Ollscoil Chathair Bhaile Átha Cliath
Dublin City University

Exploring Patterns of Engagement with Digital Health Technologies Amongst Older Adults Living with Multimorbidity

Yiyang Sheng, B.E., M.Res.

School of Health and Science

Supervised By:

Dr Julie Doyle, Dundalk institute of Technology

Dr Rajesh Jaiswal, Technological University Dublin

Dr Raymond Bond, Ulster University

Ph.D.

August 2024

Declaration

We, the undersigned declare that this thesis entitled Exploring Patterns of Engagement with Digital Health Technologies Amongst Older Adults Living with Multimorbidity is entirely the author's own work and has not been taken from the work of others, except as cited and acknowledged within the text.

The thesis has been prepared according to the regulations of Dundalk Institute of Technology and has not been submitted in whole or in part for an award in this or any other institution.

Author Name: Yiyang Sheng

Author Signature: 盛奕阳

Date: 7th August 2024

Supervisor Name: Dr. Julie Doyle

Supervisor Signature: Julie Doyle

Date: 7th August 2024

Acknowledgements

Firstly, I would like to express my deepest gratitude to my primary supervisor, Dr Julie Doyle, for her patient guidance, encouragement, and support. Throughout the journey of my PhD career, you have been like a guiding light, guiding my direction and giving me warm strength. I would also like to thank Dr Rajesh Jaiswal and Dr Raymond Bond for teaching and helping me to learn so much that I can benefit from throughout my career.

I would like to thank my colleagues in DkIT, in particular those in NetwellCASALA, for your support throughout this process. I am especially grateful to Dr Yohanca Diaz, who was like a big sister to me, for the support and help you gave me and my family when we first arrived in a strange country.

I would like to thank my parents, Xinyu and Ping, for your support and encouragement.

Finally, to my wife, Bingyu, thank you for always being there for me. Your unfailing love and support have helped me find the strength to persevere through the tough days. I would not have been able to do this without you. And, my little girls, Muxi and Zixi, you are my motivation to keep going.

Table of Contents

Table of Figures

Table of Tables

Publication by Candidate

Peer reviewed journal papers

Sheng, Y., Bond, R., Jaiswal, R., Dinsmore, J. and Doyle, J., 2024. Augmenting K-Means Clustering With Qualitative Data to Discover the Engagement Patterns of Older Adults With Multimorbidity When Using Digital Health Technologies: Proof-of-Concept Trial. Journal of Medical Internet Research, 26, p.e46287. https://www.jmir.org/2024/1/e46287/

Sheng, Y., Doyle, J., Bond, R., Jaiswal, R., Gavin, S. and Dinsmore, J., 2022. Home-based digital health technologies for older adults to self-manage multiple chronic conditions: A data-informed analysis of user engagement from a longitudinal trial. *Digital Health*, *8*, p.20552076221125957. https://journals.sagepub.com/doi/full/10.1177/20552076221125957

Peer reviewed conference abstract and presentation

Sheng, Y., Doyle, J., Jaiswal, R., 2019 11th International Conference on Machine Learning and Computing, "Home-based ambient assist living for older adults with multimorbidity"

Abbreviations:

AAL – Ambient Assisted Living

BG – Blood glucose

BP – Blood pressure

CABIE – Context-aware brokering and inference engine

CART – Classification and Regression Trees

CeHP - Community-Based e-Health Program

CGM – Continuous Glucose Monitoring

COPD – Chronic obstructive pulmonary disease

CRISP-DM – Cross Industry Standard Process for Data Mining

CSE – Computer Self-Efficacy

DBSCAN - Density-Based clustering

ECG – electrocardiography

EDA – Exploratory Data Analysis

EMA – Ecological momentary assessment

EMG – electromyography

ES – Engagement Score

ET – Elder Tree

EU – European union

eHEALS – eHealth Literacy Scale

GDPR – General data protection regulation

GSE – General Self-Efficacy

HD – Heart disease

HF – Heart failure

HSE – Health Service Executive

HTSE – Health care Technology Self-Efficacy

ID3 - Iterative Dichotomiser 3

JSON - Java script object notation

KDD – Knowledge Discovery in Databases

kNN - k Nearest Neighbours

ICTs – Information and communication technologies

MASS - Mobile Applications for Seniors to enhance Safe anticoagulation therapy

MDPQ – Mobile Device Proficiency Questionnaire

MDPS - Mobile Device Proficiency Score

mHealth – mobile Health

MHARS – Mobile Human Activity Recognition System

OAT - Oral Anticoagulation Treatment

PA – Physical Activity

PCA - Principal Component Analysis

SD - Standard deviation

SEMMA – Sample, Explore, Modify, Model and Assess

SIMS – Subject information management system

SpO2 – Blood oxygen level

SR – Self-Report

SVM – Support Vector Machine

TAL – Technology Acceptance Lifecycle

TAM – Technology Acceptance Model

VIP – Variance Inflation Factor

WHO – World Health Organization

Abstract

Multiple chronic conditions (multimorbidity) are becoming more prevalent amongst ageing populations. Digital health technologies have the potential to assist in the self-management of multimorbidity, supporting monitoring of symptom and well-being parameters, improving a person's awareness of their health and well-being, supporting a better understanding of the disease(s), encouraging health behaviour change and ultimately resulting in improved health outcomes. However, little research has explored the long-term engagement of older adults with such digital interventions.

The aim of this PhD project was to analyse how 60 older adults (average age=74 ± 6.4 [65-92 years]) with multimorbidity (two or more of the conditions diabetes, heart failure, heart disease, chronic obstructive pulmonary disorder (COPD)) engaged with digital symptom and well-being monitoring when using the ProACT digital health platform over a period of approximately 12 months. For the purposes of this thesis, only 56 participants' data records were used in the data analysis phase, as four participants had no data records in the dataset. The ProACT platform consisted of a suite of digital devices (for example a blood pressure monitor, blood glucometer, pulse oximeter, weight scales, and activity and sleep tracker) and the ProACT CareApp which participants used to view their data, self-report on other areas of health and well-being not measurable by a digital device (such as breathlessness, mood), set goals and receive education. Three studies were carried out on the resulting quantitative dataset. In the first study, data analysis focused on user retention, frequency of monitoring, intervals in monitoring and patterns of daily engagement. During the second study, principal component analysis and clustering analysis were used to group participants based on their levels of engagement, and the data analysis focused on characteristics such as age, gender and chronic health conditions, engagement outcomes and symptom outcomes of the different clusters that were discovered. In the final study, the weekly submission times for each parameter were used to obtain an engagement score (ES) and this score was compared with the Mobile Device Proficiency

Score (MDPS), a measure of an older adult's technical proficiency with mobile devices. Both cluster analysis and multiple regression were used in this study to explore whether participants' engagement with digital health technology was related to their mobile device proficiency.

The findings from the studies show that the overall engagement with the ProACT digital health platform was high, with more than 80% of participants using the technology devices for over 200 days. The submission frequency for different symptom parameters (e.g. blood glucose, blood pressure, etc.) was between three and four times per week which was higher than that of self-report (2.24) and weight (2.84). Submissions of activity (6.12) and sleep (5.67) were more frequent. The majority of interactions happened in the morning time. The most common time of submission for symptom parameters was 10 am, whereas 8 am was the most common time for weight measurements. In addition, three clusters were identified: the typical user group (n = 24), the least engaged user group (n = 13), and the highly engaged user group (n = 17) in the second stage of analysis. The findings indicate that gender and the types of chronic conditions do not influence engagement. Whether the same device was used to submit different health and/or well-being parameters; the number of manual operations required to take a reading; and the daily routine of the participants were the three primary factors influencing engagement. Findings also indicate that higher levels of engagement may improve the participants' outcomes (e.g., reduce symptom exacerbation, and increase physical activity). Finally, results from the third study indicate that engagement with digital health technology has a weak correlation with mobile device proficiency in older adults. Despite participants having low to modest technical proficiency, the majority engaged with the platform for the duration of the trial.

The findings highlight the patterns of engagement of older adults with complex chronic diseases with a digital home-based self-management platform and demonstrate the potential of a digital health platform, such as ProACT, to empower older adults with multimorbidity to engage in digital self-management. Based on the findings, a series of recommendations for researchers, designers and developers of digital health technologies are provided. For example, engagement might be enhanced by delivering reminders in the mornings and reducing the number of manual operations required to use monitoring devices. The outcomes of this PhD also have possible implications spanning digital inclusion policies, health outcomes, health systems, cost-effectiveness, and health policy. For example, through the use of digital health technologies, older adults might potentially have better health outcomes, which could ultimately reduce healthcare costs for both patients and healthcare systems.

1 Introduction

1.1 Background and Motivation

Across the world, people are living longer for a variety of reasons, including medical innovations, better publicly funded health care, improved public sanitation as well as environmental quality (Roser et al., 2013, Mariani et al., 2010). Life expectancy has doubled in all world regions over the last 200 years and the average life expectancy is 72.6 years globally in 2019 (Roser et al., 2013). Consequently, the world's population is ageing. According to the United Nations, the number of people aged 65 and older is growing faster than all other age groups (Nations, 2020). In addition, by 2050, 22% of the world's population will be over 60 years old, while 426 million people will be over 80 years old (World Health Organization, 2022b). The population of people aged 60 years and older will be 2.1 billion by 2050, almost doubled from 1 billion in 2020 (World Health Organization, 2022b). The percentage of the total population aged 60 years or over will be 30% or more in most European countries by 2050 (World Health Organization, 2022a) and the life expectancy will exceed 90 years (Oeppen and Vaupel, 2002).

While there is much to celebrate about living longer, ageing can also present challenges to individuals and health care systems. According to the World Health Organization (WHO), there is little evidence to suggest that people today are experiencing better health in their later years than their parents (World Health Organization, 2022b). To varying degrees, national health and social care systems are therefore preparing for higher incidence rates of illness and chronic disease. Many chronic conditions (e.g. heart disease (HD), diabetes, Chronic Obstructive Pulmonary Disease (COPD), dementia) are the leading causes of death globally (World Health Organization, 2020). Of particular concern is multimorbidity, defined as the co-existence of multiple chronic conditions (Marengoni et al., 2011). It was estimated that 50 million people in Europe were living with multimorbidity in 2015 (van der Heide et al., 2015). In the United states, 27.2% of the adult population had multimorbidity in 2018 (Boersma et al., 2020). The main factors that are associated with multimorbidity are older age, female gender and low income (Marengoni et al., 2011, Sakib et al., 2019). While multimorbidity is known to affect younger and middle-aged adults, particularly those experiencing social deprivation (Academy of medical sciences, 2018), it is also known that the prevalence of multimorbidity increases with age (Sakib et al., 2019). In the European Union, amongst people over 65 years old, the prevalence rate of multimorbidity is estimated to be as high as 65% (van der Heide et al., 2015). Moreover, the prevalence of 4 or more chronic conditions among older adults is more than 65% (He et al., 2018). Multimorbidity affects people's quality of life, and ability to operate normally (Fortin et al., 2004). Moreover, mental illness, such as depression, is also highly associated with multimorbidity (Birk et al., 2019). Therefore, people with multimorbidity require rehabilitation or a long period of care (Villacampa-Fernandez et al., 2017). Additionally, multimorbidity predicts increased use and cost of health services, and mortality (France et al., 2012).

Multimorbidity can be particularly challenging for older adults, who due to the additional complexities associated with ageing, can experience greater frailty, and may require support to manage their conditions (Nicholson et al., 2019). In addition, older adults with multimorbidity are at higher risk of becoming dependent on care (Koller et al., 2014). Sinnott et al. (2013) found four areas of difficulty in the management of multimorbidity which are disorganisation and fragmentation of health care; the inadequacy of guidelines and evidence-based medicine; challenges in delivering patient-centred care and barriers to shared decision-making. Older adults with multimorbidity require not only clinical face-to-face visits, medication, emergency consultations, outpatient visits, hospital admissions, etc. to keep in a good physical condition (Soley-Bori et al., 2021), but also need mental health care as depression is associated with morbidity (Charlton et al., 2013). Likewise, older adults with multimorbidity also need community care and social care for their daily life (Soley-Bori et al., 2021).

However, it takes a significant amount of health care expenditure to provide good health care for older adults with multimorbidity. In 2016, 1.1 trillion United States Dollars were spent because of direct health care treatment for chronic health conditions in the United States (Waters and Graf, 2018). In 2016, 70%-80% of all health care costs in the European Union was spent on chronic conditions which is estimated at 700 billion euros (Seychell, 2016). Moreover, the cost of health care for older adults with multimorbidity increases with age and more disease combinations (Brilleman et al., 2013, Tran et al., 2022). For example, the total expected costs (including hospitalization costs, care transition costs, etc.) for people with one to three conditions are 1.55 to 2.85 times higher than for people without any condition (Charlton et al., 2013, Hazra et al., 2018). On the other hand, people with multimorbidity are expected to use health services 2.56 times more often than people without multimorbidity (Soley-Bori et al., 2021).

Self-management can be defined as the actions taken by a person to protect and promote health and manage symptoms, lifestyle, emotions and social effects (Bartlett et al., 2020). It can also provide a bridge between the needs of the patient and the ability of health care systems to meet those needs (Barlow et al., 2002). Moreover, home-based self-management is more convenient because it can let people use their time and energy without having to travel to and from hospital to receive care (Bisio et al., 2016). For older adults with chronic conditions, home-based self-management can not only help people manage their disease, but also improve their quality of life for the rest of their lives (Kamei et al., 2020).

However, providing desired self-management support to older adults with multimorbidity is challenging and complex. First, chronic conditions vary in severity and have a wide range of characteristics (Setiawan et al., 2019). In this case, self-management for older adults with multimorbidity is diversified and complicated. Second, the stages of chronic disease and the living environment change over time (Audulv, 2013). If older adults with multimorbidity are without treatment, the condition of their health will become worse over time. Conversely, proper treatment can improve the condition. Therefore, a dynamic and appropriate self-management support is needed. Third, chronic conditions are usually lifelong (Bernell and Howard, 2016). It is challenging to keep older adults with multimorbidity sustained and engaged with long-term self-management, due to issues such as coping with loneliness, loss of independence, and changing habits (Breckner et al., 2021).

According to the European Commission, “digital health and care refers to tools and services that use information and communication technologies (ICTs) to improve prevention, diagnosis, treatment, monitoring and management of health-related issues and to monitor and manage lifestyle habits that impact health” (European Commission, 2018). Digital health technologies have potential to support older adults with multimorbidity to more effectively self-manage their health and well-being in their homes (Mshali et al., 2018, Morton et al., 2017). For example, blood glucometers (to measure blood sugar levels) combined with mobile phone apps have been used to support people with diabetes to self-manage their condition (Årsand et al., 2010, Alanzi, 2018). There are many advantages to using digital technologies to support older adults with multimorbidity to self-manage their health and well-being. First, they can help older adults understand their disease(s), manage their health, respond to changes, and communicate with health care providers (Talboom-Kamp et al., 2016, Nunes et al., 2015). Second, such technologies can encourage people to change their behaviours (e.g., diet and exercise) (Mansson et al., 2020). Third, these technologies can be tailored to individual motivations and personal needs, thus potentially improving sustained use (Klasnja et al., 2015, Tighe et al., 2020).

However, very little research has explored the patterns of how older adults with multimorbidity engage with digital self-management technologies and how to sustain the engagement. The literature has explored older adults’ attitudes towards the use of technology for self-management. Research has examined wellness (Hakobyan et al., 2016, Moran et al., 2022), social well-being (Xu et al., 2023), functional abilities (Calderón-Larrañaga et al., 2019), physical activity (PA) (Gomes et al., 2020), physical rehabilitation (Jones et al., 2023), medication management (Doyle et al., 2017, Bird et al., 2022), and chronic disease self-management (Murphy et al., 2017, Ekstedt et al., 2021, Hall et al., 2021). Older adults are willing to change their behaviour to adopt digital self-management if the intervention provides benefits, such as increased awareness of self-management behaviours and improved knowledge of their healthcare (Hakobyan et al., 2016). Furthermore, recent research indicates promising results in terms of older adults actively engaging in self-management. Various studies have shown that older adults have engaged with mHealth interventions, with one study demonstrating that older adults had higher levels of engagement with digital diabetes self-management than their younger counterparts (Compernolle et al., 2020) (Bohm et al., 2020). Despite these promising studies, there is still a lack of research on longitudinal engagement with self-management technologies by those with multiple chronic conditions, with a view to understanding how best to facilitate and promote sustained engagement to maximise benefits.

In this PhD project, a data-based evidence approach is used to examine longitudinal engagement patterns with digital health technologies. It is well understood that engagement, in the context of digital health, is multi-faceted and lacking definition and agreement on how to evaluate it (Milne-Ives et al., 2024). O'Brien and Toms presented the following definition of user engagement with technology: *"Engagement is a quality of user experiences with technology that is characterized by challenge, aesthetic and sensory appeal, feedback, novelty, interactivity, perceived control and time, awareness, motivation, interest, and affect."* (O'Brien and Toms, 2008), however such components may be difficult to measure in a digital health context. Milnes-Ives et al. (2024) outline two categories of engagement that are relevant to this PhD project: (1) What users are engaging with, e.g. the digital health technology (which can include specific features, content or interface components) or a target health behaviour (e.g. increasing physical activity); (2) how they are engaging e.g. behaviourally (usage), affectively (motivation, positive or negative feelings) or cognitively (interest, attention). Specifically, this PhD research is focused on analysing a dataset resulting from approximately 12 months of engagement with a digital self-management platform (including monitoring devices and a digital application) by older adults with multiple chronic conditions. The analysis primarily focuses on examining user engagement with monitoring of symptoms (such as blood pressure, blood glucose, heart rate, breathlessness) of multiple chronic conditions and relevant lifestyle parameters (weight, sleep and PA) using digital devices and self-reporting within a digital application. Engagement is measured by analysing logs of system usage data, such as frequency of use, time of use, features used, allowing for a reliable measure of physical use of the intervention, and the potential to identify usage patterns associated with better outcomes (Yardley et al., 2016). Little is understood about how older adults with chronic conditions engage in digital home-based self-management. For example, how often do they monitor various symptoms, how often they engage in PA, how long they sustain these behaviours, etc. This PhD project provides new insights about how to enhance engagement of older adults with multimorbidity with digital self-management interventions.

1.2 Research Aim and Objectives

1.2.1 Research Aim

The aim of this PhD project is to explore, through analysis of an existing dataset, the longitudinal patterns of user engagement of older adults with multimorbidity with digital self-management, in particular symptom and well-being monitoring, with the goal of better understanding how to promote sustained user engagement over time.

1.2.2 Research Objectives

Objective 1: Review the literature on digital home-based self-management technologies for chronic disease and multimorbidity, with a focus on literature examining user engagement, including engagement of older adults, with such systems.

Objective 2: Analyse an existing dataset to understand longitudinal patterns of user engagement of older adults with multimorbidity with symptom and well-being monitoring (e.g., blood pressure, self-reported mood).

Objective 3: Explore how different categories of users, for example users of different age groups or with different conditions, engage with symptom and well-being monitoring.

Objective 4: Examine the connections between technical proficiency and user engagement with digital health technologies.

Objective 5: Develop a set of recommendations for researchers, designers and developers of digital health technology to promote enhanced user engagement of digital health technology by older adults with multimorbidity.

1.3 Contribution

The research makes the following contributions to knowledge in the field of digital health:

- This thesis provides an understanding of the patterns of user engagement with digital self-management technologies and behaviours of older adults with multimorbidity – an understudied cohort in the field of digital health research. The findings presented in this thesis indicate that this cohort engaged in digital self-management for a period of approximately one year, with high levels of user retention and frequent and regular digital self-management routines, as demonstrated in Chapter 4.
- Findings from the analysis presented in this thesis have led to the development of recommendations for researchers, designers and developers of digital health technologies to help maximise engagement and therefore potential impact of such technologies, as shown in Chapter 5. For example, the analysis found that digital health devices with fewer manual operations are higher utilised than those with more manual operations while fixed daily routines using different digital health devices can help increase user engagement among

older adults with multimorbidity. Notifications are a useful way to help older adults with their daily routines and mornings are a good time to send them.

- As Chapter 5 shows, higher levels of user engagement with digital health monitoring may result in better outcomes, such as symptom stabilisation and increased levels of physical activity for older adults with multimorbidity. The analysis found a non-linear positive correlation between the frequency of use of digital health devices and the physical condition of participants.
- Mobile device proficiency, as evaluated through the Mobile Device Proficiency Questionnaire (Roque and Boot, 2018), designed specifically for older adults, does not predict user engagement with digital health technologies. Even though participants of the study had low levels of mobile device proficiency, they engaged with digital self-management throughout the 12-month trial period. However, consideration should be given to the development of a questionnaire to assess an older adult's digital health technology proficiency or literacy prior to them engaging in digital self-management, so that targeted, individualised training programmes can be developed with a view to maximising effective engagement. The findings are outlined in Chapter 6.
- This thesis outlines potential implications of this research, including health outcomes, healthcare system efficiencies and healthcare policy in Chapter 7. For example, empowering older adults with multimorbidity to engage in digital self-management can lead to better healthcare outcomes, which ultimately could result in less unscheduled healthcare utilisation, lower healthcare costs for both patients and healthcare systems and new reimbursement models that provide healthcare organisations with incentives to integrate digital health technologies into their practice.

1.4 Thesis Layout

The remainder of this thesis is structured as follows:

Chapter 2 presents the literature review, focusing on three main sections. The first section introduces digital health self-management technologies, including different types of technologies and approaches (e.g., wearables, mobile devices, Internet), as well as digital health technologies for different chronic diseases (e.g., diabetes, hypertension, HF), older adults and multimorbidity. The next section contains a review of the literature on user engagement in digital self-management. First, the barriers affecting engagement and the factors that enhance engagement will be discussed. This will be followed by a presentation of two theories that are closely related to user engagement, information technology acceptance and self-efficacy, including healthcare technology self-efficacy, which refers to people's belief that they have the ability to successfully use healthcare technology to the extent that it will have a significant effect on their lives (Bandura and Wessels, 1994, Rahman et al., 2016). In addition, data-driven evidence of engagement will be presented, as this is the main approach used in this PhD project. The last section of this chapter focuses on data mining approaches for digital health data. Data mining approaches will be discussed as two parts, namely descriptive data mining techniques and predictive data mining techniques. In addition, data mining techniques for health care will be presented, especially those related to k-means clustering.

Chapter 3 describes the data set that was analysed, and presents the research questions, approach and methods of the three studies conducted as part of this PhD research.

Chapter 4 presents findings from the first study, including a detailed analysis of user retention, frequency of monitoring, intervals in monitoring, and patterns of daily engagement.

Chapter 5 outlines the findings from the second study that involved clustering the participants into different groups based on frequency of engagement to identify differences between these clusters in terms of user characteristics, engagement outcomes, and symptom outcomes.

Chapter 6 investigates the relationship between engagement and mobile device proficiency scores. Two different multiple regression models were built to show the results of the research questions related to the third study.

Chapter 7 summarises the key findings of this research project, highlighting the contributions to knowledge and making recommendations for researchers, designers and developers of digital health technologies relevant to older adults with multiple conditions. Limitations of this project are also discussed, along with the conclusion and possible areas for future research.

2 Literature Review

2.1 Introduction

Digital self-management technologies have gained traction in recent years due to their potential to support people to manage their health and well-being, change their health and well-being behaviours, maintain self-management over time and ultimately to improve health and well-being outcomes. Furthermore, such technologies have the potential to improve the delivery of health care, such as facilitating better communication between patients and health care professionals, providing access to people living in rural areas and reducing health care costs. As such, there is a vast amount of research on how digital health technologies can support self-management of various chronic diseases. However, there is still comparatively little research on older adults' use of such technology, and how it can support the additional complexity of managing multiple chronic conditions. The first part of this literature review (Section 2.2) explores this research.

It is understood that engagement with digital health technologies is necessary to achieve their intended outcomes. Quality of care and health outcomes will improve with better engagement of digital health technologies (Blasiak et al., 2022). However, there are various known barriers to engaging with such technologies, including usability issues, low digital literacy, and limitations as a result of illness (Breckner et al., 2021). These can be exacerbated for older adults. Despite this, the perception that older adults are unable to engage with technology is outdated, with research indicating that older adults are often highly engaged with digital health technologies and can better self-manage their health with the use of technology compared to traditional health self-management (Branch et al., 2022). It is therefore important to consider strategies for facilitating engagement with digital health technologies, particularly for cohorts such as older adults, who can benefit considerably from their use. Section 2.3 of the literature review examines engagement with digital self-management, covering topics such as technology acceptance and adoption, and how to encourage engagement (Section 2.3).

In this PhD project, data mining and machine learning technologies were used to analyse the digital health data set. Therefore, the final section of the review (Section 2.4) explores the literature related to data mining and machine learning techniques for health care data.

The literature search was conducted using the Dundalk Institute of Technology online library, the ACM Digital Library and Google Scholar. The following search terms were used to locate articles relevant to this study: self-management, heart failure (HF), engagement, digital health, health technology, older adults, chronic conditions. Variations of these terms (e.g. chronic disease, elderly) and different combinations were used to ensure exhaustive search results.

2.2 Digital health self-management technologies

In comparison to traditional self-management, digital self-management can help older adults understand their condition, encourage behaviour change, and improve sustained engagement in self-management (Mansson et al., 2020, Pettersson et al., 2019). However, there are significant variations in the technology employed and the outcomes for older adults and various chronic illnesses. For example, diabetics need to have their blood glucose checked several times a day, and blood oxygen levels are an important parameter of health in patients with chronic obstructive pulmonary disease (COPD), but not in patients with hypertension. Variations of these technologies are often combined into self-management platforms for people with multimorbidity especially older adults.

2.2.1 A review of digital health devices and platforms

Digital health devices, ranging from wearable devices to fitness trackers and remote monitoring systems are becoming increasingly widespread and are enabling digital self-management of health and well-being. Numerous devices have been used in various configurations, for various objectives and in various deployments. The literature on digital health devices is presented in this section, covering wearable devices, mobile devices and ambient assist living systems, outlining their application and benefits for health and well-being management.

2.2.1.1Wearable devices

With the advancement of wearable devices, more and more health and well-being management functionality is becoming increasingly available for individuals, for example, measuring body temperature (Chen et al., 2015), checking blood glucose for diabetics (Bandodkar et al., 2015), recording the electromyogram (Miyamoto et al., 2017) and monitoring physical activity (PA) and sleep and other well-being parameters (Rosenberger et al., 2016, Xie et al., 2018). Medical wearables typically have two different types of sensors, biophysical sensors (e.g., fitness trackers and smartwatches) and biochemical sensors (e.g., continuous glucose monitoring system) (Xu et al., 2022).

The Fitbit is a popular consumer-based activity wearable device that has been used in many studies for different purposes, from monitoring pregnant women's PA in free-living conditions (St-Laurent et al., 2018) to supporting PA for patients with low back pain (Amorim et al., 2019). In the latter study, a Fitbit and an Internet-based application were used to support patients in the intervention group, while the control group was provided with PA information and advice booklets. After six months follow-up, the authors found that participants in the intervention group had a lower rate of care seeking than the control group by 38% (Amorim et al., 2019). Results from another study showed that by using Fitbit, breast and colorectal cancer survivors were more physically active compared to those who did not use Fitbit, and that using Fitbit had the potential to improve lifestyle (Cadmus-Bertram et al., 2019). Fitbit activity monitors have also been used alongside a self-reported diary to record food, for cancer survivors to monitor weight changes (Brown et al., 2018). The results of this study showed that participants in the intervention group lost an average of 4.6 kg, while the control group (who didn't use a Fitbit) gained an average of 0.2 kg. Fitbits have also been used to evaluate sleep of people with major depressive disorder (Cook et al., 2017). However, the authors indicate that the Fitbit is not an adequate substitute for polysomnography and that the Fitbit settings can affect its performance.

Even though wearable technology has improved in recent years, there are still many challenges that may cause users to stop using devices or engage less, such as loss of motivation, perceived inaccurate measurements, routine interference, etc. (Attig and Franke, 2020). Schall et al. (Schall Jr et al., 2018) noted that wearable sensor users are generally concerned about the efficacy and effectiveness of the sensor, and most concerned about privacy and data security. Daligadu et al. (Daligadu et al., 2018) examined the validity of the number of steps and distance travelled by patients after heart surgery by Fitbit Flex. They found that the Fitbit's output lacked consistency between standard measurements.

2.2.1.2 mHealth

The term mHealth (mobile Health) relates to the use of mobile phones and other wireless technology in medicine and health care (Heerden et al., 2012). It has a wide range of applications, including health and well-being monitoring. As smartphones and tablets become more powerful, mobile apps are including more features to support mHealth research, and have been used for self-management of pain (Reynoldson et al., 2014), mental health (Spadaro et al., 2021), weight loss and control (Carter et al., 2013, Laing et al., 2014), and to help pregnant women's self-management during the Covid-19 pandemic (Nawangsari et al., 2022). There is a significant amount of mHealth research for chronic disease self-management, and this is explored further in Sections 2.2.2 through to 2.2.7.

Typically, mobile phone text messages are used in medical interventions for reminders, delivery of medication information, regimens, disease reports, and self-education (Wei et al., 2011). Many studies have shown that the use of text messaging as a reminder can improve medication adherence (Lester et al., 2009, Islam et al., 2014) and can also motivate patients to attend medical appointments (Sims et al., 2012). Mobile text-based health care interventions can also help people with mental illnesses, such as depression and anxiety (Bockting et al., 2011, Kelders et al., 2013). Text messaging can also help people quit smoking by providing advice, support and reminders (Abroms et al., 2014).

Partridge et al. (Partridge et al., 2015) conducted a mobile medical prevention program to help young adults lose weight and improve their diets. The program included text messaging, email, coaching calls and a mobile app. The results showed that the program was useful in preventing weight gain and improving the diet of overweight young people. However, the authors also mentioned that using text messaging alone to change diet was less effective than using both text messaging and coaching calls. In this context, while mobile messaging is helpful in digital health interventions, it is better suited for integration with other technologies such as mobile apps, telemedicine and wearable devices. Therefore, text messaging can be a great digital trigger for mobile apps, wearables, etc. that can enhance user engagement with health care devices (Muench and Baumel, 2017).

2.2.1.3 Ambient assisted living systems

In its early stages, Ambient Assisted Living (AAL) aimed to increase people's autonomy and self-confidence, relieve them of daily chores, support monitoring and care of older adults or those who are sick, improve safety, and conserve resources to extend the time people can live independently in their own homes (Huch and Strese, 2005). Nowadays, AAL systems are available with many different features and functions to help people achieve these goals as well as, for example, detection of falls (Doulamis, 2010), enhancing social connection and avoiding the feeling of loneliness of older adults (Waterworth et al., 2009), and motivating older adults to exercise (Rodríguez et al., 2013).

In 2016, Ribeiro Filho et al. (Ribeiro Filho et al., 2016) presented a mobile system named Mobile Human Activity Recognition System (MHARS), aimed at tracking patients, especially with chronic diseases, in the context of AAL. This system can not only recognise the activities carried out by patients but also detect the intensity of activities in real-time. MHARS has multiple interactions with sensors. MHARS can monitor patients' daily activities and environmental information such as temperature and air quality, as well as symptom parameters such as heart rate, all of which are very important for chronic disease management. However, this system does not monitor many symptom parameters or require much interaction on the part of the participant.

Adeluyi and Lee (Adeluyi and Lee, 2015) presented the use of different medical virtual devices in AAL for older adults. In contrast to traditional devices, virtual devices have three main hardware modules, namely the sensor, display and memory modules, and a software part for processing and displaying the interface modules. The authors point out that medical virtual devices refer to virtual devices for AAL, as virtual devices implement the functions of traditional devices in the medical field in the context of AAL. In addition, they believe that much of the hardware for medical virtual devices can be used in an AAL environment, especially for older people with chronic conditions, such as electrocardiography (ECG) sensors, skin response sensors, electromyography (EMG) sensors, blood glucose meters, etc.

Triantafyllidis et al. (Triantafyllidis et al., 2016) presented a framework of using sensors in remote monitoring in AAL for people with chronic conditions. There are many components in this framework, such as sensors, a smart phone and a health professional platform which is reviewed by formal caregivers. Sensors in the patient's environment monitor heart rate, activity level, respiratory rate, temperature, and blood pressure. A mobile phone connected to the sensors via Bluetooth and the web can manage the sensed data, detect special events, receive notifications and communicate with health care professionals. The authors believe this framework encourages both passive services, which enable patients to take greater control of their own care, and active services, which are initiated by the system and enhance patient safety.

2.2.1.4 Internet based interventions

Internet-based health care interventions often include the use of health care applications, electronic records, and online video consultations to distribute health-related services and information (Schiffer et al., 2021). In addition, many studies have shown that Internet-based health care interventions can improve clinical outcomes and increase self-management among patients with chronic diseases (Al-Durra et al., 2015, Rushakoff et al., 2017).

One important function of Internet-based health care interventions is to help patients communicate with health care professionals through online video consultations. Baker et al. (Baker et al., 2005) found that Internet-based consultation services not only help patients easily communicate with their health care providers, but also reduce expenses in doctors' offices and laboratories. An Internet-based health intervention called ProYouth is used for the prevention and early intervention of eating disorders. This intervention includes an education module, a communication module for group chats (led by a psychologist), and a monitoring and support module (Bauer and Moessner, 2013). After interviewing participants in the ProYouth program, Moessner et al. (Moessner et al., 2016) found that Internet-based medical interventions could support traditional health care as well as fill gaps in the current health care system.

Internet-based health care interventions can also help health care workers. Bureau et al. (Bureau et al., 2021) developed an Internet-based cognitive-behavioural therapy intervention for health care professionals who were experiencing high levels of stress and mental distress during the COVID-19 pandemic. The results showed that this Internet-based medical intervention was embraced by health care professionals and helped them to release stress during times of high stress.

2.2.1.6 Online social media and social network based interventions

The most important functions of social media-based health care interventions are that they can help patients identify similar people, experience the benefits of group participation, and facilitate peer-to-peer communication (Highton-Williamson et al., 2015, Naslund et al., 2016b, Chau et al., 2018). Social media also allows patients to share content, connect with different users, and seek information, which can be especially helpful for people with mental illness who may have social anxiety or social difficulties (Schrank et al., 2010, Chung, 2014).

Social media-based health care interventions can improve the health of people with diabetes, such as lowering blood glucose, and can also improve health behaviour and self-care. Döğer et al. (Döğer et al., 2019) used WhatsApp to help children with type 1 diabetes manage their diabetes, communicate with health care professionals, and receive diabetes education. The results showed that this social network-based program helped patients identify the need for treatment changes, promoted self-management, and improved blood glucose control. However, this program didn't include any communication among patients, such as a group chat. Ruehlman et al. (Ruehlman et al., 2012) conducted a randomized controlled study for patients with chronic pain in which the intervention group used an online chronic pain management program that included social networking features and self-management tools. The authors found that this online management program reduced anxiety and stress in patients with chronic pain and also reduced pain severity and pain-induced fear. In addition, participants in the intervention group had an increased awareness of chronic pain compared to the control group.

Video is an important feature in social media, people can post video content to share knowledge or use video chat to connect with other people. McLaughlin et al. (McLaughlin et al., 2012) used video-sharing social networking interventions to help cancer survivors connect with other cancer survivors and gain social support and connection with family and friends. The authors believe that online social networks can support social bonding in young adult cancer survivors, especially those with weak family interactions, and help them express negative emotions such as anxiety, fear and worry.

2.2.2 Digital health self-management technologies for diabetes

Globally, in 2021 there were 537 million people living with diabetes, a number that is continuously rising (Sun et al., 2022). People with diabetes often have many different symptoms, such as unstable blood sugar, weight loss, numbness in the hands or feet, dry skin, blurred vision, etc (Centers for Disease Control and Prevention, 2022b). Living with and managing diabetes is complicated in this context. People with diabetes need a healthy meal plan; to count carbohydrates at every meal; to manage blood sugar; to exercise daily; and to maintain a healthy weight (Centers for Disease Control and Prevention, 2022b).

As such, managing diabetes presents a number of difficulties for both patients and health care professionals. For instance, diabetic patients must invest a lot of time in self-care activities like carbohydrate tracking and glucose monitoring (Safford et al., 2005). Moreover, many health care providers only have limited information about patients' glucose level records with no indication of patients' actual risk between two visits (Iyengar et al., 2016). Patients and governments also experience significant economic burden (Cefalu et al., 2014, Fraze et al., 2011). For example, the total annual cost of diabetes in the US in 2017 was $327 billion (American Diabetes Association, 2018), while the median annual cost for older people with diabetes was $5,876 in the US (Wang et al., 2022b).

There are a variety of digital health solutions available to support management of diabetes, including smartphone apps (Block et al., 2015, Fukuoka et al., 2015), digital blood glucometers to measure blood sugar levels (Elbaeva et al., 2019), telemedicine services (Holmen et al., 2014, Eberle and Stichling, 2021), and remote monitoring systems (Wang et al., 2019). The Few Touch mobile phone application was developed and used to support people with diabetes to monitor and manage their blood glucose, daily steps and food habits and to provide feedback to users related to their own personal goals (Årsand et al., 2010). The authors found that this system can increase motivation and help patients learn more about diabetes management.

Joubert et al. (Joubert et al., 2019) used a digital therapeutic system which provides automatic insulin dose recommendations and a self-monitoring glucose logbook to help patients with diabetes to self-manage. A trial of this system demonstrated a material improvement in the physical outcomes for diabetic patients using this technology, such as stable blood glucose compared with usual care. Furthermore, the trial's findings showed the potential to lower costs of outpatient and inpatient care.

Research has also explored how to support engagement with digital diabetes self-management. Chi et al. (Chi et al., 2021) used mobile text messages as tailored interventions to provide reminders and advice, to support people with type 2 diabetes to improve health outcomes. Reminder messages included reminders of scheduled events, such as clinical appointments, as well as engagement reminders. Advice messages included information about behaviour change techniques that could be implemented, and lifestyle-based advice. Participants could send a response message to the system to rate the information and advice they received. After 6 months, the majority of participants reported finding this mobile messaging support system to be useful and user-friendly, while the text messages received were viewed as positive. The authors believe that with a regular SMS text reminder, engagement with this type of system could potentially be increased. However, the authors did not show an effect on the participants' health and well-being outcomes after they had used the system for three months. Other research has also used mobile text messages to support and improve diabetes self-care activities, finding that messages that are positive, precise, and written in plain English are more likely to be received favourably, for example, using "sugar" instead of "glucose", or "half of a banana" instead of "25 grams of fibre" (Gatwood et al., 2020)..

