, they will be prompted to do so. Once logged in, a session cookie is stored and reused for authorized API access. The app then fetches the complete Garmin data, which is stored locally using AsyncStorage and rendered into charts using the *gifted-charts* library. The visualized charts are captured using the ViewShot library, converting the view into an image. Finally, a monthly summary is generated as a PDF and saved to the device.

3.4.1 PATHeD application

The smartwatch data monitoring application is part of a larger application called PATheD [67]. This platform addresses a significant gap in the European healthcare system, where the sharing of patient data across different countries in the EU remains limited, mainly due to strict regulations and language barriers. The primary goal of the application is to provide a unified solution for storing and sharing medical records with healthcare providers across the European Union. A key feature of PATHeD is the translation of medical records, which is very practical and useful when patients seek medical care abroad. This functionality ensures that healthcare providers can access a patient’s medical history in their own language, significantly reducing the risk of misdiagnosis and improving the patient experience and the overall quality of cross-border care.

3.4.2 Smartwatch Data Monitoring

Smartwatch data monitoring involves connecting a Garmin smartwatch to the mobile application, allowing the user to view detailed health metrics collected by the device and export this data into a PDF report. The main screen specifically displays a daily summary of the user’s steps, floors climbed, average heart rate, active kilocalories, intensity minutes, and stress levels. The user can also select a specific date to view metrics from previous days. Tapping on any of those metrics opens a detailed view with additional information, including charts for the selected week or month, along with weekly and monthly averages of that metric. For heart rate data, the user can further view the hourly averages across the selected day, offering a more in-depth view of cardiovascular trends throughout the day.

At the top right corner of the main screen, two key options are available: one for manually syncing the latest data from the Garmin API endpoint, and another for navigating to the smartwatch menu screen. Within this screen, the user can generate a health report for a selected period of time and manage the connection status of their smartwatch.

The following sections provide a more detailed overview of each screen, along with their respective functionalities. Each interface was designed with user-centric principles in mind to ensure the accessibility and ease of use of application.

3.4.2.1 Smartwatch Dashboard Screen

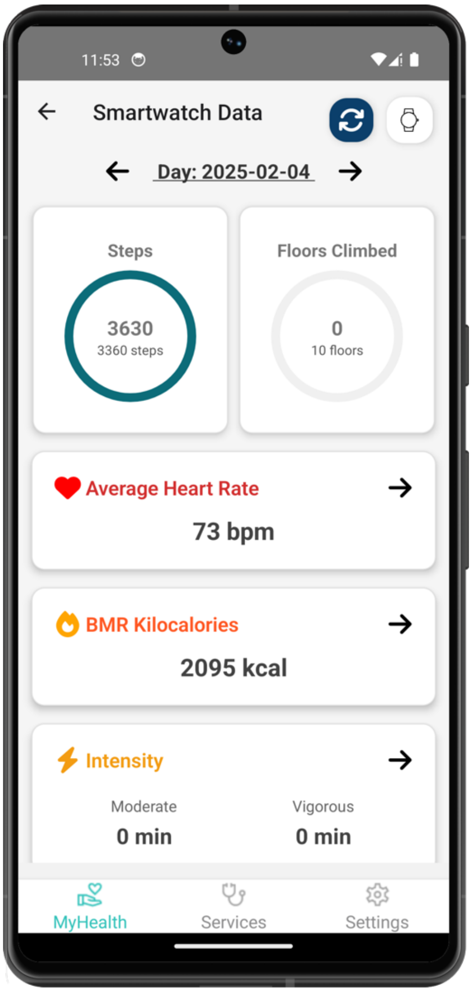

Figure 3.5 Dashboard Screen

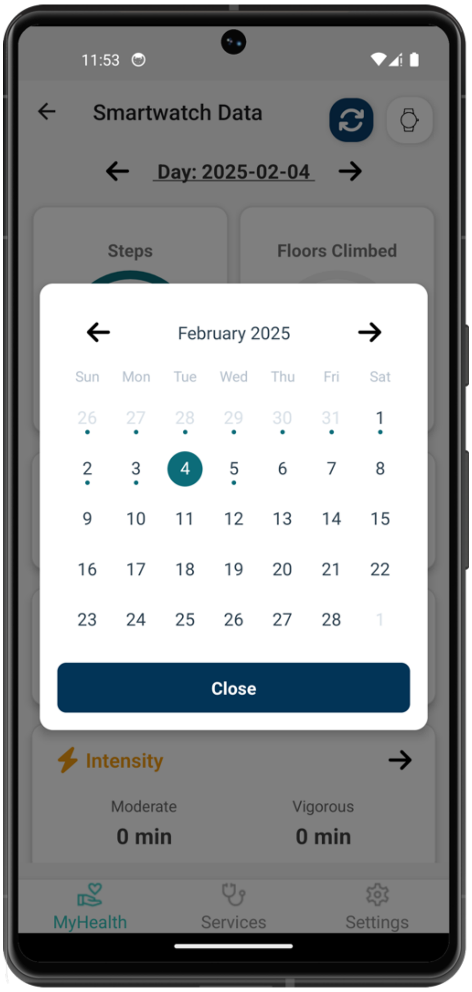

Figure 3.6 Calendar Modal

The Smartwatch Dashboard screen works as the central hub for the user's daily health data. It displays a summary of all key metrics collected on the selected day, including steps, floors climbed, heart rate, kilocalories, stress levels, and intensity minutes. Each metric is shown as an interactive card with the metric information. By tapping on any of these cards, the user is navigated to the corresponding detailed view that displays a chart with visual representation of the numbers of that metric.

At the top of the screen, the selected date is displayed. By tapping this date as shown in figure 3.6, a calendar view is triggered, allowing the user to browse and select any previous day for which data has been collected. This provides flexibility in selecting specific day of health data and supports more informed health tracking over time.

At the top-right corner of the screen, two icons are available:

- **Sync Icon:** Initiates a manual pull of the latest health data from the Garmin API via the 3aHealth endpoint (more information on that below).

- **Menu Icon:** Navigates to the Smartwatch Menu screen, which allows users to generate PDF reports or manage their smartwatch connection.