Digital health interventions to support diabetes self-management have shown many benefits over non-digital interventions (Shea et al., 2006, Young et al., 2020). For example, Kim and Utz (Kim and Utz, 2019) compared the outcomes of 151 patients with type 2 diabetes who were randomly assigned to either usual care or a health literacy-sensitive diabetes management intervention delivered through telephone or social media. The authors found that patients in the usual care group with high levels of health literacy had higher levels of activation compared to patients in the usual care group with low levels of health literacy. However, this significant difference disappeared in the social media group, suggesting the usefulness of using social media to help patients with low health literacy become more engaged in digital health interventions. Alternatively, McLeod et al. (McLeod et al., 2020) compared an online self-management programme based on mobile and web health care platforms with usual care for people with type 2 diabetes and pre-diabetes. They found that those who took part in the online programme had more short-term improvements in weight and blood glucose compared to usual care.

2.2.3 Digital health self-management technologies for hypertension

Worldwide, hypertension affects 1.28 billion adults between the ages of 30 and 79 (World Health Organization, 2021). There are usually no signs or symptoms of hypertension, although some people may experience blurred vision, shortness of breath, chest pain and headaches (Centers for Disease Control and Prevention, 2021, British Heart Foundation, 2023). Measuring blood pressure is the only way to determine if people have hypertension or not (Centers for Disease Control and Prevention, 2021). Self-management of hypertension requires the patient to monitor their blood pressure, have a good quality diet, get adequate PA, monitor and control their weight, and adhere to medication (Melaku et al., 2022).

The majority of people with hypertension have access to effective blood pressure-lowering medications, but blood pressure control often remains unsatisfactory due to infrequent blood pressure monitoring, poor medication adherence, and clinical inertia (Merai et al., 2016, Okonofua et al., 2006, Serumaga et al., 2011). Utilizing digital health technologies in self-managing hypertension can improve self-monitoring, increase medication adherence, and reduce health care utilization (McKinstry et al., 2013, Pickering et al., 2008, Minetaki et al., 2011). With proper assessment and clinically validated digital health technologies, people with hypertension can be encouraged to take a more active role in their own health (Kitt et al., 2020).

A number of arm-band type digital blood pressure monitors are available on the market, that support sending data directly to a mobile app for review (for example Withings[1]). However, it has been suggested that small wearable monitoring devices, such as wrist-based measurement devices can help people with hypertension to measure their BP frequently, while causing less discomfort and muscle compression than traditional arm-band blood pressure measurement devices (Kario, 2020). Mobile apps can help people with hypertension manage their medication, track their blood pressure, and communicate with health care professionals (Morawski et al., 2018, Petrella et al., 2014). Moreover, much research has shown the positive effects of using mobile phones and mobile apps to manage hypertension, such as reducing blood pressure (Marquez Contreras et al., 2019, Lee et al., 2019). It has been suggested that regular digital blood pressure monitoring combined with ambient context monitoring, could enable the interpretation of blood pressure data in relation to daily stressors and various settings (Verdezoto and Grönvall, 2016, Kario, 2020). A study by Bengtsson et al. (Bengtsson et al., 2016) showed that their mobile phone-based self-management support system can help patients with hypertension manage and reduce blood pressure. In addition, following a short period of using the system, participants' blood pressure was significantly reduced, especially those participants who had moderate to high blood pressure. However, this study only lasted for eight weeks which can only show the short-term effects of this system. Longer term studies are required to better understand user engagement with such a system.

[1] https://www.withings.com/ie/en/

2.2.4 Digital health self-management technologies for heart failure

Heart failure (HF) is a complex, fatal illness with major morbidity and high expense which affects over 64 million people worldwide (Savarese et al., 2022, Vos et al., 2020). Particularly for older adults, the load of risk factors and comorbidities is substantial and rising (Groenewegen et al., 2020). The most common symptoms of HF include breathlessness, fatigue, swelling in the ankles and legs, and feeling dizzy (National Health Service, 2022). In addition, the management of HF requires patients to abstain from alcohol and smoking, adhere to their medication, monitor their weight and monitor for signs and symptoms of fluid overload (Inamdar and Inamdar, 2016).

Clinical results in HF patients may be improved by digital health technologies that track objective parameters including weight, voice, hemodynamic, and patient-reported symptoms (Farwati et al., 2021). Weight monitoring is an important part of HF self-management which has been recommended by health care providers, as a sudden increase in weight may be indicative of oedema (or water retention / swelling). Digital weight scales and apps can support weight monitoring and tracking (Collier et al., 2020), as well as sharing of data (between a patient and health care professional for example). Shoes with wearable sensors can also help HF patients to continuously monitor their weight with less effort (Elian et al., 2016). By using an acoustic microphone and a neck-mounted accelerometer to track changes in a person’s voice volume, Murton et al. (Murton et al., 2017) found that voice quality may correlate with HF symptoms, which could be used to monitor the status of patients with HF. Implantable hemodynamic monitoring can help health care professionals to monitor intracardiac and pulmonary artery pressures (Abraham and Perl, 2017, Givertz et al., 2017). Such advancements in technology support easier and faster symptom monitoring compared with traditional methods, such as reporting symptoms via telephone, allowing for early intervention to optimize treatment (Farwati et al., 2021). Moreover, wearable health technology can also help facilitate HF care and outcomes, such as the ability to monitor people’s daily activity level (Redfield et al., 2015, Dontje et al., 2014), weight (Elian et al., 2016), and atrial fibrillation (Chan and Choy, 2017) to prevent HF and improve HF care (DeVore et al., 2019).

Park et al. (Park et al., 2019) used digital interventions which are supported by mobile applications and smart devices (BP cuff and digital scale) to remotely monitor 58 HF patients after discharge from hospital. Findings from the study indicated that these digital interventions can not only improve patient outcomes, but also reduce hospital readmissions and costs. Likewise, Radhakrishnan et al. (Radhakrishnan et al., 2021) used a mobile application and smart devices to help older adults with HF improve their self-management. The mobile application in this randomised controlled study is a sensor-controlled digital game that triggers game rewards, progress, and feedback based on the user's interactions with smart devices and sensors, such as a scale. The results showed that participants in the intervention group were more motivated by daily weight monitoring and PA compared to the control group with only smart devices. In addition, the intervention group also had a lower rate of HF hospitalisation than the control group. The results of another study also showed that digital health technologies can significantly reduce the likelihood of hospital readmission for patients with HF (Gjeka et al., 2021). The intervention group of this study received a digital disease management platform which included smart devices, electronic medical record, mobile phone application, and online health platform. This platform monitors patients in real time and helps patients communicate with their health care providers, as well as alerting them to abnormal vital sign readings.

2.2.5 Digital health self-management technologies for chronic obstructive pulmonary disease

In 2019, 3.23 million people died from COPD, which is the third most common cause of death in the world (World Health Organization, 2022c). Symptoms of COPD usually include: frequent coughing, shortness of breath, sputum or phlegm, and deep breathing difficulties (Centers for Disease Control and Prevention, 2022a). For people with COPD, quitting smoking is paramount (Mitchell et al., 2014).

it is also necessary to have a good nutrition plan, adequate PA routines and an understanding of how to self-manage breathing difficulties (Effing et al., 2012). COPD is linked to decreased physical, emotional, and social functioning, which worsens quality of life (Barnett, 2005, Brien et al., 2016). Living well with COPD requires effective self-management, and proactive participation has been linked to fewer hospitalizations and exacerbations as well as an improvement in health-related quality of life (Pauwels, 2000). Digital health technologies can improve self-management by fostering engagement and self-efficacy for people with COPD, and assisting health care professionals in promoting preventative care-provision practises (Slevin et al., 2020).

Velardo et al. (Velardo et al., 2017) used a digital health system to support patients with COPD in self-managing their condition. There are two parts to this system: a mobile application on the users' tablet and a backend server for health care professionals to manage patients' self-management. During a 12-month trial, 110 participants were given a tablet computer and a pulse oximeter and were encouraged to use these devices to complete symptom diaries and oxygen saturation measurements. The authors found that patients can maintain self-management over a longitudinal period by using digital health technologies, including features such as videos and personalised alerting. In addition, the authors cite a number of benefits of patient-centred digital health system design, such as enhanced patient compliance, increased ease of use, and facilitation of high-quality data collection. A randomized feasibility study of digital mobile health techniques for people with COPD is presented in (Bentley et al., 2020). All participants in the intervention group were given a smartphone app and an activity tracker to help them stay physically active after pulmonary rehabilitation. In comparison to those who withdrew, they discovered that research participants who finished the trial had better baseline health and more prior exposure with digital technologies. They highlight that simplicity and usability are very important factors to foster engagement with digital health technologies.

Hardinge et al. (Hardinge et al., 2015) used a mobile telemedicine based application to support the self-management of COPD patients over a period of six months. They concluded that it is feasible for patients with COPD to use mobile health interventions at home, where patients can comfortably report their daily symptoms, medication use, pulse rate and oxygen saturation measurements.

2.2.6 Digital health self-management technologies for older adults with chronic conditions

Chronic conditions tend to be more prevalent in the ageing population (National Institute on Aging, 2017, Boutayeb and Boutayeb, 2005). According to reports, increased usage of technology by older adults is linked to better health, higher levels of social connectivity, and overall higher quality of life (Greenwald et al., 2018, Low et al., 2021). Additionally, the use of digital health technologies amongst older populations has potential to:

1. Improve self-management (Alhussein and Hadjileontiadis, 2022), and improve health outcomes, for example stabilise blood glucose (Makroum et al., 2022), blood pressure control (Buis et al., 2019), and weight loss (Fanning et al., 2020).

2. Improve drug adherence and persistence, for example, using artificial intelligence and a smart phone application to visually identify the medication, the patient and the confirmed ingestion (Labovitz et al., 2017); monitoring the medication ingestion by an ingestible sensor (DiCarlo et al., 2012); and monitoring medication usage by using predefined Quick Response Codes attached to the medication box, scanning the codes with a smartphone app and recording the medication(Capranzano et al., 2021).

3. Enhance nutritional therapy by monitoring nutrition, and personalised nutritional therapy (Nelson et al., 2017, Flodgren et al., 2015).

4. Improve physical support, fitness and rehabilitation. Wearable devices and monitors that collect physiological and behavioural data can help older adults with exercise adherence and rehabilitation safely and effectively (Piau et al., 2021, Piotrowicz et al., 2016, Piotrowicz et al., 2020).

5. Improve the interaction and communication between health care providers and older adults, which can in turn improve disease management, increase social support, improve self-competence, and enhance well-being (Flocke and Stange, 2004, Sparks and Nussbaum, 2008, Czaja et al., 2018, Morton et al., 2018).

Lee et al. (Lee et al., 2016) tested the Mobile Applications for Seniors to enhance Safe anticoagulation therapy (MASS) that enhances oral anticoagulation treatment (OAT) in older people with HF or atrial fibrillation and is used to further increase patient independence and self-management. MASS is a mobile-based health technology intervention that includes many different modules such as education, self-monitoring, reminders and social features (e.g. family, friends, medical professionals). After three months of testing with 18 older people, the results showed that MASS can help older people gain more knowledge about oral anticoagulants. However, for other outcomes, such as quality of life, depressive symptoms, anxiety symptoms and OAT medication adherence, there remained no difference.

Wu et al. (Wu et al., 2022) developed a Community-Based e-Health Program (CeHP) which was supported by a mobile device application for older adults with chronic conditions. The CeHP has three main components to help older people with chronic conditions to self-manage, including health education, health monitoring and an advisory system. Based on the questionnaires and health outcomes before and after the pilot study, the authors found that the CeHP was viable in that it engages older adults living in the community and empowers them to manage their chronic conditions. Also, the authors believe that the CeHP has great potential to encourage self-management, promote social support, and reduce health care costs.

Unlike the previous two studies, which were supported by mobile devices, Gustafson et al. (Gustafson et al., 2015) presented a web-based information and communication technology named Elder Tree (ET). ET is designed for older people and caregivers to improve the quality of life of older adults, and it is based on the previous digital health intervention CHESS (Gustafson et al., 2014). The intervention is based on a mobile phone application which includes communication with caregivers and health care professionals, audio-guided relaxation, emergency alert, and self-monitoring. The authors conducted an unblinded randomised clinical trial to assess the effects of ET on the quality of life of older adults with multiple chronic conditions (Gustafson Sr et al., 2022). In this trial, 390 older adults with multiple chronic conditions were divided into two groups, with one group of participants having access to ET and the control group not having access to ET. The results of this trial showed that there was no significant difference between these two groups and that participants who had the access to ET did not gain more benefits, such as quality of life, depression, and independence, compared to the control group.

Active Plus is an effective computer-tailored PA stimulating intervention for older adults to increase the PA in daily life (Van Stralen et al., 2008). Such interventions can provide older adults with tailored information to increase awareness of PA and to maintain PA based on the user's situation, specific needs and desires. The Active Plus intervention can help improve public health by increasing the PA of older people in a cost-effective way (Golsteijn et al., 2014). However, Volders et al. (Volders et al., 2021) conducted a randomised controlled trial of Active Plus with older adults with at least one chronic condition. The authors found that the PA behaviour of participants who, on three occasions, received computer-tailored PA stimulating advice was similar to that of the control group who did not use Active Plus. They also argue that this is because the Active Plus intervention by itself is not sufficient to increase PA in older adults with chronic conditions.

2.2.7 Digital health self-management technologies for multimorbidity

Self-management of multiple chronic conditions poses a considerable burden for people with multimorbidity (Haggerty, 2012). Older adults with numerous chronic disorders have average overall health care expenses that are 5.5 times greater than those of older adults without multiple chronic conditions (Bähler et al., 2015). Moreover, multimorbidity prevalence rates are estimated to be 65% in those over 65, and they increase with age (Marengoni et al., 2011). However, only a small number of studies have explored how digital health can help solve problems associated with multiple morbidities.

Zulman et al. (Zulman et al., 2015) conducted a focus group study to understand the challenges faced by people with multiple conditions and to identify opportunities to use e-health technology to support these people. Several opportunities were identified, including having a uniform medical record which can facilitate care coordination; online information for the management of multimorbidity, especially for the interaction and conflicts of different chronic conditions; using mobile apps to support self-care tasks and social communication; and secure technology for the communication between various stakeholders.

Melchiorre et al. (Melchiorre et al., 2018) surveyed 101 programmes in Europe, 85 of which incorporated e-health solutions, and 42 of which targeted at older adults. Remote consultation and monitoring, self-management (e.g., electronic reminders, online decision support), health care management technology like patient databases and e-referral systems, and electronic health records were among the e-health technologies used in these programs. The authors believe that e-health may enhance integrated care for older people with multimorbidity. However, neither in-depth analyses nor evaluations of these technologies were provided in this paper.

Doyle et al. (Doyle et al., 2019) conducted a study to understand design requirements for a digital self-management tool for older adults with multiple chronic conditions. They highlight that self-management of multiple conditions can be more challenging and time consuming than management of a single condition. They propose three design recommendations when designing for multimorbidity self-management. First, “prioritise self-management activities to reduce complexity”. For example, a digital daily checklist could be used to highlight daily tasks and appointments. Algorithms could be used to highlight what tasks should be prioritised, based on a person’s current status. For example, if a person’s blood pressure is increasing, the checklist could include a suggestion to take blood pressure readings or to view a piece of education related to reducing blood pressure. Second, “to effectively support self-management, consider the whole person, their co-morbidities, age-related impairments and current status of conditions.” All suggestions in terms of care activities for people with multimorbidity should be based on the person’s complete condition profile. For example, while activity is an important part of self-management for people with diabetes, a suggestion such as to increase activity is likely not appropriate for someone with limited mobility. Finally, “support people with multimorbidity and informal carers to progressively learn how to digitally self-manage, with context-relevant prompts.” Doyle et al. point out that patients and their informal carers receive little information about how to effectively self-manage their conditions and facilitating this learning should therefore be a goal of digital systems supporting self-management.

Likewise, Caldeira et al. (Caldeira et al., 2021) interviewed 17 older adults with multimorbidity to find out the conflicts in multiple chronic conditions management. They found that incompatibilities between treatments for different conditions needed to be given more considerations in care. In such cases, treatment decisions must be made not only for the specific disease, but also for the patient's overall condition. The conflict between medical conditions and self-management activities can also be difficult to balance. For example, PA can help older people with multimorbidity to improve and maintain their health, but for some conditions, exercise can have a negative impact that can lead to injury. Moreover, some older adults talked about being nervous about previous health problems or possible future illnesses, in addition to the chronic conditions they already had. These two different types of conflict had an impact on their health care choices. All of the above conflicts should be considered when designing digital health technology for older adults with multimorbidity.

Medication management is an important part of self-management of multimorbidity in older people, not only because older adults with multimorbidity have many medications, but also as medication errors can cause serious health issues (Forster et al., 2003). Siek et al. (Siek et al., 2010) designed a personal health application called Colorado Care Tablet to help older people with multimorbidity manage their medications. In this application, users can create and maintain the medication list, check the medication information, and communicate with the health care professionals. Dalgaard et al. (Dalgaard et al., 2013) presented MediFrame, a tablet based personal medication management system to support older adults at home. This intervention can help older adults record the medications they need, shows information about the medications and how often they are used, delivers reminders to take medications, and gives advice on medications based on the individual's physical condition. To better understand how to design a medication management app for older people with multimorbidity, Doyle et al. (Doyle et al., 2017) interviewed 124 participants, including older adults, caregivers, and health care professionals. The authors identified the following six key requirements for the application of medication management for older people with multimorbidity. Firstly, the application needs to support the creation, maintenance and updating of a list of medications that patients can control, as well as a list of medications that caregivers and health care professionals can access. Second, educate patients on the conditions and symptoms that correspond to the various medicines and prescriptions. Meanwhile, the application should support the management of regularly changed medications and prompt a detailed medication review. In addition, the app can schedule medication intake and includes information on how to use medication devices such as nebulisers and inhalers.

There are limited longitudinal studies that explore how older adults with multimorbidity use digital technology to self-manage their health and well-being. One such study was the ProACT proof-of-concept trial, whereby 120 older adults across Ireland and Belgium used the ProACT digital health platform to self-manage multiple chronic conditions, including diabetes, COPD, HF and heart disease (HD) (Doyle et al., 2021). Exploration of the engagement and health and well-being data from the Irish trial is the subject of this thesis (as outlined in Chapter 3).

2.2.8 Summary

It is clear from the literature that digital health technology is important for people with chronic diseases to support self-management, improve quality of life, and enhance health status. There is also a wide range of digital health technologies and interventions such as digital monitoring devices, remote monitoring, smartphone apps, social media and Internet-based interventions that can meet the different needs of patients with different chronic conditions. However, digital health technologies should also be tailored and personalised to the different states of the user, such as age, different types of chronic condition, multiple chronic conditions and living environment. For example, older adults often have more difficulty using digital medical devices compared to younger adults (Kim and Choudhury, 2020), while different chronic conditions require monitoring of different symptom and well-being parameters. Furthermore, people with multiple chronic diseases need to monitor several parameters and participate in multiple additional self-management tasks, increasing the complexity of multiple disease management compared to single disease management. Another concern is how to enhance engagement with digital health technologies. This is discussed in the next section, with a focus on the barriers affecting engagement, different ways to increase engagement, and the benefits of engagement.

2.3 User engagement with digital self-management

As outlined in the previous section, digital health technologies hold great potential to support people to manage chronic conditions, allowing for monitoring and tracking of symptoms and lifestyle behaviours, promoting behaviour change and ultimately improving outcomes. However, intended and effective outcomes can only be realised if people engage in digital self-management (Yardley et al., 2016). User engagement includes many different components such as interactivity, perceived control and time, motivation, interest, emotion, feedback and awareness (O'Brien and Toms, 2008). However, the definition of user engagement in the context of digital health still lacks definition and agreement. In order to measure user engagement in digital health, engagement is divided into two categories: the first category is what users engage with, such as different kinds of digital health technologies and targeted health behaviours. The second category is how users engage behaviourally (usage), affectively (motivation, feelings), or cognitively (interest, attention) (Milne-Ives et al., 2024). There are many barriers that affect the acceptance, adoption, and continued use of digital health technologies especially for older adults with chronic conditions, such as user health status, social support, technology experience, psychomotor and system features (e.g., user interface, functionality, data privacy) (Czaja et al., 2013, Heart and Kalderon, 2013, Liu et al., 2019). In addition, unlike a single chronic disease, people with multimorbidity might also face additional barriers due to the complexity of managing multiple health care self-management tasks as well as conflicts in health care delivery (Doyle et al., 2019, Caldeira et al., 2021). However, there are also facilitators known to improve engagement with digital health technologies, for example, user-centred design, technology support, social support, and system credibility (Matthew-Maich et al., 2016, Portz et al., 2016).

This section will first describe the barriers to and facilitators of engagement with digital health technologies. The literature on technology acceptance and healthcare technology self-efficacy is then examined. Finally, the literature on data-based evidence of engagement with digital health technologies will be explored, as this PhD project uses data from a 12-month trial to examine the engagement between older people with multimorbidity and digital health technologies.

2.3.1 Barriers impacting user engagement with digital health technology

There are many challenges in engaging people in digital health self-management, such as low usage, high attrition, small effect sizes (Morrison, 2015), technical difficulties (Stellefson et al., 2013), engagement decreasing over time (Kirwan et al., 2013), and financial resources (Mulvaney et al., 2011). Other research has identified barriers including technology access issues, time constraints for homecare providers, gaps in health care delivery, and geographic and social location leading to inadequate patient engagement (Hunting et al., 2015). To better understand the barriers affecting digital health technology engagement, this section will focus on three different types of barriers specifically related to users (e.g. user demographics, user beliefs, user knowledge and skills), programmes (e.g. content, usefulness, guidance), and technology (e.g. technical factors, privacy) (Borghouts et al., 2021).

2.3.1.1 User-related barriers

Some demographic variables have been shown to influence engagement with digital health technology, including gender (Crisp and Griffiths, 2014, Achtyes et al., 2019), age (Mattila et al., 2016, Beatty et al., 2017), education level (Stevens et al., 2018), employment status (Kannisto et al., 2017), income level (Erhunmwunsee et al., 2020), and health conditions (Eisner et al., 2019). Mikolasek et al. (Mikolasek et al., 2018) evaluated the feasibility of a mobile application for cancer patients that involved self-report measures (e.g., symptoms, quality of life), as well as data collection on time spent on mindfulness and relaxation practices. They found that female patients had better adherence to the mobile application. Similarly, Smail-Crevier et al. (Smail-Crevier et al., 2019) found that women in e-mental health programs were more willing to use the Internet to access medical and health information compared to men. In addition, the authors noted that women prefer to use features related to exercises, self-help interactive programs, and interactions with health care professionals.

A number of studies have examined the correlation between age and digital health technology use, with varying findings. For example, Bol et al. (Bol et al., 2018) analysed the user data of many different mobile health applications (e.g., fitness apps, nutrition apps, self-care apps, sleep apps, etc.) in the Netherlands and found that younger adults are more likely to use mobile health applications than older adults. However, the authors also note that younger people generally use fitness and reproductive health apps, while users of self-care and vital signs apps are typically older. In the case of diabetes, research has found that higher age was negatively associated with the use of mobile health apps and search engines among type 1 diabetics, but there was no age difference in the use of e-health among type 2 diabetics (Hansen et al., 2019).

People with lower education levels generally have higher dropout rates when using digital health technologies, including online mental health programmes (Alfonsson et al., 2016); internet-delivered PA and nutrition promotion programmes (Robroek et al., 2012); and online health communication programmes (Van't Riet et al., 2010). Likewise, people with higher income levels and who are employed are usually more willing to use digital health interventions than people with lower income levels and the unemployed (Graham et al., 2018, Hamideh and Nebeker, 2020). Poor health, such as poor self-reported health status, (Mahajan et al., 2021), or depressive symptoms in mental health (Crooks et al., 2017) can also lead to reduced use of digital health technology (Yao et al., 2022).

In general, patients are usually motivated to engage in digital self-management if they think the technology will help them with their major health problems (Hunting et al., 2015). Firstly, it is important to educate patients not only about digital health, but also about their own health and build their belief in digital health technology, which can increase engagement and prevent drop-out (Melville et al., 2010, Aref-Adib et al., 2019). Many studies have pointed out that limited knowledge of digital health technology is one of the barriers impacting engagement (Mishuris et al., 2015, Kruse et al., 2018). Likewise, Tieu et al. (Tieu et al., 2015) suggest that training and support is essential for those who are vulnerable to chronic diseases, especially for those with limited health knowledge. In addition, patients with weak beliefs about digital health technology may find digital interventions distracting and may choose to switch off the mHealth intervention to avoid interruptions that might disrupt sleep patterns or structured daily activities (Switsers et al., 2018).

2.3.1.2 Program content-related barriers

The content and features of digital health interventions can also impact engagement with them. For example, the credibility of the content (Wallin et al., 2016); the perceived fit and usefulness (O'connor et al., 2016, Berry et al., 2019); the level of guidance and support (Band et al., 2017); and social connection (Pung et al., 2018, Pywell et al., 2020).

An interview study with 32 health care professionals from hospitals and clinics to explore the barriers they see in using digital health technology to manage COPD found that data quality is a barrier for using digital health technology (Slevin et al., 2020). For example, inaccurate readings can cause undue health anxiety, which can lead to distrust of digital health technology. In addition, these health care professionals need more evidence of the effectiveness of digital health, as well as clinical guidelines, which could increase their willingness to use and recommend digital health technologies. A cross-sectional survey of 149 participants to understand people's interest and barriers to using mobile apps for depression and anxiety disorders also found that the most cited barrier was that participants needed to see evidence that the app was useful (Lipschitz et al., 2019).

From the patient perspective, some reasons for reduced use of health apps include lack of trust in health apps, concerns about data privacy and fear of misdiagnosis (Rasche et al., 2018). Lundgren et al. (Lundgren et al., 2018) conducted a study of web-based cognitive behavioural therapy for people with HF and depression. They noted that participants needed real-time communication (e.g., phone and video calls) with health care professionals and caregivers, which made them feel cared for. However, too much interaction with patients can have the opposite impact by making them feel forced to use digital health technologies (Feijt et al., 2018). Therefore, a delicate balance is required.

2.3.1.3 Technology-related barriers

Privacy and confidentiality of digital health technology have been mentioned as barriers to technology engagement and use in a number of different studies. Specifically users will lose trust in technology and abandon its use if a data breach occurs, while many users report concerns about their personal health data being shared with organizations without their explicit or informed consent. (Garg et al., 2015, Lennon et al., 2017, Borghouts et al., 2021).

Rickard et al. (Rickard et al., 2016) developed a mobile application to monitor people's daily emotional well-being changes in real time. They utilised three methods of collecting data from users: (1) automated monitoring online behaviours (e.g., Facebook, Twitter, music); (2) self-reported emotional well-being; (3) questionnaires of psychological assessment. After 30 days of testing with 11 participants, the feedback reflected that some participants were concerned about their privacy. They argued that the location information should not be specific to GPS points and that it would be better if the location information only showed postcodes. In addition, some participants felt that it would be better to give the permission to the application for social media sharing after they had used the app for a while and built trust.

Klonoff and Kerr (Klonoff and Kerr, 2018) note that digital health technology for people with diabetes needs to satisfy users not only in terms of the safety and effectiveness of the technology, but it must also be compatible with existing electronic tools, electronic health records and clinical guidelines. Moreover, digital health technology should demonstrate clinical benefit to satisfy clinicians and economic benefit to satisfy payers. For example, to help prescribers and payers embrace the use of digital health technologies as part of standard diabetic care, doctors need data on effectiveness from clinical trials.

A further barrier to people using digital health technology is the cost, for example the cost related to the need for a mobile device, wearable devices, internet access, and in-app purchases (Luque et al., 2013, Borghouts et al., 2021). Moreover, technical issues with digital health technology are one of major barriers to engagement, such as mobile apps crashing, wearable devices unexpectedly shutting down, and loss of internet access (Naslund et al., 2016a). Poor design features of digital health technology could also impact the engagement of users, such as complicated navigation and difficult-to-read screen presentations (Ting, 2012). On the other hand, good design can make users feel more favourable towards the technology and fosters a positive user experience (Torous et al., 2018).

2.3.2 Factors enhancing user engagement with digital health technology

There is a large body of research examining the factors that enhance engagement with digital health technologies. There are many different methods integrated into technology design to encourage motivation and continued engagement, including notifications (Potts et al., 2020, Morrison et al., 2014); game-based approaches (Monk, 2002, McCallum, 2012); personalisation (Asimakopoulos et al., 2017, Potts et al., 2020, Schubart et al., 2011); and peer support (Maher et al., 2014, Yardley et al., 2016).

In 2017, Asimakopoulos et al. (Asimakopoulos et al., 2017) conducted a study to explore motivation and user engagement in fitness tracking. They presented a number of general design guidelines to enhance the user experience and user engagement, including:

1. Personalisation – allow the user the determine their own fitness goal.

2. Navigation/input – ensure it is clear to the user that there are options/further ways of personalising single functions. Gamification of the process of navigating and personalising is critical.

3. Positive feedback – assess motivation and/or self-efficacy levels (for example through user-defined ratings and questionnaires) and provide new goals based on the outcomes from these assessments; expose users to positive and constructive feedback.

4. Multi-activity motivation analysis – Users expressed a desire for features that enable them to better analyse relations between data/information, activities and motivation/self-efficacy behaviour, for example, the relationship between diet and high or low motivation. Users may be able to categorize activities based on the motivation or self-efficiency improvements they see, as well as to explore behaviours that promote higher motivation or increased self-efficacy.

5. Context integration – Capturing reflections on life events and emotional or social interactions during fitness tracking may be an important facilitator of motivation and self-efficacy. This can create an added sense of sociability or social user experience known to drive motivation and behaviour change in health care.

6. Provide intelligence to encourage more targeted behaviour change – Giving users a means to explore their gathered data to increase their self-efficiency and fitness levels, can make the experience more meaningful. Interpreted data can be helpful but making sense of activity trends and patterns and tying those to “victories” or self-defined goals might improve self-efficacy.

7. Sustain user motivation by leveraging intrinsic motivation into a playful experience – Use game elements and small rewards to support different stages of self-monitoring, making it possible to meet user needs for autonomy, competence, and relatedness that support the development of intrinsic motivation.

The authors outline three specific factors that impact user motivation with health care wearable devices for recording daily activity (e.g., walking, cycling, yoga) which are, "(a) Seeing if I met my goal (movement/sleep/calories count); (b) Looking and feeling good as a result of activity, improving mood and avoiding sitting; and (c) Getting tips and recommendations from the app".

2.3.2.1 Notifications

Notifications in digital health technology act like triggers in Fogg's behavioural model (Fogg, 2009) and can increase people's motivation to engage with digital health devices or applications (Morrison et al., 2017). Fogg’s behavioural model states that a person needs to be sufficiently motivated, have the ability to perform the behaviour, and be triggered to perform the behaviour, then the person will perform the behaviour, which can be simplified to motivation, ability, and triggers. Notifications should be delivered at times that do not interrupt people’s daily routine (Fukuoka et al., 2012, Bentley and Tollmar, 2013). Otherwise, people can find it irritating if notifications appear at the wrong time or place and are impossible to follow (Dennison et al., 2013). However, it has been noted that the content of the notice is more important than the time people receive it (Fischer et al., 2010). As such, it is important to figure out when and what content users are more likely to view and respond to notifications, and how many notifications are appropriate.

Morrison et al. (Morrison et al., 2017) conducted a study to test whether smart sensor-driven machine learning models could find the right time and number of smartphone-based stress management interventions to send to people. Participants were split into one of three groups, with one group receiving notifications based on the machine learning model, one group receiving daily notifications at pre-determined times and the final group receiving occasional notifications at pre-determined times. The authors found that frequent notifications increased engagement with digital health interventions. However, the timing of notifications tailored by machine learning models did not increase the uptake of digital health interventions compared to the group that received daily notifications.

Potts et al. (Potts et al., 2020) used ecological momentary assessment questions via notifications to the mobile devices of people with dementia and their caregivers. The authors analysed the event logs from the mobile devices and found that users were more willing to respond the questions between 9 PM to 10 PM.

2.3.2.2 Gamification

Digital health technology could engage patients through game-based approaches. The enjoyment from games can lead to high engagement, aesthetic attraction, and narrative completeness (Monk, 2002). Games can also promote physical and social/emotional health for patients (McCallum, 2012). Kappen et al. (Kappen et al., 2017) conducted an online survey to explore the gamified motivational affordances and feedback elements of PA technology, such as Nintendo's Wii Fit game, and the Fitbit wearable device in different age groups. The authors divided the motivational effects of gamification into two categories, namely intrinsic elements (e.g., goals, challenges, achievements, tasks) and extrinsic elements (e.g. badges, rewards, points). The authors concluded that for both younger and older participants, techniques with appropriate motivational affordances can increase initiation and adherence to PA, thereby promoting physical and mental health. However, there are some potential negative aspects of game-based self-management technology, for example, 1) Focusing on gaming more than treatment; 2) Competition may lead to over engagement (Nunes et al., 2015).

Herpich et al. (Herpich et al., 2017a) designed a gamified context-aware recommender system for older adults. The authors concluded that this system could improve quality of life and support solitary living in older adults. The recommendation system uses pictures (e.g., motives, pets, flowers), photos of family members, and appropriate content to prompt different physical and mental activities. Moreover, the system includes some well-known digital game principles to enhance user engagement with the system, e.g., live feedback, special rewards. (Herpich et al., 2017b). The authors found that user motivation is increased by personalising rewards for different tasks. At the same time, feedback and rewards for physical activities should take into account the user's personal situation (e.g., age and illness) in order to avoid user frustration.

2.3.2.3 Personalisation

Many research studies show that personalised and tailored digital health interventions are more effective than those non-tailored (Noar et al., 2007, Krebs et al., 2010, Lustria et al., 2013). Personalised and tailored digital health interventions often engage with users based on their unique personal conditions and preferences, such as suggesting PA based on physical condition and different nutritional recommendations for people with or without diabetes (Kreuter et al., 2000, Rimer and Kreuter, 2006). Schubart et al. (Schubart et al., 2011) identified two characteristics that contribute to engagement with Internet interventions for patients with chronic health conditions: "(1) the intervention targets participants with pressing health concerns, and (2) the intervention adapts to individual needs".

By connecting users to digital health interventions using tailored messages and communications, users can more easily understand the information and increase their motivation to participate in digital health interventions (Hawkins et al., 2008). Because messages for digital health interventions are often deeply tailored to the user's personal characteristics and preferences, for example, information for older adults and those with lower levels of health literacy will be more plainly understandable (Lustria et al., 2016, Nguyen et al., 2020). Nelson et al. (Nelson et al., 2016) point out that technology-delivered self-care interventions with more tailoring (e.g., meet users' individual needs, personalisation) may have higher engagement levels than those with less tailoring for adults with type 2 diabetes.

Dobson et al. (Dobson et al., 2018) conducted a parallel randomised controlled trial to find out the effectiveness of a tailored, text messaging-based diabetes support programme. The control group received usual care for 9 months, while the intervention group received usual care and tailored text messages, which were sent by an automated content management system, for 9 months. The authors found that the reduction in blood glucose was significantly greater in the intervention group than in the control group. Although this study was not primarily a comparison of tailored and non-tailored interventions, the authors still mentioned that participants in the intervention group showed a high level of satisfaction with the quality and dosage of tailored, personalised messages.

2.3.2.4 Support

Peer support is often defined as the ability for others with similar experiences to relate more easily, thus providing more genuine empathy and recognition (Mead and MacNeil, 2006). Andalibi and Flood (Andalibi and Flood, 2021) conducted an interview study with users of a digital mental health peer support system (Buddy Project) that allows two users to become peer supporters of each other. The authors found that a technology-mediated peer support system can be an effective coping tool for young people with mental health challenges. Such technology gives a clear commitment to reduce the stigma of mental health discussions between partners and provides a shared understanding.

Support from health care professionals and informal caregivers who can provide emotional support, medical support, and technical assistance, is important to enhance engagement in digital health (Fortuna et al., 2019). Doyle et al. (Doyle et al., 2022) explored relationships among older adults with multimorbidity using a digital health platform and a nurse-led telephone triage service that responds to alerts. The authors analysed the results of semi-structured interviews with participants and triage nurses, which revealed several positive effects. Firstly, the triage nurse can enhance the education and motivation of the participants. For example, during the call, the triage nurse might have conversations with the participant about diet and give some tips about activity goals. In addition, the authors found that participants were very willing to listen to and participate in the triage nurse's advice, which also made participants more adept at managing their own conditions facilitated by digital health technology. However, the authors also noted that some participants felt anxious because they felt watched, or they perceived the triage nurse's call as bad news, meaning that their symptoms were out of range.

2.3.2.5 Other approaches

Morrison (Morrison, 2015) explored integrating theories from psychology into digital health behaviour change interventions. Based on the self-determination theory that autonomous motivation can be enhanced by supporting an individual's autonomous, relatedness and competence (Ryan and Deci, 2000), Morrison (Morrison, 2015) pointed out that motivation theories provide useful design strategies to enhance motivation to change health-related behaviour and to use and engage with digital interventions. For example, giving choice and flexibility within tunnelled architectures (Deci et al., 1994), encouraging users to reflect on their internal reasons for changing their health behaviours or using digital interventions (Yardley et al., 2014), and providing opportunities for the user to offer feedback which can make users feel they are listened to (Yardley et al., 2011). Klasnja and Pratt (Klasnja and Pratt, 2012) suggest that patients having access to their data, for example their blood glucose readings, may also improve engagement. However, there are still some uncertainties in relation to implementation, for example whether providing positive feedback on goal progress serves as an extrinsic motivator that undermines autonomy, or whether providing choice will become burdensome and overwhelming, which might discourage continued usage of the digital intervention (Morrison, 2015).

2.3.3 Information technology acceptance

User acceptance is defined as an individual's perception of a technology leading to its use or non-use (Venkatesh, 2000, Venkatesh et al., 2003, Venkatesh and Bala, 2008), which is also the key for using health care technologies (Nadal et al., 2022). Several factors impact user acceptance of information technologies. Venkatesh et al. (Venkatesh et al., 2003) think performance expectancy, effort expectancy, social influence and facilitating conditions are the four critical determinants of user acceptance in the Technology Acceptance Model (TAM). The performance expectations of users are the extent to which they believe that using the system will help them to perform better (Venkatesh et al., 2003). The effort expectancy of a system is determined by how easy it is to use (Venkatesh et al., 2003). The social impact of a system is determined by how others who are considered important by its users perceive it (Venkatesh et al., 2003). Facilitating conditions refer to the extent to which the user believes the system is supported by an adequate organisational and technical infrastructure (Venkatesh et al., 2003).

Nadal et al. (Nadal et al., 2020) believe that the Technology Acceptance Lifecycle (TAL) can provide a better understanding of the process of technology acceptance and clarify the measurement of technology acceptance. They divided the TAL into three different stages: pre-use acceptability, initial use acceptance, and sustained use acceptance. In the pre-use acceptance stage, users begin by seeking advice and then selecting the technology that is right for them. The initial use acceptance stage begins with the first interaction and ends one week later, and the final stage is the ongoing use acceptance stage, which includes three time-specific milestones: one month, three months and one year. The authors concluded that TAL can demonstrate technology acceptance at different user journey stages and during the acceptance of the technology. Furthermore, they suggest that technology acceptance is a process, rather than a discrete measure, and that technology acceptance assessment should consider both the temporal dimension and the possible evolution of acceptance. They also argue that technology acceptance is more likely to be influenced by technology usage and user engagement in both the initial and sustained phases.

Peek et al. (Peek et al., 2014) found there are several factors that can influence acceptance of health and well-being home-based technology for older adults. The authors group these factors into six themes:

1. Concerns regarding technology (e.g., privacy concerns, high cost, and usability concerns)
2. Expected benefits of technology (e.g., increased safety and perceived usefulness)
3. Need for technology (e.g., subjective health status and perception of need)
4. Alternatives to technology (e.g., support and help from family members)
5. Social influence (e.g., support from family and friends as well as professional caregivers)
6. Characteristics of older adults (e.g., personal preference for ageing in place)

Chen et al. (Chen et al., 2020) conducted research in long-term care facilities by using a humanoid social robot (Kabochan) to examine changes in technology acceptance for older adults with dementia. The authors conducted a two-arm 32-week randomised control trial and questionnaire surveys were administered before and after using Kabochan to assess attitudes and beliefs about the technology. The results of the questionnaire showed that older adults with dementia had improved attitudes and beliefs about technology, which also increased their perceived ease of use of technology.

Other studies have also looked at ways to increase the acceptance of technology among older adults. Wilkowska and Ziefle (Wilkowska and Ziefle, 2009) examined the long- and short-term effects of technology acceptance in older adults of a personal digital assistant. The authors found that older adults' acceptance is mainly impacted by their learning history with technology, but tutorial training can significantly affect technology acceptance outcomes. Jarvis et al. (Jarvis et al., 2020) conducted a study to examine the acceptance of communication technology in residential care for older adults. The authors found a significant relationship between behaviour intention, facilitating conditions, attitude to life and satisfaction, as well as education level, with user acceptance. However, gerontechnology anxiety and age were found to have significant negative influence on user acceptance. These studies indicate that older adults may need support to enhance technology acceptance and overcome gerontechnology anxiety.

2.3.4 Self-efficacy and healthcare technology self-efficacy

As a concept, self-efficacy refers to people's belief that they can produce certain levels of performance that may have a significant effect on their lives (Bandura and Wessels, 1994). As a result of a strong sense of efficacy, a person's accomplishments and personal well-being are enhanced in many ways (Bandura and Wessels, 1994). The crux of self-efficacy is the initiation and persistence of behaviours and courses of action. There are three decisive factors that determine self-efficacy: (1) outcome value (certain outcomes, consequences); (2) outcome expectancy (behavioural means and their effectiveness in producing those outcomes); (3) self-efficacy expectancy (beliefs and expectations regarding the ability to successfully implement selected courses of action in light of behavioural skills and capabilities) (Maddux and Gosselin, 2012).

Another research study explored the relationship between the use of ICT and self-efficacy in older adults (Lozoya et al., 2022). There were 380 retired older adults involved in this study. The authors found that self-efficacy is associated with the use of technologies for communication and learning, indicating that digital literacy benefits older adults' quality of life as well as their health performance (e.g., memory, communication). For example, mobile devices and social networks can help older adults to obtain emotional support and socialize. Moreover, the use of ICT influences older adults to feel empowered and to believe in their own abilities which affects the self-efficacy of older adults' daily activities and impacts quality of life. Quinn et al. (Quinn et al., 2015) examined the use of a mobile phone diabetes intervention for older adults with Type-2 diabetes. During the study, participants used a mobile phone and patient Web portal to input blood glucose values and diabetes self-management information. The results demonstrated that self-efficacy of older adults was increasing over time, and these participants were initially motivated. However, this study had a small simple size (7 participants) and a relatively short study period (4 weeks). Therefore, the variation of self-efficacy was not statistically significant.

A systematic training program and subsequent use of computers was examined by Wild et al. to discover differences in computer-related self-efficacy and anxiety among older adults (Wild et al., 2012). The authors administered two questionnaires about computer self-efficacy and anxiety to participants before training and again one year later. The results show a reduction in anxiety and an increase in confidence among participants in general. However, in comparison to cognitively intact participants, participants with mild cognitive impairment demonstrated less efficacy and confidence at baseline.

Three self-efficacy factors that influence personal attitude toward healthcare technologies, namely General Self-Efficacy (GSE), Computer Self-Efficacy (CSE) and a new context-specific self-efficacy factor, Healthcare Technology Self-Efficacy (HTSE) were identified in a study (Rahman et al., 2016). The authors believe that the traditional self-efficacy constructs (e.g., GSE or CSE) do not have any significant influence on the use of health care technology. Therefore, they proposed a new technology-specific construct, HTSE which also appears to be significantly associated with both GSE and CSE. In addition, a mediating role appears to be played by HTSE in the effects of GSE and CSE on attitudes toward health care technologies. Although the authors did not give a definition of HTSE, they argue that to better understand the HTSE concept, it is necessary to look at the concept in terms of three dimensions (technology dimension, service dimension and information dimension).

There are several studies exploring health care technology self-efficacy (Reychav et al., 2019, Rahman et al., 2016, Balapour et al., 2019). In addition, studies have examined the impact of health care technology on older adults' self-management self-efficacy health care (Karavidas et al., 2005, Wang et al., 2022a), as well as the impact of health care technology on self-management self-efficacy in patients with chronic conditions (Gellis et al., 2014, Dang et al., 2017). Wang et al. (Wang et al., 2022a) assessed the relationship between e-health literacy and health promotion behaviours in older adults and explored the interlocking mediating roles of self-efficacy and self-care competence. The authors found that eHealth literacy was strongly associated with health promotion behaviours and influenced health promotion behaviours through self-efficacy and self-care ability. In another study on self-efficacy and self-management skills in managing HF, the authors developed a mobile phone management program that assessed self-care efficacy, knowledge, behaviours and quality of life in 61 participants over a three-month period (Dang et al., 2017). The author found that the mobile phone-based self-management program improved self-care efficiency and quality of life. These studies demonstrate that high levels of health care technology self-efficacy can improve quality of life, especially for older adults. However, comparatively little research focuses on health care technology self-efficacy for older adults with multimorbidity.

It is also important to understand how to improve the self-efficacy of older adults in using health care technology. Self-efficacy of health care technology can be improved in two ways. First, improving users’ confidence of using the health care interventions, for example, through support to achieve goals (Litman et al., 2015); and communication and support from the community (Willis, 2016). Second, enhance users’ trust of the health care interventions, for example, improving the reliability of health care interventions, as well as data safety and validity (Chamorro-Koc et al., 2021).

2.3.5 Data-driven evidence of user engagement

There is a small body of research that examines engagement with digital health technologies based on data collected from usage logs of such technologies over a period of time. Potts et al. (Potts et al., 2020) assessed engagement with Ecological Momentary Assessment (EMA), questions delivered through a digital reminiscence app for people with dementia and their caregivers, to gather accurate real-time data. While the purpose of the application used by participants was not health self-management, it is relevant as participants were asked to answer self-report EMA questions and answering questions in relation to health and well-being is often a feature of digital health applications.. The authors found that the overall question dismissal rate was 30.9%. They discovered that participants were more likely to answer EMA questions between 9 p.m. and 10 p.m. However, the authors suggest that presenting questions multiple times in one day is burdensome for participants, increasing the rate of dismissal. Morrison et al. (Morrison et al., 2014) point out that participants seem happy to answer questions if they know what the personal benefits are to answering the questions and are more inclined to answer study measures when the intervention is helpful.

A mixed-methods study evaluated user engagement, acceptability, and usability of an mHealth intervention aimed at reducing sedentary behaviour of older adults (Compernolle et al., 2020). The authors collected system usage data, time spent sitting (using a sensor device) and conducted semi-structured interviews with participants. By analysing the usage data and interview data, the authors found that older adults were highly engaged with this study's intervention and most of the participants showed positive feelings and consulted the feedback frequently. The system usage data showed that participants wore the self-monitoring device for a median of 20 out of 21 days, eight out of 28 participants accessed the app every day while five participants used the app on at least 80% of trial days. However, this study only lasted for three weeks, which is too short to show long-term engagement. Moreover, the results of the study showed no reduction in sedentary time of older adults after the three-week period, which is likely because the intervention period of three weeks was also too short to change habitual behaviour.

A diabetes support application was used by 9051 individuals for 180 days and real-world data from this application was analysed to identify which patient characteristics are associated with technology engagement (Bohm et al., 2020). The application has five different modules, including a continuous glucose monitoring (CGM) module (that captures blood glucose at a certain point in time when users perform the relevant actions); a blood glucose (BG) module (where users manually measure their blood glucose and enter it into the app); an exercise module (measures a user's activity in terms of duration, distance, calories burned, etc); a food module (the user enters details of their meal and the application shows the carbs, fat, protein and calories); and a medication module (the user enters their medication intake). The authors found that more than half of users used the application for one single purpose at the beginning. They also found that the number of users who initially used the BG module (55.41%), medication module (43.45%) and food module (42.22%) was much higher than the number of users that initially used the exercise module (17.45%) and CGM module (6.18%). However, the total user activity ratio and average user engagement of the BG, medication and food modules was overall much lower than the CGM and exercise modules, with the authors suggesting that this is because the BG, medication and food modules require manual data entry. The authors also found that older people and those who were recently diagnosed with diabetes used the app more actively. However, the data in this study did not include more detailed engagement information, for example log-in times, so it is unclear how engaged users actually were.

The Habits Heart App is used to support people with HF to self-manage. Wei et al. (Wei et al., 2021) outline a study to assess the feasibility of and patient engagement with the Habits Heart App. 15 participants were randomised into an intervention group (who used the Habits Heart App) and there are 13 participant in the control group (who used paper education material). In the Habits Heart App, there are four modules: To-Do (presents a checklist of tasks for the day); Symptom track (measures weight using a digital scales and presents a symptom survey if changes in weight are deemed a potential exacerbation; Diet and exercise track (asks the user to choose what they have eaten from a list of possible food; and tracks PA by asking the user to manually enter length and mode of exercise); Learn (13 interactive educational videos recorded by cardiologists); and Coach (participants send messages and communicate with the study team and cardiologists) . In terms of engagement, 50% of the patients who were able to use the application interacted with it more than once a day throughout the study and by the end of the study, 75% of the patients in the intervention group regularly had interaction with the application. The authors also found that participants in the Habits Heart App group had better HF knowledge, improved quality of life, and experienced more weight loss than the control group, however given the small sample size the authors suggest caution in interpreting the results.

2.3.6 Summary

From the literature we can see that engagement with digital health technologies is influenced by various facilitators and barriers. Barriers are, for example, user-related (age, gender, education level), program content-related (credibility, guidance), and technology-related (data security, privacy). On the other hand, factors such as personalisation of content, notifications, gamification, support, and feedback can enhance engagement with digital health technologies. Furthermore, concepts such as technology acceptance and health care technology self-efficacy can influence engagement with digital health technologies.

2.4 Data mining and data mining for digital health data

2.4.1 Introduction

Data mining is a useful way to analyse a large volume of data to find patterns, trends and to understand how to use that data (Kincade, 1998, Milley, 2000). Data mining techniques can be broadly classified into three categories: descriptive, predictive and prescriptive (El Morr et al., 2019).

However, this classification is not definitive, and there are those who classify data mining techniques into two categories: descriptive and predictive (Jiawei et al., 2016). A descriptive technique tells us all about the input data's properties, and a predictive technique can perform inference in the input data and generate or predict the hidden information (Agarwal, 2013).

2.4.1.1The process of data mining

In the field of data mining, there are three standard processes, including Knowledge Discovery in Databases (KDD), Sample, Explore, Modify, Model and Assess (SEMMA), and Cross Industry Standard Process for Data Mining (CRISP-DM) (Azevedo and Santos, 2008).

KDD is a process of data mining for extracting useful knowledge from volumes of data (Fayyad et al., 1996). The KDD process has five stages (Selection, Pre-processing, Transformation, Data Mining, and Interpretation/Evaluation), as shown in Figure 1. In the selection stage, a target data set or a focused subset of variables is created to be performed. The pre-processing stage includes data cleaning and pre-processing to obtain consistent data. The transformation stage includes many transformation methods, such as dimensionality reduction and data projection, in order to reduce the number of valid variables under consideration. The data mining phase includes pattern search, based on data mining objectives such as prediction and clustering. The interpretation and evaluation phase involves interpreting and evaluating the patterns found, and then documenting and reporting these patterns as knowledge. In addition, the KDD process is interactive and iterative, and users can decide on the number of steps depending on their dataset (Brachman, 1996).

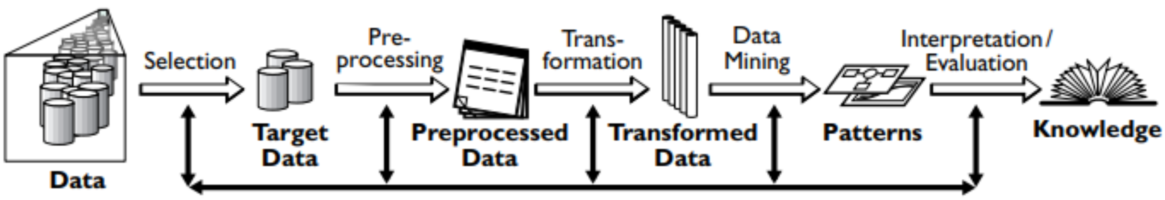

Figure 1. Overview of the steps constituting the KDD process (Fayyad et al., 1996)

The SEMMA process consists of five stages, namely Sample, Explore, Modify, Model and Assess (Shafique and Qaiser, 2014, Azevedo and Santos, 2008). The first stage is to sample the data and extract a dataset that has enough important information and which is also small enough to be analysed quickly. The exploration stage explores unanticipated trends and anomalies in the data, which can help people make sense of the data set and gain ideas. As for the modification stage, the variables in the data are selected and transformed to help with the model selection. The modelling stage allows the software to automatically search for combinations of data and produce the required predictions. The final stage assesses the findings by evaluating the reliability and estimating the performance of the results of the previous stage.

The CRISP-DM process is a cycle with six stages (Figure 2), namely business understanding, data understanding, data preparation, modelling, evaluation, and deployment (Wirth and Hipp, 2000). The business understanding phase entails understanding the project objectives from a business perspective and translating them into data mining questions. For the data understanding phase, the researcher needs to collect data and become familiar with it, then identify data quality issues and detect useful subsets of the data. There is a close link between the business understanding stage and the data understanding stage, as translating project objectives into data mining questions requires an understanding of the available datasets. During the data preparation phase, the initial raw data should be reconstructed into a final dataset for further modelling. In the modelling stage, different modelling techniques are selected and applied to find the most suitable techniques for the data mining problem. There is also a close link between the data preparation stage and the modelling stage, during which some data issues may require the data set to be reconstructed. Before final deployment, the model needs to be evaluated to determine if it is achieving its objectives correctly or if there are business issues that have not been adequately considered. The building of a model is not the end of the project, for example, a report on the process is needed or a repeatable data mining process that can be used by the client - these are all part of the deployment stage.

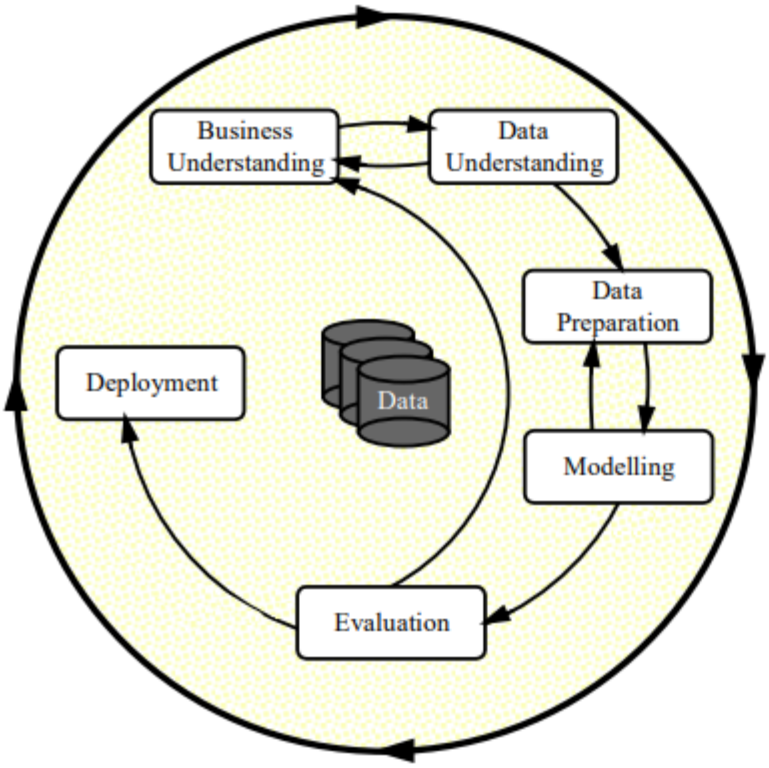

Figure 2. The process model of CRISP-DM life cycle (Wirth and Hipp, 2000)

In this PhD project, KDD is used as the process of data mining the dataset.

2.4.2 Descriptive data mining techniques

2.4.2.1 Data cleaning

In general, the process of data cleaning includes data analysis (e.g., data profiling), definition of transformation workflow and mapping rules, verification, transformation, and data reflow after cleaning (Rahm and Do, 2000). There are usually two types of techniques for data cleaning, namely error detection and error repair, to detect and repair different data quality issues such as duplicate data, missing values and outliers (Chu et al., 2016). All these errors can be divided into four categories based on the sources of error, which are data entry errors, measurement errors, distillation errors, and data integration errors (Hellerstein, 2008).

Data profiling is usually the first step in data cleaning and is used to ensure and assess data quality, such as measuring the accuracy of data and detecting missing values and duplicates, in order to obtain data with the correct value and use it for the next stage of analysis (Olson, 2003, Kusumasari, 2016). Abedjan et al. (Abedjan et al., 2015) presented a classification of data profiling tasks as shown in Figure 3. All the data profiling tasks were divided into three different categories, which are single column tasks, multiple column tasks and dependency detection. The single column tasks normally include various counts of the data, such as the number or percentage of null values, the number of rows, the maximum and minimum of numeric values, and the number of unique values. Multiple column profiling extends the scope of single column profiling activities to include multiple columns, while also reveal inter-value relationships and column similarities. Dependency tasks can show the relationships between different columns, including uniqueness, inclusion dependencies, and functional dependencies. Uniqueness analysis can discover unique column combinations, or determine the unique values in a key column (Heise et al., 2013). Inclusion dependencies analysis can help discover foreign keys and show whether a foreign key has the same data as a primary key in a data attribute (De Marchi et al., 2002, Kusumasari, 2016). Functional dependencies can be used to discover relationships and dependencies between different data attributes, e.g., to show that the values of certain columns can determine the values of another column (Yao and Hamilton, 2008, Abedjan et al., 2015).

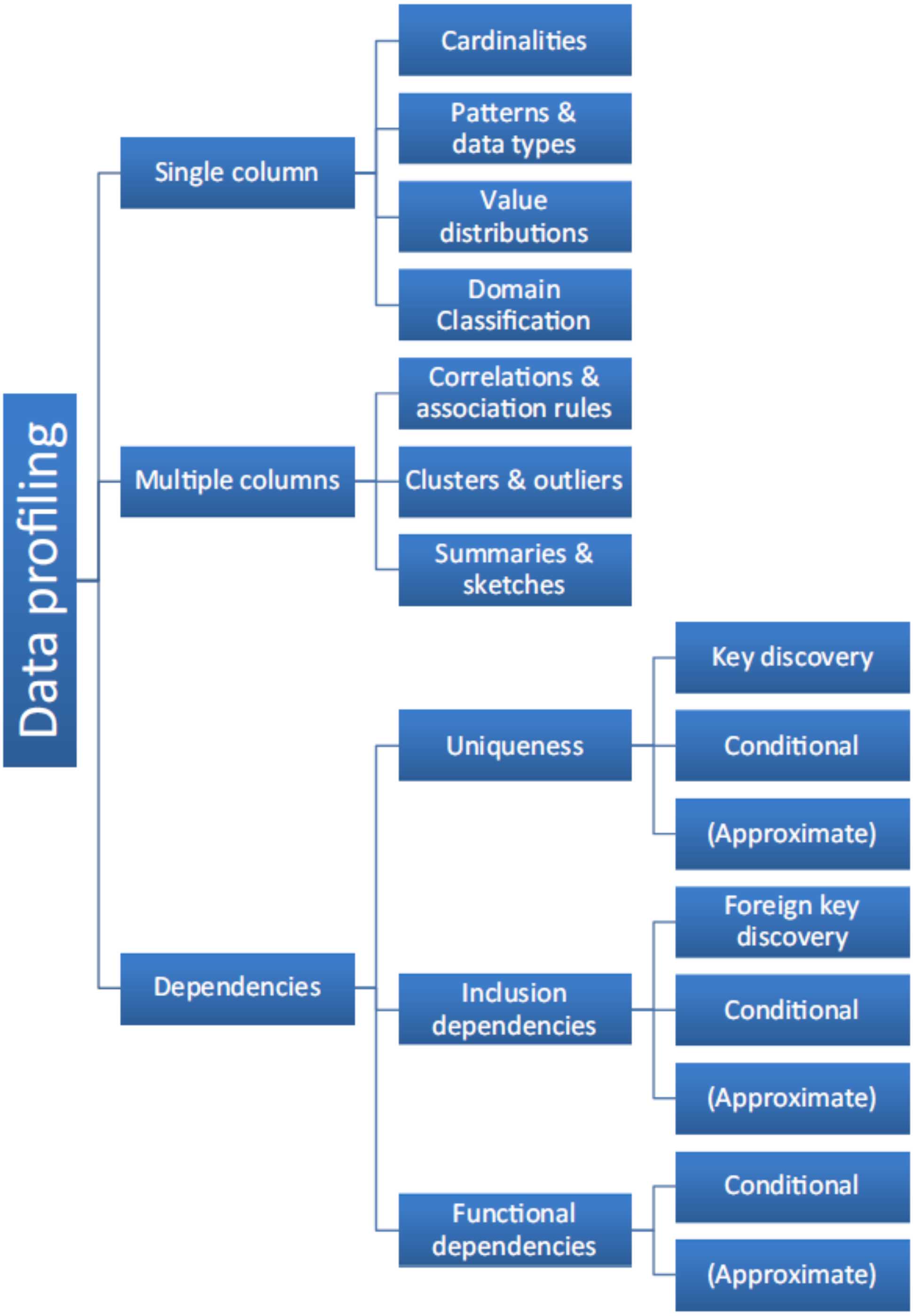

Figure 3. A classification of data profiling tasks (Abedjan et al., 2015)

Two aspects that are integrated and included in the data transformation are the development of measurement guidelines and the determination of functional relationships between variables (Fink, 2009). For example, determining typical values, creating a useful metric, and transforming as differential stretching and shrinking. There are many data transformation methods that are important and useful in data cleaning and data mining, such as normalization (Faraway, 2002), feature subset selection (Wei et al., 2015), discretization (Garcia et al., 2012), and standardisation (Gal and Rubinfeld, 2019). Moreover, data transformation can improve the performance of software quality models (Menzies et al., 2006), and the power of outlier detection (Adikaram et al., 2015). Li et al. (Li et al., 2011) proposed a fuzzy-based data transformation method that extends classification-related information from the original data attribute values of small medical datasets. Six different medical datasets were used to test the data transformation method, and all the transformed data were used as input data for the support vector machine to test the efficiency and accuracy of the method. The results show that this fuzzy-based data transformation method has better classification performance than principal component analysis and kernel principal component analysis in small-scale datasets.

For missing data, data imputation is the most recognised method of dealing with missing data, which allows a reasonable value to be estimated to replace the missing data (Jadhav et al., 2019). The methods of data imputation are broadly divided into two categories: single imputation method and multiple imputation method (Donders et al., 2006). The single imputation method involves imputing each missing value for a particular variable in the data set and then analysing all data according to their original observations (Jadhav et al., 2019). However, the validity of the imputed values may be uncertain, which requires that the uncertainty of the imputed values be incorporated into the methodology for missing data (Little and Rubin, 1989). Rubin (Rubin, 2004) therefore developed the multiple imputation method for averaging the results over multiple imputed datasets. The multiple imputation method consists of three stages. First, multiple single imputations of missing values are performed, producing several different complete data sets after imputation. After imputation, each complete dataset is analysed and, finally, the results of each analysed dataset are combined (Jadhav et al., 2019). Based on the approaches used in the imputation, there are many different imputation methods, such as, mean imputation, regression imputation, and k Nearest Neighbours (kNN) imputation (Little and Rubin, 2002, Jadhav et al., 2019). The mean imputation method uses the mean of the response units to replace the missing values. The regression imputation method replaces the missing value with the regression prediction of the missing item on the observed item for that unit, usually calculated from units where both the observed and missing variables are present. As for the kNN imputation, missing values are replaced by values copied from similar records in the same dataset, while the distance function determines the similarity of the two attributes.

2.4.2.2 Data visualisation

Data visualisation is the process of displaying data in a graphical or pictorial style to make it easier to understand, to help explain the facts, and to help choose a course of action (Sadiku et al., 2016). There are many data visualisation techniques, such as table, pie chart, bar chart, histogram, line chart, scatter plot, bubble chart and multiple data series (Khan and Khan, 2011).

Tables are a simple, common and easy to interpret data visualisation technique. Usually, rows represent variables, and columns are also representatives of records with a set of values (Ajibade and Adediran, 2016). The circle of a pie chart is divided into sectors, each describing a proportion of the overall quantity (Spence, 2005). Pie charts can be used to determine the size of the target data wedge compared to other data wedges (Khan and Khan, 2011). Bar charts and histograms look very similar, and both of these techniques are commonly used in data visualisation. However, bar charts are most commonly used for categorical data, while histograms usually present the distribution of continuous data (Lakshmanan, 2014). The line chart shows the relationship between variables, and displays the variations over a period of time (Ajibade and Adediran, 2016). Moreover, the line chart can be considered as an extension of the scatter plot (Khan and Khan, 2011). The scatter plot is a graphical representation of a set of data in right-angle coordinates that illustrates the relationship between two variables by using the horizontal and vertical distances of the data points from the coordinate axes as the independent and dependent variables, respectively (Utts, 2014). Scatter plots are often used to visualize multiple dimensions of data and to identify the relationship between two variables (Keim et al., 2010). Bubble charts usually present three dimensions of the data, one for the X-axis, one for the Y-axis, and a third value showing the size or volume of the data (Viegas et al., 2007). In addition, data visualisation is usually the first priority of exploratory data analysis (EDA) (Morgenthaler, 2009). EDA has no restrictions on the programs to be used and is a result of the exploratory attitude adopted by the data analyst. When using EDA data analysts can come up with many new ways to look at data.

Data visualisation has been widely used in different areas of health care and medical treatment. For example, an electronic medical record system with visual medical data can help physicians more easily and quickly identify anomalies in a patient's medical record and assess the patient's condition compared to traditional medical records (Khan et al., 2017). In addition, the use of line charts provides a clearer picture of the patient's physical condition over time (Stadler et al., 2016). Jiang et al. (Jiang et al., 2016) developed a web-based health care data visualisation system that focuses on incorporating geospatial and temporal information in health care data. The authors developed two new visualisation techniques, namely spatial texture and spiral theme plot, for public health data. The spatial texture technique is suitable for multidimensional attributes and time series data, while the spiral theme plot technique is suitable for visualizing time-varying patient data. The authors believe that this system aids health care professionals in identifying disease outbreaks, especially for large public health data sets. Polhemus et al. (Polhemus et al., 2022) reviewed 31 studies and summarized the impact of data visualisation on self-management of mental health conditions with remote devices. They found that data visualisation increased self-awareness of self-management, led to more effective communication with care providers, and enhanced engagement with remote monitoring devices.

2.4.3 Predictive data mining techniques

Machine learning, as an important part of predictive data mining techniques, refers to the process of teaching machines to perform tasks based on historical data or past experiences, such as predicting, recommending, estimating, etc. (Mitchell and Mitchell, 1997, Wiens and Shenoy, 2018, El Morr et al., 2019). There are four main categories of machine learning methods, supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (Vieira et al., 2020). Table 1 shows the main and popular machine learning algorithms of different categories.

Table 1. The categories of machine learning methods with popular algorithms (Mahesh, 2020, Alloghani et al., 2020)

Machine learning methods	Machine learning algorithms
Supervised learning	Naïve Bayes Classifier Algorithm Support Vector Machine Algorithm Linear Regression Logistic Regression Decision Trees K Nearest Neighbours
Unsupervised learning	K means Clustering Algorithm Principal Component Analysis Association Rule Mining
Semi-supervised learning	Generative models Transductive Support Vector Machine
Reinforcement learning	Artificial Neural Networks

In supervised learning, the system is trained with labelled sample data by various algorithms to predict the group or value of a data set (Kavakiotis et al., 2017, Nasteski, 2017). There are two types of learning tasks in supervised learning - classification and regression. Classification is for predicting distinct groups ('classes' or categories), while regression is for predicting values (Kavakiotis et al., 2017). In addition, there are many supervised learning algorithms, such as decision tree, linear regression, Bayesian classification, etc.

With regard to unsupervised learning, the training data is unlabelled data, and the system is trained to discover the structure of the data set and correlations between different variables (Kavakiotis et al., 2017, Nasteski, 2017). There are three categories of unsupervised learning. First, clustering is the main technique of unsupervised learning which can be used to separate a data set into different groups (Kavakiotis et al., 2017, Shailaja et al., 2018). Second, dimensionality reduction such as principal component analysis and linear discriminant analysis is used to help find the dimensions that have the higher power of explanation of the data set (Dallas, 2013). Finally, association rule mining is used to discover relationships and associations between data in databases, such as basket data analysis, catalogue design, and so on (Kumbhare and Chobe, 2014).

Semi-supervised learning requires both unlabelled and labelled data as the training data, which can generate a function or classifier (Nasteski, 2017, Shailaja et al., 2018). Generally, Reinforcement Learning describes a family of techniques that involve direct interaction between the system and the environment in order to maximize some notion of cumulative reward (Alpaydin, 2020).

The remainder of this sub-section focuses mainly on supervised learning and unsupervised learning, as these are the two main methods of machine learning. Furthermore, these methods were used in this PhD project (see Chapters 3.3.2 and 3.4.2).

2.4.3.1 Classification in supervised learning

There are many supervised machine learning classification techniques. In this section, the four most used techniques will be discussed, including Decision Trees, Bayesian Networks, k-Nearest Neighbour (kNN) and Support Vector Machines (SVM) (Soofi and Awan, 2017).

Decision trees, the most commonly used technique in classification, have a simple and easy to understand classification process (Brodley and Utgoff, 1992, Twa et al., 2005). Kesavaraj and

Sukumaran (Kesavaraj and Sukumaran, 2013) note that the core goal of a decision tree is to generate a model that determines the values of the desired variables based on the input variables. Typically, the decision tree technique consists of two phases, the tree growth phase and the tree pruning phase (Patil et al., 2010, Rutkowski et al., 2012). In the tree-growing phase, the training set is recursively partitioned until most of the records are contained in partitions with the same class labels based on the local optimum criterion. Then, the size of the tree is reduced to make it easier to understand during the tree pruning phase. Different decision tree algorithms also have some weaknesses, for example the Iterative Dichotomiser 3 (ID3) algorithm cannot handle missing values, while the C4.5 algorithm is not suitable for small data sets (Sharma et al., 2013).

The Bayesian Network is considered as a graphical model of probabilistic relationships between a set of variables (Phyu, 2009). The learning process of a Bayesian Network is divided into two sections, network directed acyclic graph structure learning, and parameters determination (Soofi and Awan, 2017). Bayesian Network models are not subject to minor changes that can render them inoperable, and the same Bayesian network models can be used for regression and classification (Myllymaki, 2010). In addition, Bayesian networks can handle missing values. However, Bayesian network classifiers also have some problems. For example, Bayesian network classifiers need to discretize continuous attributes, otherwise they cause noise and missing information. If continuous attributes are not discretized, the conditional density of the attributes needs to be evaluated (Friedman and Goldszmidt, 1996, Wang et al., 2016).

The KNN technique uses the k-value to determine how many nearest neighbours are required to examine and describe the class of a sample data point (Cover and Hart, 1967). KNN techniques can be divided into two different types based on structure (Wu et al., 2007, Bhatia, 2010). Structure-based techniques deal with data that have fewer mechanisms associated with the training data. Structureless techniques divide the data into sample data and training data, where the nearest neighbour is the point with the smallest distance between the sample and training points. In addition, KNN techniques are effective and robust to large noisy training data, and easily understandable and implementable (Cunningham and Delany, 2021).

SVM is one of the most prominent and convenient techniques when it comes to solving problems related to data classification, learning and prediction (Haijun et al., 2007, Nizar et al., 2008). SVM is very useful in multi-domain applications in big data environments, but it is also a mathematically complex and computationally expensive technique (Suthaharan and Suthaharan, 2016). Ismail et al. (Ismail et al., 2020) presented a smart health care system to help older adults living independently at home and patients in hospital. According to the authors, the system is based on speech recognition, augmented by SVM with dynamic time-warping algorithms to access and control Internet of Things devices. The results showed that the system was 97% accurate in controlling smart devices through speech commands.

2.4.3.2 Regression in supervised learning

Typically, there are three types of regression analysis in supervised learning, linear regression, polynomial regression, and logistic regression (Gupta et al., 2017).

Linear regression can be divided into two categories based on the number of independent variables. Simple linear regression has one independent variable, while multiple linear regression has two or more independent variables (Kadam et al., 2020). Simple linear regression is a linear model used to establish the association between a single predictor variable and an outcome measure (Marill, 2004). Multiple linear regression models are used to describe the concurrent correlation of multiple variables with continuous outcomes (Eberly, 2007). Linear regression models have been used in many areas, for example Rayner et al. (Rayner et al., 2016) found a positive relationship between depression and cost in patients with chronic pain using a multiple linear regression model. Likewise, Presti et al. (Presti et al., 2019) found that social sustainability (e.g., efficiency of access, usefulness of information, safety, relationship between patients and doctors) can directly influence the loyalty to a digital health platform by using multiple linear regression analysis.

Polynomial regression is usually used when the relationship between a dependent variable and an independent variable is curvilinear (Ostertagová, 2012). Ohba et al. (Ohba et al., 2016) performed data recovery using polynomial regression techniques because polynomial regression tolerates missing data and is suitable for expressing continuous features. On the other hand, the author mentions that polynomial regression does not perform well when the expressed features have many inflection points.

Logistic regression is commonly used to predict binary outcomes, such as the presence of a disease by analysing the relationship between a qualitative dependent variable and one or more independent variables (Lawton, 2022). The logistic regression model can be divided into simple logistic regression and multiple logistic regression (Nick and Campbell, 2007). The simple logistic model has only one predictor variable, while the multiple logistic regression model includes categorical and continuous predictor variables.

2.4.3.3 Clustering in unsupervised learning

There are two categories of clustering algorithms - hierarchical clustering and partitional clustering (Jain and Dubes, 1988). Hierarchical clustering produces a clustering tree that shows the order of clusters, each of which is a partition of the dataset, as a result (Leung et al., 2000). Hierarchical clustering algorithms can be classified into two types based on the clustering tree generation process. Divisive hierarchical algorithms use splitting to generate clustering trees, while agglomerative hierarchical algorithms use merging (Omran et al., 2007). Commonly used hierarchical clustering methods are single linkage, complete linkage and average linkage (Serra and Tagliaferri, 2019). The single linkage method of merging clusters usually relies on the minimum distance between two points, where each point belongs to one of the two clusters (Jarman, 2020). The complete linkage method relies on the maximum distance, while the average linkage method relies on the average distance. Another less popular hierarchical clustering method is the centroid linkage method, which combines clusters based on the distance between the central data points of the clusters (Jarman, 2020).

Partitional clustering can handle large datasets with lower computational requirements, while hierarchical clustering is more advantageous in terms of logic and consistency (Singh and Srivastava, 2020). There are many different partitional clustering algorithms, such as K-means, K-mediods, Fuzzy C-means, ISODATA, and Fuzzy K-modes (Kaur and Garg, 2014). Among all of these partitional clustering algorithms, the K-means algorithm is probably the most popular and widely used (Bindra and Mishra, 2017). The K-means algorithm is simple and fast, especially for low dimensional data, but K-means cannot identify outliers (Sonagara and Badheka, 2014). Much research compares the K-means algorithm with other clustering algorithms. For example, Madhukumar and Santhiyakumari (Madhukumar and Santhiyakumari, 2015) did a qualitative comparison of K-means and Fuzzy C-means segmentation on MR images of tumour edema complex. They found that K-means identified all six tissue categories, which performed much better than Fuzzy C-means, which identified only three categories. Moreover, another study demonstrated that K-means performed much faster than Fuzzy C-means (Cebeci and Yildiz, 2015).

2.4.3.4 Dimensionality reduction in unsupervised learning

In unsupervised learning, there are many different dimensionality reduction techniques, which can be divided into two main categories, linear dimensionality reduction techniques and non-linear dimensionality reduction techniques (Ayesha et al., 2020).

The principal component analysis (PCA) is an unsupervised linear technique for reducing the dimensionality of data while retaining most of its variation (Jolliffe, 2005). The main goal of PCA is to display in maps the pattern of similarity between observations and variables based on the results of extracting the information from the table, transforming it into new orthogonal variables called principal components, and displaying it as a set of new orthogonal variables (Abdi and Williams, 2010). Martis et al. (Martis et al., 2012) use PCA to help analyse electrocardiogram signals. The authors first use PCA, followed by neural network and Least Square-Support Vector Machine methods to classify the electrocardiogram signal. The results show that using principal components of segmented electrocardiogram can obtain a higher accuracy, sensitivity and specificity. In addition, PCA has been developed into many different variants for different data types and structures. For example, Local PCA has better performance for voice and image data compared to PCA (Kambhatla and Leen, 1997). As for palm print recognition and tracking moving objects from video, 2D-PCA is better than raw PCA (Li et al., 2005, Wang et al., 2007). Moreover, Lu et al. (Lu et al., 2008) developed a multi-linear PCA for face recognition systems with better performance than the original PCA and 2D-PCA.