3.4.2.2 Detailed metrics view

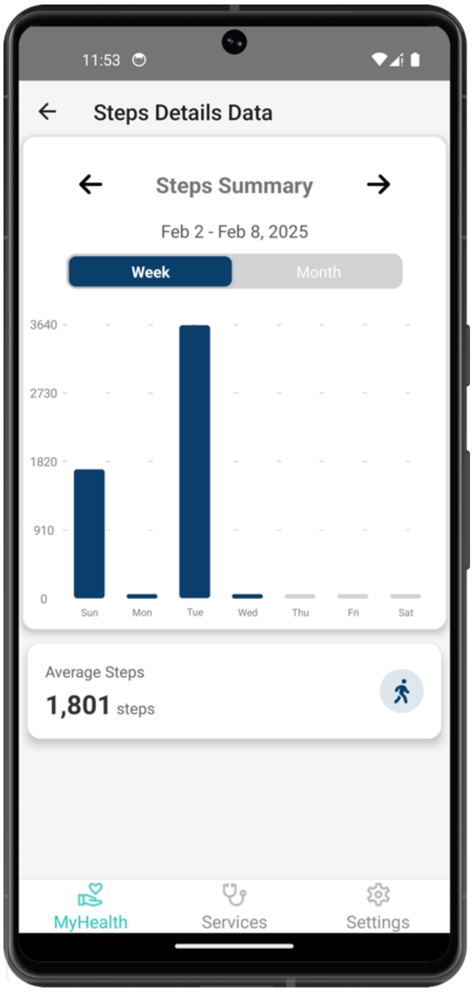

Figure 3.7 Weekly Summary Screen

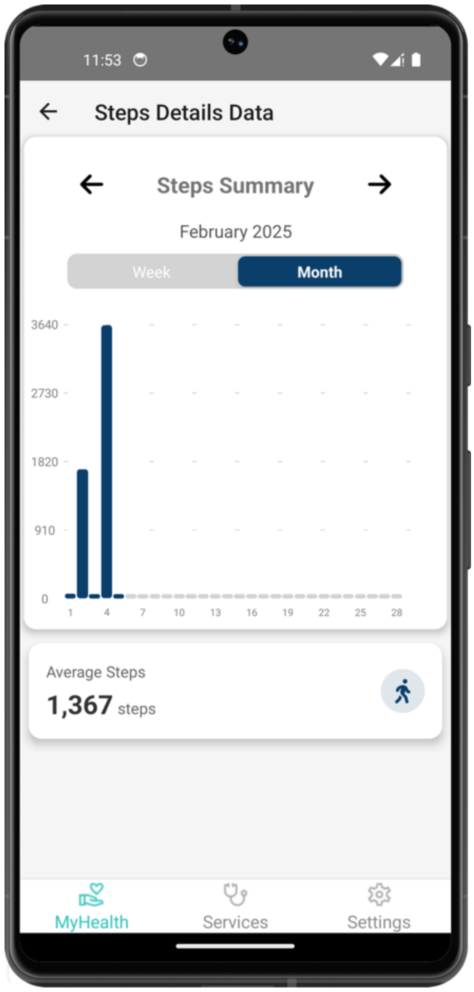

Figure 3.8 Monthly Summary Screen

After selecting a metric from the smartwatch dashboard screen, the user is navigated to a dedicated Details View screen. This screen provides a more comprehensive visualization of the selected health metric, including weekly and monthly summaries of that metric in the form of a bar chart, and in the case of heart rate data, hourly summaries in the form of a line chart for the selected day. At the bottom there's a summary of the average value over the selected period.

These visualizations enable users to better understand trends in their daily physical activity and well-being, making the data more actionable both personally and clinically. Each screen features a clean and minimalistic layout focused on a chart section with key statistics below. Additionally, the consistent interface allows users to quickly find and view the desired metric.

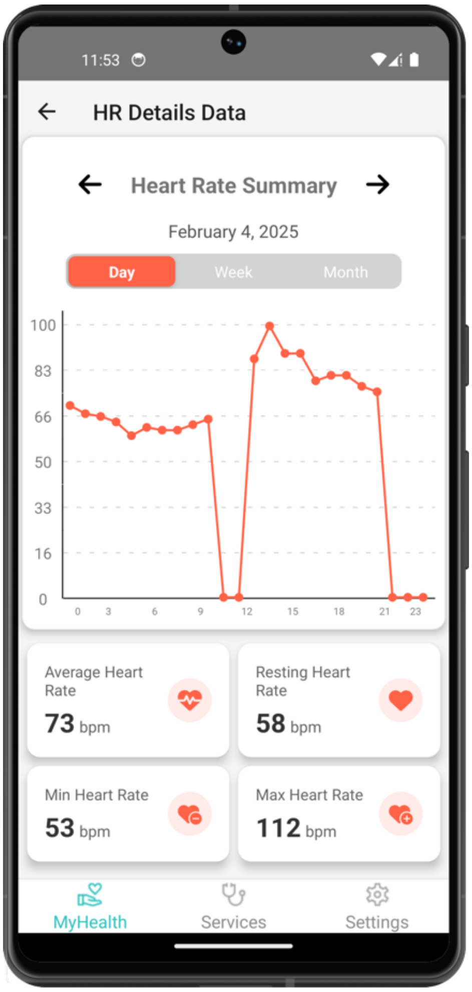

Figure 3.9 Daily Heart Rate View

The Heart Rate screen offers the ability to switch between daily, weekly, and monthly views. The daily view is unique in that it shows a line chart representing hourly average heart rate readings, providing more granular insight into cardiovascular activity throughout the day.

Below the chart, key summary indicators are presented:

- Average heart rate
- Resting heart rate
- Minimum heart rate
- Maximum heart rate

This view is especially useful for identifying peaks during physical activity and periods of rest.

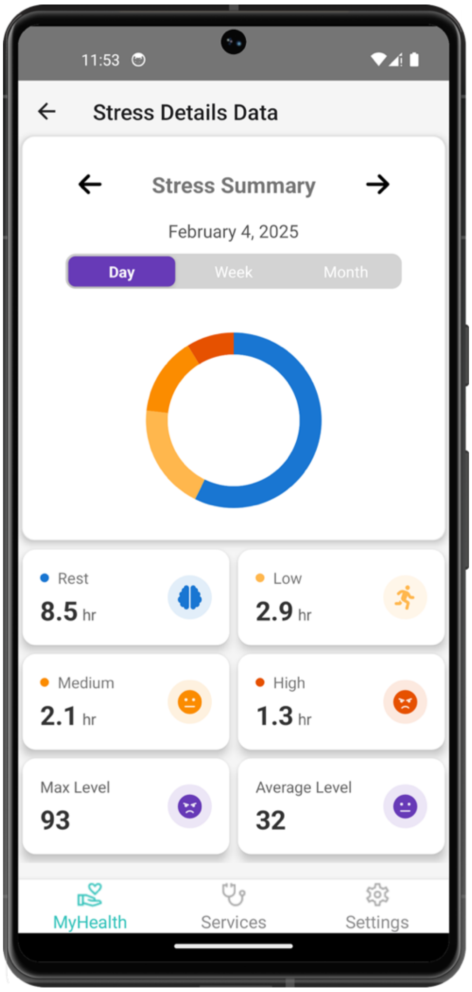

Figure 3.10 Daily Stress View

The Stress screen is the only metric that includes both a daily pie chart and detailed durations of each stress level. In the daily view, a pie chart shows the distribution of time spent in each stress category: Rest, Low, Medium, and High.

Additionally, the screen displays:

- Total minutes in each category
- Maximum stress level of the day
- Average stress level

In the weekly and monthly views, a bar chart displays the average daily stress level, accompanied by a summary of the overall average.

3.4.2.3 Smartwatch menu screen

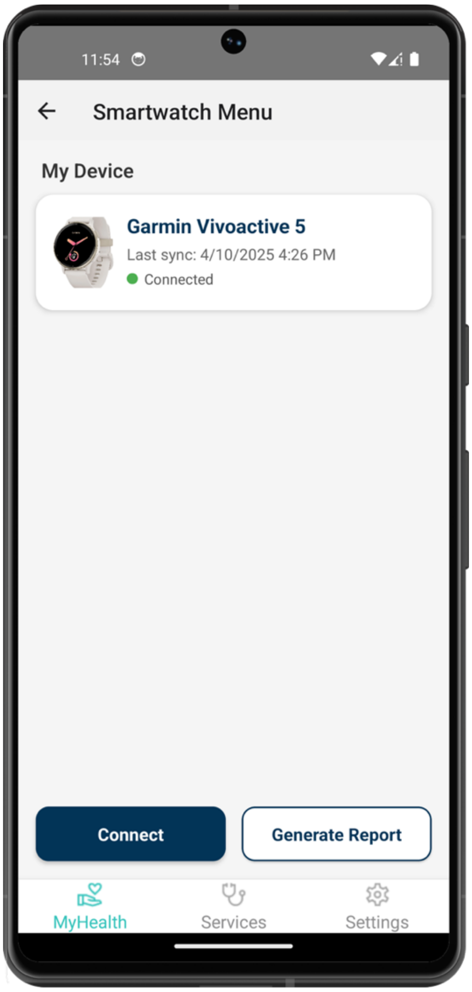

Figure 3.11 Menu Screen

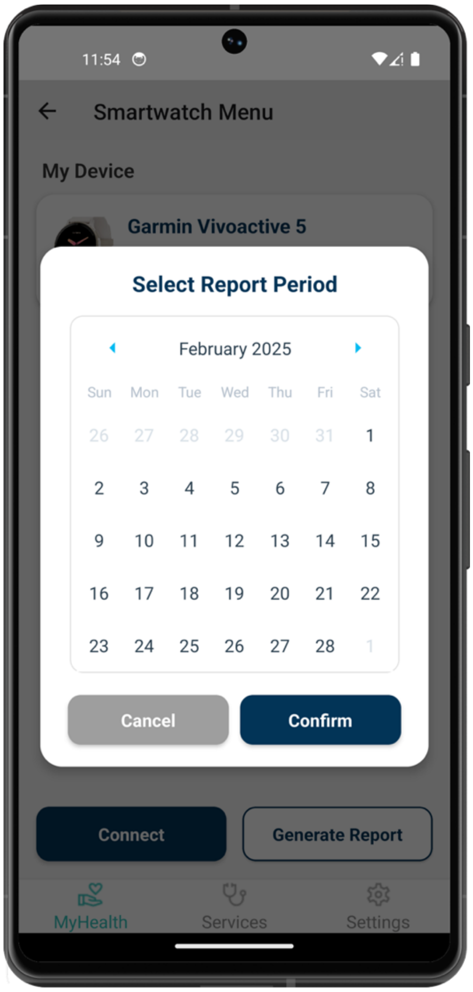

Figure 3.12 Report Period Screen

The Smartwatch Menu screen provides users with a centralized interface to manage their device connections and generate summary reports. Specifically, this screen presents information about the Garmin watch, such as the last time the data was successfully synced and the connection status, which is directly associated with whether the user has authenticated their Garmin account to view the 3aHealth OAuth process (covered in Section 3.4.2.1).