In addition to PCA, there are many other linear dimensionality reduction techniques. For example, Singular Value Decomposition can be used for digital image processing, gene expression data and bioinformatics for metric equation and data reduction (Simek, 2003, Cao, 2006, Santos et al., 2011). Latent Semantic Analysis is a vector-based technique that compares and represents text from high-dimensional corpus data as low-dimensional based on PCA computation (Wiemer-Hastings et al., 2004). The Independent Component Analysis is also another unsupervised linear dimensionality reduction technique that is widely used to explore multichannel data (Comon, 1994), while the Linear Discriminant Analysis is a linear classifier that applies to linear combinations of features (Tharwat et al., 2017).

Similarly, there are many nonlinear dimensionality reduction techniques for complex nonlinear structures. Isomap is one of the most popular unsupervised nonlinear dimensionality reduction techniques, which can obtain a low-dimensional representation of the data and preserve geodesic distances (Lee et al., 2004). Schölkopf et al. (Schölkopf et al., 2005) proposed the kernel principal component analysis method, which computes the principal eigenvectors of the kernel matrix of a nonlinear mapping. Kruskal and Wish (Kruskal and Wish, 1978) introduced the Multidimensional Scaling method to maintain similarity measures between pairs of data points, which has been used in many fields such as multivariate analysis and visualisation. Local Linear Embedding is another unsupervised nonlinear dimensionality reduction technique that uses feature vectors to identify the flow structure and retains only the local attributes of the data (Saul and Roweis, 2000).

2.4.4 Data mining in health care

A large body of research implements data mining techniques using data acquired from home-based health care data sets. Data mining techniques, such as data visualisation, clustering, classification and prediction etc., can help researchers understand users, behaviours and health care phenomena by identifying novel, and interesting patterns. These techniques can also be used to build predictive models (Koh and Tan, 2011, Alsayat and El-Sayed, 2016, Katsis et al., 2017, Elbattah and Molloy, 2017). In addition, data mining techniques can help in designing health care management systems and tracking the state of a person's chronic disease, resulting in appropriate interventions and a reduction in hospital admissions (Koh and Tan, 2011, Madigan and Curet, 2006). Vast quantities of data can be generated when users interact with digital health technologies, which provides an opportunity to understand chronic illnesses as well as to elucidate how users engage with technologies in the real world.

The k-means algorithm has been used to identify previously unknown patterns of clinical characteristics in homecare rehabilitation services (Armstrong et al., 2012). The authors used k-means cluster analysis to analyse data from 150,253 clients and discovered new insights into client characteristics and their needs which lead to more appropriate rehabilitation services for home care clients. Therefore, the authors believe that such cluster analysis methodologies can be used to further researchers' understanding of patterns or groups in the rehabilitation population.

Madigan et al. (Madigan and Curet, 2006) used CART (Classification and Regression Trees) to investigate a home-based health care data set that comprised of 580 patients who were at least 85 years old and had three specific conditions - COPD, HF and hip replacement. They suggested that data mining methods can support a benchmarking approach to establish guidelines for home-based health care. Moreover, they found that data mining methods identified the dependencies and interactions that influence the results, thereby improving the accuracy of risk adjustment methods and establishing practical benchmarks.

Machine learning methods have also been used to analyse multiple health care data sets including: breast cancer, heart disease, diabetes, and liver disease (Islam et al., 2019). In this study, the accuracy of the disease detection was over 95%, and the cost was 90% lower than local hospital medical services. The use of such methods could help patients receive the best and most cost-effective health care treatment.

Lonini et al. (Lonini et al., 2018) used wearable sensors to collect movement data from older adults with Parkinson's disease. The study included 20 participants involved with a course of multiple clinical assessments that included 13 common tasks (e.g., walking, standing, drawing on paper), and a clinician-rated symptom severity. All the collected data was used to train convolutional neural networks and statistical ensembles which can detect the signs of bradykinesia or tremor in a segment of movement. The authors found that a wearable sensor placed on the back of the hand was sufficient to detect bradykinesia and tremor in the upper extremities, whereas using sensors on both sides didn't result in enhanced performance of detection. Moreover, a greater amount of training data can improve performance, but repeating assessments with the same subjects does not result in substantial improvements in detection.

There are many research studies that use data mining and machine learning methods on different kinds of health care data, for example, clinical health care data (Zacharaki et al., 2009, Zheng et al., 2017, Wong et al., 2018), sensor health care data (Goodfellow et al., 2018, McGinnis et al., 2018, Kanjo et al., 2019), and omics data (Gurovich et al., 2019, Mamoshina et al., 2018). However, most of these studies are focused on predicting or detecting diseases, and very little research explores data from users of digital health technologies to study the behaviours of participants.

2.4.4.1 K-means clustering in health care

There are many different approaches to clustering analysis of health care data sets, such as k-means, Density-Based clustering (DBSCAN), agglomerative hierarchical clustering, self-organising maps, partitioning around medoids algorithm, hybrid hierarchical clustering, etc. (Delias et al., 2015, Lefèvre et al., 2014, Ahmad et al., 2015, Mahoto et al., 2014). K-means clustering is one of the most commonly used clustering/unsupervised machine learning algorithms (Zahi and Achchab, 2019, Alsayat and El-Sayed, 2016), and it is relatively easy to implement and is relatively fast (Jian, 2009, Silitonga, 2017, Shakeel et al., 2018). In addition, k-means has been used in research studies related to chronic conditions, such as diabetes (Berry et al., 2017), COPD (Harrison et al., 2014, Lopes et al., 2019) and HF (Cikes et al., 2019).

Shakeel et al. (Shakeel et al., 2018) used a cloud-based framework with k-means clustering technique for the diagnosis of diabetes. They found that k-means clustering is more efficient and suitable for handling extensive datasets in cloud computing platforms when compared to hierarchical clustering. Furthermore, the results also show that people aged between 45 and 64 have a greater prevalence of diabetes than other age groups.

Data from 408,994 patients aged 45 to 64 years with multimorbidity was analysed using k-means clustering to ascertain multimorbidity patterns (Violán et al., 2018). The authors stratified the k-means clustering analysis by gender, and six multimorbidity patterns were found for each gender. For example, the author found that the most prevalent coincident diseases in both genders are metabolic disorders, hypertensive diseases, mental and behavioural disorders due to psychoactive substance use, other dorsopathies and other soft tissue disorders. They also suggest that clusters identified by multimorbidity patterns obtained using non-hierarchical clustering analysis (e.g., k-means, k-medoids, etc.) are more consistent with clinical practice.

2.4.5 Summary

As the above literature shows, there are many different approaches in data mining. However, before analysing the raw data, data cleaning is always required to restructure the dataset, remove duplicates, deal with missing data, and validate the data. In addition, many different approaches have been used for mining health care data. In this PhD project, both descriptive data mining approaches (e.g., data cleaning, data visualisation) and predictive data mining approaches (e.g., principal component analysis, K-means clustering, regression analysis) were used.

2.5 Research gap and summary

As the literature review shows, there are many studies on the use of digital health technologies for chronic condition self-management that aim to understand how people use digital health technologies and the impact of digital health. However, few studies have examined the use of such technology by older adults, and in particular older adults with multimorbidity. In addition, while there are some studies on digital health technology engagement, there are gaps in understanding the engagement of older people with multiple conditions with digital health technology. On the other hand, most studies on digital health technology engagement use qualitative data, such as interview responses, and only a few studies use quantitative data (e.g., device logs, submissions) to study digital health technology engagement in a data-driven way. In this PhD project, the engagement of older people with multimorbidity with digital health technologies is studied through the use of different data mining methods to analyse log data from devices. Interview responses will also be used to help interpret the results of the data analysis.

3 Research Design and Methodology

3.1 Introduction

As outlined in Chapter 1, the aim of this PhD project is to explore, through analysis of an existing dataset, the longitudinal patterns of engagement of older adults with multimorbidity with digital self-management, in particular symptom and well-being monitoring, with the goal of better understanding how to promote sustained engagement over time. This chapter provides an overview of the research design and methodology for the three studies presented in Chapters 4 – 6 that address this aim.

All three studies in this project are based on a post-positivist epistemological stance (Ryan, 2006). In order to fully perceive and measure the reality of how older adults are using digital health technology, all studies were based on quantitative analyses of data from digital health technology logs, and only some of the findings used qualitative data to help explain the results of the quantitative analyses.

Firstly, an overview of the ProACT trial and the ProACT dataset is provided in Section 3.2, which begins with a description of the data provenance and data collection, followed by a description of the data cleaning methodology for this PhD project. A brief description of the qualitative interview data transcripts that were reviewed as part of the second study is also provided. An overview of the participants of the ProACT trial is presented in Section 3.3. Sections 3.4 – 3.6 provide an overview of the three studies conducted as part of this thesis, outlining the research questions, research approaches and methods of each study. Finally, the summary of this chapter is presented.

3.2 Overview of the ProACT trial and data set

3.2.1 Data provenance

The dataset used in this PhD was collected as part of the ProACT Horizon 2020 project trial (Dinsmore et al., 2021). The PhD researcher was not involved in data collection, only the analysis of the data. While 120 older adults with multiple chronic conditions (two or more of chronic obstructive pulmonary disease (COPD), Heart Failure (HF), Heart Disease (HD), Diabetes) across Ireland and Belgium consented to take part in the trial, this PhD thesis explores data from the 60 participants who consented in Ireland. Participants were recruited through purposive sampling and were recruited from multiple sources including through health care organisations (general practitioner clinics, specialist clinics), relevant older person networks, chronic disease support groups, social media, and local newspaper advertising. Recruitment strategies included the use of study flyers, advertisements and giving talks and platform demonstrations.

Participants used the ProACT platform, consisting of a suite of sensor devices (including a blood pressure monitor, weight scale, glucometer, pulse oximeter, activity watch) and a tablet-based application to monitor their conditions. All participants received a blood pressure monitor (to measure blood pressure and heart rate), a smart watch (to measure activity and sleep) and a weight scale. Those with diabetes were provided with a blood glucometer to measure blood glucose, and those with COPD were provided with a pulse oximeter to measure blood oxygen levels. All participants also received an iPad with a custom-designed application, the ProACT CareApp, to view their data, self-report on their well-being (e.g. mood, satisfaction with social life) and those symptoms that could not be easily monitored by a digital device (for example, breathlessness, sputum colour), receive targeted education based on their current health status, set activity goals and share their data with others. The ProACT platform was designed and developed following an extensive user-centred design process. This involved interviews, focus groups, co-design sessions (hands-on design activities with participants) and usability testing prior to the platform's deployment in the trial. A total of 58 people with multimorbidity and 106 care network participants, including informal carers, formal carers and health care professionals, took part in this process. Findings from the user-centred design process have been published elsewhere (Doyle et al., 2018, Doyle et al., 2019). Further details on the ProACT platform, including the application used by trial participants, can be found in (Doyle et al., 2021).

The trial took place between April 2018 and June 2019. Recruitment onto the trial was staggered between April and August 2018. The approximate length of time participants were on the trial was 12 months, though some were on for 14 and others 9 (for example, those that came onto the trial at later time points.

During the trial, participants were asked to take readings using the devices and self-report within the ProACT app as they wished. They were not asked to do this daily, as one of the objectives was to understand real world engagement. During the trial, participants were supported with a technical help desk that responded to any queries in relation to the technology and home visits were conducted as required to resolve issues. In addition, a clinical triage service monitored participant readings and contacted the participant in cases where there was an alert (for example, an abnormal blood glucose or blood pressure reading). Participants also got a monthly check-in phone call from one of the triage nurses.

3.2.2 Data collection

Table 2 outlines the types of health and well-being metrics that were collected, as well as the collection method and the number of participants who collected that type of data. The health and well-being metrics were determined from the interviews and focus groups held with health care professionals during the design of the ProACT platform to determine the most important symptom and well-being parameters to monitor across the conditions of interest (Doyle et al., 2019). The digital devices used during the trial were off-the-shelf devices from two providers, NokiaHealth/Withings[2] and iHealth. Data was pulled from these providers into NetwellCASALA's custom-built CABIE-SIMS system, which was developed as a data aggregator and store for health and well-being data. All the devices required the user to perform some manual action with the device, with some requiring more interaction than others (Table 2). For example, taking a blood glucose reading required a number of steps, while physical activity (PA) and sleep only required opening of an application to sync data directly from the activity watch. These readings would then appear in the CABIE-SIMS system in close to real-time. In relation to the activity watch, this device was supposed to sync automatically, without user interaction. However, inconsistencies with syncing meant that users were advised to open the Withings application if they wanted to sync their data to ProACT. Otherwise, CABIE-SIMS pulled activity data at regular intervals throughout the day, while sleep data for the previous night was pulled each morning. CABIE-SIMS then pushed data back to the ProACT CareApp where participants could view and interact with their data. Ethical approval for the ProACT trial and analysis of the data presented in this thesis was obtained prior to this PhD project beginning, from the research ethics committee within the School of Health and Science in Dundalk Institute of Technology, and the Health Service Executive (HSE) north-east research ethics committee.

[2] Just prior to the trial starting, Withings was bought by NokiaHealth. Some devices being used in the trial were branded as Withings and some as NokiaHealth, however devices operated in the same way regardless of branding. From here on, these devices will be referred to as Withings.

Table 2. Types of data, collection methods, and the number of participants collecting that data

Data Type	Collection Method	No. participants (at start of trial)
Blood pressure	Place device on arm and turn on device, which opens Withings app to collect data; Press ‘start’ in app to take reading.	60
Pulse	Collected as part of blood pressure measurement	60
Blood glucose	Turn on device and open app to take reading	34
Blood oxygen level	Place device in current orientation on index finger. Turn on device and open app to take reading	22
Weight	Stand on weight scales. Reading automatically transferred via Wifi to app)	60 (as lifestyle parameter) including 11 (as symptom parameter for HF)

Physical activity	Participants advised to open Withings application at least once per day to ensure syncing of data.	60
Sleep	Participants advised to open Withings application at least once per day to ensure syncing of data.	60
Self-report (general well-being, e.g. mood, anxiety, satisfaction, medication adherence)	Answered through ProACT CareApp and automatically pulled into CABIE-SIMS. Most questions delivered daily.	60
Self-report (COPD symptoms, e.g. breathlessness, sputum)	Answered through ProACT CareApp and automatically pulled into CABIE-SIMS. Questions delivered daily.	22
Self-report (HF symptoms, e.g. swelling, night-time breathlessness)	Answered through ProACT CareApp and automatically pulled into CABIE-SIMS. Questions delivered daily.	10

3.2.3 Data cleaning

The original dataset in CABIE-SIMS is in Java script object notation (JSON) format. As a first step, a JSON to CSV file converter was used to make the dataset more accessible for analysis. The main focus was on dealing with duplicate data and missing data during the data cleaning phase. Duplicate data might occur where a user uploads their blood oxygen level three times in two minutes as a result of mis-pressing the button. In such cases, only one record was added to the cleaned data file. Regarding missing data, the dataset file was filled with 'N/A' for all missing data. Also, when the "Pulse" or "Blood Pressure (BP)" record is equal to zero, which might be because a participants placed the BP monitor incorrectly, "N/A" was used to replace it since it is not possible for a pulse or blood pressure value to be zero.

The cleaned data set was analysed using the R language and the R package of ggplot2 (ggplot2, 2023) was mainly used to generate graphs. Sections 3.4 to 3.6 present the research questions and the data analysis methods used in each of the three studies performed on the dataset.

3.2.4 Qualitative data transcripts

During the ProACT trial, semi-structured interviews were conducted with participants at four time-points. Interviews at the first time-point focused on self-management pre-ProACT and expectations for the trial while interviews at time-points 2, 3 and 4 explored usage of ProACT, perceptions, challenges and thoughts on the digital devices and the ProACT CareApp. All of the interviews were audio recorded, transcribed verbatim and analysed by the ProACT project researchers using NVivo. While a full qualitative analysis was outside the scope of this PhD project, transcripts from the second, third and final time-points were reviewed by the PhD candidate to provide context to the findings from the second research study (see Section 3.5.2 and Chapter 5).

3.3 Participants

The average age of participants was 74 ± 6.4 (65-92 years); 60% (n=36) were male and 40% (n=24) were female. The most common combination of conditions was diabetes and HD (n=30), followed by COPD and HD (n=16); HF and HD (n=7); diabetes and COPD (n=3); diabetes and HF (n=1); COPD and HF (n=1); HF, HD and COPD (n=1) and COPD, HD and diabetes (n=1). N=11 participants had HF while N=55 had HD. Over the course of the trial 8 participants withdrew and 3 passed away. However, this study included data from all participants in the beginning, as long as the participant had one piece of data. In this case, 56 participants' data were included, and 4 participants were excluded because no data was recorded.

3.4 Study 1 – Exploring patterns of engagement of older adults with multimorbidity with digital self-management

This study addresses Objective 2 of this PhD project:

O2: Analyse an existing dataset to understand longitudinal patterns of engagement of older adults with multimorbidity with symptom and well-being monitoring (e.g., blood pressure, self-reported mood).

3.4.1 Research questions

The study had four research questions:

(1) What is the distribution of user retention for using digital health technologies at home?

(2) What are the frequencies (times per week) at which participants submit their data?

(3) What is the average and standard deviation of the intervals (in days) between each submission?

(4) What preferred hours of the day do people submit blood pressure (BP), pulse, blood oxygen level (SpO2), blood glucose (BG) and weight readings?

3.4.2 Research approach and methods

After the data was cleaned, each participant's data was separated into two files. The first file is the main file which includes Date, BP systolic, BP diastolic, Pulse, Time, SpO2, SpO2 time, BG, BG time, Weight, Weight time, Daily Distance Walked, Daily Step Count, Daily Time Walking, Self-report, Sleep. In this file, all the time slots are represented as "HH: MM: SS" and the "Self-report" and "Sleep" variables only include a "Yes" or a "No", which indicates if that day included a "Self-report" and/or a "Sleep" log. The second file includes all of the sleep data which contains "Date", "Time" and "Level". "Level" denotes the level of sleep quality which can be "awake", "light", "deep" or "ends" (four different levels).

In this dataset, there are 60 rows and 419 columns including participants' trial-ID, gender, year of birth, height, conditions and 18,150 daily logs. The total number of interactions with all technology devices is 80,515. For the purposes of this study, if two interactions were recorded from the same devices within 10 minutes of each other, this was counted as one episode of interaction, and only the first submission is counted. This repetition of submissions might be caused by participants who wanted to double check a reading.

3.5 Study 2 – Using k-means clustering to discover engagement patterns of older adults with multimorbidity when using digital health technologies

This study addresses Objective 3 of this PhD project:

O3: Explore how different categories of users, for example users of different age groups or with different conditions, engage with symptom and well-being monitoring.

3.5.1 Research questions

The study had four research questions:

(1) How do clusters differ in terms of participant characteristics, such as age, gender, and conditions?

(2) How do clusters differ in terms of patterns of engagement, such as the number of days a week participants take readings, e.g., weight, blood pressure etc.?

(3) How do engagement rates with the different devices correlate with each other?

(4) How do engagement rates affect participants' condition symptoms, such as blood pressure, blood glucose, weight, SpO2 (the level of oxygen in the blood) and physical activity?

3.5.2 Research approach and methods

The cleaned dataset was pre-processed by Microsoft Excel, the R programming language and R studio. The pre-processed dataset includes participants' details (ID, gender, age, conditions) and the number of days for weekly submissions of every parameter (BP, pulse, SpO2, BG, weight, PA, self-report, sleep). All following analysis was implemented in the R programming language and R studio (including, correlation analysis, principal component analysis and k-means clustering).

Correlation analysis and principal component analysis were used to determine which part of the data would be included in the k-means clustering. Correlation analysis determined which characteristics or parameters should be selected, and principal component analysis determined the number of dimensions that should be selected as features for clustering. In the clustering process, the weekly submission of each parameter was considered as an independent variable for the discovery of participant clusters, and the outcome of the clustering was a categorical taxonomy that was used to label the three discovered clusters. T-test and one-way ANOVA methods were used to compare different groups of variables. T-test was used to compare two groups of variables, while one-way ANOVA was used to compare two or more groups of variables. If the p-value is greater than 0.05, then there is no statistically significant differences between the groups of variables (Ross and Willson, 2017).

As for the qualitative data from the interviews, keyword searches were used after a review of the entire interview. For example, when the data analysis was related to blood pressure and weight monitoring, a search with the keywords "blood pressure" or "weight" or "scale" was performed to identify relevant information. In addition, when the aim was to understand the impact of digital health technology, responses to specific questions from the interview protocol were examined, such as ' Has it had any impact on the management of your health?'.

3.6 Study 3 - The correlation between mobile device proficiency (technical proficiency) and user engagement of older adults with multimorbidity with digital health technologies

This study addresses Objective 4 of this PhD study:

O4: Examine the connections between technical proficiency and engagement with digital health technologies.

3.6.1 Research questions

The study had three research questions:

(1) How do the mobile device proficiency score (MDPS) and engagement score (ES) correlate with each other?

(2) How do the ES and each sub score on the mobile device proficiency scale correlate with each other?

(3) How do the MDPS and each device usage variable (weekly submission of each device) correlate with each other?

3.6.2 Research approach and methods

To better understand mobile device proficiency and user engagement, the Mobile Device Proficiency Score (MDPS) and Engagement Score (ES) were used as parameters in the analysis. The MDPS is the final score calculated from the Mobile Device Proficiency Questionnaire (MDPQ) which is a measure of the mobile device proficiency of older adults (Roque and Boot, 2018).

At the beginning of the ProACT trial, the short 16-question version of the MDPQ (MDPQ-16) was used, which is a highly reliable and valid measure of mobile device proficiency in a large sample. This questionnaire was chosen for use in the trial by the ProACT trial researchers, rather than this PhD researcher. In MDPQ-16, there are eight sections, and each section includes two questions (Table 3). Every question is answered on a 5-point scale (1 = Never tried; 2 = not at all; 3 = not very easily; 4 = somewhat easily; 5 = very easily). The MDPS is obtained by calculating the average score of each section and adding up all 8 sections, with total possible scores ranging from 8 to 40 with all questions are answered. However, there were some questions that were not answered in this study, and these questions would be considered to have a score of zero.

Table 3. Mobile Device Proficiency Questionnaire (MDPQ-16) (Roque and Boot, 2018)

Sections	**Questions: Using a mobile device I can:**
Mobile Device Basics	Navigate onscreen menus using the touchscreen
	Use the onscreen keyboard to type
Communication	Send emails
	Send pictures by email
Data and File Storage	Transfer information (music, picture, documents on mobile device to computer)
	Transfer information (music, picture, documents on computer to mobile device)
Internet	Find information about my hobbies and interests on the Internet
	Find health information on the Internet
Calendar	Enter events and appointments into a calendar
	Check the date and time of upcoming and prior appointments
Entertainment	Use the device's online "store" to find games and other forms of entertainment (e.g., using Apple App Store or Google Play Store)
	Listen to music
Privacy	Set up a password to lock/unlock the device
	Erase all Internet browsing history and temporary files

Troubleshooting and Software Management	Update games and other applications
	Delete games and other applications

A custom ES was calculated using the weekly submission times for each parameter. In order to improve the performance and training stability of clustering and modelling, the number of weekly submissions for each parameter was standardised first by z-score standardisation, and then the ES is derived from the standardised number of weekly submissions for each parameter. The details of the ES calculation and formula will be discussed in Section 6.1.2 of Chapter 6.

To assess the correlation between MDPS and ES, scatter plots were used. Participants were clustered into different clusters based on their MDPS and ES. Both research questions 2 and 3 will use multiple regression analysis was used to build a model for dependent and independent variables, to answer research questions 2 and 3. Two models were built through multiple regression analysis, the first with ES as the dependent variable and the MDPQ sub-scores as the independent variables. The second model had MDPS as the dependent variable and the number of weekly submissions for each device as the independent variable.

3.7 Summary

In this chapter, the research design and methodology of this PhD project was presented. The chapter began with an overview of the provenance of the dataset analysed in this PhD project. The ProACT trial, involving 60 Irish older adults with multimorbidity interacting with a suite of devices for health and well-being self-management, was then presented, including an outline of the devices used by participants, the types of data collected and how the data was collected. A description of the data cleaning process was provided. Each of the three studies of this PhD project, all of which are focused on how older adults with multimorbidity engage with digital health technologies, was presented, including the research questions and methodology of each study.

There were some challenges encountered during the implementation of the project. Firstly, the project was related to multimorbidity, older adults, and self-management, and as a computer science student, these topics were not familiar and there was a lot of new knowledge and definitions to learn. Similarly, cleaning such a large dataset was challenging, and was not a familiar task. There was a lot of missing data and duplicates that needed to be identified and processed. The biggest challenge of the project related to data analysis and machine learning, such as the implementation of k-means clustering and multiple regression analyses, as well as the results of their analyses, again as these were unfamiliar topics. There are also some limitations to the methodology. Firstly, while the sample size of 60 was relatively large for a digital health study, the sample size for some parameters was small because not all participants monitored all parameters. Secondly, the participants were clustered based on weekly submissions of parameters only in the second study. If more features were included in the clustering, such as the intervals of submissions, participants might have been grouped differently.

4 Findings Study 1 - Exploring Patterns of Engagement of Older adults with Multimorbidity with Digital Self-management

4.1 Introduction

This chapter provides an understanding of longitudinal patterns of engagement in symptom and health monitoring among older adults with multimorbidity by analysing the ProACT dataset to demonstrate user retention, frequency of monitoring, intervals between monitoring and patterns of daily engagement. Section 4.2 presents the results of user retention in the ProACT trial. Section 4.3 outlines the frequency of monitoring, while Section 4.4 presents the intervals between monitoring. The final section describes the times of the day when participants would like to use digital health devices.

4.2 The distribution of user retention for using digital health technology at home

The distribution of user retention shows the average retention of how many participants were taking readings, using devices and self-reporting over the trial period. The user retention was counted from each participant's start date and end date.

Figure 4a shows that most participants used ProACT for at least 200 days. There are two key drops shown in the graph. One is at the 200 day point, and the second is at 300 days. It seems that user retention has a higher rate of decline after 200 days, hence 200 days after first using the technology is a key landmark. Figure 5a shows that there are more participants whose user retention is over 300 days than there are participants whose user retention is less than 300 days.

The submission of self-report (SR) data is different than that of each of the digital health devices. The user retention curve in Figure 4b drops faster than in Figure 4a. At the 200 day point, the drop-off is also more significant than device usage. Besides, Figure 5b shows the number of participants whose user tenure is over 300 days is less than Figure 5a and close to half of the participants did not submit their SR after 300 days.

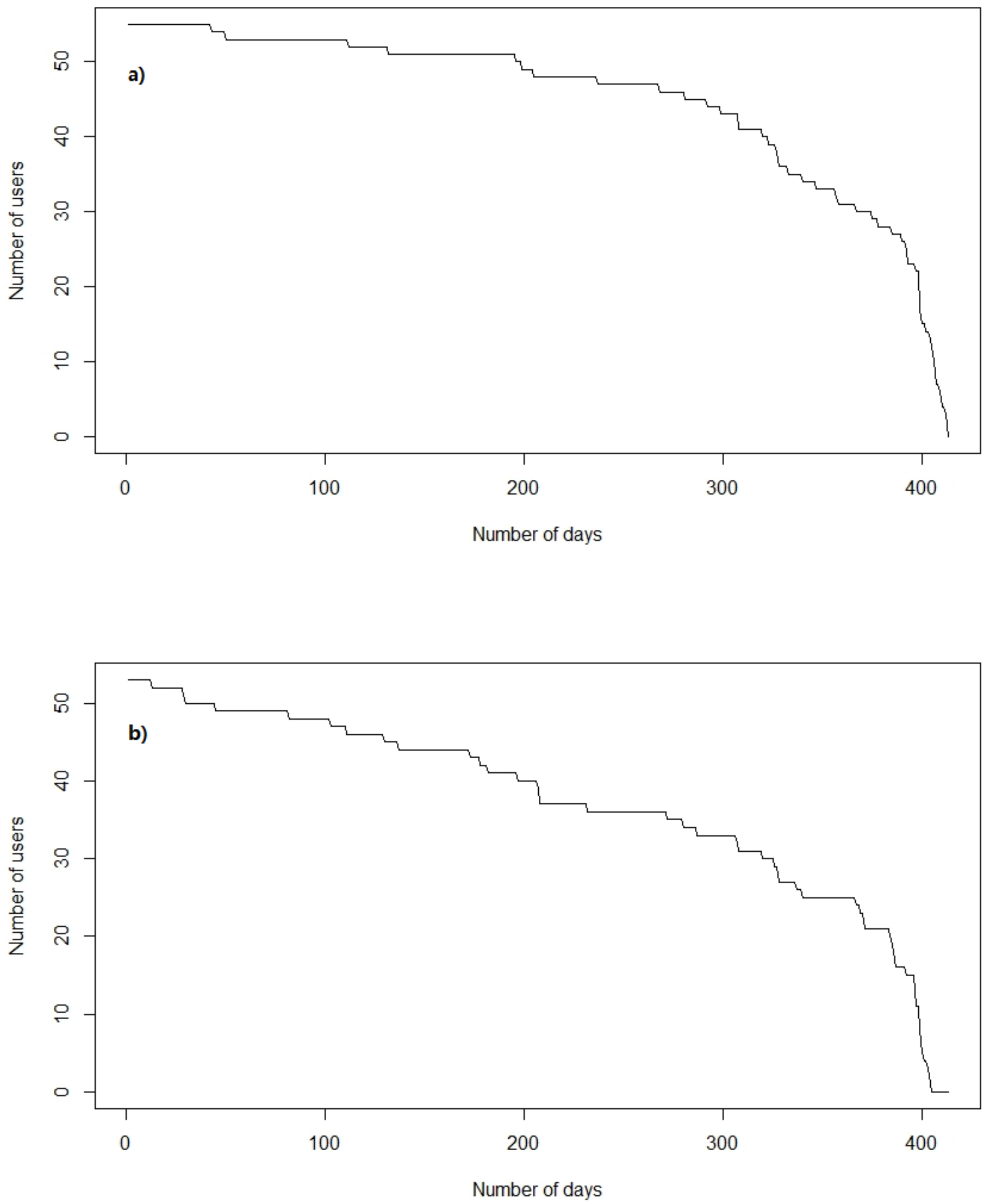

Figure 4. (a)User retention curve of using technology devices (b) User retention curve of participants using the ProACT CareApp to self-report on their conditions and well-being

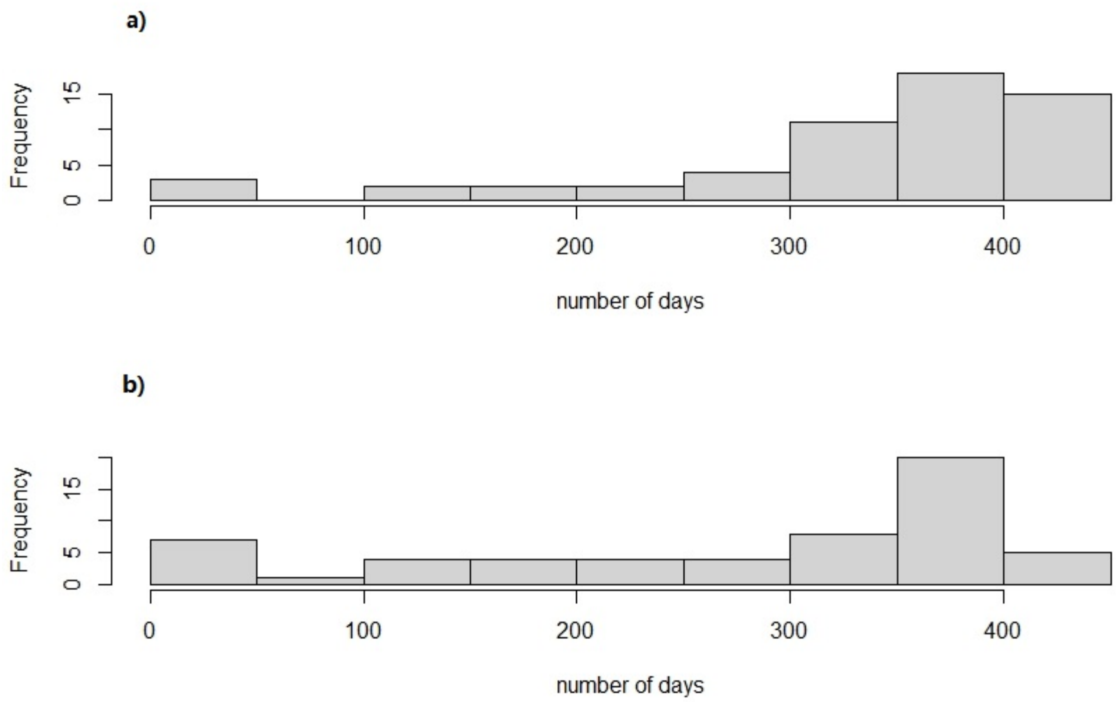

Figure 5. (a)Distribution of user retention for using technology devices (b) Distribution of user retention for participants using the ProACT CareApp to self-report on their conditions and well-being.

4.3 The frequencies (times per week) at which participants submit their data

This user retention curve only indicates how many days there are between the first day and the last day that each participant submitted data. It does not indicate the frequency of submission. Figure 6 presents the kernel density of the weekly submission for every parameter. As can be seen, daily exercise data, which includes daily distance walked, daily step count and daily time walking, came into the system six times a week. Similarly, the frequency of sleep coming into the system is close to six times a week for most of the participants. For blood glucose (BG), blood oxygen level (SpO2), blood pressure (BP) and pulse, the submission frequency was mainly between twice a week to five times a week. For weight and SR, the submission frequency is mainly once a week. It should be noted that those participants with heart failure (HF) monitored weight as a symptom parameter, while all other participants monitored weight as a lifestyle parameter.

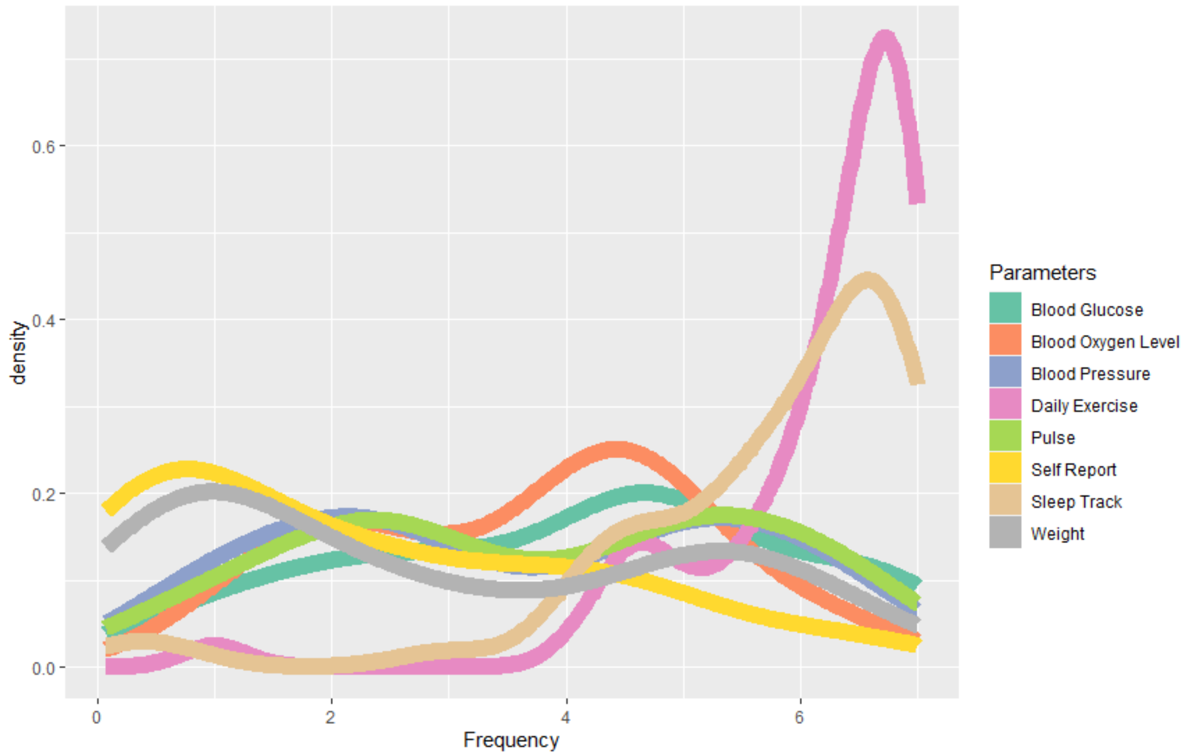

Figure 6. Kernel Density for user weekly submission frequency

4.4 The average and standard deviation of the intervals (in days) between each submission

Figure 7 and Figure 8 show the average and standard deviation (SD) of the intervals between each submission (in days) of each parameter.

As seen in Figure 7, the median of all parameters is less than 5, and the upper quartile of BP, pulse, BG and SpO2 are also less than 5. However, Figure 8 shows that the median SD of BP, pulse, BG and SpO2 are all larger than 20 and close to 25. This means that many participants had large intervals during the trial. Also, the mean of average intervals and the mean of SD intervals can show differences of submissions between every parameter. For example, the mean of the average intervals between each submission (in days) for weight is 6.55, which is similar to daily exercise (5.75) and sleep (6.4). Still, the mean of SD intervals between each submission for weight is 35.61 which is much larger than daily exercise (13.51) and sleep (19.54).

On the other hand, as seen in Figure 7, both the upper quartile and median of daily exercise and sleep are larger than BP, pulse, BG and SpO2, but in Figure 8, the median of daily exercise and sleep are much lower than others. In this case, the intervals of daily exercise and sleep are less than symptom parameters like BP. As can be seen from Figure 7, only the minimum of the boxplots of daily exercise and sleep reaches zero, meaning that some participants submitted these two parameters every day during the trial. However, there are some differences between the daily exercise box plot and the sleep box plot, even though these two parameters are collected by the same device. Therefore, sleep data has more outliers than daily exercise data. For example, one of the outliers in SD of intervals for sleep reaches 100, while for daily exercise, none of the outliers is larger than 75.

As seen in Figure 7 and Figure 8, the median of SR is much higher than other box plots, which means SR data have more intervals and larger intervals. For example, one participant had average intervals of 23.1 and SD intervals of 278. This is because this participant not only has a few small intervals between May 2018 and June 2018 but also has a very large interval from 6th June 2018 to 25th March 2019.

Unlike symptom parameters, in Figure 7, the box plot of weight is higher and larger than BP, pulse, BG and SpO2. As with other parameters, there are a few participants who have large average intervals and SD intervals. P-025’s average intervals are 29.2 and SD intervals are 138.1, while the total number of submissions of weight is 14. P-009’s average intervals are 12, SD intervals are 177.6 and the total number of submissions of weight is 44.

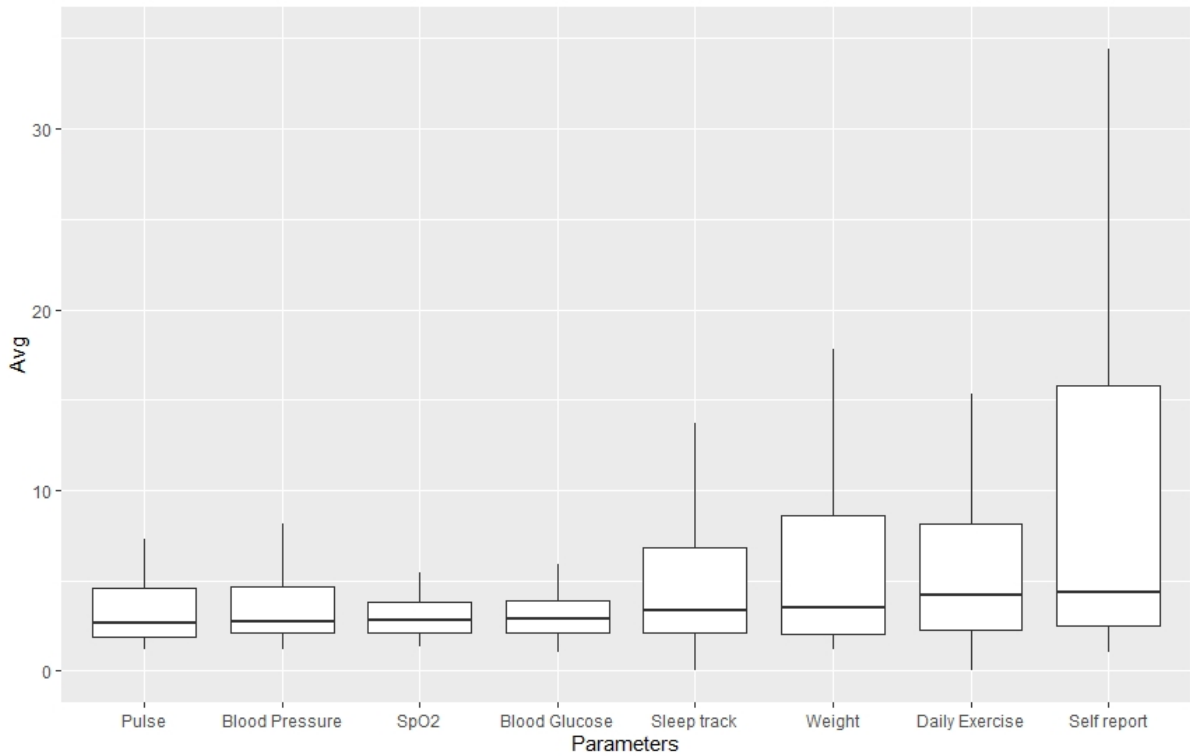

Figure 7. The average of the intervals (in days) between each submission (without outliers)

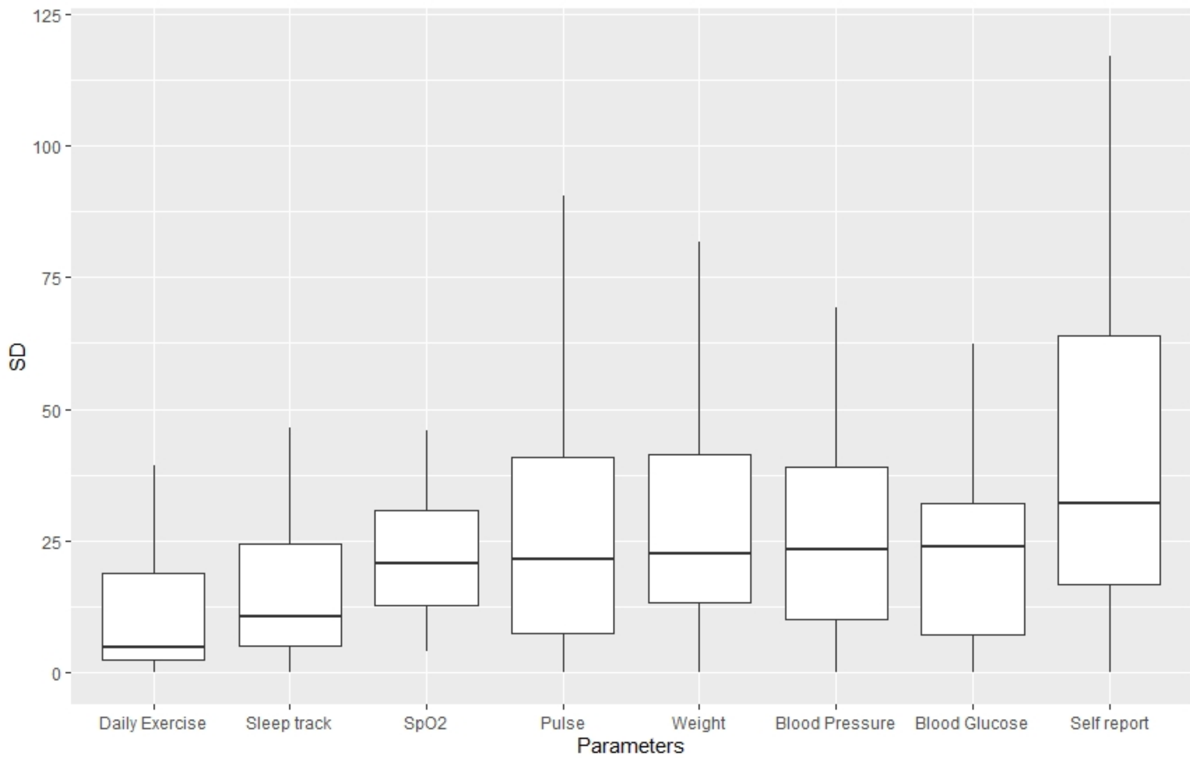

Figure 8. The standard deviation of the intervals (in days) between each submission (without outliers)

4.5 What hours of the day do people submit BP, Pulse, SpO2, BG and Weight readings?

For the majority of days, participants used each device once a day, but some participants engaged more than once a day. If multiple readings from a particular device were submitted to the system within 10 minutes, these are considered as one usage, and only the first submission is counted.

Figure 9 shows 10:00 as the most common time for participants to choose to measure their BP, and 16:00 is the least common day-time hour. There are a few readings during night-time hours, such as 04:00 and 05:00. There are two peaks in Figure 9, one is at 10:00, and another small peak is at 23:00. 42.79% of the submissions are between 08:00 to 13:00.

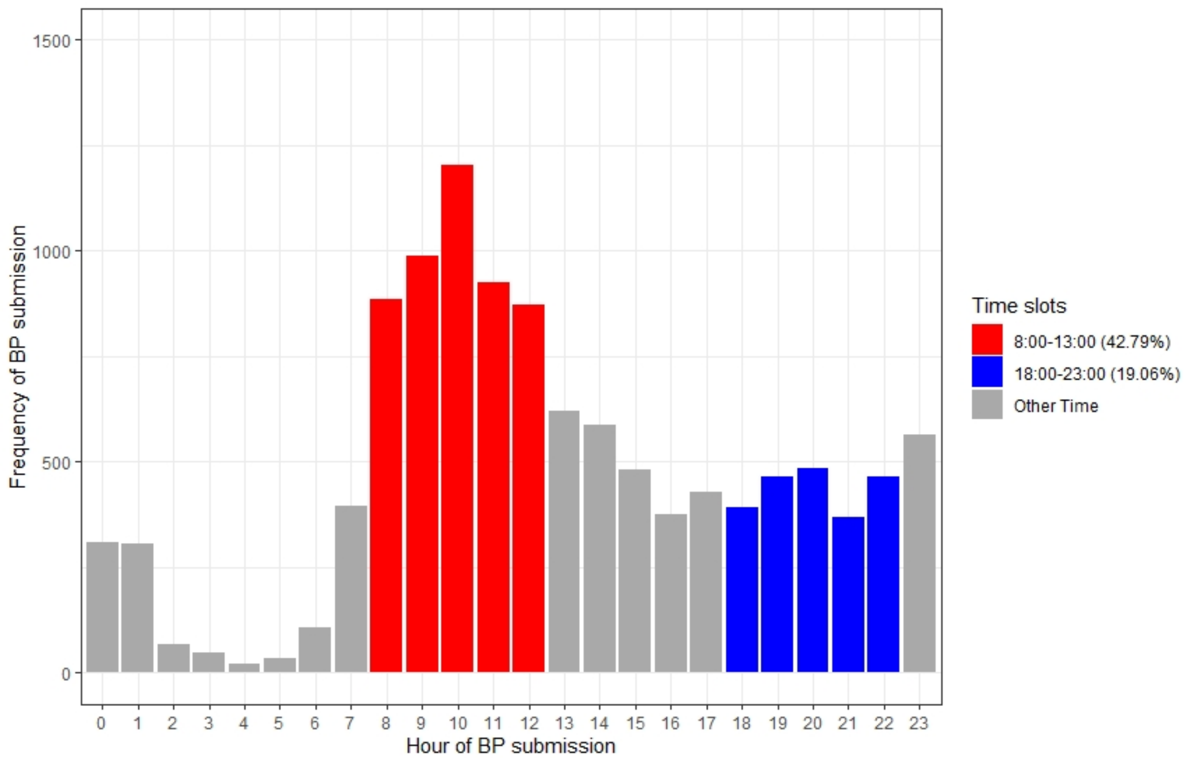

Figure 9. Bar chart of hours that participants submit their BP (42.79% between 8:00-13:00; 19.06% between 18:00-23:00)

As seen in Figure 10, the hours of pulse submissions have much in common with BP. 10:00 is the most popular hour and 16:00 is the least popular day-time hour. Also, there are two peaks of submissions at 10:00 and 23:00.

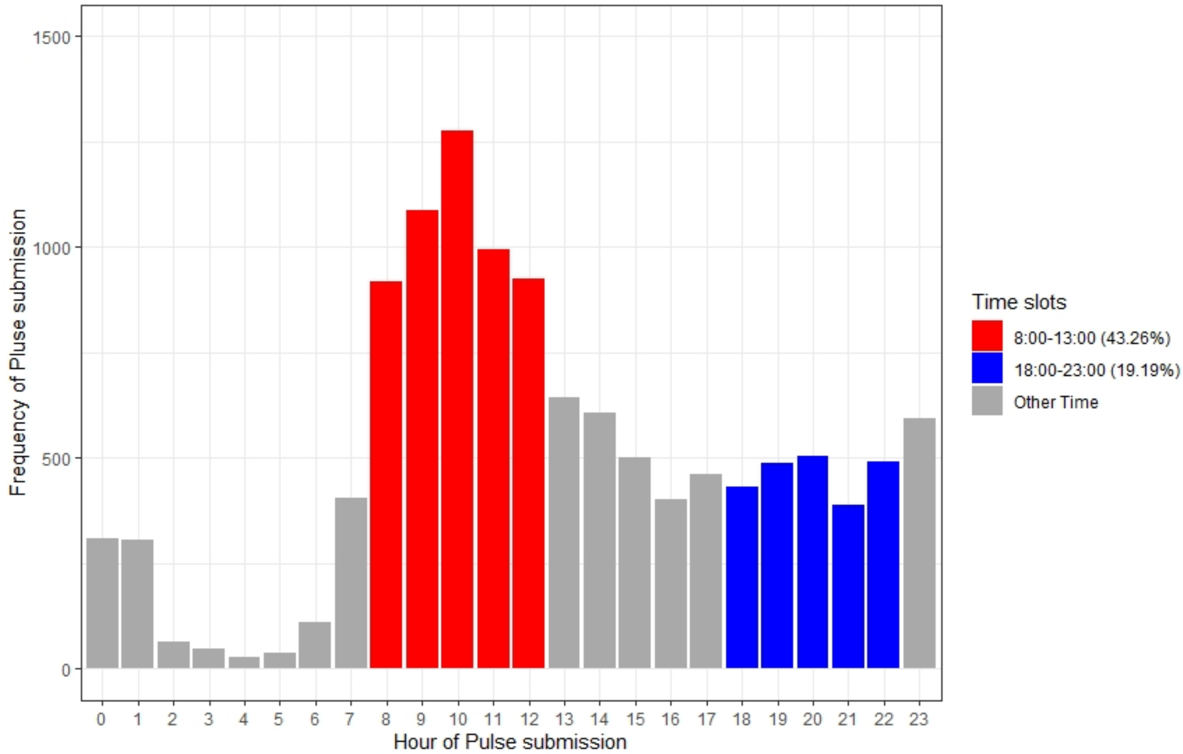

Figure 10. Bar chart of hours that participants submit their Pulse (43.26% between 8:00-13:00; 19.19% between 18:00-23:00)

Figure 11 illustrates that the total submissions of SpO2 are much less compared with BP and pulse, but 10:00 is still the most popular hour of submission, and there are two peaks at 10:00 and 23:00 Also, the proportion of submissions between 08:00 to 13:00 is reduced from 43% to 34%.

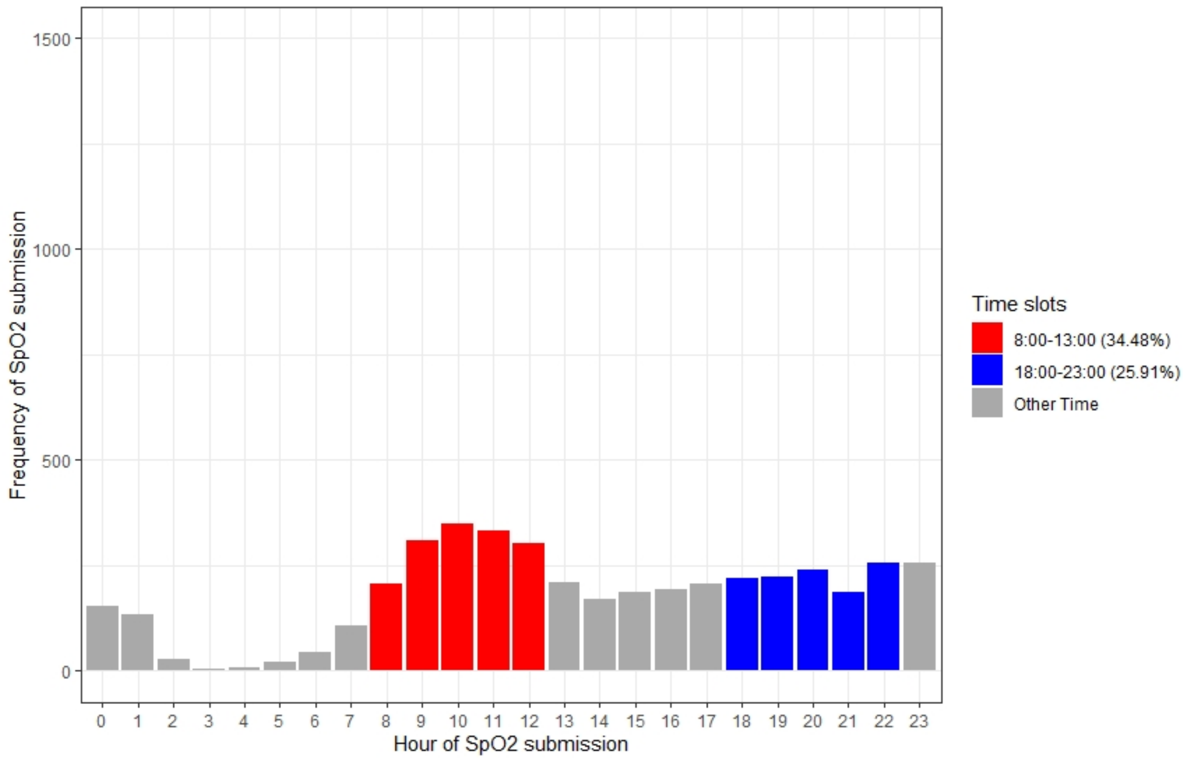

Figure 11. Bar chart of hours that participants submit their SpO2 (34.48% between 8:00-13:00; 25.91% between 18:00-23:00)

Figure 12 shows that as with BP, pulse and SpO2, the most popular hour to submit BG readings is at 10:00, and 17:00 is the least popular day-time hour. Also, there are two peaks at 10:00 and 23:00. However, the peaks at 10:00 and 23:00 in BG submissions are more significant than BP, Pulse and SpO2. The percentage of BG submissions at 10:00 and 23:00 are 11.6% and 7.01% which are higher than BP (10.58% / 4.96%), pulse (10.62% / 4.95%) and SpO2 (8.01% / 5.89%).

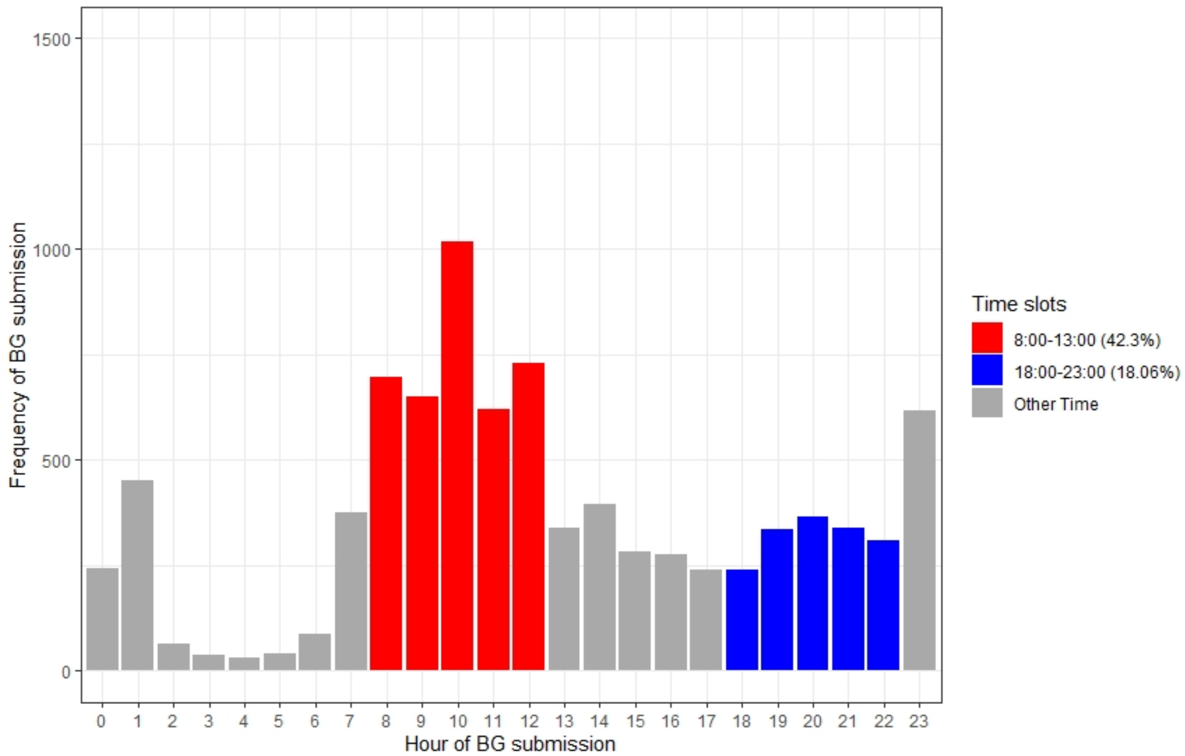

Figure 12. Bar chart of hours that participants submit their BG (42.3% between 8:00-13:00; 18.06% between 18:00-23:00)

Unlike other parameters, the most popular hour for participants to take a weight reading is 08:00, whilst 03:00 is the least popular hour (Figure 13). 62.52% of submissions are between 08:00 to 13:00. In addition, 45.85% of submissions are after 08:00, and before 11:00.

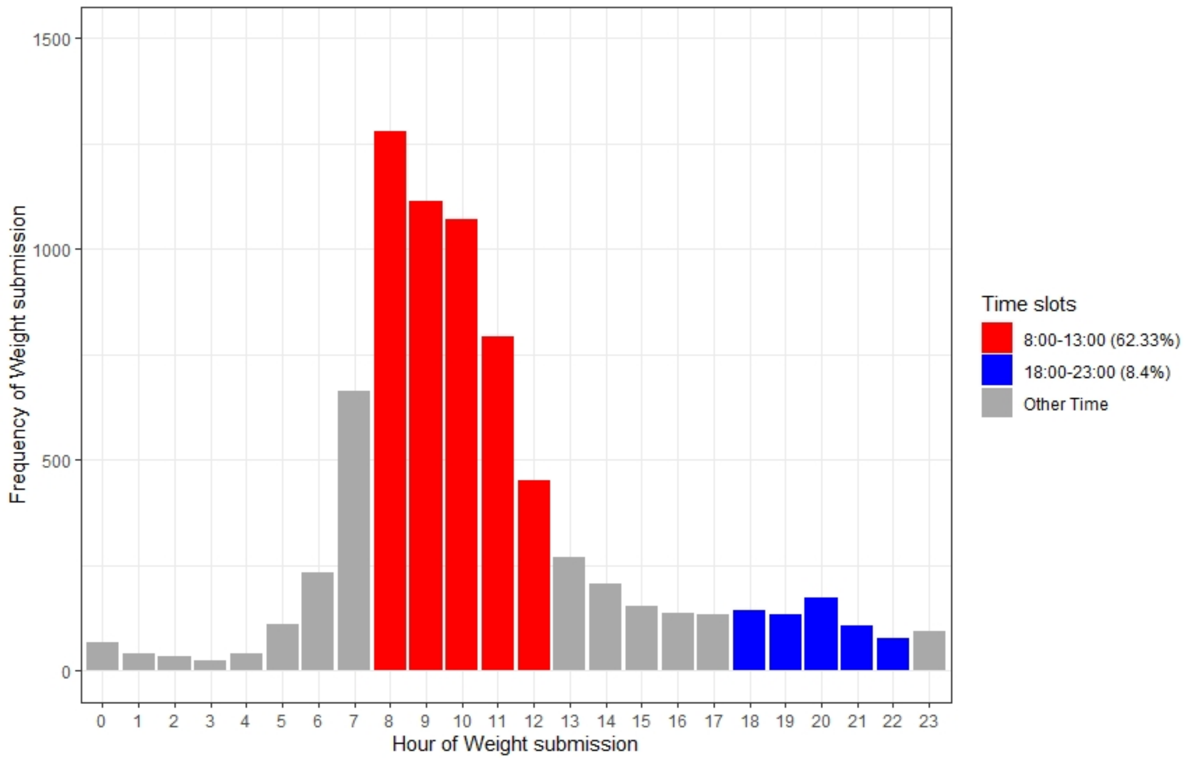

Figure 13. Bar chart of hours that participants submit their weight (62.33% between 8:00-13:00; 8.4% between 18:00-23:00)

4.6 Summary

In this chapter, the findings of Study 1, which were related to the patterns of engagement of this PhD project, were presented. The chapter began with the distribution of user retention for this project, providing an overview of participants' overall levels of engagement with digital health technology. The frequency of submissions and the time between each submission were then outlined. Finally, the time of day that participants submitted readings was presented. Key findings are:

- Overall engagement and retention with ProACT were high. Only 8 participants withdrew, and some of these participants had already collected data for over 100 days before withdrawing.

- Engagement with digital devices for self-monitoring was high. The majority of participants engaged with ProACT devices for more than 200 days, with many using them on more than 300 days. This could be considered to be in contrast to other research that has suggested that digital health technologies suffer high attrition rates(Morrison, 2015), (Stellefson et al., 2013).
- Engagement and retention with self-reporting (including answering questions on symptoms not measured by a digital device, as well as general well-being questions) via the ProACT digital application were lower than with digital devices. There were also larger gaps, or intervals, between self-reporting days.
- The most popular time of day for engaging with monitoring of various symptoms was morning time, with small peaks of engagement evident in the late evening, just before bedtime.

The findings are discussed in further detail in Chapter 7.

5 Findings Study 2 - Using K-means Clustering to Discover Engagement Patterns of Older adults with Multimorbidity when using Digital Health Technologies

5.1 Introduction

This chapter first presents the process of clustering participants into three clusters based on their frequency of weekly submissions. Section 5.2 describes the correlation between all the submitted parameters in order to select the appropriate parameters for clustering. Section 5.3 demonstrates the process of removing outliers using PCA and the k-means clustering process to categorise participants into three clusters. The next four sections present, in turn, the characteristics of the participants in the three clusters, the health outcomes of the participants in the three clusters, the correlations between the different digital health devices, and the variations in the health outcomes of the participants in the three clusters over the course of the trial.

5.2 Correlation of submission parameters

To help determine which ‘distinct’ usage characteristics/parameters (such as the weekly frequency of BP submissions) should be selected as features for clustering, the correlations between each parameter were calculated. Figure 14 shows the correlation matrix for weekly submissions (days) of all parameters. In this study, a moderate correlation (correlation coefficient between 0.3 to 0.7 and -0.7 to -0.3) (Dancey and Reidy, 2007, Akoglu, 2018) is chosen as the standard for selecting parameters. After performing normality tests on the data submitted each week, it was discovered that the data were not normally distributed. Spearman's correlation was used to check the correlation between the parameters. First, as outlined in Chapter 3, every participant received a blood pressure monitor to measure BP and pulse was collected as part of the BP measurement.

Moreover, the correlation coefficient between BP and pulse is 0.93, a strong correlation. In this case, BP is selected for clustering rather than pulse. As for the other parameters, the correlation of weight (0.51), PA (0.55), SR (0.41) and sleep (0.55) with BP are all moderate correlations except for SpO2 (0.05) and BG (0.24). In addition, the correlation between SpO2 and weight (-0.25), PA (0.16), SR (0.29) and sleep (-0.24) are all weak correlations. Likewise, the correlation coefficient between BG and weight (0.19), PA (0.2), SR (-0.06), and Sleep (0.25) are weak. In addition, only participants with diabetes were required to record BG, whereas participants with COPD were required to record SpO2. As such, participants without diabetes or COPD had empty BG and SpO2 records, so when clustering, the blood glucose and oximetry records would have too much influence on the clustering results due to the large difference in blood glucose and oximetry records between these two groups of participants, thus affecting the final results. Thus, SpO2 and BG were not selected for clustering, while BP, weight, PA, SR and sleep were selected for clustering.

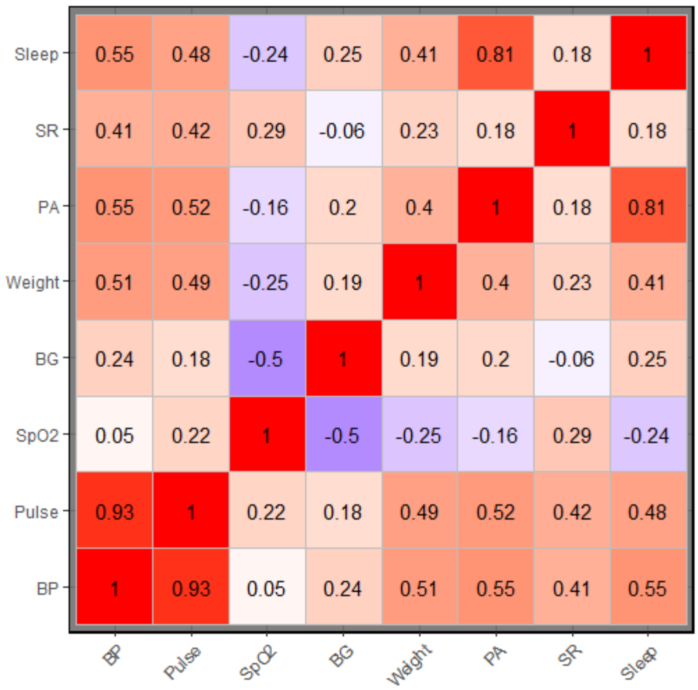

Figure 14. Correlation matrix for weekly submissions(days) of all parameters.

5.3 Principal component analysis and clustering

The fundamental question for k-means clustering is: how many clusters should be discovered (K)? To determine the optimum number of clusters, we further investigated the data through visualisation offered by PCA. As can be seen from Figure 15, the first two principal components explain 73.6% of the variation, which is an acceptably large percentage. However, as Figure 16 shows, there are three participants - P038, P016 and P015 – who contributed a lot to principal component one (PC1) and principal component two (PC2). Following a check of the original data set, P038 only submitted symptom parameters on one day and P016 only symptom parameters on two days. Conversely, P015 submitted almost every day during the trial. P038 and P016 were therefore omitted from clustering.

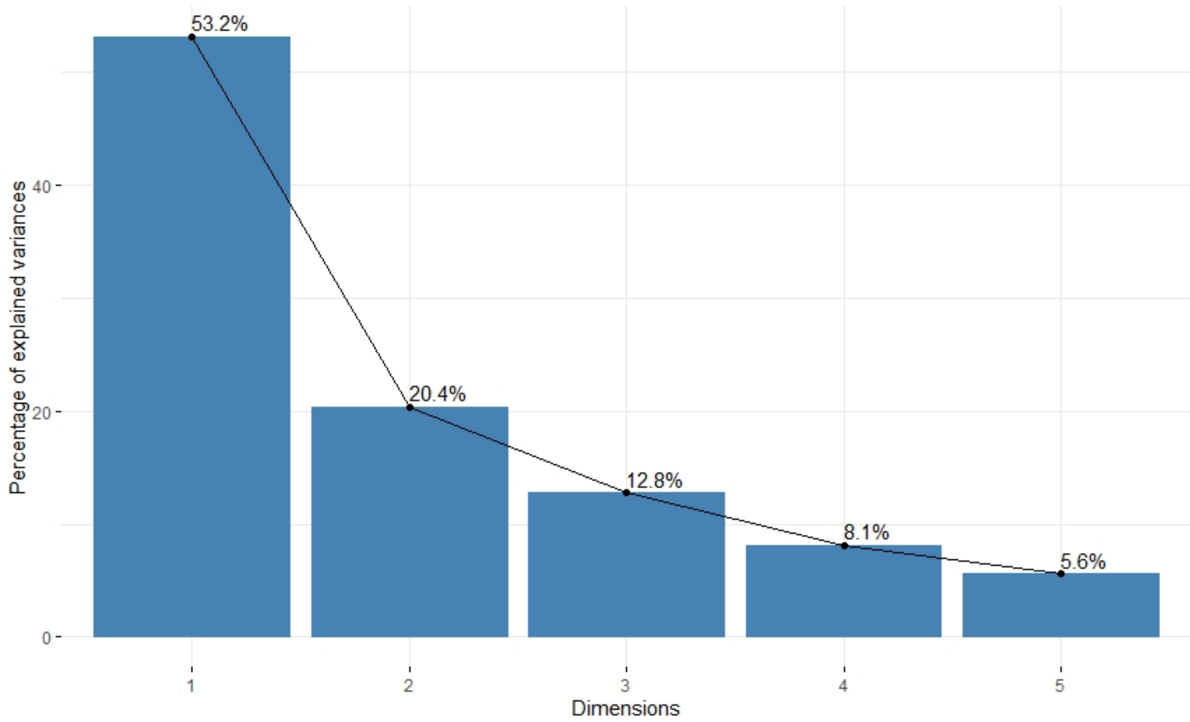

Figure 15. The scree plot of every dimension by Principal Components Analysis

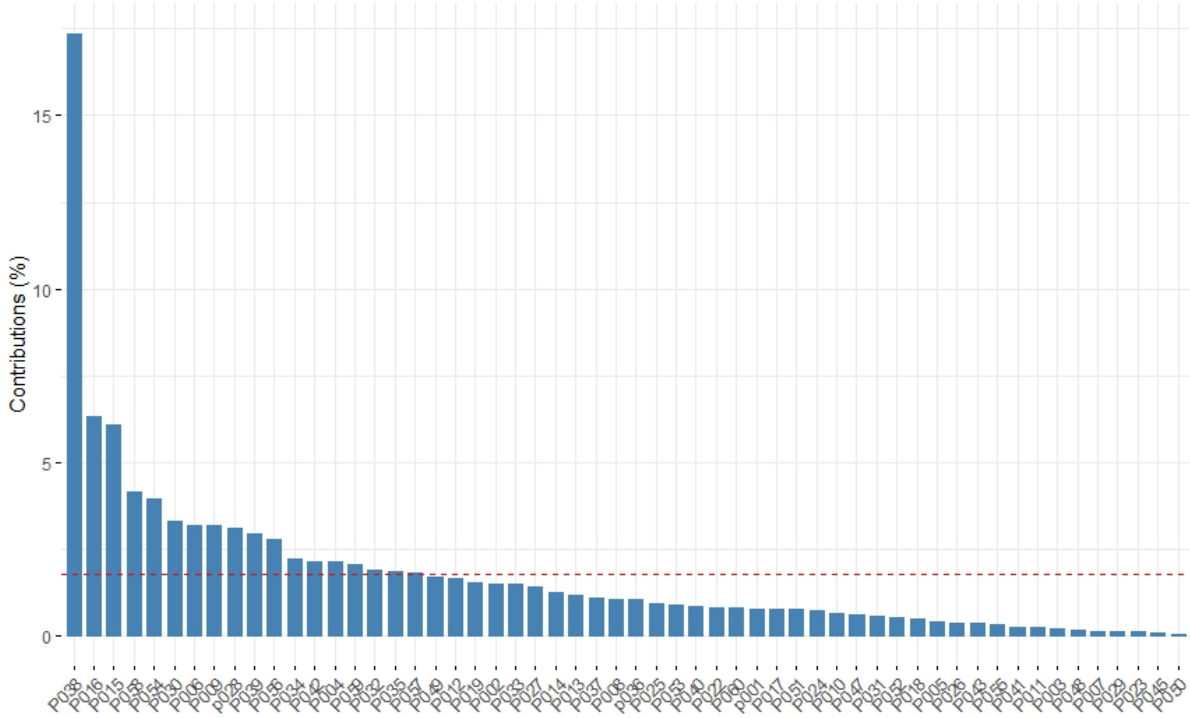

Figure 16. The bar plot of all participants' contributions to PC1 and PC2

After removing the outliers (P038 and P016), as Figure 17 shows the first two principal components explain 70.5% of the variation which is an acceptably large percentage.

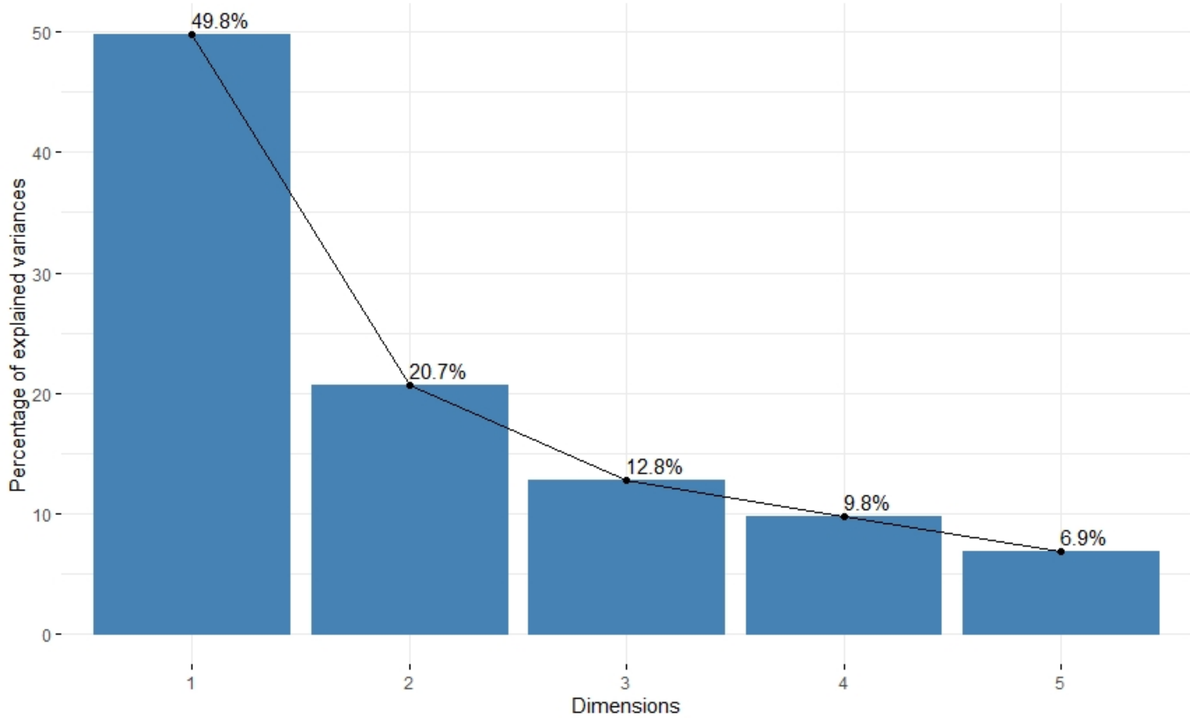

Figure 17. The scree plot of every dimension by Principal Components Analysis (without outliers)

The clusters were projected into two dimensions as shown in Figure 18. Each sub-figure in Figure 18 shows a different number of clusters (K). When K=2, the data is obviously separated into two big clusters. Similarly, when K=3, the clusters are still separated very well into three clusters. The clusters are well-separated when K=4, but compared with the three clusters graph, two clusters are the same and Cluster 1 only has three participants which is a relatively small cluster. As for the graph with K=5, there is some overlap between Cluster1 and Cluster2. Likewise, Figure 19 shows the optimal number of clusters using the elbow method. In view of that, three clusters of participants separate the dataset best. The three clusters can be labelled as the **least engaged user (Cluster 1), the highly engaged user (Cluster 2), and the typical user (Cluster 3)**.