At the bottom of the screen, two main actions are available:

- **Connect:** This functionality allows users to authorize the app to access their Garmin health data. It is a critical step, as without completing this connection, the app cannot retrieve any metrics. This ensures that the data visualized throughout the application is directly personalized and sourced from the authenticated user's device.

- **Generate Report:** This feature opens a date selector that enables users to choose a specific time period for exporting their health data. The app then generates a PDF summary, embedding charts for each metric. This report can be used to communicate with healthcare professionals, providing a structured and visual overview of recent health trends. It is especially useful during medical checkups to give doctors quick insights into the user's well-being.

3.5 Methodology

The project involved creating a smartwatch section in the mobile application called PATHeD [56], connecting a smartwatch, and displaying all the metrics collected from those devices. PATHeD in general is an application that facilitates electronic health records (EHR), and provides users with the ability to access their health data.

Workflow

During the development of the mobile application, I followed a solo Agile workflow and adjusted to the needs and dynamics of working independently. My methodology and process were flexible, iterative, and responsive to feedback. I began with a general idea of the application's goals and core features, but instead of completing all the planning from the start, I allowed the design and functionalities to evolve throughout the development cycle. This approach aligned with key Agile principles, particularly emphasizing the importance of responding to changing functionalities and delivering working software frequently.

Development proceeded through a series of informal iterations, during which I would identify a feature or task, implement it, test it, and refine it based on the outcome. This approach allowed me to continuously improve the application and make decisions in real time, often prioritizing functionality and user experience based on insights that emerged during hands-on development. Although I did not follow formal Agile workflows like daily stand-ups or retrospectives, I frequently reviewed my progress, addressed challenges, and adjusted priorities accordingly. This self-directed and adaptive workflow proved effective for solo development, enabling me to maintain momentum while remaining flexible and aligned with the project's evolving needs.

3.5.1 Application structure and core functionalities

The smartwatch section of the mobile application is built using a modular structure based on the principles of component-based development in React Native. Each core feature, such as syncing Garmin data, visualizing metrics, and generating reports, is encapsulated within a dedicated component or screen, following the practices of separation and reusability.

When the user presses the sync button on the Smartwatch Dashboard screen, the application initiates a data fetch request to the 3aHealth server, which acts as a middleware to the Garmin Health API. This request retrieves a complete JSON dataset of the user's health records from the day access was granted until today. The response is stored locally on the device using *AsyncStorage*

Once stored, the data is parsed and visualized in the form of interactive bar and line charts. This is handled using *react-native-gifted-charts* and *react-native-svg*, allowing users to explore their metrics across daily, weekly, and monthly views.

For documentation or sharing reasons, the user can generate a PDF health report directly from the app. This process works by rendering each chart in the background using *react-native-view-shot,* which captures them as image snapshots, and embeds them into an HTML, which then is downloaded as a PDF using *react-native-html-to-pdf*. The final document is saved on the device’s Downloads folder using *react-native-fs*.

Chapter 4

Pilot Study and Evaluation

4.1 Pre-questionnaire analysis

The purpose of this pilot study was to evaluate the user experience and usability of the smartwatch data monitoring application. The pilot was carried out as a preliminary evaluation to gather user feedback, identify any likely design improvements, and determine the overall acceptance and effectiveness of the features developed among real users. Originally, the evaluation was intended to be conducted exclusively with healthcare professionals (such as nurses and doctors) during an in-person presentation. However, due to the limited participation during the event, the study was expanded to include a broader sample of individuals, including friends and family, in order to increase the number of participants and improve the reliability of the observations.

Participants were not required to own a Garmin smartwatch. Instead, they were provided with a pre-configured version of the mobile application that displayed health data collected from a Garmin Vivoactive 5 device previously worn by the author. This approach allowed participants to interact with the app as if they were real users, exploring the various features that it includes.

Each participant was given around 20 minutes to explore the app on their own. The main goal of this hands-on activity was to let them try out the core features as if they were regular users, check the dashboard, switch between days, view the detailed metrics, and test the PDF export. There was no fixed list of tasks to follow. Instead, participants were simply asked to go through the app naturally, just like they would if they had downloaded it themselves. This helped show which parts of the app felt intuitive and easy to use and which ones might be confusing and require extra effort.

During this time, participants were observed while they interacted freely with the application. At the beginning of the session, it was explained that the health data displayed had been collected from a Garmin Vivoactive 5 device and that all features of the app were functional and interactive. Participants were encouraged to ask questions and share their thoughts as they explored the interface. After that, they were asked to complete a questionnaire to evaluate the application's usability, design, and general user experience (see below). Additional feedback was also collected through brief informal interviews (see Section 4.2), in which participants were encouraged to reflect and suggest possible improvements.

4.1.1 Participant Demographics

Participants completed a brief survey that collected basic demographic information and assessed their familiarity with mobile health (mHealth) technologies. These data provide important context for understanding the usability results discussed in later sections.

Gender and Age distribution

The pilot study involved 31 participants (23 males and 8 females), including healthcare professionals, students, and people from other backgrounds. Demographic information was collected to better understand the sample group's background diversity. The key demographic attributes gathered were gender, age, and professional role.

Participants' ages were categorized into six groups, as shown in Figure 4.1. The majority of participants (18 individuals) fell into the 20–30 years category, followed by 5 participants aged 50–60, 3 participants aged 40–50, 3 participants aged 70 and above, 2 participants aged 30–40, and no participants in the 60–70 age group.

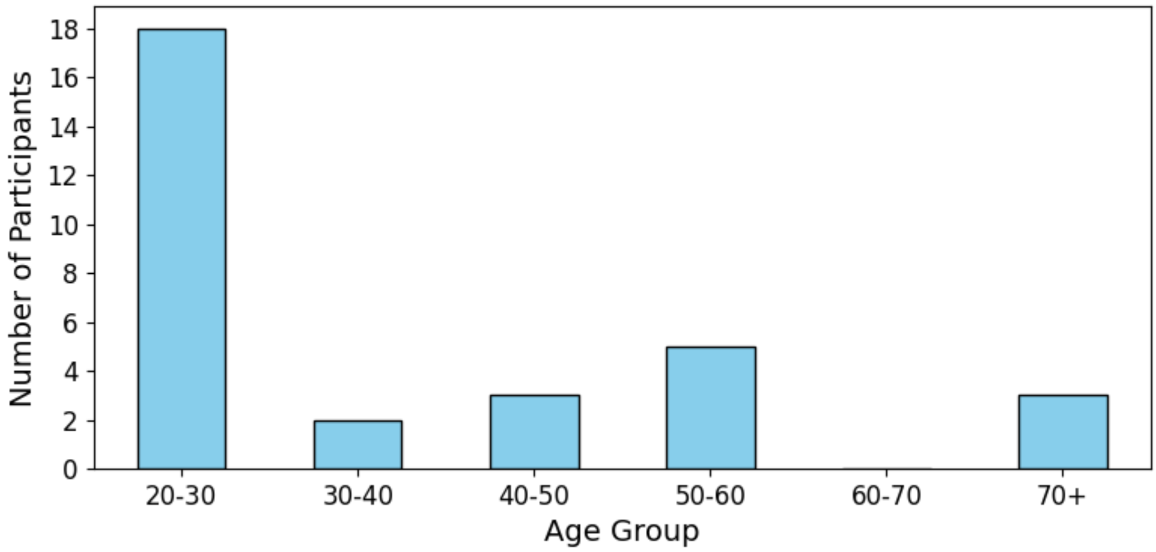

Figure 4.1 Age Group Distribution

Professional role

Participants were also asked to indicate their professional background. The responses included a mix of healthcare and non-healthcare fields. Specifically, 3 participants identified as nurses, 2 as doctors, 16 as students, 3 as elderly, and 6 as general users from a non-healthcare profession.

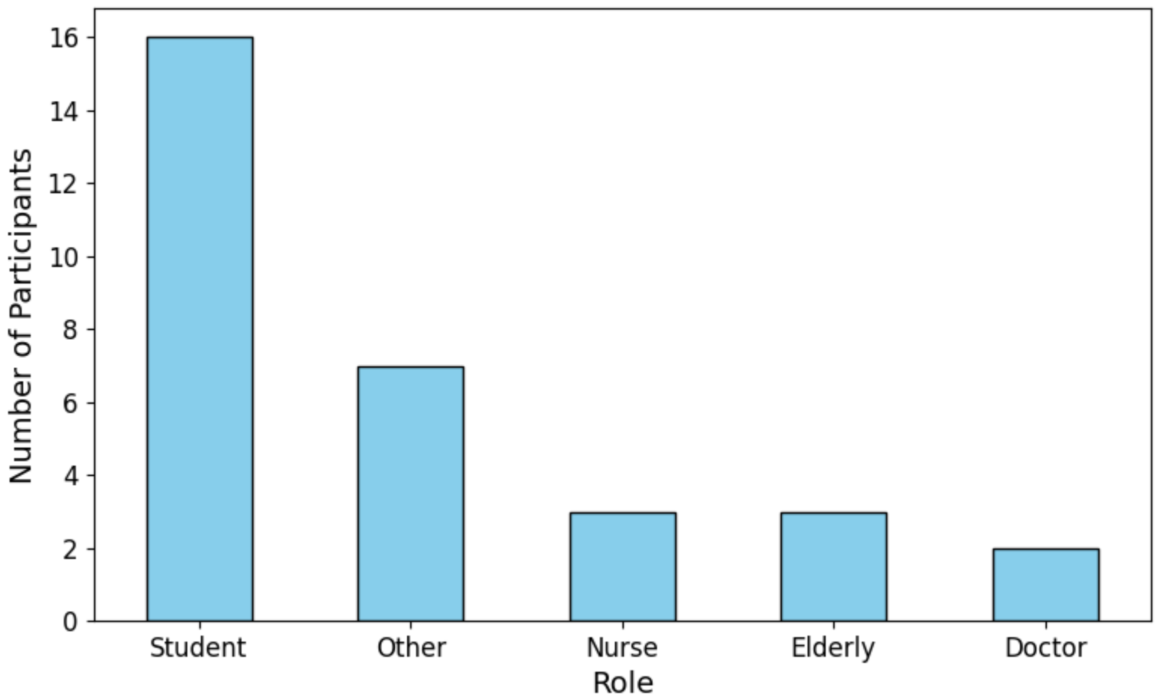

Figure 4.2 Participant Distribution By Role

4.1.2 Familiarity with mHealth and EHRs

To better understand the participants' baseline knowledge and expectations, two additional questions were included in the pre-questionnaire before the interaction with the app. These questions asked participants to indicate their familiarity with mHealth applications and electronic health records (EHRs). Both items were rated on a 5-point Likert scale, where 1 meant "Not familiar at all" and five meant "Very familiar." This helped to provide insight into how experienced participants were with digital health technologies in general. These self-evaluations allowed the analysis to account for prior exposure, which can influence how users use the app and judge its usefulness. Participants with higher familiarity might have had clearer expectations compared to those who are less familiar, who may have approached the app with more hesitation.

Familiarity with Mobile Health Applications:

Figure 4.4 displays the participants' self-assessed familiarity with other mobile health apps. The majority of participants reported moderate familiarity, with most responses being around 3 and 4 on the scale.

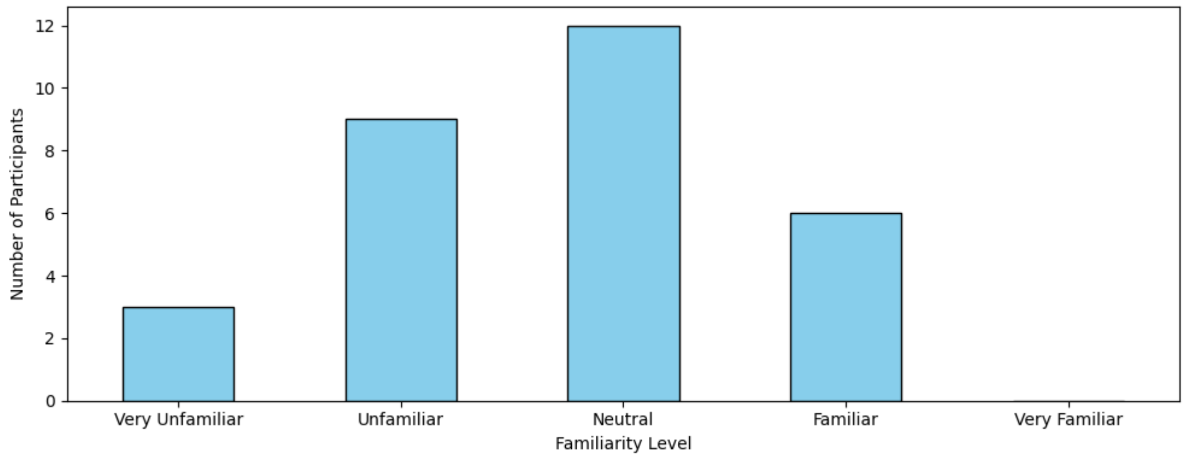

Figure 4.3 Familiarity With Mobile Health

This suggests that while many users were already accustomed to mobile applications related to health, a significant portion still needed a more intuitive onboarding experience.

Familiarity with Electronic Health Records (EHR):

Similarly, Figure 4.5 shows participants' familiarity with Electronic Health Records (EHRs). Responses were more widely distributed, with a slight direction towards lower familiarity (scores of 2–3). This indicates that while users may understand general health apps, specific concepts like structured EHR systems may still require better in-app explanations or user support.

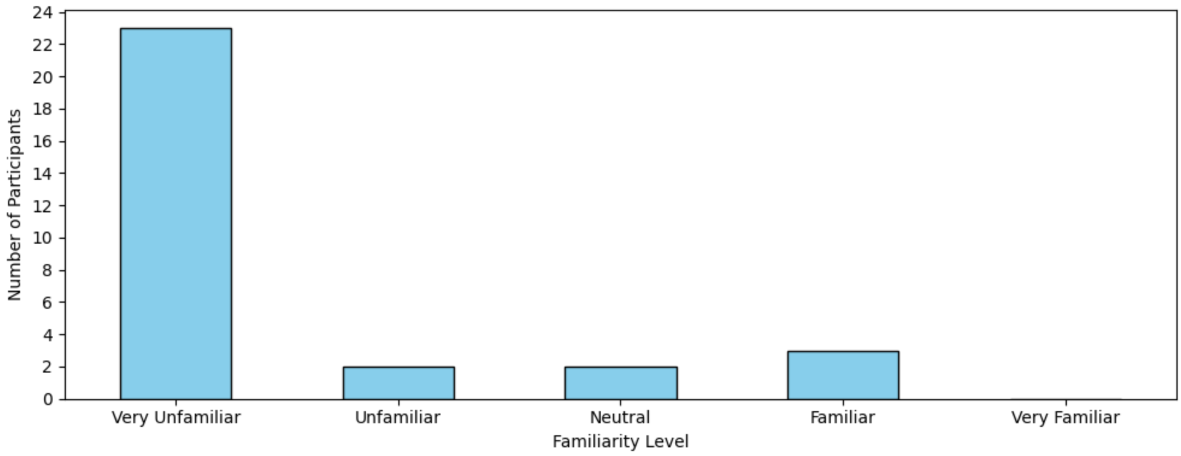

Figure 4.4 Familiarity With Electronic Health Records (EHRs)

The responses show that familiarity with Electronic Health Records (EHRs) was generally lower than familiarity with mobile health applications. This suggests that concepts such as patient record systems, clinical workflows, and EHR data were less understood by participants, especially those without a healthcare background. The broader and lower distribution of EHR familiarity scores indicates that structured health record systems were less familiar overall compared to general health apps within the sample group.