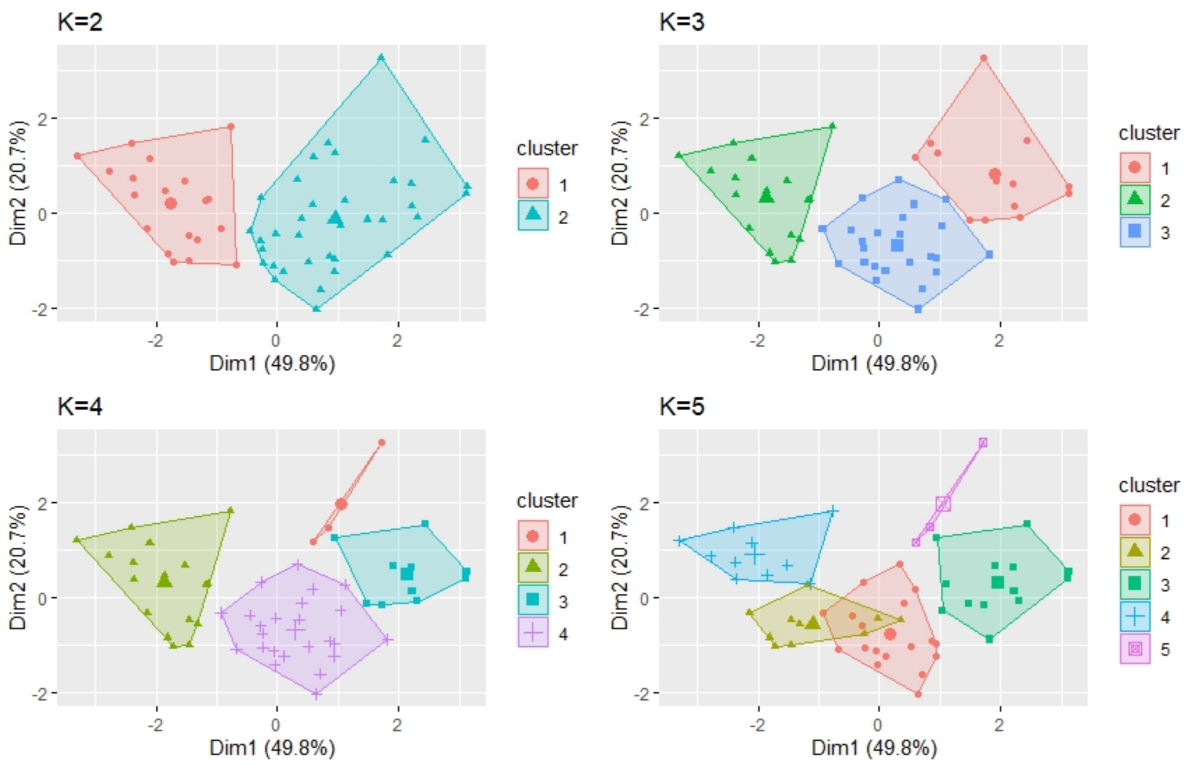

Figure 18. the visualisation of clustering with the number of clusters ranging from 2 to 5

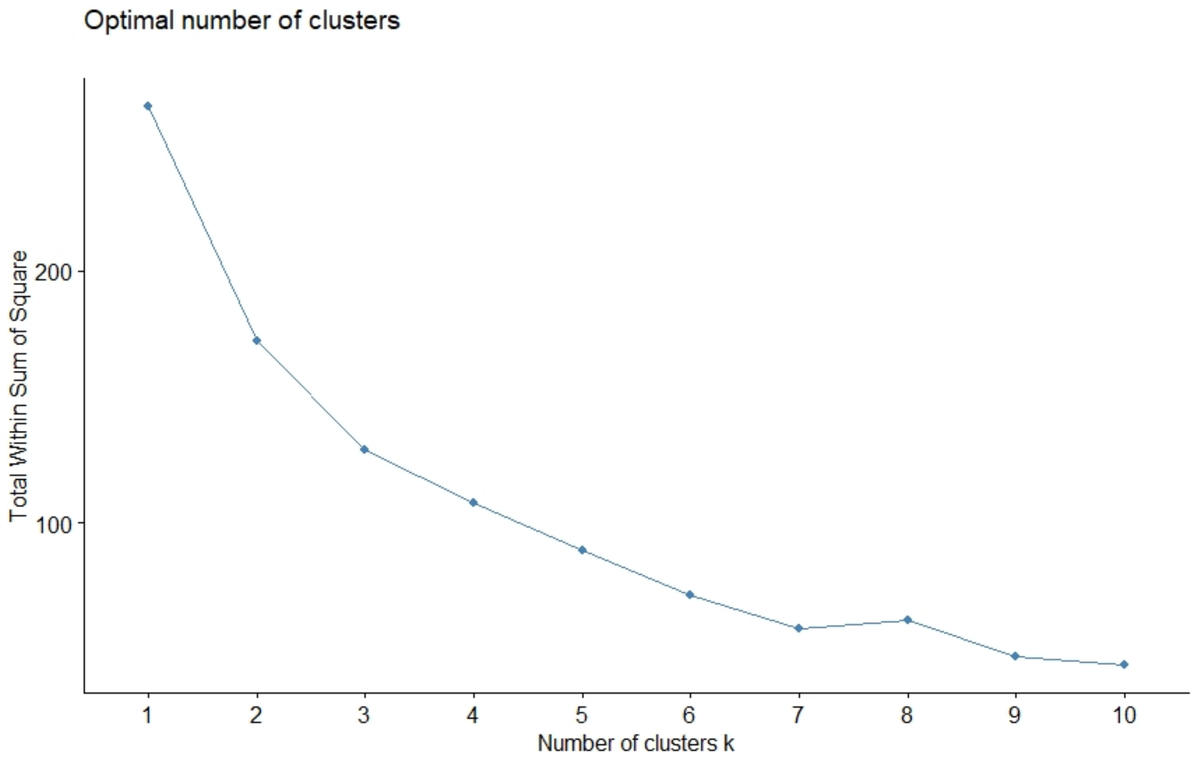

Figure 19. the optimal number of clusters by elbow method

In the remainder of this section, the clusters are examined with respect to participant characteristics and the weekly submissions (days) of different parameters in a visual manner to reveal potential correlations and insights. Finally, the correlations between all parameters will be examined by PCA.

5.4 Participant characteristics

As seen in Figure 20, the distribution of age within the three clusters is similar, with the p-value of one-way ANOVA being 0.93, as all the participants in this trial were older adults. However, the median age of the Cluster3 boxplot (74.8) is slightly higher than the other two clusters, and the average age of Cluster2 (74.1) is lower than Cluster1 (74.6) and Cluster3 (74.8) (Table 4). As Table 4 shows, 6 out of 23 female participants (26%) are in Cluster1 which is higher than 7 out of 31 male participants (23%). However, male participants in Cluster2 (10 out of 31; 32%) and Cluster3 (10 out of 23; 45%) represent higher proportions of total male participants than female participants in

Cluster2 (7 out of 23; 30%) and Cluster3 (10 out of 23; 43%). Figure 21 shows the proportion of the four chronic conditions within the three clusters. Cluster1 has the largest proportion of participants with chronic obstructive pulmonary disease (COPD) and the smallest proportion of participants with diabetes. Moreover, Cluster3 has the smallest proportion of participants with heart failure (HF) (3 out of 24; 13%) (Table 4).

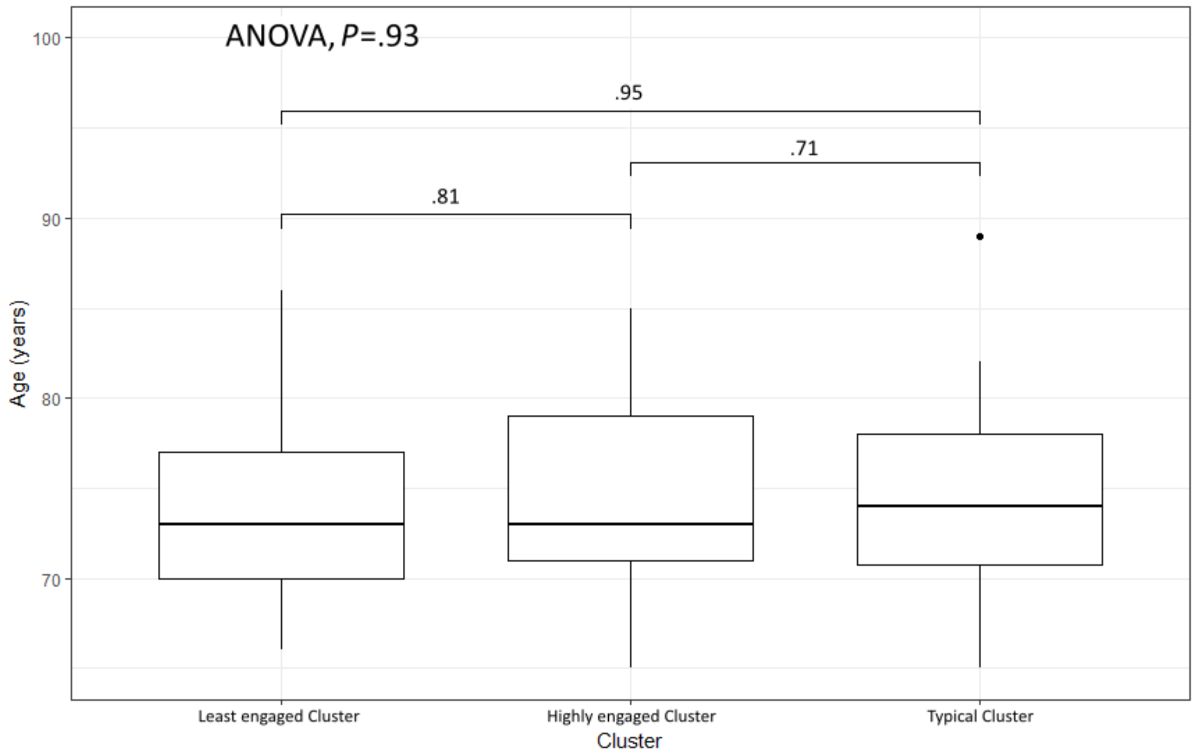

Figure 20. The variation of age within the three clusters based on the weekly submissions

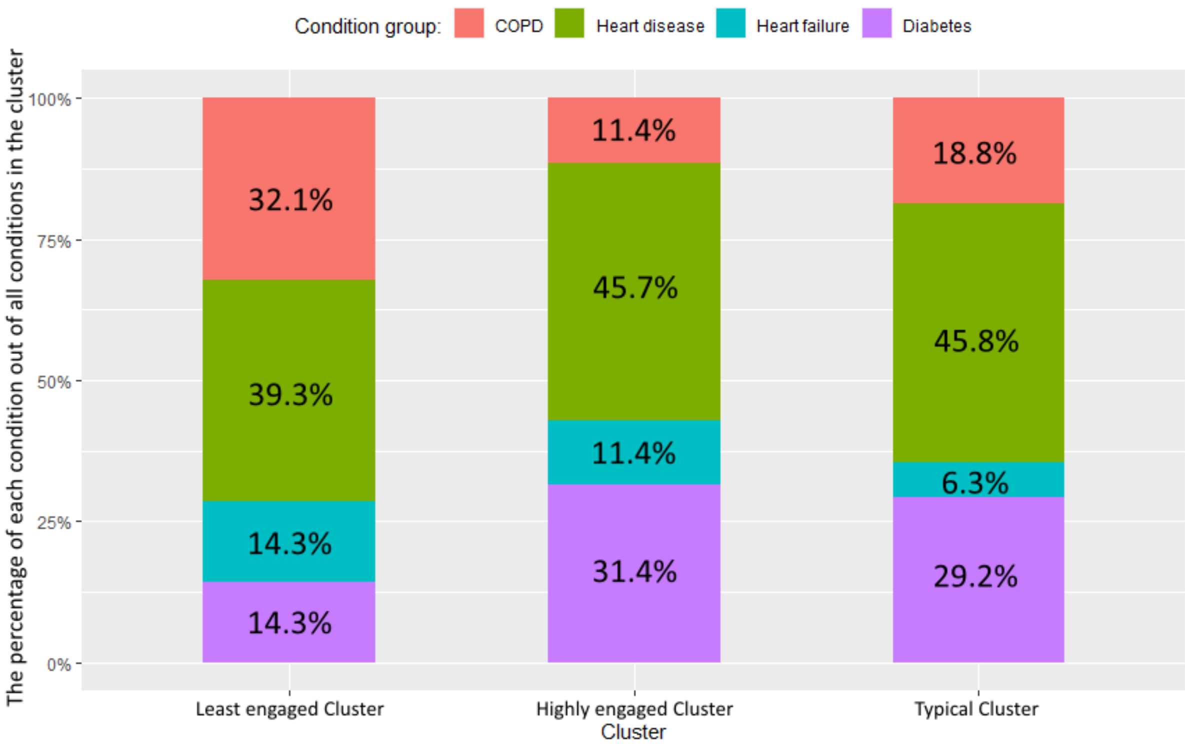

Figure 21. The variation of conditions within the three clusters. Each bar presents the percentage of each condition out of all conditions in the cluster (bearing in mind that participants can have multiple conditions). For example, there are 13 participants, and 28 records under the 4 condition groups in cluster 1. Hence 32.1% of the conditions in cluster 1 are COPD (however 69% [n=9] of participants in cluster 1 have COPD as presented in Table 4).

Table 4. Characteristics of the Participants in every cluster

Characteristics	Cluster1 (N=13)	Cluster2 (N=17)	Cluster3 (N=24)
Age (years)			
Range; mean±SD	66-86; 74.6±6.2	65-85; 74.1±5.5	65-89; 74.8±5.9
Gender, n (%)			
Male	7 (54)	10 (59)	14 (58)
Female	6 (46)	7 (41)	10 (42)
Chronic Conditions, n (%)			
COPD	9 (69)	4 (24)	9 (38)
Heart Condition	11 (85)	16 (94)	22 (92)
Congestive HF	4 (31)	4 (24)	3 (13)
Diabetes	4 (31)	11 (65)	14 (58)

5.5 Participant engagement outcomes

Firstly, Cluster 2 has the longest average enrolment time at 352 days, Cluster 3 at 335 days and Cluster 1 at 330 days. In Figure 22, the overall distribution of the BP weekly submissions is different, as the p-value of the one-way ANOVA is 8.4e-09. The BP weekly submissions (days) of Cluster2 exceed Cluster1 and Cluster3, which means participants in Cluster2 have a higher frequency of BP submissions than the other two clusters. The median and maximum of Cluster3 are higher than Cluster1, but the minimum of Cluster3 is lower than Cluster1. Likewise, as seen in Table 5, the mean of Cluster1 (2.5) is smaller than Cluster3 (2.9), and the standard deviation (SD) of Cluster1 (1.4) is also smaller than Cluster3 (2.9).

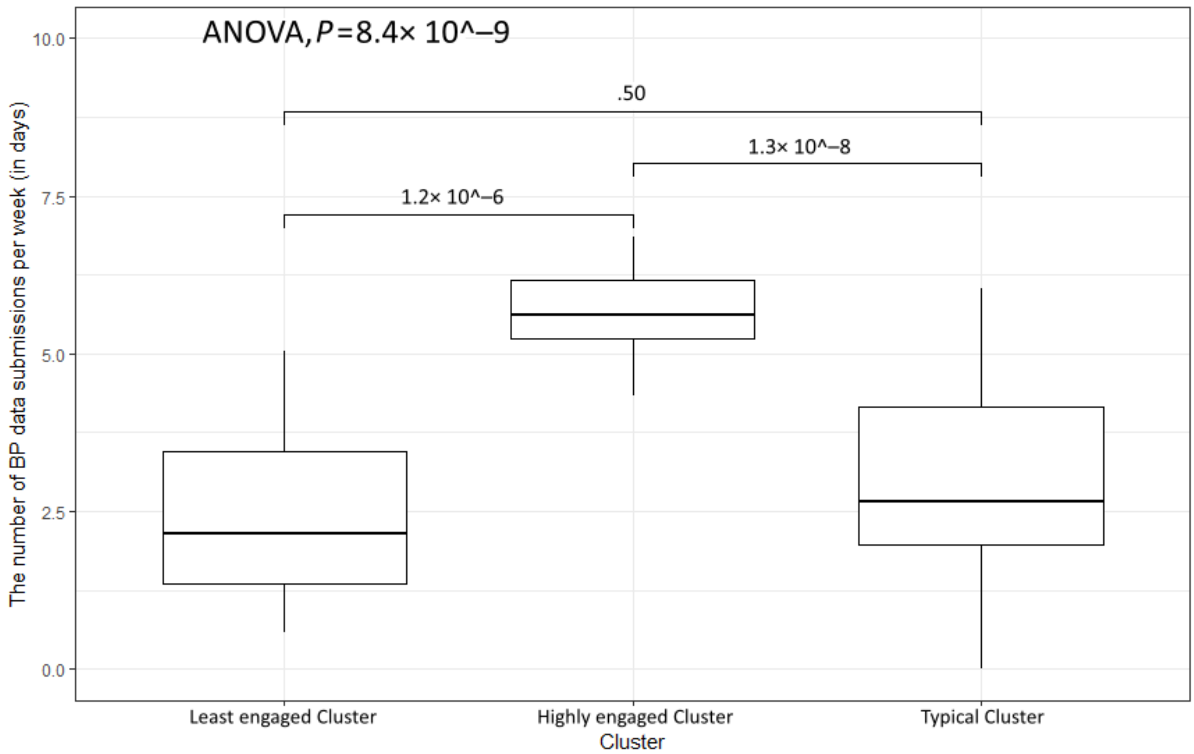

Figure 22. The variation of weekly submissions (days) for blood pressure (BP) data within the three clusters

Table 5. Weekly submissions (days) of parameters (green = largest submission rate across the clusters)

Parameter, mean±SD	Least Engaged Cluster (24.1%)	Highly Engaged Cluster (34.5%)	Typical Cluster(44.4%)
Blood pressure	2.5±1.4	5.7±0.7	2.9±1.6
Weight	1.2±0.9	5.4±0.8	1.8±1.5
Physical activity	5.2±0.7	6.7±0.5	6.5±0.4
Self-report	1.9±1.4	3.7±2.1	1.6±1.4
Sleep	4.2±1.3	6.5±0.4	6.1±0.6

As Figure 23 shows, the overall distribution of the weight weekly submissions is different, as the p-value of the one-way ANOVA is 1.4e-13, since the participants of Cluster2 submitted weight parameters more frequently than Cluster1 and Cluster3. Also, similar to the BP submissions, the median of Cluster3 is higher than Cluster1. In Figure 23, there are three outliers in Cluster2. The top outliers are participant-015, who submitted a weight reading almost every day. During the trial, this participant mentioned many times in the interviews that he had a goal of losing weight, and he used the scale to check his progress, *"I've set out to reduce my weight. The doctor has been saying to me you know there's where you are and you should be over here. So, I've been using the weighing thing just to clock, to track reduction of weight"* (Participant-015). The other two outliers are participant-051 and participant-053, both of whom mentioned taking their weight as part of their daily routine: *"Once I get up in the morning the first thing is I weigh myself. That's, the day starts off with the weight, right"* (Participant-053).

Even though the times of weekly weight submissions are lower than all other participants in Cluster2, they are still higher than most of the participants in the other two clusters.

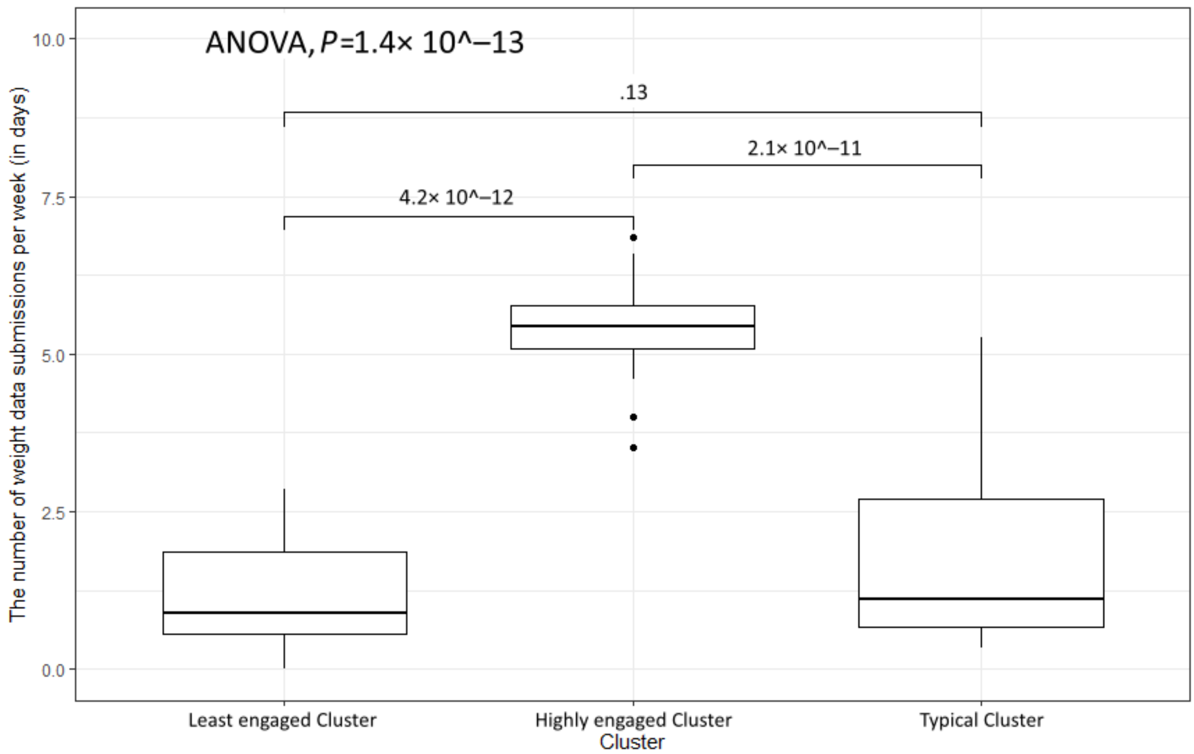

Figure 23. The variation of weekly submission(days) for weight data within the three clusters

In Table 5, it is easy to observe that the average weekly submissions of PA and Sleep for every cluster is higher than other variables, and the SD is relatively low. This is likely because participants only needed to open the Withings app once a day to ensure syncing of data. However, the overall distribution of PA and sleep submissions are different in Figure 24 and Figure 25, as the p-value of the one-way ANOVA are 1.1e-09 and 3.7e-10. Moreover, as Figure 24 and Figure 25 show, there are still some outliers who have a low frequency of submissions, and the box plot of Cluster1 is lower than Cluster2 and Cluster3 in both figures. The reasons for the low frequency of submissions can mostly be explained by: 1) technical issues, including Internet connection, devices not syncing and devices needing to be re-paired: *"I was without my watch there for the last month or three or four weeks [due to technical issues], and I missed it very badly because everything I look at the watch to tell the time, I was looking at my steps"* (Participant-042); 2) participants forgetting to put the watch back on after taking it off; 3) participants who stop using the devices, for example, some participants don't like wearing the watch while sleeping or when they go on holiday, *"I don't wear it, I told them I wouldn't wear the watch at night, I don't like it"* (Participant-030).

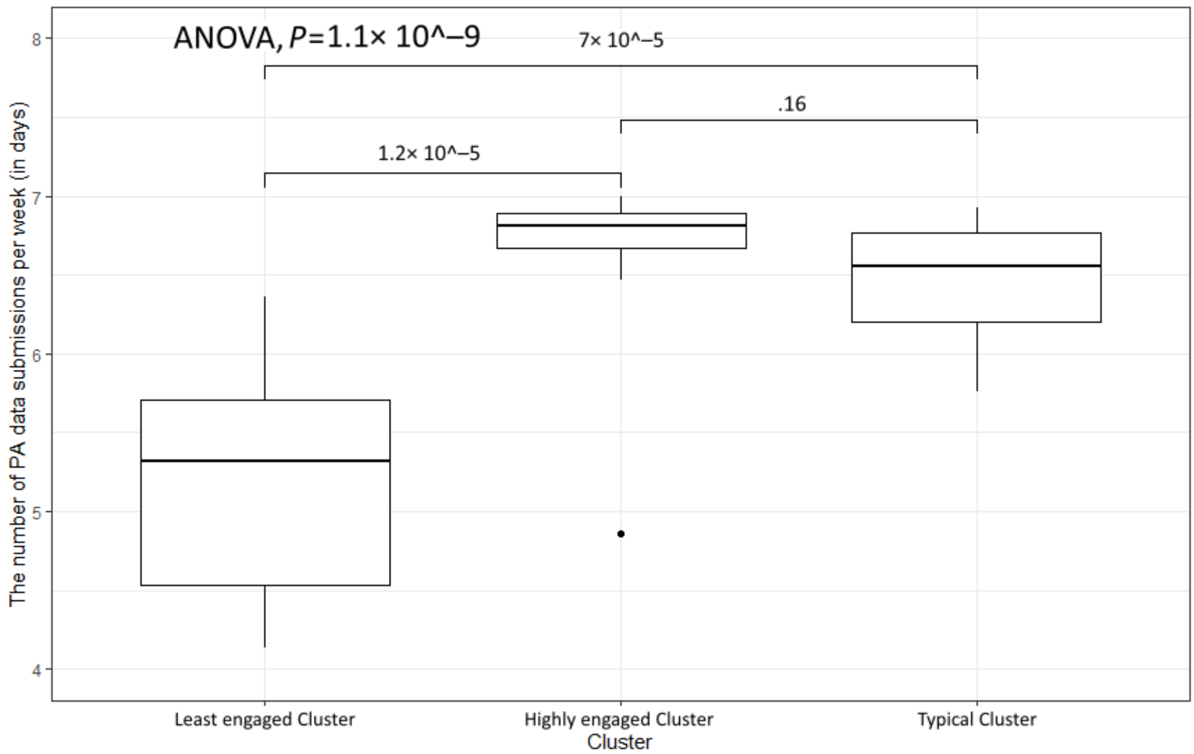

Figure 24. The variation of weekly submission(days) for physical activity (PA) within the three clusters

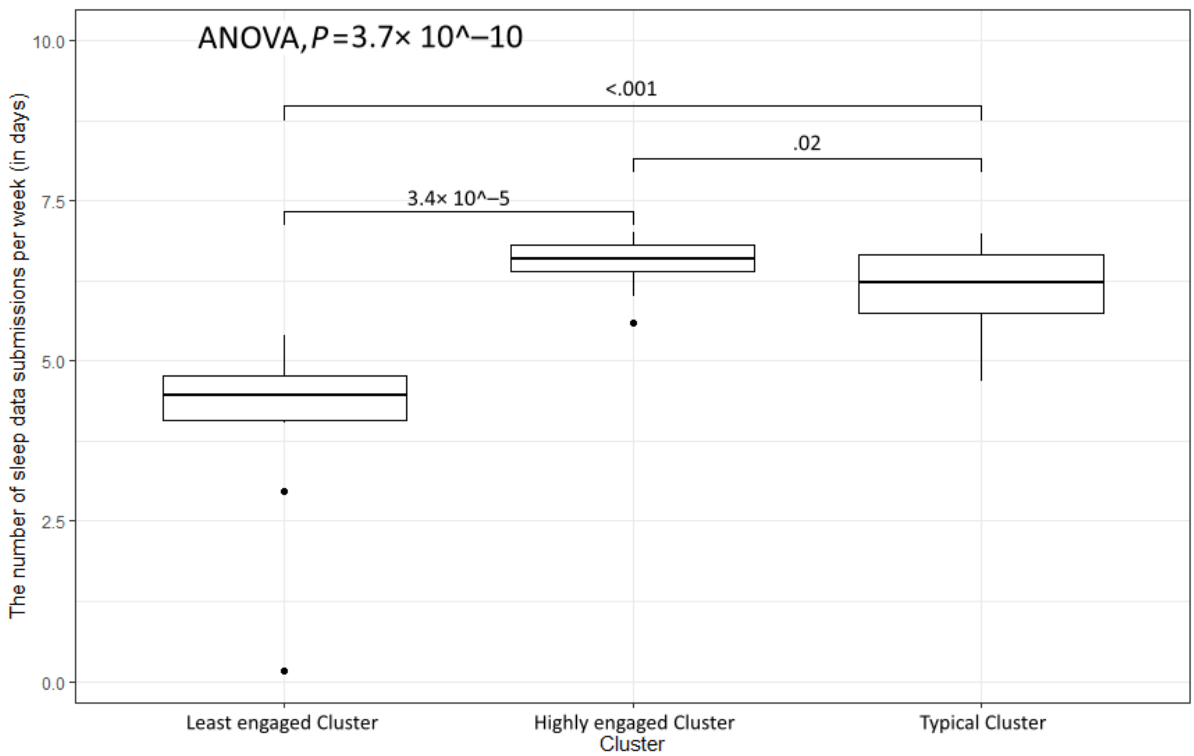

Figure 25. The variation of weekly submission(days) for sleep data within the three clusters

Unlike other variables, the submission of SR through the ProACT CareApp required that participants reflect on each question and their status before selecting the appropriate answer. Participants had different questions to answer based on their conditions. For example, participants with HF and COPD were asked to answer symptom-related questions, while those with diabetes were not. All participants were presented with general well-being and mood questions. Therefore, for some participants, self-reporting could possibly take more time than using the health monitoring devices. As shown in Figure 26, the average weekly submissions of SR within the three clusters are relatively small and the SD is large, which means the frequency of SR submissions is lower than other variables. Furthermore, there were approximately five questions asked daily about general well-being, and some participants would skip the questions if they thought the question was unnecessary or not relevant: R: *"And do you answer your daily questions?"* P027: *"Yeah once a week."* R: "*Once a week, okay"*. P027: *"But they're the same."*

As Figure 26 shows, the distribution of SR submissions is different, as the p-value of one-way ANOVA is 0.0013. In Figure 26, the median of Cluster2 is higher than the other two clusters, and compared with other variables, but unlike other parameters, Cluster2 also has some participants who had very low submission rates of SR which were close to zero. SR is the only parameter where Cluster1 has a higher median than Cluster3.

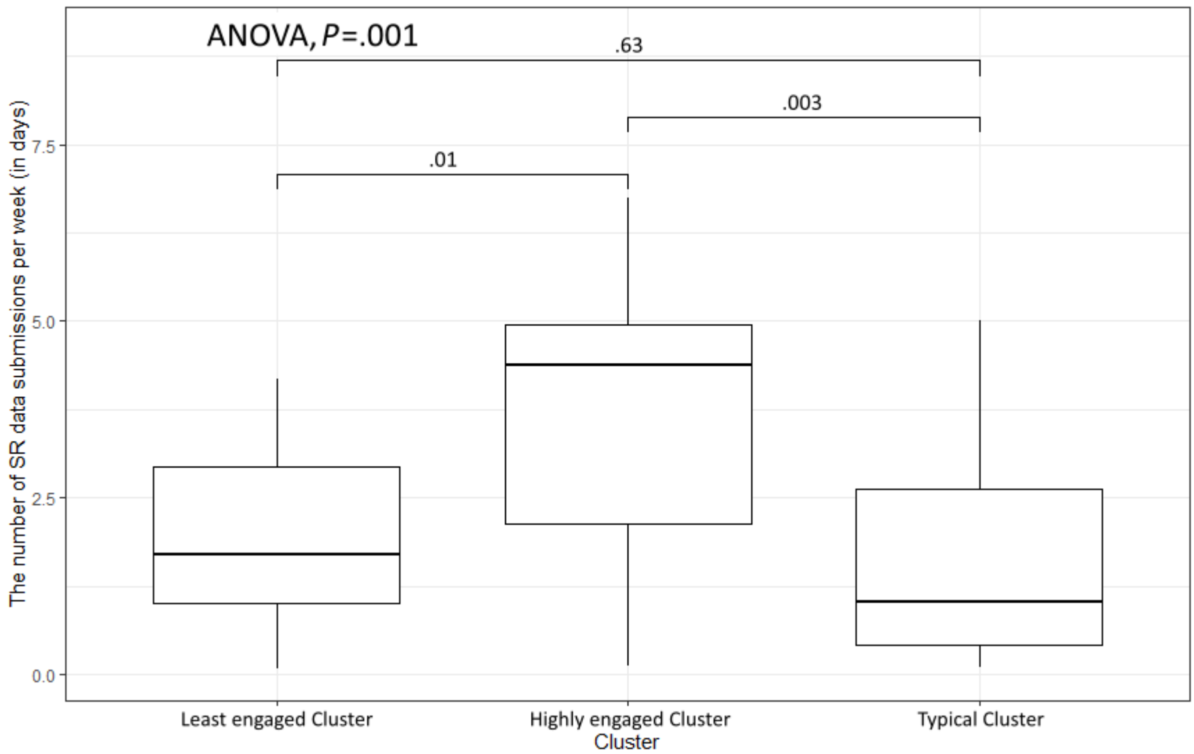

Figure 26. The variation of weekly submission(days) for self-report (SR) within the three clusters

5.6 The correlation between parameters

As seen in Figure 27, the arrows of BP and weight point to the same side of the plot, which shows a strong correlation. Likewise, PA and sleep also have a strong correlation. As noted previously, the strong correlation between PA and sleep is due to the fact that the same device collects these two measurements, and participants only need to sync the data once a day. On the other hand, BP and weight were collected by two different devices but are strongly correlated. During interviews, many participants mentioned that their daily routine with the ProACT platform involved taking both blood pressure and weight readings: *"Usually in the morning when I get out of the bed first. I go into the bathroom, wash my hands and come back then, weigh myself, do my blood pressure, do my bloods".* (Participant-008); *"I now have a routine that I let the system read my watch first thing, then I do my blood pressure thing and then I do the weight".* (Participant-015)*; "As I said it's keeping me in line with my, when I dip my finger, my weight, my blood pressure".* (Participant-040)*; "I use it in the morning and at night for putting in the details of blood pressure in the morning and then the blood* *glucose at night. Yes, there's nothing else is there? Oh, every morning the (weight) scales".* (Participant-058).

On the other hand, as shown in Figure 27, SR has a weak correlation with other parameters, for reasons noted above.

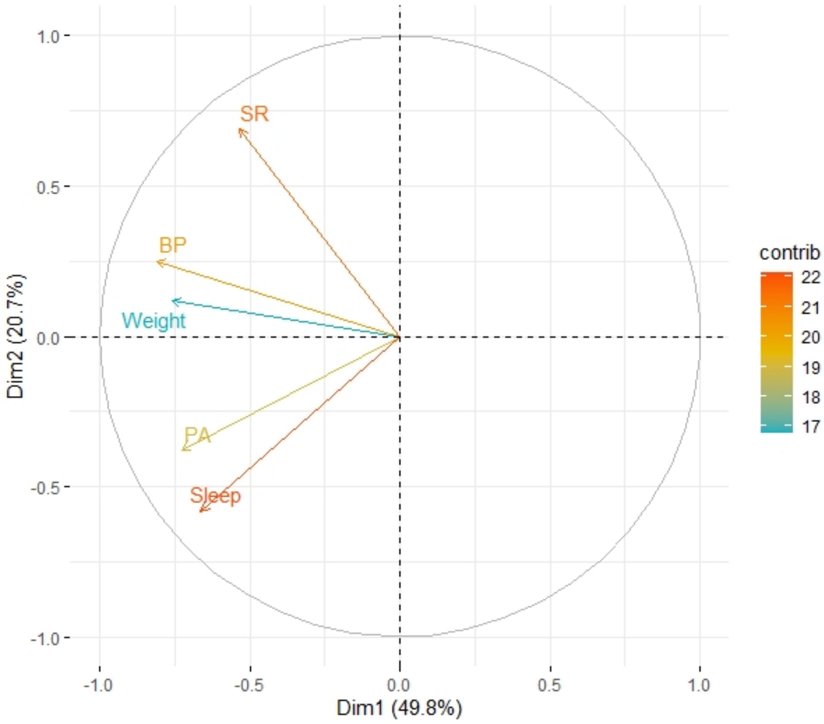

Figure 27. The Principal Component Analysis for variables

5.7 The variation of each parameter in the three clusters between different time periods

Analysis was conducted to determine any differences between the clusters in terms of symptom and well-being parameter changes over the course of the trial. Table 6 provides a description of each cluster in this regard. As Figure 28 shows, the boxplot of Cluster2 is comparatively short in every time period of the trial and the median of Cluster2 and Cluster3 is more stable than Cluster1. Also, the median of Cluster1 is increasing over time, while Cluster2 and Cluster3 are decreasing and within the normal SBP of older adults (Master et al., 1950) (Figure 28 a). As can be seen in Table 7, Cluster2 has a P-value of *P*= .51(Systolic BP) and *P*= .52(Diastolic BP), which is higher than Cluster1 (*P*= .19 and *P*= .16) and Cluster3 (*P*= .27 and *P*= .35). Therefore, participants of Cluster2, as the highly engaged users, have more stable BP values than the other two clusters. On the contrary, participants of Cluster1, as the least engaged users, have the most unstable BP values.

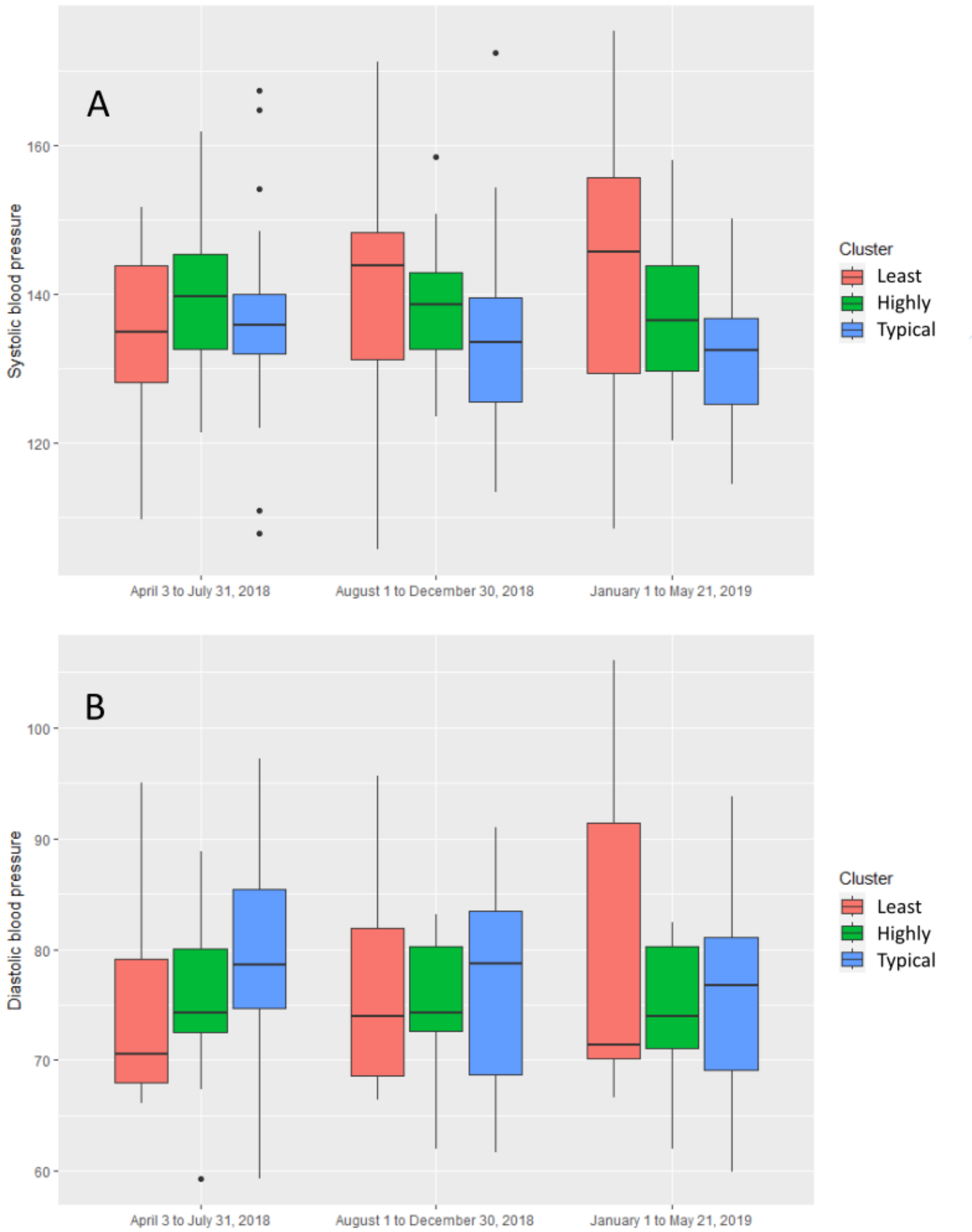

Figure 28. (a) The variation of Systolic Blood Pressure in three clusters between different time periods of the trial (b) The variation of Diastolic Blood Pressure in three clusters between different time periods

Table 6. The description of every cluster

Cluster	Description	Label
Cluster1	In Cluster1, each feature/submission rate is lower than the other two clusters, and Cluster1 has the least participants in this group. Typically, users have increasing systolic BP over time, decreasing weight over time and unstable BG over time.	Least engaged user
Cluster2	In Cluster2, every parameter's submission is higher than the other two clusters, the average submission rate is high, and the SD of the submissions is low except for SR. Typically, users have a stable BP over time, which also within the recommended thresholds.	Highly engaged user
Cluster3	In Cluster3, the submission rates for PA and Sleep are high, and the submissions of the other three parameters are lower than Cluster 2. However, Cluster3 is the largest cluster, including 44% of the participants. The users' systolic BP usually decreases over time.	Typical user

Table 7. The p-value of every cluster among all time slots by one-way ANOVA

Cluster	Parameters	P-value
Cluster1 (Least Engaged)	BPS	0.19
	BPD	0.16
	SpO2	0.66
	BG	0.50
	Weight	0.47
	PA	0.68
Cluster2 (Highly Engaged)	BPS	0.51
	BPD	0.52
	SpO2	0.59
	BG	0.41
	Weight	0.72
	PA	0.049
Cluster3 (Typical)	BPS	0.27
	BPD	0.35
	SpO2	0.25
	BG	0.22
	Weight	0.61
	PA	0.86

In Figure 29, the median of Cluster2 is relatively higher than the other two clusters. The median of Cluster3 is increasing over time. In the second and third time periods of the trial, the boxplot of Cluster1 is comparatively short. Normal SpO2 levels are between 95 to 100 percent, but older adults may have SpO2 closer to 95% (John P. Cunha, 2021). In addition, for patients with COPD, SpO2 levels range between 88% and 92% (Echevarria et al., 2021). In this case, there is not much difference in terms of values of SpO2 and most of the SpO2 values are between 90% to 95% in this study. However, the SpO2 of Cluster1 and Cluster2 were maintained at a relatively high level during the trial. As for Cluster3, the SpO2 was comparatively low, but relatively the same as the other two clusters in the later period of the trial. Therefore, the value of Cluster3 (P = .25) SpO2 is relatively unstable compared with Cluster1 (P= .66) and Cluster2 (P = .59). As such, there is little correlation between SpO2 values and engagement with digital health monitoring.