4.2 Post-questionnaire Analysis

This section presents the results of the mHealth App Usability Questionnaire (MAUQ) [69] that participants completed after their 20-minute interaction with the application. The MAUQ is a psychometrically validated tool for evaluating mobile health applications. The questionnaire included 18 questions on a 7-point scale, where one represented "Strongly Disagree" and seven represented "Strongly Agree".

4.2.1 MAUQ Usability Results

Figure 4.6 presents the aggregated responses for each item of the MAUQ. Overall, participants revealed positive opinions, with high levels of agreement regarding key items such as ease of use, usefulness, and interface satisfaction for health monitoring.
Specifically, the ease of navigation between screens (S3) received one of the highest average scores, indicating that participants found it intuitive to move between different parts of the application. Similarly, the clarity and organization of information (S7) were highly rated, suggesting that users easily understood and accessed the data presented. Furthermore, overall satisfaction with the app (S12) was also notably high, reflecting a generally positive user experience.

In contrast, slightly lower, but still positive ratings were observed for using the application when the internet connection was poor (S17) and regarding the extent to which the app helped users take control of their health (S15). Despite these minor variations, all average scores remained above 5, indicating a strong overall level of satisfaction with the usability and design of the application.

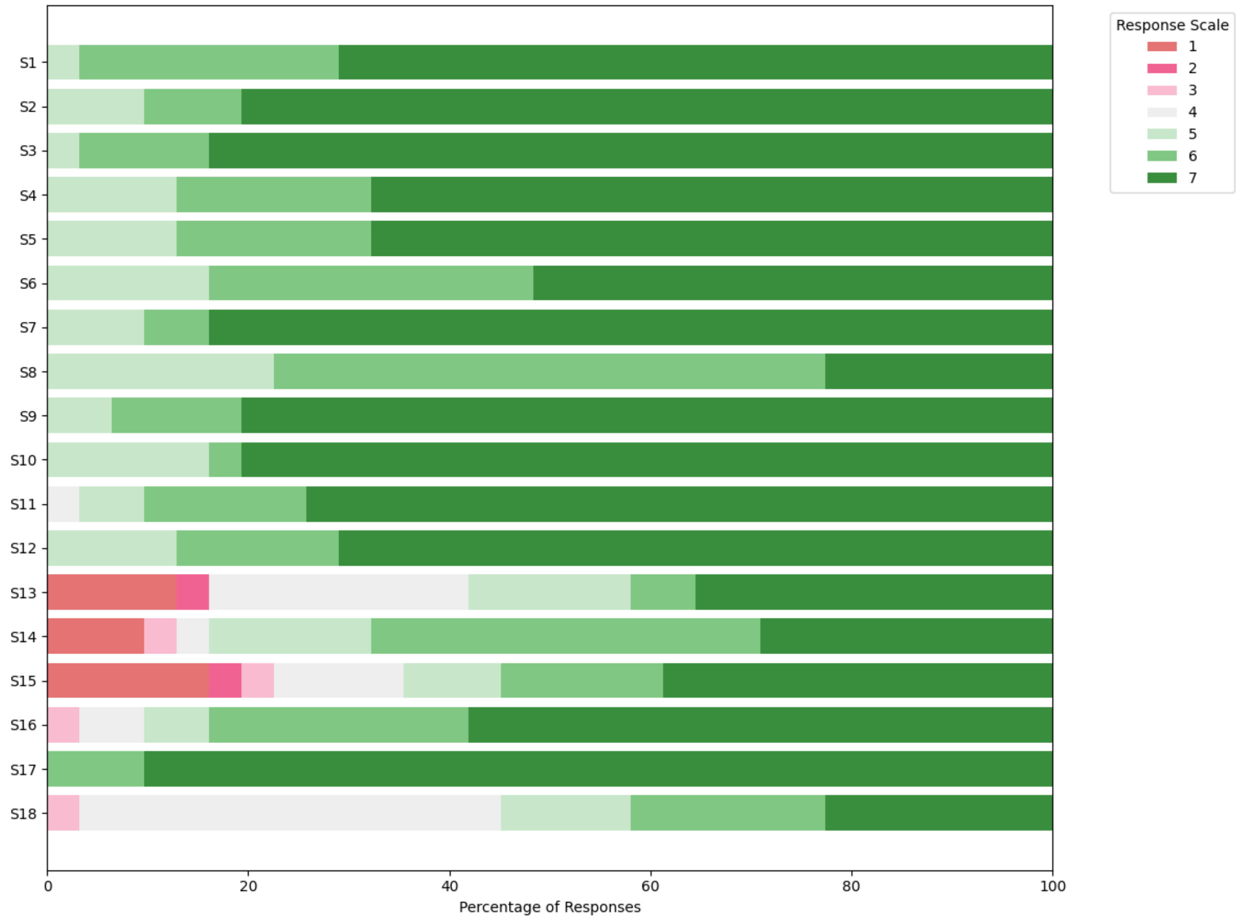

Figure 4.5 MAUQ Response Distribution (Likert Scale 1-7)

Nevertheless, all average scores remained above 5, indicating generally high satisfaction with the usability and usefulness of the application.

4.2.2 Overall Usability Score

The overall usability score was calculated by averaging all responses to the 18 MAUQ questions across all participants. The bar chart below shows each participant's mean (their 18-item average):

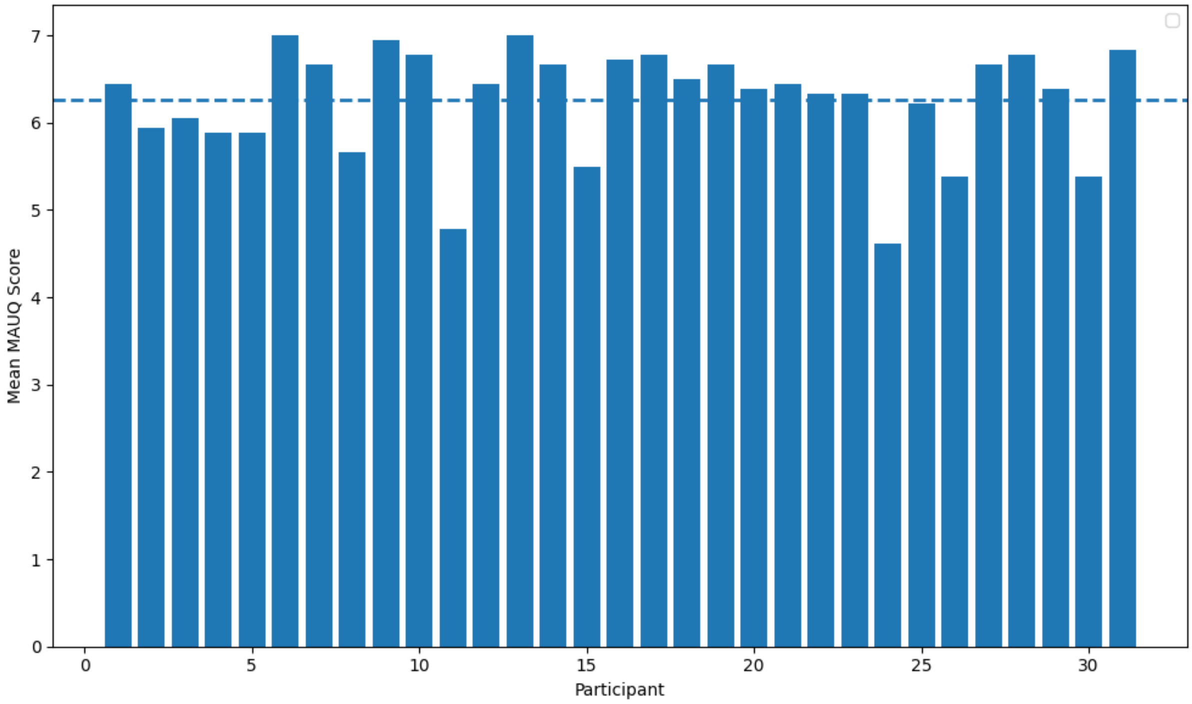

Figure 4.6 Overall Usability Score per Participant

The overall score was computed using the following formula:

$$Overall\ Usability\ Score\ =\ \frac{\sum All\ S1 - S18\ responses}{18\ x\ Number\ of\ Participants}$$

Figure 4.7 Overall Usability Score calculation formula

The calculated overall usability score was **6.26 out of 7**.

According to the MAUQ interpretation guidelines, a score between 6.0 and 7.0 indicates excellent usability, while lower ranges indicate good or moderate usability. Given the obtained score, the smartwatch data monitoring application can be classified as having excellent usability, suggesting that it offers a highly effective, user-friendly, and satisfying experience for general users.

4.2.3 Question-to-Question Correlation Analysis

The eighteen MAUQ questions were compared in pairs to see how similarly participants responded to different parts of the app's usability. Using the 31 questionnaires that were fully completed, a Spearman-rank [47] correlation matrix was generated and is presented as a heat-map in Figure 4.7. Spearman's method was used because the answers were given on a seven-point rating system, which means they represent ordered categories rather than precise numerical values.

Across the 153 possible pairs, Spearman correlation coefficients ranged from –0.15 to +0.93, with a median absolute value of $|\rho| = 0.41$. This mid-range figure suggests a healthy balance: the questions are similar enough to show they relate to the same overall concept, but not so closely linked that they are all asking the same questions. Of all item pairs, 57 showed strong correlations ($|\rho| \geq 0.5$), and 55 were weakly correlated ($|\rho| \leq 0.3$), which supports the idea that the scale captures a mix of consistency and nuance. For this reason, we chose to use a systematic and validated questionnaire rather than opting for a custom set of questions. The established reliability of the MAUQ questionnaire makes it especially suitable for assessing user experience in digital health applications. The overall consistency of the answers, measured by Cronbach's alpha [46], was 0.88. This level of consistency is considered "good" for a pilot study and shows that the total score can be trusted to provide a reliable picture of usability.

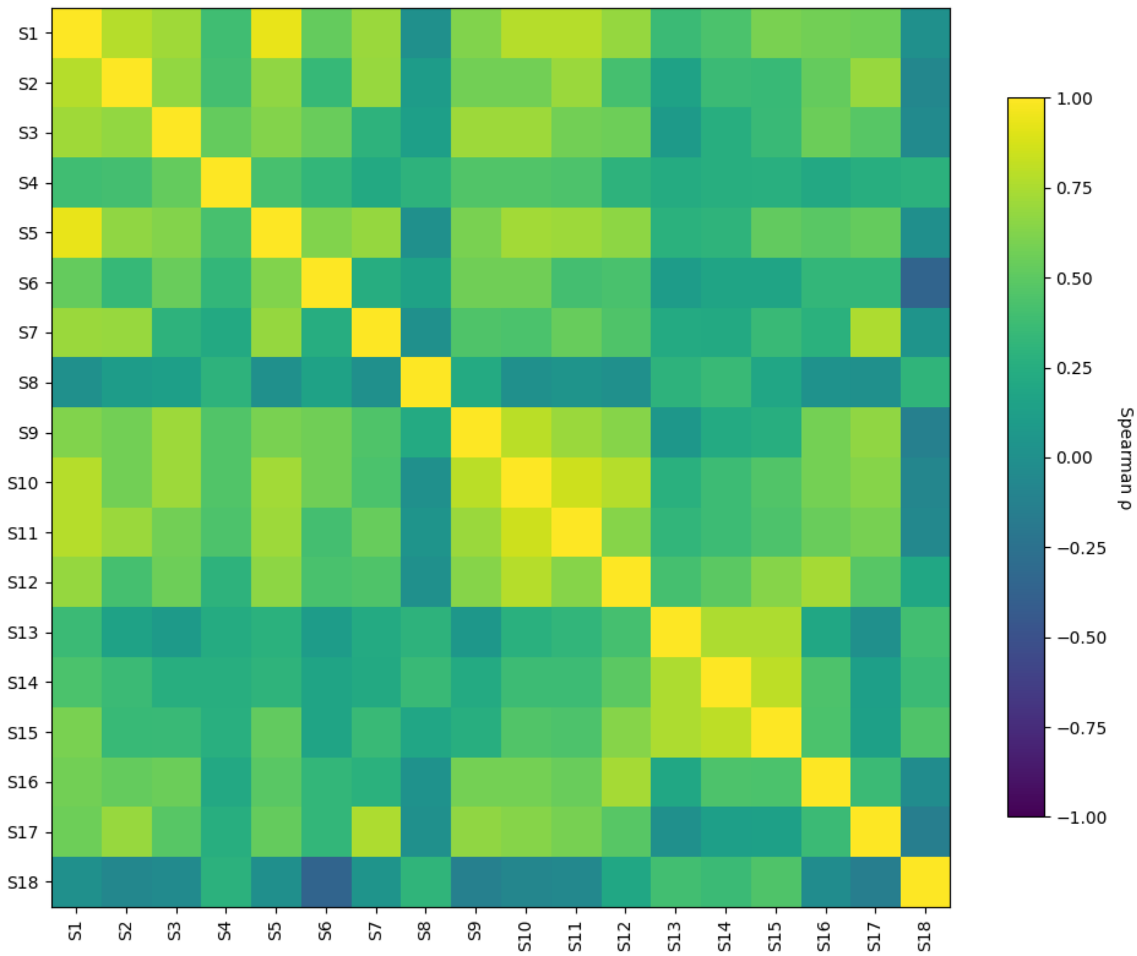

Figure 4.7 Correlation Matrix of MAUQ Questionnaire Items (S1-S18)

This heatmap visualizes the Spearman correlation coefficients between the 18 MAUQ questions. Warmer colours (toward yellow) indicate stronger positive correlations. Cooler colours (toward purple) reflect weaker or negative correlations.

As shown in Figure 4.7, several clusters of strong correlations can be seen, especially among the items that are about ease of use, screen navigation, and information layout. Items such as S1, S2, S3, S5, and S10, all concerned with how clearly information is displayed or how easily a user can move through the interface, share coefficients well above $\rho = 0.70$. This tight grouping suggests that participants did not experience those features in isolation. Instead, they fused them into a single, highly consistent impression of *navigational usability*.

By contrast, the four questions that ask how medically useful the application is (**S13–S16**) reveal a more mixed pattern. Most cross-item correlations are weak ($|\rho| \leq 0.30$), yet S13, S14, and S15 cluster closely with one another ($\rho \approx 0.75$–0.80). This split can be explained by the background of the participants: the majority of participants were friends and family with no clinical backgrounds, while the rest were healthcare professionals. Nurses and doctors evaluated the app based on whether the data would actually inform care decisions and assist them in their work, unlike general participants. Non-professionals, when faced with questions such as "The app would be useful for my health-care practice," selected a lower-range option simply because the question did not fit their day-to-day reality. As a result, even when everyone agreed that the interface was smooth, the non-professionals still rated clinical usefulness lower. The key takeaway is that clinical staff typically recognized the clear value of the data the app offers in a clinical setting, whereas many non-professionals did not, as they are not healthcare professionals, and that difference is what keeps the usefulness scores from moving in lock-step with the navigation scores.

No strong negative correlations appear in the matrix, so none of the items work in the opposite direction to the others. The moderate overall connections between the questions, together with the absence of any large negative relationships, show that the questionnaire works well for its purpose while still being able to reflect different parts of the user experience separately.

Finally, because the sample size is relatively small, the correlation values should be viewed with some caution. A difference of 0.15 to 0.20 in either direction could occur purely by chance with a sample size of only thirty-one people. For that reason, the present analysis isn't meant to rank each individual pair of questions too precisely. Instead, it focuses on identifying broader patterns, like clusters of related items or signs of overlap between questions, that can help guide improvements to the questionnaire in the future.

4.3 Interview Feedback

In addition to the structured questionnaires, brief informal interviews and open-ended comments were collected from participants after they completed their interaction with the application. The feedback collected focused on the app's strengths, weaknesses, and suggestions for improvements.

The overall response expressed by the participants was positive. Many described that the application was "clear", "well-organized", and "easy to navigate", particularly praising the presentation of health metrics and ease of navigation through the dashboard interface. Some of the respondents stated that the app was "quite good" in its current form.

At the same time, participants provided several constructive suggestions for future improvements. A common feedback was the desire to expand the range of monitored health parameters. Multiple participants suggested adding new data types such as ECG readings and SpO_2 (oxygen saturation) to offer a more complete health monitoring experience.