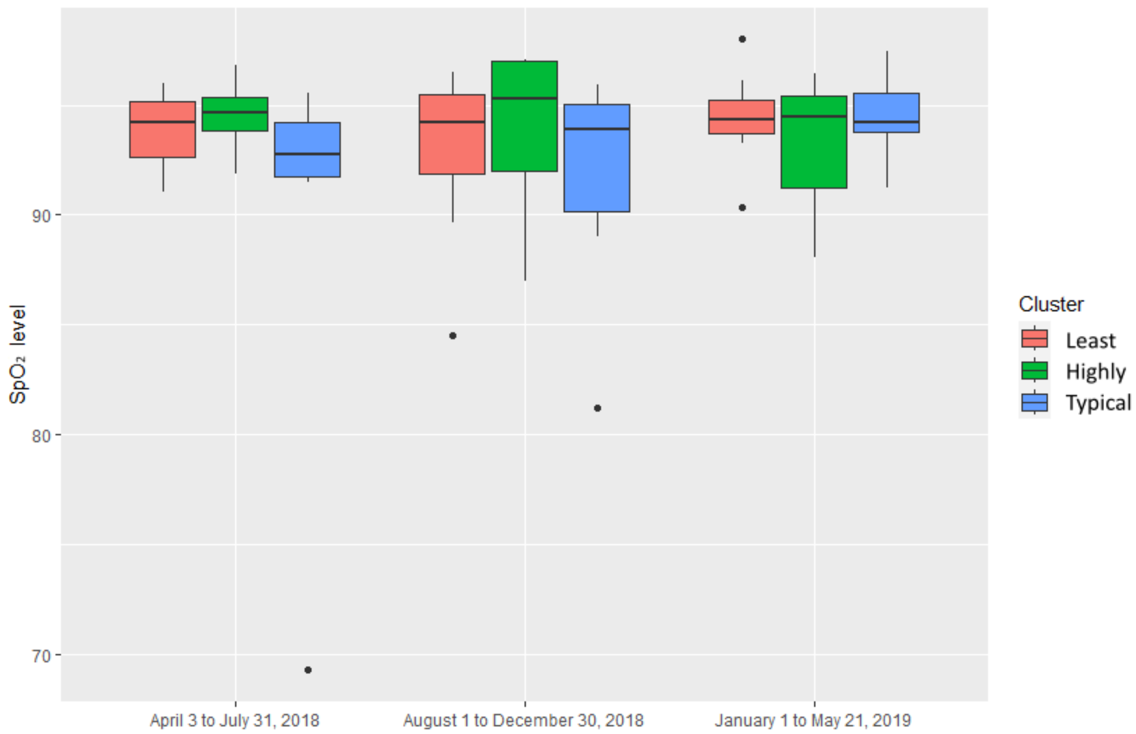

Figure 29. The variation of SpO2 in three clusters between different time periods

In relation to BG, Figure 30 shows that the boxplot of Cluster2 is relatively lower than the other two clusters in the second and third time periods. Moreover, the medians of Cluster2 and Cluster3 are lower than Cluster1 in the second and third time periods. Cluster2 and Cluster3 decreased at later periods of the trial compared to the beginning of the trial, but Cluster1 increased. Cluster3 (P = .25), as the typical user group, had more significant change than Cluster1 (P = .50) and Cluster2 (P = .41). Overall, participants with a higher engagement rate had better blood glucose control.

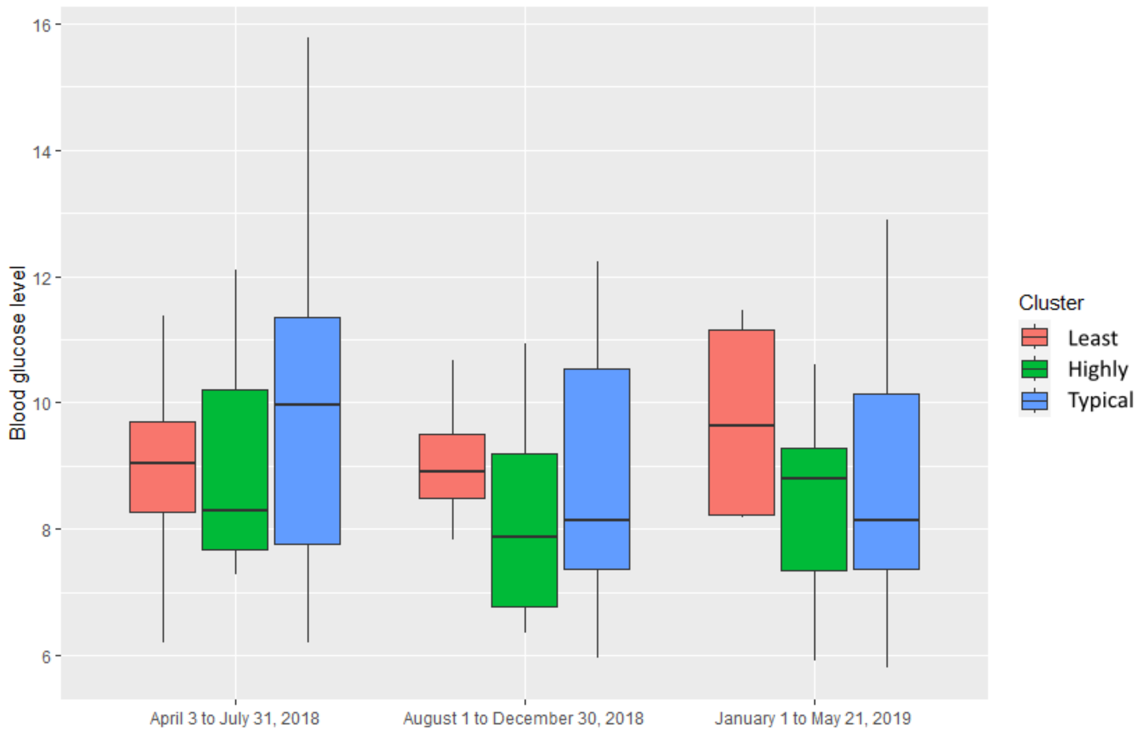

Figure 30. The variation of Blood Glucose in three clusters between different time periods

In relation to weight, Figure 31 shows that the boxplot of Cluster2 is lower than the other two clusters, and comparatively short. As Table 7 shows, the p-value of Cluster2 weight is *P*= .72, and higher than Cluster1 (*P*= .47) and Cluster3 (*P*= .61). Therefore, participants in Cluster2 have a relatively stable weight during the trial. In addition, the median weight of Cluster1 is decreasing, while Cluster3 is increasing in weight.

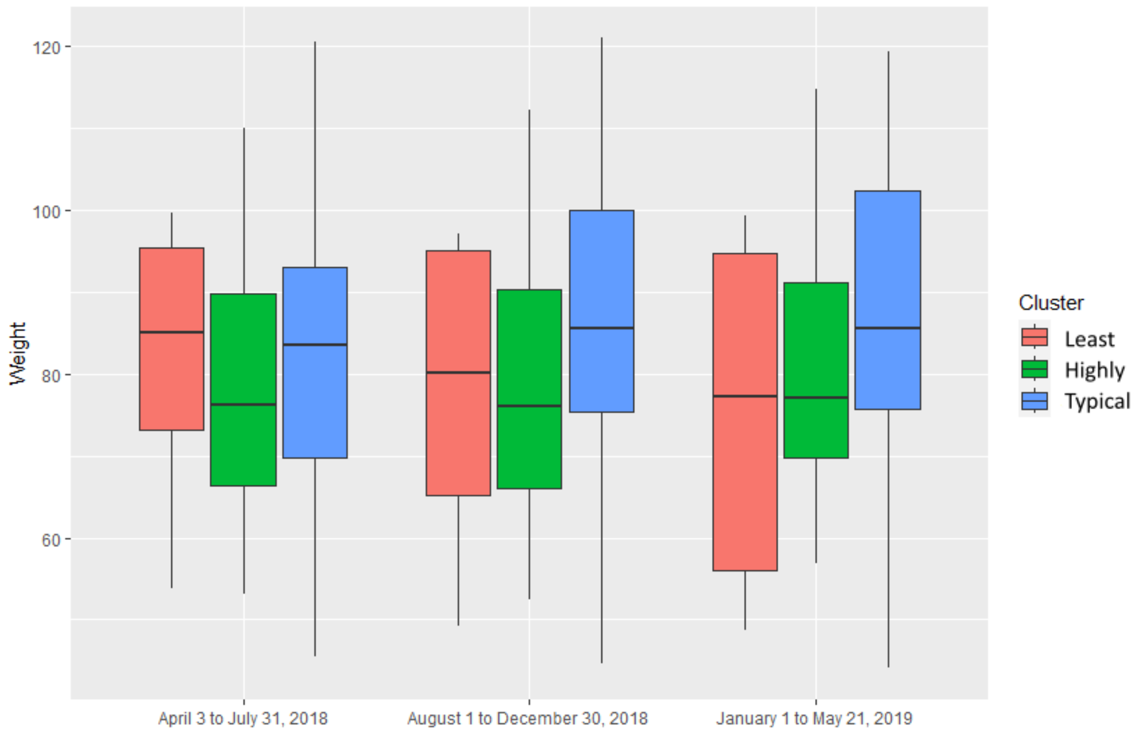

Figure 31. The variation of Weight in three clusters between different time periods

As Table 7 shows, the p-value of Cluster2 PA (*P*= .049) is lower than 0.05, which means there are significant differences among the three time slots in Cluster2. However, the median of Cluster2 in Figure 32 is still higher than the other two clusters. In Cluster2, 50% of daily PA (steps) are above 2500 steps. Overall, participants with a higher engagement rate also had a higher level of PA.

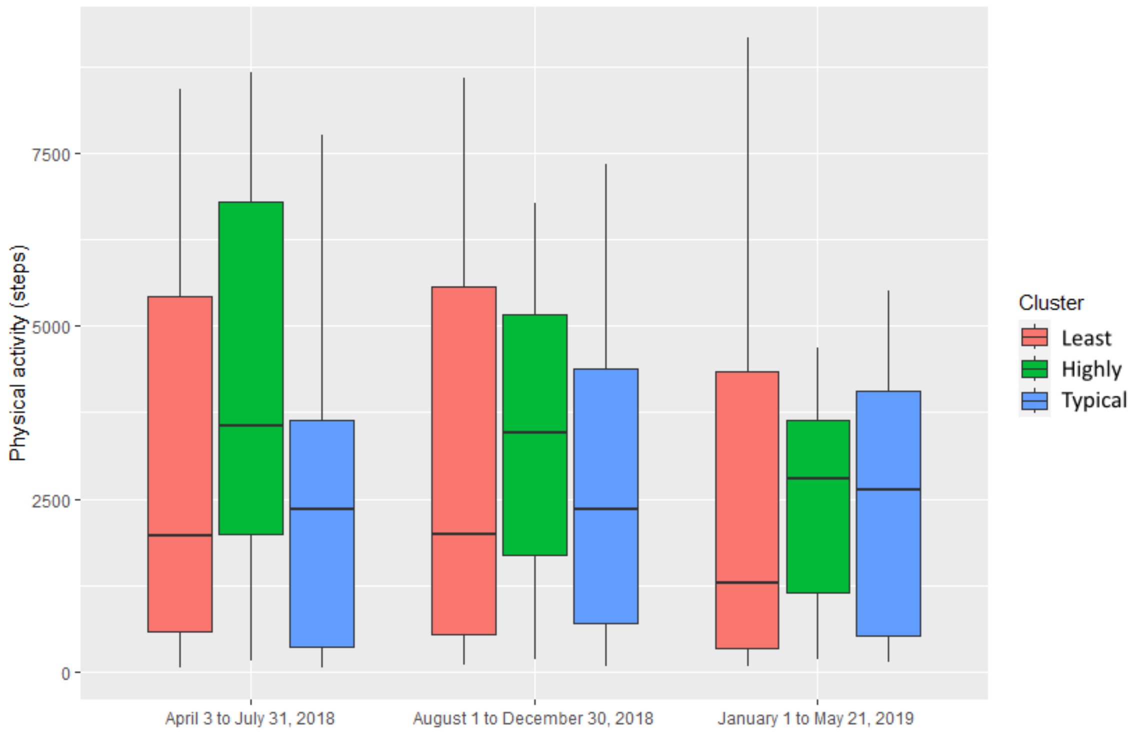

Figure 32. The variation of PA in three clusters between different time periods

5.8 Summary

In this chapter, the findings of Study 2, which were related to using k-means clustering to discover engagement patterns, were presented. This chapter started with using Spearman's correlation and principal component analysis to select the parameters and remove the outliers from the data set for k-means clustering. After the data set was clustered into three different clusters, the participants' characteristics, participants' engagement outcomes and correlation between parameters were presented. Finally, the variation of participants' health conditions in the three clusters between different time periods was provided. The key findings from the study are:

- There is no significant difference in participants' characteristics between the clusters in general. The highly engaged group had the lowest average age and there was no significant difference for gender and conditions between these clusters. The least engaged user group had fewer males and participants with diabetes.

- There are three main factors influencing the correlations between the submission of different parameters. The first is whether the same device is used to submit the parameters; the second is the number of manual operations required to submit the parameter; and the third is the daily routine of the participants.
- Increased engagement with devices may improve the participants’ health and well-being outcomes (e.g., symptoms and levels of physical activity). However, the difference between the highly engaged user group and the typical user group is relatively minimal compared to the difference between the highly engaged user group and the least engaged user group.

These findings are further discussed in Chapter 7.

6. Findings Study 3 – The Correlation Between Mobile Device Proficiency (Technical Proficiency) and User Engagement of Older Adults with Digital Health Technologies

6.1 Introduction

This chapter presents the correlation between mobile device proficiency (technical proficiency) and user engagement. Mobile device proficiency will be presented through the mobile device proficiency score (MDPS) derived from the mobile device proficiency questionnaire (MDPQ) (see section 6.1.1 for more details), while user engagement will be presented through an engagement score (ES) to show the level of user engagement (see section 6.1.2 for more details). Therefore, the correlation between mobile device proficiency and user engagement can be presented by analysing MDPS and ES using K-mean clustering and multiple regression analysis. An overview of the relationship between MDPS and ES by k-means clustering is presented in Section 6.2. Section 6.3 describes the results of multiple regression analysis for ES and the score of the various sub-sections in the MDPQ. Finally, Section 6.4 presents the results of multiple regression analysis for the MDPS and the weekly submissions of each device.

6.1.1 Mobile device proficiency score

In this study, the MDPS was collected at the start of the trial and had a mean score of 22.02. Table 8 presents the average score and standard deviation for each of the sub-sections of the MDPQ. As can be seen, the average score of “Data and File Storage” has the lowest score (1.79) amongst all sub-sections, while the “Mobile Device Basics” section has the highest score (3.82).

Table 8. The average and standard deviation of MDPS and the sub-sections for ProACT participants

	Average Score	Standard deviation
Total (Sections)	22.02 (2.75)	9.94 (1.72)
Mobile Device Basics	3.82	1.54
Communication	3.07	1.60
Data and File Storage	1.79	1.40
Internet	3.31	1.78
Calendar	2.63	1.78
Entertainment	2.80	1.54
Privacy	2.42	1.64
Troubleshooting and Software Management	2.19	1.55

6.1.2 Engagement score

The aim of this study was to explore the relationship between mobile device proficiency and engagement. K-means clustering and multiple regression models were used in the following analysis. In this case, the number of weekly submissions for each parameter is standardised by z-score standardisation to convert these numbers into similar scales, which improves the performance and training stability of the clusters and models (Ali et al., 2014). In addition, z-score standardisation is a very useful statistic in machine learning that allows programmers to calculate the probability of a score appearing in a normal distribution and to compare two scores from different normal distributions (Al-Faiz et al., 2018).

The formula of z-score standardisation (Ali et al., 2014):

$$valueAfterStandardisation = \frac{valueBeforeStandardisation - meanOfAllValue}{StandardDeviationOfAllValue}$$

In order to show the level of engagement of every participant and to facilitate subsequent data analysis, we used the weekly submission times for each parameter to derive an engagement score (ES). All the weekly submission times of every participant were calculated into z-score first, then the average of all z-scores was considered as the ES.

6.2 Overview of the relationship between the Mobile Device Proficiency Score and Engagement Score

As Figure 33 shows, the spots on the scatter plot of MDPS and ES are dispersed and irregular. Therefore, there is generally no correlation between older adults' proficiency with mobile devices and their engagement with home-based health care technologies.

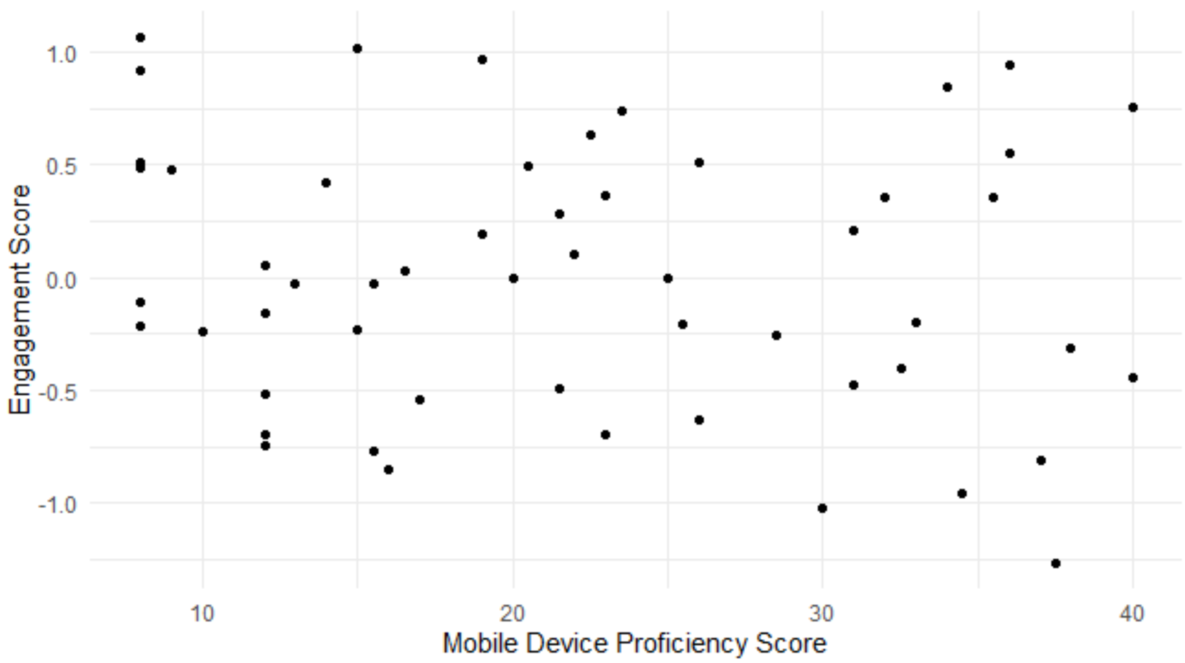

Figure 33. The scatter plot of the Mobile Device Proficiency Score and the Engagement Score

To better understand the relationship between the MDPS and ES, k-means clustering was used to classify participants into different groups based on the MDPS and ES. Each sub-figure in Figure 35 shows a different number of clusters (K). When K=3, the data is obviously separated into three big clusters. Likewise, the clusters are also separated very well into four clusters when K=4. The clusters are well-separated when K=5, but cluster3 has few participants, making it a relatively small cluster. Similarly, when K=6, there are four clusters that have few participants. Figure 34 shows the optimal number of clusters using the elbow method. In view of that, four clusters of participants separate the dataset best. The four clusters can be labelled as low engagement with low MDP users (Cluster1), high engagement with high MDP users (Cluster2), high engagement with low MDP users (Cluster3), and low engagement with high MDP users (Cluster4).

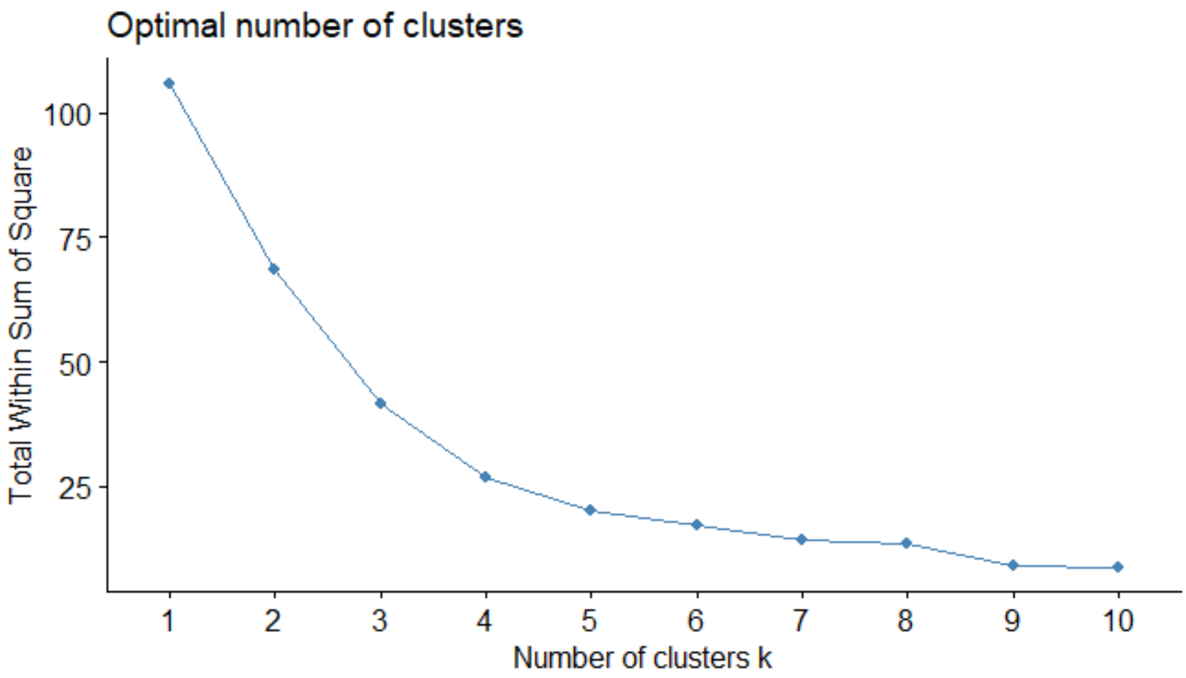

Figure 34. Elbow method of ES and MDPS

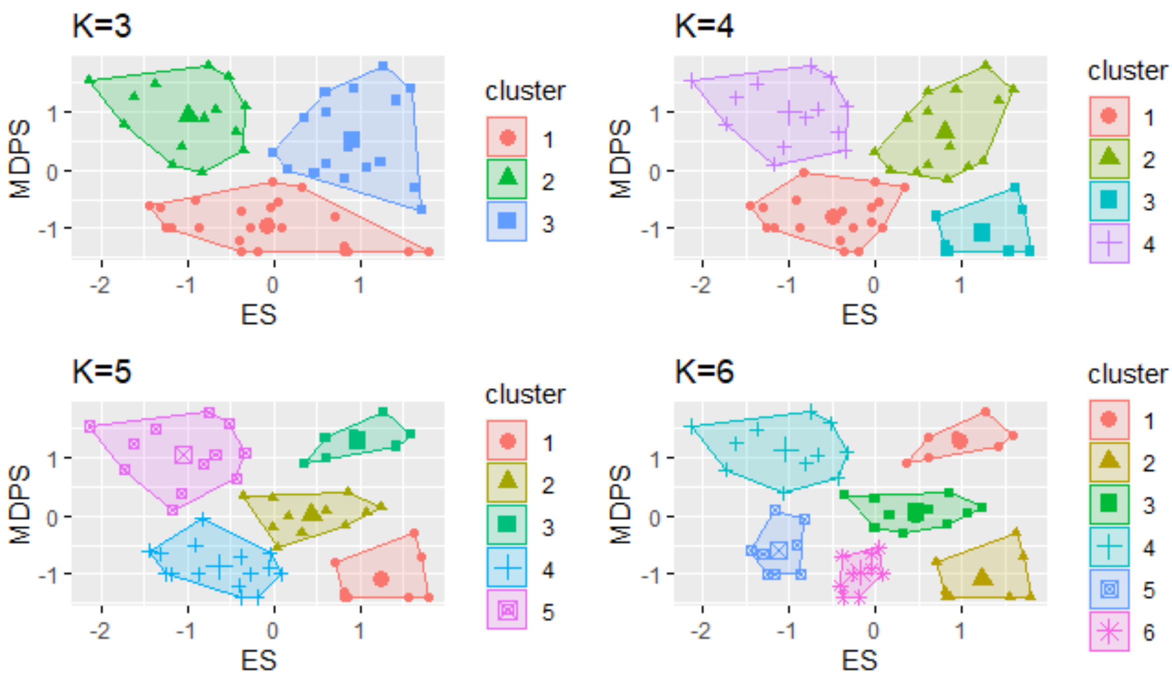

Figure 35. the visualisation of clustering with the number of clusters ranging from 3 to 6

As Table 9 shows, Cluster1 is the largest user group with 18 participants, while Cluster3 is the smallest user group with 8 participants. Cluster1 (14.17) and Cluster3 (11.13) have similar but relatively low average MDPS, while Cluster2 (28.57) and Cluster4 (32.04) have similar and relatively high average MDPS. In contrast, Cluster1 (-0.30) and Cluster4 (-0.59) both have low average ES, but the difference between these two clusters is -0.29, almost equal to the average ES of Cluster1. Similarly, both Cluster2 and Cluster3 are marked as high ES user clusters, and the average ES of Cluster3 (0.73) is much higher than that of Cluster2 (0.48).

Table 9. The engagement score and mobile device proficiency score of each cluster

Cluster	Cluster1	Cluster2	Cluster3	Cluster4
Participants, n (%)	18 (33.3)	15 (27.8)	8 (14.8)	13 (24.1)
ES (mean)	-0.30	0.48	0.73	-0.59
MDPS (mean)	14.17	28.57	11.13	32.04
ES (max)	0.19	0.95	1.07	-0.20
MDPS (max)	21.5	40	19	40
ES (min)	-0.85	-0.002	0.42	-1.26
MDPS (min)	8	20.5	8	23

6.3 Multiple regression analysis for engagement score and each sub score on the MDP scale

In this multiple regression analysis, the dependent variable is the engagement score, while the independent variables are the sub-scores of the MDPQ. As Table 3 shows, the subsections of the MDPQ include Mobile Device Basics; Communications; Data and File Storage; Internet; Calendar; Entertainment; Privacy; and Troubleshooting and Software Management.

As Table 10 shows, the multiple R squared value is 0.1135 which indicates that the sub-score of MDPS can only explain 11.35% of the ES, and this model therefore doesn't fit the data very well. Moreover, the p-value is larger than 0.05 (Table 10), which implies weak evidence of the relationship between the ES and MDP sub-scores. Likewise, Table 11 shows that the p-value of intercept and all sub-score of the MDPS are greater than 0.05, which also indicates that evidence of the relationship between ES and each MDP sub-score is very weak.

Table 10. Result of Multiple Regression for engagement score and mobile device proficiency sub score

Multiple R Squared	0.1135
Adjusted R Squared	-0.0441
Standard Error	0.606
F-statistic	0.7202
p-value	0.6726

Table 11. the Coefficients of the multiple regression model for engagement score and mobile device proficiency scores of each sub-section

	Estimate	Std.Error	t-statistic	p-value
Intercept	0.193595	0.227502	0.851	0.399
Section 1	-0.029742	0.077696	-0.383	0.704
Section 2	0.134596	0.085183	1.580	0.121
Section 3	-0.029657	0.085696	-0.346	0.731
Section 4	-0.049789	0.076658	-0.649	0.519
Section 5	-0.074326	0.065522	-1.134	0.263
Section 6	-0.073417	0.091101	-0.806	0.425
Section 7	-0.008511	0.094508	-0.090	0.929
Section 8	0.066481	0.094321	0.705	0.485

Figure 36 shows that the linearity (top right plot) of this model is poor and the plot for homogeneity of variance (middle left plot) shows the dots are not equally spread and have apparent deviation. The influential observations plot (middle right plot) shows there is no influential points. In addition, the multicollinearity (bottom left plot) shows that the variance inflation factor (VIF) of all variables are between 1 to 5, which indicates that the variables are moderately correlated (James et al., 2013). As for the normality of residuals (bottom right plot), most of the points fall along the reference line and deviations are small, but it is not perfect, as there are few points deviating from the reference line at the beginning and end.

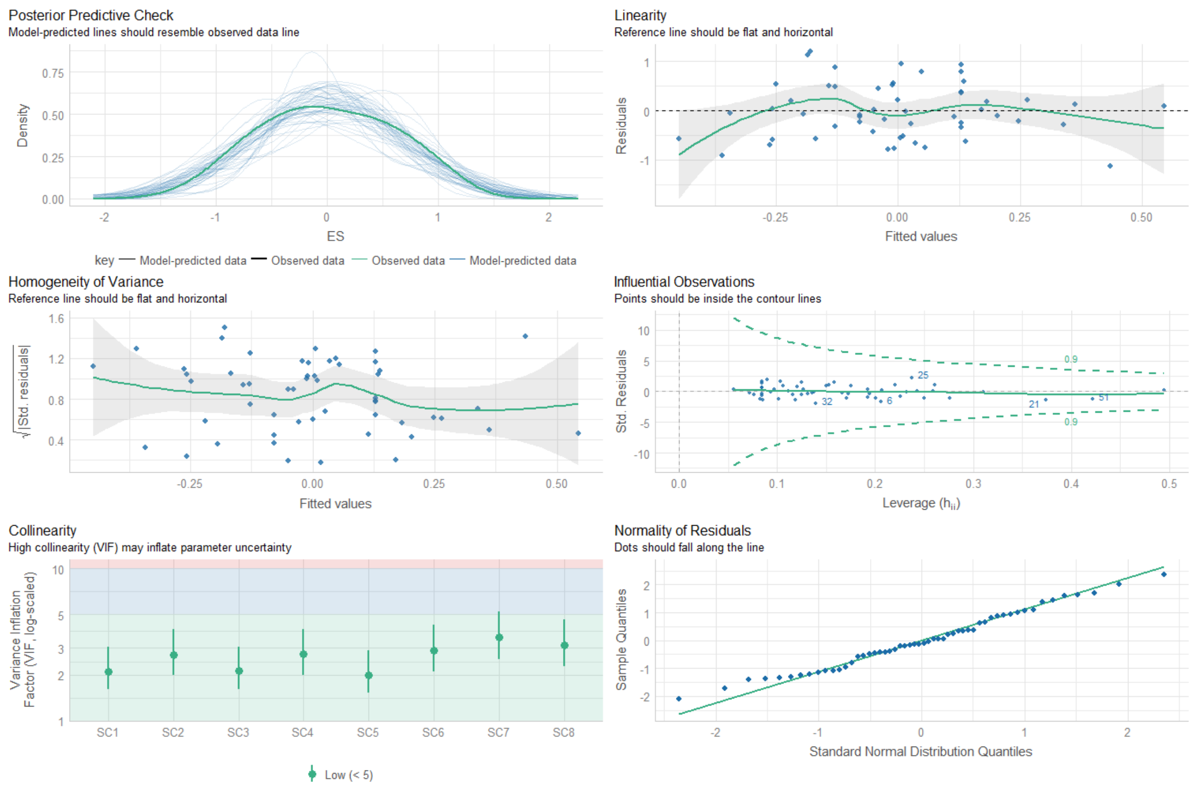

Figure 36. Model performance of engagement score and mobile device proficiency sub score

6.4 Multiple regression analysis for MDPS and each device usage variable (weekly submission of each device)

In this multiple regression analysis, the dependent variable is the MDPS, while the independent variables are the weekly submissions of parameters from every device. BP and pulse were monitored using the same device (Withings), so BP is used to represent the usage of this device.. Therefore, the independent variables in this multiple regression analysis are tagged as BP, SpO2, BG, Weight and Self-report.

As Table 12 shows, the multiple R squared is 0.1432 which indicates that the weekly submission of parameters from each device only explains 14.32% of the MDPS, and this model doesn't fit the data very well. Moreover, the p-value is larger than 0.05 (Table 12), which implies weak evidence of the relationship between MDPS and weekly usage of health care devices. However, unlike the previous model, the p-values for intercept, SpO2 and BG in this model were all less than 0.05. This indicates that the intercept term is statistically different than zero. Likewise, the weekly submissions of BG and SpO2 have a statistically significant relationship with the MDPS.

Table 12. the result of multiple regression for mobile device proficiency score and weekly submission of each device

Multiple R Squared	0.1432
Adjusted R Squared	0.05394
Standard Error	9.757
F-statistic	1.604
p-value	0.177

Table 13. the Coefficients of the multiple regression model for mobile device proficiency score and weekly submissions of each device

	Estimate	Std.Error	t-statistic	p-value
Intercept	25.4149	3.2001	7.942	2.7e-10 ***
BP	1.1508	0.9692	1.187	0.2409
SpO2	-1.8284	0.8489	-2.154	0.0363 *
BG	-1.3501	0.6574	-2.054	0.0455 *
Weight	-0.1700	0.8209	-0.207	0.8369
Self-report	-0.6593	0.8348	-0.790	0.4336

Figure 37 shows that the linearity (top right plot) of this model is poor. In addition, the plot for homogeneity of variance (middle left plot) shows that the dots have apparent deviation and are not equally spread. The influential observations plot (middle right plot) shows there are no outlier points. The VIF of all variables is between 1 to 5 as shown in the plot of multicollinearity (bottom left plot), which means the variables are moderately correlated (James et al., 2013). The normality of residuals (bottom right plot) of this model is not perfect. There are many points deviating from the reference line.

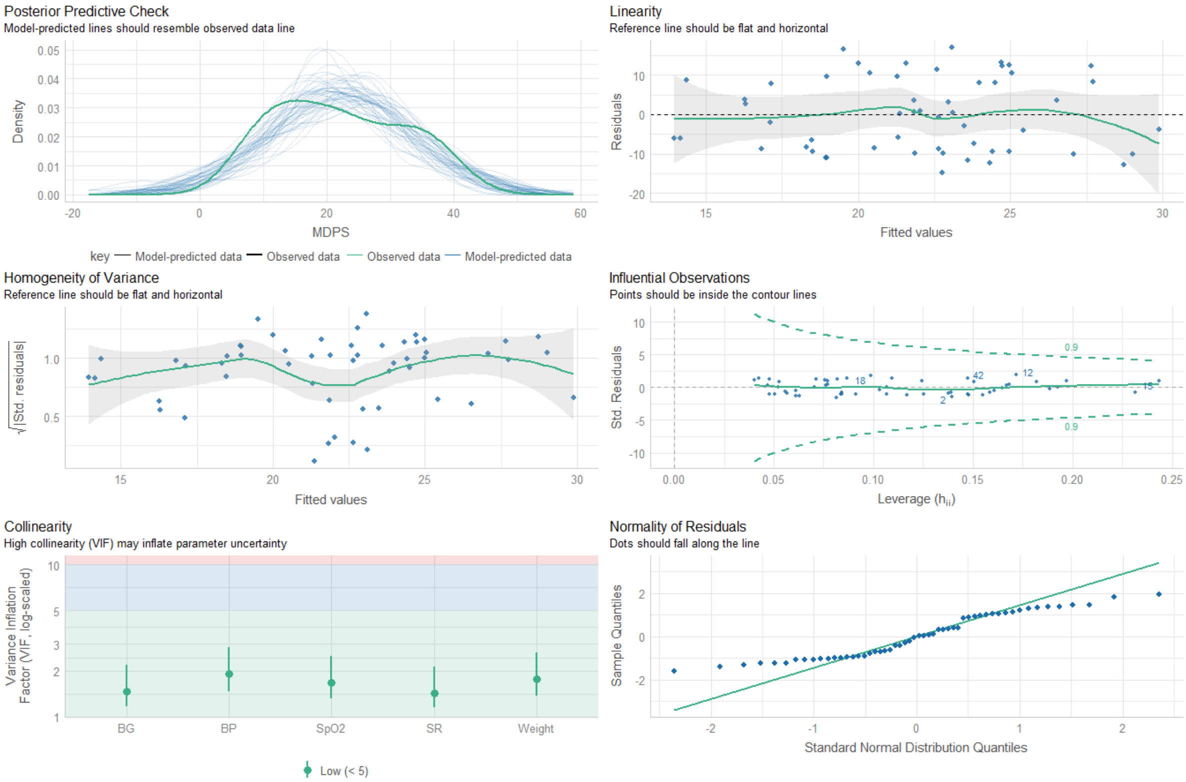

Figure 37. Model performance of mobile device proficiency score and weekly submissions of each device

6.5 Summary

This chapter presents the findings of Study 3, which showed the correlation between mobile device proficiency and user engagement. Firstly, the details of the mobile device proficiency score (MDPS) and engagement score (ES) were presented. The overview of the relationship between MDPS and ES was then outlined. Multiple regression analyses were used to derive correlations between ES and MDPS sub scores, as well as correlations between MDPS and device use variables. Therefore, the findings of this project show that there is a weak correlation between mobile device proficiency and user engagement. Key findings are:

- In this study, participants' technical proficiency did not correlate with participants' engagement with digital health technology.