Another important suggestion concerned the user interface design. Several participants expressed a preference for adding a dark mode option to enhance visual comfort during use. Some minor usability improvements were also proposed, such as adding an indicator during data synchronization processes to prevent confusion when updates are occuring in the background. Engaging with the graphical elements also came up as an issue. Specifically, one participant suggested implementing a touch-and-hold feature on the charts, where pressing on a graph could dynamically show exact measurement values, rather than requiring precise taps on specific bars or points.

Finally, accessibility was also mentioned by a few participants. One suggestion was to include a brief, quick-start guide or in-app demo for users unfamiliar with digital technology, particularly for older adults.

Overall, the feedback provided was constructive, confirming that while the application provides a strong foundation in its current version, future iterations could greatly benefit from additional features aimed at expanding functionality, improving accessibility, and further enhancing the user experience.

Chapter 5

Discussion

5.1 Discussion of Findings

This chapter discusses the results collected from the pilot study that is presented in Chapter 4 and explains what those results mean for the smartwatch data-monitoring application. It also examines how demographic factors such as age, professional background, and familiarity with mobile health apps and Electronic Health Records influence user feedback. By examining both the quantitative data from the mHealth App Usability Questionnaire (MAUQ) and the feedback gathered from participant interviews, this study identified the core strengths of the application that users found intuitive and effective, as well as the areas that require further improvement. Also, the results obtained largely influence the direction of future changes, including new features, broader device compatibility, and improved user experience.

5.2 Demographic Influence

Although the pilot involved only thirty-one participants, the mix of ages, professional roles, and prior exposure to digital health tools influenced the way participants judged the prototype. Understanding these variations is essential before generalizing the results.

Age:

Nearly two-thirds of participants were 20 to 30-year-olds who rated usability highly and primarily suggested improvements related to user interface and overall experience. In contrast, participants aged 50 to 60 also gave positive feedback but placed more emphasis on accessibility, such as larger touch areas on charts and easier onboarding features like a quick start guide or instructional video. These observations highlight how minor interface adjustments can significantly improve accessibility for older users without altering the core functionality of the application.

Professional role:

Five participants were healthcare professionals (three nurses and two doctors). While they also found the interface intuitive, their feedback centered more on the clinical utility of the app. They suggested the addition of additional metrics, such as ECG and SpO_2 trends. Meanwhile, students and general users focused more on user experience features such as dark mode and synchronization indicators. Different priorities across different audiences clarify why clinical-usefulness items do not correlate strongly with navigation and interface scores, the relevance of such features depends heavily on users' backgrounds and expectations.

Technological Knowledge

Self-ratings revealed overally a moderate familiarity with consumer mHealth apps (median = 4 on the five-point scale) and lower familiarity with structured Electronic Health Records (median = 3). Most participants were confident navigating features similar to mainstream fitness dashboards and were less confident when it came to more structured or clinically oriented systems like Electronic Health Records.

Gender

The sample was predominantly male (23 males and 8 females). While no significant gender-based differences were observed in this pilot, future studies should aim for a more balanced gender distribution. A more representative sample would help ensure broader applicability and potentially reveal gender-related differences in interaction styles or feature preferences.

5.3 Positive Feedback and Strengths

The questionnaire's score of 6.26 out of 7 was the most immediate and encouraging result, which is grouped within the "excellent" range according to the MAUQ usability guidelines. This result encapsulates what many participants expressed during their interaction with the application: a meaningful, well-organized, and easy-to-navigate app. Internal consistency metrics (Cronbach's $\alpha = 0.88$, as discussed in Section 4.2.3) further confirm that the eighteen questions functioned well as a unified scale while still capturing distinct aspects of user experience. The correlation analysis (Figure 4.7) reveals more subtle patterns in the data. Items related to screen navigation and the clarity of information layout (S1, S2, S3, S5, S10) formed a closely linked cluster, which indicates that users perceived these aspects as part of a unified concept of navigational usability.

In contrast, the four items that assess the perceived medical usefulness showed a weaker internal structure. While S13 to S15 were strongly correlated, they showed weak associations with interface-related items. This suggests that a well-designed user interface does not necessarily mean that users, especially those without a clinical background, perceive the application as medically valuable to them, simply because these concepts do not apply to their lifestyle. Without relevant experience or clinical context, non-professional users may find it difficult to assess features tied to clinical decision-making.

Individual questions addressing ease of navigation, clarity of information, and overall satisfaction received the highest mean scores, indicating that users found the interface easy to use and the layout to understand. This means that the user interface was considered to be intuitive, and the app's structure was simple to comprehend

The open-ended comments and interviews were also encouraging. Participants were generally satisfied with the way the application was structured and functioned, which suggest the application was up to their expectations.

5.4 Limitations and Suggestions

Although the general feedback was encouraging, participants also identified some areas that could be improved. One of the most frequent suggestions was increasing the amount of health metrics in the app. Several participants expressed that they would prefer to have extra metrics data like SpO_2 (oxygen saturation) and ECG (electrocardiogram readings), which would provide an overall better idea of an individual's health status.

However, the implementation of these features is currently constrained by limitations in the API provided (Section 3.3.2.1). While the present version of the application does not support these metrics, future work can be done to support these as well.

In addition to functionality, some minor usability concerns were mentioned. Some feedback that was mentioned from a few participants involved the lack of visual feedback when the app synchronized data from the smartwatch in the background. The participants expressed that this led to occasional confusion or the impression that the application had stalled. A way to address this is by implementing a loading indicator that helps the user identify the state and reduce this uncertainty during use. Furthermore, some participants provided comments on improving the interaction with graphical elements in the app. For example, it would be more suitable to have a press-and-hold feature on graphs to display the exact metric value rather than requiring precise taps on data points.

Another minor limitation is in sample size and composition. Due to the fact that the number of participants comprising of health professionals was small, the sample size expanded to include friends and family members. While this broadened the data set, it also meant that some questions, particularly those intended for healthcare professionals, could not be adequately answered by general users since they were not in a position to provide informed responses.

These limitations, while not critical, offer valuable insights for refining the application's functionality, interactivity, and usability of the application in future developments.

5.5 Future work

There are several opportunities for future development and enhancements of the smartwatch data monitoring application. One key area involves expanding the range of health metrics collected by the app. Future versions of the application could integrate additional metrics such as real-time ECG monitoring, SpO_2 (oxygen saturation), and sleep tracking. These additions would improve the app's value significantly for personal health monitoring and clinical usefulness. Another area of improvement is definitely the user interface. Several participants expressed a preference for a dark mode to improve eye comfort, and future updates should include this feature along with better visual feedback during the syncing with the smartwatch and an improved date and time format at the top of the dashboard in the main screen.

Device compatibility is also another important topic of consideration. Currently, the app is limited to only supporting Garmin smartwatches, so the app could extend the support of other brands as well, in doing so improving usability and adoption by a broader user base. In terms of functionality, the application could also integrate personalized insights and smart notifications based on user habits and data trends, making it more proactive in helping users into healthier habits.

A particularly useful and promising direction for future integration, as it was also mentioned and suggested as feedback during the pilot study, is combining the application with the emergency button functionality that will be available in future updates of the PATHeD application. Specifically, in the event of an emergency, this integration would allow first responders or healthcare professionals to immediately access the vital data of the wearer during an emergency, improving response efficiency and the safety of the patient.

Finally, although the pilot study provided valuable early feedback, future evaluations need to include real-world testing with participants using their own smartwatches over extended periods. This would allow for the collection of more realistic usage patterns, longer-term activity data, and better insight into users' behavior in engaging with the application in their daily routines.

Chapter 6

Conclusion

6.1 Overall Evaluation

This thesis presented the design, development, and pilot evaluation of a smartwatch based, health-monitoring application intended to improve day-to-day care and self-management of health. The proposed solution responds to the growing demand for accessible, and user-friendly tools that enhance remote health supervision.

The application allows users to synchronize data from a Garmin smartwatch and display key health indicators like steps, heart-rate metrics, stress level, active kilocalories, and intensity minutes, in an organized and interactive interface. All information is visualized through clear charts and can be exported as a PDF report for personal use or clinical consultation. The system is designed to be intuitive and easy to use, allowing even users with limited technical experience to navigate and operate the application easily. These design choices were validated through a pilot study involving a diverse group of participants, including healthcare professionals, students, elderly individuals, and general users.

The results of the pilot study showed high levels of satisfaction with the application's ease of use, accessibility, and practical value. The overall usability score of 6.26 out of 7, as it was evaluated from the questionnaire, which confirms that the application meets the needs of its intended users successfully. Participants highlighted the clarity of information presented, the seamless navigation, and the intuitiveness.

In conclusion, the smartwatch data monitoring application mentions about the practical gap in digital healthcare accessibility and addresses the potential for smart wearable technologies to support early health interventions. With the technology advancing, solutions like this will have an important role in a more efficient healthcare delivery, especially as demographic trends show a rising average age. Future work may include expanding the device compatibility, further improving the user experience, and integrating with other systems, further bridging the gap between patients and healthcare providers.

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Appendix A - MAUQ [69] Full Questionnaire

The following items comprise the full mHealth App Usability Questionnaire (MAUQ) used in this study. Participants responded using a 7-point Likert scale, where 1 = Strongly Disagree
And 7 = Strongly Agree

Ease of Use & Interface Design

- S1. The app was easy to use.
- S2. It was easy for me to learn to use the app.
- S3. The navigation was consistent when moving between screens.
- S4. The interface of the app allowed me to use all the functions (such as entering information, responding to reminders, viewing information) offered by the app.
- S5. Whenever I made a mistake using the app, I could recover easily and quickly.
- S6. I like the interface of the app.

Information Structure & Feedback

- S7. The information in the app was well organized, so I could easily find the information I needed.
- S8. The app adequately acknowledged and provided information to let me know the progress of my action.
- S9. I feel comfortable using this app in social settings.
- S10. The amount of time involved in using this app has been fitting for me.

Satisfaction & Willingness to Reuse

- S11. I would use this app again.
- S12. Overall, I am satisfied with this app.

Perceived Usefulness in Healthcare

- S13. The app would be useful for my health care practice.

- S14. The app improved my access to delivering health care services.
- S15. The app helped me manage my patients' health effectively.
- S16. This app has all the functions and capabilities I expected it to have.

Reliability &Accessibility

- S17. I could use the app even when the Internet connection was poor or not available.
- S18. This mHealth app provided an acceptable way to deliver health care services, such as accessing educational materials, tracking my own activities, and performing self-assessments.

Appendix B – Technical Manual: Smartwatch Data Monitoring Application

This appendix complements Chapters 3.4 and 3.5 by providing an implementation-focused overview of the app. It emphasizes components, responsibilities, runtime interactions, and user interface logic, with selective use of pseudocode to clarify more complex flows.

B.1 System Architecture Overview

The smartwatch data-monitoring system is designed around a wearable → cloud → mobile data pipeline. The user wears a Garmin Vivoactive 5 device that tracks health metrics throughout the day. This data is synced via Garmin's infrastructure and retrieved through a secure API connection. The mobile application, built with React Native, enables users to view, analyze, and export personalized health reports.

The architecture consists of multiple interconnected components—both hardware and software—each with distinct responsibilities. The following table summarizes these components and how they interact within the overall system.

#	Component	Layer	Responsibility	Key Interfaces
1	Garmin Vivoactive 5	Device	Collects raw biometrics (HR, steps, floors, stress, intensity, kcal).	BLE-sync to Garmin Connect mobile-app / cloud.
2	Garmin Connect	Cloud	Stores daily summaries; exposes REST endpoints behind OAuth.	`GET /dailies` via 3aHealth bridge.
3	3aHealth Bridge	Cloud Proxy	Simplifies OAuth flow.	Cookies/Sessions, host `garmin-ucy.3ahealth.com`.

4	Mobile App (React Native)	Client	User UI, data retrieval, local cache, analytics, report generation.	Sub-components 4a–4f.
4a	Auth Module	Client	Presents WebView for Garmin login, persists session cookie.	React-Native-WebView, `withCredentials`.
4b	Sync Manager	Client	Calls `GET /garmin/dailies`, writes payload to AsyncStorage.	Fetch API.
4c	Data Store	Client	Key–value cache for payload and connection flag.	@react-native-async-storage.
4d	Chart Engine	Client	Renders SVG charts (gifted-charts) per metric × month.	Off-screen <ChartCapture/>.
4e	Report Generator	Client	Builds inline-image HTML report.	`getReportHTML()` utility.
4f	File Exporter	Client	Converts HTML→PDF, moves file to Downloads	RNHTMLtoPDF, RNFS

Design Assumptions:

- Internet connection only needed for manual sync.
- PDF report must generate offline from cache.

B.2 Runtime Flow – Functional Overview

The flow-chart (Figure 3.4) shows seven consecutive stages. The mobile-app implementation mirrors that sequence, each stage maps to a specific screen or component.

Step #	Flow-Chart Node	RN Component / Function	Key Responsibility	Error Handling/ Fallback
1	Garmin OAuth Login	WebView OAuth Screen	Present 3aHealth-wrapped Garmin login; persist session cookie.	Displays error Alert
2	Manual Sync Trigger	Sync button (Dashboard) → syncButtonHandler()	Fetch /garmin/dailies; cache JSON; update last-sync.	Displays a toast + sets isConnected = false on failure
3	Local Cache	AsyncStorage utils (loadGarminCachedData, save…)	Store payload + flags for offline usage.	Returns empty array if read fails
4	Daily Dashboard View	Smartwatch Details Screen	Display latest day; let user browse historical days & open metric details.	"No data" placeholder if array empty

5	Period Selection	Calendar Modal + handleConfirmPeriod()	User chooses start/end; derives month list for charts.	Rejects if range > 12 months
6	Chart Rendering & Capture	Hidden ChartCapture swarm	Draw six metrics × N months; capture PNGs.	Retries capture 3 times, then aborts export
7	PDF Export	generatePdfReport()	Build HTML, convert to PDF, move to Downloads, show success/error.	try/catch → Alert + log stack

B.3 Key Interaction Narratives

B.3.1 Garmin OAuth Flow

Entry: User Taps Connect button
Action: `WebView` opens 3ahealth login page that redirects to Garmin login page
Outcome: On success, a session cookie is stored, `isConnected` flag is updated

B.3.2 Sync Button & Cache

Pseudocode:

```
FUNCTION syncButtonHandler()
    response ← syncGarminData()
    IF response.success THEN
        saveToAsyncStorage(response.data)
        updateLastSyncTime(NOW)
        setIsConnected(TRUE)
    ELSE
        setIsConnected(FALSE)
        showError(response.error)
    END
```

- Cached data enables offline access and UI rendering

B.3.3 Daily Dashboard View

UI Element	Purpose
Date Selector	Navigate days using < and > or open calendar modal and navigate to selected day.
Metric Tiles	Taps open detailed views (HR, Steps, Stress, etc.)
Sync Button	Triggers manual data refresh
Smartwatch Icon Button	Opens menu

Pseudocode:

```
ON mount:
    entries ← loadGarminCachedData()
    IF entries THEN
        selectedDay ← entries[0]
        currentDate ← selectedDay.date
        metrics ← selectedDay.metrics
    END
```

B.4 Metric Details Screens

All metric screens reuse a unified `ChartDetails` component.

Screen	Chart Types	Summary Cards
HRDetails	Line / Bar	Average, Min, Max, Resting
StressDetails	Pie / Bar	Duration of each stress level, Max/Average Stress
StepsDetails	Bar	Daily/weekly/monthly averages
IntensityDetails	Bar	Moderate, Vigorous duration
FloorsDetails	Bar	Average weekly/monthly floors climbed
KcalDetails	Bar	Average weekly/monthly Calories burned

B.5 Report Generation Flow

B.5.1 User Flow

1. User taps Generate Report.
2. Selects date range via calendar modal.
3. Charts for each metric and month are rendered off-screen.
4. Captured chart URIs are compiled into an HTML template.
5. HTML is converted to PDF and saved to the device.

Pseudocode:

```
WHEN completedCharts == expectedTotal DO
    html ← buildHTML(startDate, endDate, chartURIs)
    pdf ← convertToPDF(html)
    moveToDownloads(pdf)
    showSuccessAlert()
END
```

B.6 Implementation Notes

- Offline Support: All charts and reports can be generated from cached data.
- Storage Compliance: PDF is saved to `/Downloads` using Android's scoped storage APIs.
- Security: OAuth tokens are stored in WebView cookies; no raw credentials are stored locally.
- Accessibility: All screens were designed with readability, contrast, and large tap areas to accommodate older adults.