- The method used in this study to assess technical proficiency (MDPQ) was likely not appropriate. Many sections of the MDPQ are not related to the use of digital health devices. As such, a new method is required to evaluate technical proficiency for older adults using digital health devices.

These findings are further discussed in Chapter 7.

7 Discussion

7.1 Introduction

Digital health platforms have great potential to improve health and well-being management and improve health outcomes (Milani et al., 2017). However, the potential benefits can only be realised if users engage with such platforms (Quinn et al., 2018). This thesis has investigated the engagement between older adults with multimorbidity and digital health and well-being self-management technologies. This chapter presents a discussion of the findings presented in Chapters 4, 5, and 6 and draws comparisons to related research to highlight the implication and contribution of the findings within the field of digital health research for older adults with multimorbidity.

As the findings presented in Chapter 4 demonstrate, the majority of participants of the ProACT trial were willing to use digital health technology and overall user retention was high. However, the level of engagement varied amongst participants. Therefore, all participants were categorised into one of three groups based on their weekly frequency of submitting data. Three clusters were identified - the highly engaged user group, the typical user group and the least engaged user group. There were no significant differences in characteristics (e.g., age, gender, condition) between these user groups, but higher levels of engagement were associated with benefits to participants' health outcomes, such as stable blood pressure and blood glucose reduction. Other research has also found similar results (Milani et al., 2017, Sepah et al., 2017). In relation to patterns of usage, many participants chose to use the digital health devices and submit data in the morning, which was similar to another study by (Potts et al., 2020). Additionally, devices with fewer manual actions had higher levels of engagement than devices with more manual actions, as was also found by (Bohm et al., 2020). There was a strong correlation between some of the devices in the daily routines of the participants, which would make these devices promote each other's utilisation rates. Finally, technical proficiency, as measured by the MDPQ, did not predict engagement, with a weak correlation observed between technical proficiency and user engagement. This differs from other studies such as (Turnbull et al., 2021) which found technical proficiency can impact the usage of digital health technologies for people with diabetes.

The remainder of the chapter is organised as follows. Section 7.2 reviews the aim and objectives of this PhD project and outlines how the objectives were addressed. The following two sections then discuss the user and technical aspects impacting participants' engagement in digital self-management, based on the findings of Study 1 and Study 2. Section 7.5 discusses the findings from Study 3 which focused on the relationship between mobile device proficiency and engagement. Section 7.6 presents the limitations of this research. Finally, Section 7.7 outlines future work of interest, while Section 7.8 concludes this thesis.

7.2 Review of aim and objectives

The overall aim of this study was to explore how older adults with multimorbidity use digital health technologies, particularly symptom and well-being monitoring technologies, by analysing an existing dataset to better understand how to promote long-term sustained use. The objectives were addressed as follows.

Objective 1: Review the literature on digital home-based self-management technologies for chronic disease and multimorbidity, with a focus on literature examining engagement, including engagement of older adults, with such systems.

An initial review of the literature in the areas of digital health, older adults' health, and multimorbidity self-management was carried out. As the review continued, topics became more refined, such as digital health for different chronic conditions, the impact of barriers to digital health and factors that promote engagement, technology acceptance, and self-efficacy. To better understand the analysis of digital health datasets, the review also includes an overview of different data mining techniques and the application of data mining techniques to the digital health field.

Key findings are:

- There is a vast amount of research on the use of digital health technologies for the self-management of single chronic diseases, with comparatively little on multiple disease self-management.
- There is little research on the engagement of digital health technology by older adults and in particular those with multimorbidity. Those studies that have explored engagement typically assess engagement through interviews or questionnaires, rather than quantitative data (logs of engagement) (Sinnott et al., 2013).
- There are several factors that can impact engagement with digital health technologies, with barriers being user-related (Bol et al., 2018), technology-related (Rickard et al., 2016) or content-related (Lipschitz et al., 2019) and facilitators being personalistion, support and notifications (Dobson et al., 2018, Fortuna et al., 2019, Potts et al., 2020).

Objective 2: Analyse an existing dataset to understand patterns of engagement of older adults with multimorbidity with symptom and well-being monitoring (e.g., blood pressure, self-reported mood).

To address this objective, an analysis of the ProACT trial dataset was conducted. The dataset was collected from 60 older adults with multimorbidity (two or more of the conditions heart failure (HF), diabetes, chronic obstructive pulmonary disease (COPD), heart disease (HD)) who used digital health technology for self-management over a 12-month period. The average age of the participants was 74 years, and a total of eight different parameters were monitored during the trial, including blood pressure (BP), pulse, blood glucose (BG), blood oxygen level (SpO2), weight, physical activity (PA), sleep, and self-report (SR). The focus of this initial analysis was to uncover patterns of engagement of this cohort, such as popular times for submissions and general submissions of each data parameter. Specifically, this analysis asked four questions of the data relating to; the distribution of user retention for self-monitoring using digital devices and self-report, the frequencies (times per week) which participants submit their data, the average and standard deviation of the intervals (in days) between each submission and the time of day participants submit BP, pulse, SpO2, BG and weight readings.

Key findings are:

- Overall engagement and retention with ProACT were high. Only 8 participants withdrew, and some of these participants had already collected data for over 100 days before withdrawing.
- Engagement with digital devices for self-monitoring was high. The majority of participants engaged with ProACT devices for more than 200 days, with many using them on more than 300 days. This could be considered to be in contrast to other research that has suggested that digital health technologies suffer high attrition rates (Stellefson et al., 2013, Morrison, 2015).
- Engagement and retention with self-reporting (including answering questions on symptoms not measured by a digital device, as well as general well-being questions) via the ProACT CareApp were lower than with digital devices. There were also larger gaps, or intervals, between self-reporting days. This could show the potentially negative impact of manual operations necessitating a sequence of steps (as required for self-reporting) on engagement, compared to the use of devices requiring fewer user interactions (Bohm et al., 2020).
- The most popular time of day for engaging with monitoring of various symptoms was morning time, with small peaks of engagement evident in the late evening, just before bedtime. Knowing preferred engagement times can support the delivery of timely, personalised notifications and reminders to engage with less frequently used features, which might also improve user engagement (Potts et al., 2020).

Objective 3: Explore how different categories of users, for example users of different age groups or with different conditions, engage with symptom and well-being monitoring.

The participants were clustered into different user groups based on their weekly data submissions using the k-means method. Three different clusters of users were identified, including a highly engaged user group, typical user group, and low engaged user group. The differences amongst the three clusters, in terms of user characteristics and user engagement, were outlined. In addition, the correlation between different devices and the relationship between user engagement and well-being outcomes were also analysed.

Key findings are:

- There is no significant difference in participants' characteristics between the clusters in general. The highly engaged group had the lowest average age (Table 4) and there were no significant differences for gender and conditions between these clusters. The least engaged user group had fewer males and participants with diabetes.
- There are three main factors influencing the correlation between the submission of different parameters. The first is whether the same device is used to submit the parameters; the second is the number of manual operations required to submit the parameter; and the third is the daily routine of the participants (Bohm et al., 2020, Woodward et al., 2021).
- Increased engagement with devices may improve the participants' health and well-being outcomes, such as symptom stabilisation and increased levels of PA. Likewise, Milani et al. (2017) also found that digital health care interventions can help people achieve BP stabilisation. However, the difference between the highly engaged user group and the typical user group is relatively minimal compared to the difference between the highly engaged user group and the least engaged user group.

Objective 4: Examine the connections between technical proficiency and engagement with digital health technologies.

The concept of an 'engagement score' was developed, which is the average of the standardised weekly submissions of each participant. Multiple regression was used to build a model using the engagement score and mobile device proficiency score to explore the correlation between technical proficiency and engagement with digital health technology.

Key findings are:

- Unlike other studies, in this study, participants' technical proficiency did not correlate with participants' engagement with digital health technology (Turnbull et al., 2021).
- The method used in this study to assess technical proficiency (MDPQ) was likely not appropriate. Many sections of the MDPQ are not related to the use of digital health devices. As such, a new method is required to evaluate technical proficiency for older adults using digital health devices.

Objective 5: Develop a set of recommendations for researchers, designers and developers of digital health technology to promote enhanced engagement of digital health technology by older adults with multimorbidity.

At the end of each of the remaining sections in this chapter, a series of recommendations are presented, based on the findings from the three studies presented in this thesis and related research.

7.3 User engagement and retention

7.3.1 Overall engagement

The distribution of user retention for submission of data shows the average retention of how many participants were using and engaging with the ProACT platform (self-management technology devices connected to the ProACT CareApp (Figure 4)). Most participants used ProACT for at least 200 days, with a large drop-off occurring at the 300 days time-point. There are two different reasons for the drop-off. First, 8 participants withdrew from the trial while 3 participants passed away during the trial. Second, some participants started later than others, due to difficulties with recruitment, and so their overall number of days in the trial was less than other participants. This meant that those participants who started on the trial later stopped using the devices after approximately ten months in the trial, which accounts for the significant drop-off between 300 days and 400 days. The user retention curve in this study was compared with the user retention curves for other health care apps (Baumel et al., 2019). Given that the retention curves in other apps take on an 'L' shape, this comparison demonstrated that the user retention with ProACT is much better than that of many other health care apps. A discussion of the possible contextual reasons for sustained engagement with ProACT is outside the scope of thesis but has been discussed elsewhere (Doyle et al., 2021). As reported in (Doyle et al., 2021), participants spoke of how they used the data to support their self-management (for example, taking action based on their data), and experienced various benefits including increased knowledge of their conditions and well-being, symptom optimisation, reductions in weight, increased activity and increased confidence to participate in certain activities as a result of health improvements. The peace of mind and encouragement provided by the clinical triage service as well as the technical support available were also identified during the interviews as potential factors positively impacting engagement (ibid). In addition, the platform was found to be usable and of low burden. These findings supplement the quantitative findings presented in this thesis.

A study on engagement with fitness trackers by Asimakopoulos et al. (Asimakopoulos et al., 2017) suggests that being able to review one's goal progress though data and receiving tips and education, can foster engagement. These features were present in the ProACT CareApp and therefore may also have played a role in sustained engagement during the trial. Research on older adults engaging with digital health technologies over longitudinal periods is limited. However, Böhm et al. (Bohm et al., 2020) found that older people and those who were recently diagnosed with diabetes used a diabetes self-management app more actively than younger participants over a period of 180 days. Our findings demonstrate that older participants also engaged well with digital self-management, with more than 80% of participants using the technology devices for over 200 days. Our findings extend those of Bohm et al. as participants in our study self-managed two or more chronic conditions and used the technology for a longer period of time (on average 12 months). Compared with other similar research, such as Wei et al. (Wei et al., 2021), Compernolle et al. (Compernolle et al., 2020) and Bengtsson et al. (Bengtsson et al., 2016), there were more participants in our study (n=60) and a longer study period. Our findings show that older adults with multiple chronic conditions engaged in digital self-management and maintained that engagement over a longitudinal period of time.

7.3.2 The impact of participants' characteristics on user engagement

Study 2 of this project demonstrated that the difference in engagement with digital health technologies between genders is not significant. Six out of 23 female participants (26%) are in the least engaged user group, which is higher than 7 out of 31 male participants (23%). Moreover, there are lower proportions of female participants in the highly engaged user group (7 out of 23 (30%)) and typical user group (10 out of 23 (43%)) compared with male participants (10 out of 31 (32%) and 14 out of 31 (45%) respectively). Other research has found that engagement with mobile health technology for BP monitoring was independent of gender (Kaplan et al., 2017). However, there are also some studies that show female participants are more likely to engage with digital mental health care interventions (Mikolasek et al., 2018, Harjumaa et al., 2015). Therefore, gender cannot be considered as a separate criterion when comparing engagement with digital health technologies, and it was not found to have significant impact on engagement in this study. Regarding age, many studies have shown that younger people are more likely to use health care technologies than older adults (Kannisto et al., 2017, Abel et al., 2018). However, older adults still have the ability to learn how to use technology and manage age-related diseases (Durick et al., 2013). While all participants in our study are older adults, the highly engaged user group is the youngest group in this study.

However, there is no significant difference in age between the clusters, with some of the oldest users being in Cluster3, the typical user cluster.

Similarly, the conditions a participant has did not significantly impact their level of engagement. Other research (Kaplan et al., 2017) found that participants who were highly engaged with health monitoring had higher rates of hypertension, chronic kidney disease, and hypercholesterolemia than those participants with lower engagement levels. Our findings indicate that the highly engaged user group had a higher proportion of diabetes, and the least engaged user group had a higher proportion of COPD. Further research is needed to understand why there might be differences in engagement dependent on conditions. In our study, participants with COPD also self-reported on certain symptoms, such as breathlessness, chest tightness and sputum amount and colour. While engagement with specific questions wasn't explored, participants in the least engaged cluster, Cluster 1, self-reported more frequently than those in Cluster 3, the typical users. Our findings also indicate that those participants monitoring BG and BP experienced better symptom stabilisation over time than those monitoring SpO2. It has been noted that the expected benefits of technology (e.g., increased safety and usefulness) and need for technology (e.g., subjective health status and perception of need) are two important factors that can influence acceptance and use of technology for older adults (Peek et al., 2014). It is also well understood that engaging in BG monitoring can help people with diabetes to better self-manage and make decisions about diet, exercise and medication (Weinstock et al., 2020).

7.3.3 The relationship between engagement and well-being outcomes

In Study 2, the participants were categorized into three user groups based on their engagement data. Such an approach can be helpful to understand the trajectory of users' engagement with technology depending on their individual motivations (Torous et al., 2020). The last finding of Study 2 indicates that higher levels of engagement with digital health monitoring may result in better outcomes, such as symptom stabilisation and increased levels of PA. Milani et al. (Milani et al., 2017) found that digital health care interventions can help people achieve BP control and improve hypertension control compared with usual care. In their study, users in the digital intervention group took an average of 4.2 readings a week. Compared to our study, this is lower than Cluster2 (5.7), the highly engaged user group, but higher than Cluster1 (2.5) and Cluster3 (2.9). In our study, those participants with a higher engagement rate experienced more stable BP, and for the majority of these participants, levels were maintained within the known recommended threshold of 140/90 mm Hg (Williams et al., 2018).

Many studies have shown that as engagement in digital diabetes interventions increases, patients will experience greater reductions in BG than those with lower engagement (Quinn et al., 2018, Sepah et al., 2017). However, in our study, BG in both the highly engaged user group (Cluster2) and the least engaged user group (Cluster1) increased in the later stages of the trial. Only the BG of the typical user group (Cluster3) decreased over time, which could be because the participants of Cluster3 had more PA in the later stages of the trial than other time periods, as Figure 32 shows. Cluster2, the highly engaged user group, maintained a relatively high level of PA during the trial period, although it continued to decline throughout the trial. Other research shows that more PA can also lead to better weight control and management (Carroll et al., 2017, Demark-Wahnefried et al., 2018), which could be one of the reasons why Cluster2 participants maintained their weight. It is well known that there are many factors that can influence body weight, such as PA, diet, environmental factors etc. (Atkinson Jr et al., 2003). As Figure 31 shows, engagement with digital health and well-being monitoring may help control weight but the impact is not significant. Overall, as noted above, participants in the highly engaged user group demonstrated better physical condition outcomes. However, the highly engaged user group represented only 31% of the participants, and the typical user group also showed stable BP readings, relatively low BG, stable weight, and increased PA. Therefore, using digital health technologies, if the level of user engagement is within a reasonable interval range, can result in better health outcomes being achieved. However, too high a level of engagement may put too much pressure on users, which can have negative effects such as reduced use and negative emotions (Yeager and Benight, 2018, Middle and Welch, 2022).

7.3.4 Recommendations

- A range of factors may influence retention and sustained engagement with digital health technologies, including a user-centred design process focusing on needs and requirements to ensure benefits are experienced by users (e.g., sending reminders based on participants' characteristics and daily routine) (Bentley and Tollmar, 2013, Potts et al., 2020), usable technology (e.g., cost of devices, devices stability, internet access) (Borghouts et al., 2021), the use of certain features such as goal-setting and human and technical support (Fortuna et al., 2019, Doyle et al., 2021). Researchers could develop a checklist of suggestions to enhance engagement while those designing and delivering digital health solutions should consider implementing each of these suggestions.
- Age and conditions did not impact engagement with digital health technologies in this study. Designers and developers of digital health platforms need to consider older adults with chronic conditions as potential end users of their platforms and design to meet their needs. While some research has cautioned that there are several barriers to older adults engaging in digital self-management, such as health status itself, technology experience and social support (Czaja et al., 2013, Heart and Kalderon, 2013, Liu et al., 2019), other research has also shown older adults' acceptance of technology and healthcare technology. For example, older adults are more likely to accept technology if they already have a history of using some form of technology and if they received appropriate training (Wilkowska and Ziefle, 2009). Further, use over time can result in more positive attitudes and beliefs about healthcare technology (Chen et al., 2020).
- More frequent engagement can lead to better health and well-being outcomes. It is important for users of digital health technology to recognize the importance and benefits of

taking frequent measurements according to their condition, such as daily BG testing for diabetics and daily weight testing for HF patients. Educating users on this at the start of their digital health journeys will likely be important. As shown by the findings presented in Chapter 5 of this thesis, and other research (Carroll et al., 2017, Quinn et al., 2018), more engagement can produce better results in terms of health and well-being outcomes, but a 'right' amount of engagement with digital health technology can also produce satisfactory outcomes (Yardley et al., 2016). Designers and developers of such technologies need to consider balancing motivational methods for engagement, ensuring such techniques are only delivered when needed, so as not to over-alert users. Context-sensitive reminders and prompts could be delivered to users through digital health apps, for example if outcomes are worsening and engagement is reducing (Smith et al., 2016).

7.4 Patterns of self-management

7.4.1 Self-management frequency

The data showed that daily exercise and sleep data were the most frequently submitted data on a weekly basis, with users submitting such data six times a week. This is likely because participants simply had to wear the watch and open an app to sync the data. Further, the watch was battery operated so charging was not required. However, there are still some intervals of exercise and sleep submissions during the trial which can mostly be explained by: 1) technical issues, including Internet connection issues or devices not syncing; 2) participants stop using the devices for a period of time, for example, when they go on holiday; 3) participants forget to put the watch back on after taking it off; 4) some participants prefer not to wear the watch overnight.

Böhm et al. (Bohm et al., 2020) analysed real-world data from a diabetes support app and found that the total user activity ratio of modules with manual data entry is lower than those without manual data entry, but initial user engagement exhibits the inverse of this. Andersen et al. (Andersen et al.,

2020) conducted a qualitative interview study with participants with chronic heart disease who were invited to wear a wearable activity tracker for three to twelve months. The overall engagement in this study was high with an average of 26.1 weeks usage, but in this study, there were only three parameters (real-time heart rate, sleep and step count) which did not require much manual data entry from participants (Andersen et al., 2020). However, these two studies were only focusing on one disease. In the ProACT study, the symptom data (e.g., BP, pulse, SpO2, BG) required a number of interaction steps such as placing the device, turning it on and interacting with an app, and this data was submitted between twice to five times a week. Participants engaged with BG most (around 4 days a week on average) which could be because people with diabetes need to check their BG regularly. For weight and self-report (SR), the weekly submission frequency is lower than other parameters. Only participants with HF might be expected to take a daily reading of weight, given that weight change is an important indicator of a potential exacerbation. Those monitoring weight as a lifestyle parameter would likely weigh themselves less often, which probably accounts for the lower submission frequency. Also, gaining weight and engaging in less PA can lead to stopping weight monitoring (Frie et al., 2020).

The findings in Study 1 demonstrate that the user retention of self-reporting data dropped more than the user retention of using the technology, particularly at the 200 days time-point. However, in another study by Potts et al. (Potts et al., 2020), the engagement was low at the start and end of the trial and high at the middle of the trial. In addition, Study 1 highlighted that the frequency of submitting SR was lower than other parameters. There are a couple of possible reasons for this. Firstly, submitting SR data involved more conscious interaction from the participant, given that they had to open the ProACT CareApp, navigate to the questions section, then reflect on the questions in order to input an accurate answer, making this a fully manual task. This process can help participants understand their current health conditions (Grönvall and Verdezoto, 2013). However, there are other potential reasons for lower engagement with self-reporting. The same questions were asked throughout the trial, so participants may have become fatigued with answering the same questions.

For those participants not monitoring COPD and HF, all of the questions related to general well-being, and participants possibly did not find value in these, and this process of self-reporting could therefore take more time for some participants than using the health monitoring devices. Further analysis of this dataset could examine engagement with self-reporting more closely, for example to see if those who had to answer symptom questions (COPD and HF) had higher engagement with self-reporting when compared to other participant groups.

7.4.2 Self-management routines

Analysing the time of submissions can reveal what time of day participants prefer to interact with digital health interventions. Potts et al. (Potts et al., 2020) found that the most popular time for people with dementia to answer EMA questions is between 21:00 and 22:00. They also found that dismissal rates are relatively low at postprandial times, such as, 09:00 and 18:00 (Potts et al., 2020). In the ProACT study, participants were not given any instruction as to how often or at what time of day they should monitor symptom or well-being parameters. The majority of participants interacted with the various devices to monitor symptoms in the morning, with peaks of usage also found in the evening time. Understanding the times that people favour in terms of taking readings could be important for future similar studies. For example, if we know that a person is likely to be engaging with a self-management app at a certain time of the morning, notifications could be pushed at this time reminding them to answer self-report questions. However, pushing multiple notifications at regular intervals throughout the day can reduce the user retention of an app compared with notifications pushed once or twice a day (Pham et al., 2016). In addition, sending notifications while participants are using the devices can lead to a higher dismissal rate (Potts et al., 2020).

Reminders could also be sent for other parameters at certain times, such as before and after mealtimes for those measuring BG, or early in the morning for those with HF monitoring weight. Woodward et al. (Woodward et al., 2021) found that there is a disconnect between evidence-based design recommendations and current practice after they analysed notifications from 50 mHealth apps. They suggest that notifications for participants should not only be based on time, but also according to their context such as symptom parameters. It is also important to consider the type of device being used. For example, if the self-management app is on a tablet device, notifications will likely only be noticed when the person is actually interacting with the device. Different types of persuasive reminders can also influence a participant's decision to engage (Smith et al., 2016). For example, Smith et al., found that two types of reminders, 'Authority' (e.g., 'According to experts, a swollen ankle is a sign of HF. Please check your ankle now') and 'Liking' (e.g., 'Your family would appreciate it if you performed your daily weight check so they don't need to worry about you as much. Please check your weight now') were the most popular types of reminders (Smith et al., 2016). However, Stawarz et al. (Stawarz et al., 2015) also pointed out that reminders, in addition to keeping users engaged and helping them repeat behaviours, can have side effects, such as users relying on reminders rather than remembering them themselves.

7.4.3 The correlation between different devices

Many research studies use p-values to show the level of similarity or difference between clusters (Rahman et al., 2017, Booth et al., 2021, Sulistyono et al., 2021, Oskooei et al., 2021). For most of the engagement outcomes presented in Chapter 5 of this thesis, all clusters significantly differ as the one-way ANOVA p-values are less than 0.001, with the exception being self-report (SR) (P = .0013). In addition, as the results from Study 2 demonstrate, the t-test p-values show that Cluster2 is significantly different from Cluster1 and Cluster3 in BP and Weight submissions, while Cluster1 is significantly different from Cluster2 and Cluster3 in PA and sleep submissions. As for SR submissions, all three t-tests had p-values greater than 0.001, meaning that there were no significant differences between any two of these clusters. Therefore, all five parameters used for clustering are separated into three groups based on the correlations of submissions, one for BP and weight, one for PA and sleep, and one for SR. PA and Sleep submissions have a strong correlation because they use the same device to record daily activities and sleeping conditions. SR submissions have a weak correlation with other parameters' submissions. Study 1 highlighted that user retention of submitting SR was poorer compared to retention of using the digital health devices, possibly because SR has more manual operations than other parameters, or because the same questions were regularly asked, as noted in section 7.4.1.

In contrast to the other two groups, BP and Weight are collected using different devices. While measuring BP required using a BP monitor and manually synchronising the data, measuring weight simply required standing on the scale, with the data being automatically synchronised. Therefore, the manual operations between submitting BP and Weight are slightly different. However, the results showed a strong correlation between BP and weight, as many participants preferred to measure both BP and weight together and incorporate them into their daily routines. Research has indicated that if the usage of a health care device becomes a regular routine, then participants will use it without consciously thinking about it (Kim and Malhotra, 2005). Likewise, Yuan et al. (Yuan et al., 2015) note that integrating health apps into people's daily activities and forming regular habits can increase people's willingness to continue using health apps. However, participants using health care technology for long periods of time might become less receptive to exploring the system than to using it based on the established methods they are accustomed to (O'Connor et al., 2013). In this study, many participants bundled their BP measurements with their weight measurement during their morning routine. Therefore, the engagement rates of interacting with these two devices were enhanced by each other. Future work could explore how to integrate additional measurements such as SpO2 monitoring, as well as self-reporting, into this routine, for example through prompting the user to submit these parameters while they are engaging with monitoring others such as BP and weight.

7.4.4 Recommendations

- Developers of digital health technologies, including monitoring devices and digital apps, should reduce the number of steps required to monitor health and well-being and the need for manual data entry, which could enhance user engagement (Bohm et al., 2020). For example, in this project, submission rates were higher for parameters with less manual data entry (e.g., physical activity) and lower for parameters with more manual data entry (e.g., self-reporting).

- Self-reporting through answering a series of questions is very important to capture symptom and well-being data that cannot be captured through a digital device. Designers need to consider how to schedule and deliver self-report questions so that users are not overburdened with answering the same questions. Further research is also needed to understand under what situations this might be necessary. For example, those with COPD might only be asked to answer self-report questions on breathlessness, phlegm amount etc. if their SpO2 reading is below a particular threshold. Similarly, questions on mood and anxiety could be delivered in response to certain situations, such as a change in other parameters of health or well-being.
- Mornings are a good time for reminders. In addition, reminders should be adapted to the participant's daily routine and his or her condition. For example, reminders could be scheduled based on when a user used the scale in the previous two weeks; those with diabetes could be reminded to test their BG before meals (Potts et al., 2020). However, too many reminders or notifications can also have side effects, such as over-reliance on reminders or lower user retention (Stawarz et al., 2015, Pham et al., 2016).
- Devices and reminders should be set based on correlations between different digital health devices. For example, if a user wishes to use a scale after a BP measurement, a reminder to use the scale may be sent after the BP measurement. In addition, if the user already has a daily routine, such as using a weight scale after a BP measurement, reminders for other devices can be set after the routine so that the daily routine includes more devices, thereby increasing the participation of all devices in the routine.

7.5 Mobile device proficiency and user engagement

As discussed in Section 2.2 of Chapter 2, many studies have shown that the use of digital health technologies to support self-management can improve quality of life and health outcomes, with significant benefits for older adults with chronic conditions. However, there are a number of reasons behind the fact that many older adults adopt technology at a lower rate than the general population. For example, older adults need additional support in overcoming technology anxiety, increasing technology acceptance and self-efficacy (Jarvis et al., 2020, Lozoya et al., 2022). Another important factor that influences users' use of digital health technology is technical proficiency (Weigel and Hazen, 2014). In the ProACT trial, the MDPQ was administered to participants at the start of the trial to assess the technical proficiency of the participants.

7.5.1 The impact of mobile device proficiency on user engagement

The overall mobile device proficiency of participants in this study was moderate (Table 8), with a mean score of 22.02 (SD 9.94) out of a total possible score of 40 and a mean score of 2.75 (SD 1.72) out of a possible score of 5 across the sub-sections, indicating that at the outset of their participation in the ProACT trial, participants could not very easily perform the various tasks being assessed in the MDPQ. In another study using the MDPQ (Moret-Tatay et al., 2019), the mean mobile devices proficiency score (MDPS) of older adults was 13.13 (SD 8.86), which was lower than in the present study. However, in the Moret-Tatay et al. study, the mean age of the older adults was 78.17 years, which was older than the present study (74 years), and this could have contributed to the low MDPS. Similarly, Muñoz Esquivel et al. (Muñoz Esquivel et al., 2023) used the MDPQ in a study relating to older people using wearable devices, and participants in their study with a mean age of 70.5 years scored higher on each section (3.53) than in this study.

Study 3 found that the mobile device proficiency scores of participants have no correlation with participants’ engagement with digital health technology. Participants in this study had moderate

MDPS, but high user retention and engagement. This is an important finding, particularly as it is in contrast with many studies that note that technical proficiency affects the use of and engagement with digital health technologies. During the COVID-19 pandemic, Benis et al. (Benis et al., 2021) surveyed 473 participants, primarily from Israel and Uruguay, with online questions about telemedicine use. The authors found that a participant's overall technical proficiency and comfort level with web-based telemedicine influenced and increased the use of such technology. However, this study collected surveys via the Internet, so people who do not use the Internet and may be less technical proficiency were excluded from this study. Turnbull et al. (Turnbull et al., 2021) interviewed 21 participants who used digital health technology to help them self-care for their type 2 diabetes. The authors found that technical proficiency and cost were the two main barriers to accessing and using digital health technologies cited by participants. While the data-driven analysis of the ProACT trial data as presented in this thesis cannot provide an explanation as to why participants engaged despite having modest levels of mobile device proficiency, as noted in Section 7.3.1 above, participants of the ProACT trial experienced benefits as a result of their participation and had the support of clinical triage nurses and a technical helpdesk and these factors may have counteracted any potential negative impact of modest technical proficiency.

Another finding from Study 3 was that the correlation between the scores of each individual sub section of the MDPQ and user engagement is weak, with all the p-values being larger than 0.05 (Table 11). However, of all the subsections of the MDPQ, two have relatively strong correlations with engagement scores: communication and calendar. Without qualitative feedback from participants, it is difficult to know whether this is a potentially meaningful finding. However, it is likely that the weak correlations with the majority of the sub-sections is due to the lack of relevance of the MDPQ to digital health self-management activities and tasks.

König et al. (König et al., 2022) developed an assistive technology system, MEMENTO, which consists of two tablets and a smartwatch to help people with dementia and their caregivers to facilitate daily life. The trial lasted for three months with 15 participants in the test group and 15 participants in the control group. At the beginning of the trial, the technical proficiency of the participants who needed to use the system was assessed using a Likert scale based on their information and usual use of technical equipment. The results showed that the participants were willing to engage with the system, but the correlation between the frequency of MEMENTO usage with technical proficiency was low for both patient and caregiver. However, the MEMENTO study only had 30 participants who used the system for 3 months, which is a relatively short period of time compared with the ProACT study. In addition, the authors assessed user engagement through surveys (e.g., User Engagement Scale (O'Brien and Toms, 2010) and System Usability Scale (Brooke, 1996)), but did not assess system usage data, which is also different from this PhD project.

A possible interpretation of the finding that correlation between technical proficiency and engagement with digital health self-management is weak is that technical proficiency does not predict engagement. However, as noted above, the methods of assessment used might impact this. For example, the MDPQ does not assess proficiency with digital self-management activities, while the Memento study used questionnaires rather than system data to assess engagement. In relation to technical proficiency, it may be useful to find a more suitable way to evaluate participants' technical proficiency as it relates to digital self-management activities. This could potentially support personalised and targeted training for individuals prior to their usage of digital health technology, which could positively impact engagement. Nowadays, many studies are beginning to use the eHealth Literacy Scale (eHEALS) (Norman and Skinner, 2006) to assess participants' perceived skills in using information technology for health promotion, which can also determine the fit between eHealth programmes and participants (Oh et al., 2021). In addition, the eHEALS has been used in many studies related to chronic disease or older adults. However, the eHEALS questionnaire does not provide an explicit assessment or rating of digital health literacy, which could be used to determine someone's ability to use eHealth technology (Faux-Nightingale et al., 2022). Another way to better understand participants' technical proficiency in studies such as ProACT is to customise a method (such as a questionnaire or test) to assess technical proficiency. For example, unlike the MDPQ, the questions in this customised approach may relate to wearables, tablet use, and health devices such as BP monitors and glucometers.

7.5.2 The correlation between mobile device proficiency and self-management routines

According to the results of multiple regression, the correlations between devices submissions and mobile device proficiency are weak (Table 12). However, the submitted SpO2 and BG values were correlated strongly with the MDPS (p-value < 0.05). Only participants with diabetes were required to measure BG, while participants with COPD were required to use pulse oximetry to measure SpO2 (SpO2). That is, if participants had a low MDPS, then they had a low number of BG and SPO2 submissions, and if they had a high MDPS, then they had a high number of BG and SPO2 submissions. Furthermore, most of the participants with low BP and SPO2 submission counts did not have diabetes or COPD, so they had zero submission counts. In this case, participants with COPD and diabetes had higher MDPS than those without COPD and diabetes. However, based on the discussion in the previous two subsections, the correlation between MDPS and engagement was weak. Thus, the high correlation of BG and SpO2 submissions with the MDPS may be due to the fact that participants with diabetes and COPD require the use of medical devices due to their condition, which is unrelated to the MDPS.

7.5.3 Recommendations

- Design, test and validate a customized questionnaire for specific digital health technology to evaluate participants' technical proficiency in relation to digital self-management activities. Administering such a tool prior to an individual's use of a digital health platform would allow for training targeted to areas of specific need.

7.6 Implication of the findings

There are several implications of older adults engaging with digital health self-management, that span digital inclusion policies, health outcomes, health systems, cost-effectiveness, and health policy.

As outlined in the Introduction chapter, the global population is ageing. In 2020, the number of people aged 60 and over exceeded the number of children under 5 (World Health Organization, 2022b). The world's population of people aged 60 years and over will be 2.1 billion by 2050. As the problem of ageing continues to grow, incident rates of chronic diseases are increasing and health care systems are under increasing pressure, both in terms of staffing and finances. In 2016, the average health care cost for people over 65 in the U.S. was $11,316 per person per year (Androus, 2023). In 2015, cardiovascular diseases cost the EU almost €111 billion (European Commission, 2021). In addition, the shortfall of health care workers (physicians, nurses and other health care professionals) in the EU was 1.6 million in 2013 and is projected to reach 4.1 million by 2030 (World Health Organization, 2016). Digital health technologies, designed to support people to manage their health and well-being at home, have potential to improve health outcomes and alleviate health system pressures. For older adults with multimorbidity, self-management of their conditions and daily routines can be very difficult, not only because ageing can lead to different conditions such as hearing loss, eye problems, back pain and memory loss (World Health Organization, 2022b), but also because the complexity of multimorbidity requires older adults to perform a variety of tasks for their own well-being, such as health monitoring, medication taking, nutrition and daily activities (UK National Guideline Centre, 2016). While digital health technology can help older adults with multimorbidity cope with complex tasks, there are a number of factors that affect digital health technology engagement, such as technology acceptance (Peek et al., 2014) and healthcare technology self-efficacy (Rahman et al., 2016). Peek et al. (Peek et al., 2014) point out that expected benefits of technology, need for technology, and social support can influence the acceptance of health and well-being home-based technology for older adults. Likewise, healthcare technology self-efficacy can be improved by support from a community and can enhance users' trust of health care interventions (Willis, 2016, Chamorro-Koc et al., 2021).

However, the results of this PhD project show that older adults are willing and able to use digital health technology, with high levels of engagement overall. In addition, in this study, the health of older adults with multimorbidity improved over the trial period. There are a number of implications of this finding, when viewed in the context of ageing populations and increased pressure on health systems. Firstly:

- Governments should consider digital health policies that are inclusive of older adults, for example by providing cost-effective access to digital health technology, implementing training programmes to improve digital and health literacy, and ensuring the necessary infrastructure, such as broadband availability.
- Designers and developers of digital health technology should not dismiss older adults as potential end users of their products and should strive to develop technology that is as easy to use as possible and that is designed with older adults' needs in mind. The development of guidelines and standards for the design of such technologies, particularly for older adults, will be important.
- Healthcare systems should integrate digital health technologies into their practice, prescribing them as part of their patients' care plans. For example, wearable devices could be issued to older adults with chronic conditions to record healthcare data and for self-monitoring. Healthcare professionals should not discount older adults as possible users of such technology. Government reimbursement models could encourage uptake of digital health technologies by both healthcare organisations and individuals.

7.7 Limitations

There are some limitations to the research project presented in this thesis which should be noted. Firstly, while the sample size of 60 was relatively large for a digital health study, the sample size for some parameters was small because not all participants monitored all parameters. Secondly, the participants were clustered based on weekly submissions of parameters only in the second study. If more features were included in the clustering, such as the intervals of submissions, participants might have been grouped differently. It should also be pointed out that correlation is not a causality with respect to analysing engagement rates with outcomes. For example, the higher proportion of people with diabetes in the highly engaged user group does not mean that diabetes is the reason for the higher engagement of these participants. Finally, the mobile device proficiency questionnaire was possibly not appropriate for this study to assess participants' technical proficiency as it relates to digital self-management activities. As discussed in Chapter 6, there were many questions in the MDPQ that were not related to digital health devices and this may account for the weak correlations observed.

7.8 Opportunities for Future Work

There is scope for future work to further the research presented in this PhD thesis. The dataset used in this thesis could be further analysed through time series analysis. For example, the relationship between the number of submissions and time (in days) throughout the trial could be analysed to determine if there is a seasonal pattern over the course of a month or a year. Time series analyses could also be used to understand how participants' health conditions change over time. Additionally, such analyses could show how long the participants' health remained stable after using the healthcare devices. Another interesting question might be to look at engagement before and after an exacerbation (e.g. a high or low symptom reading causing an alert). For example, did people reduce their engagement in monitoring or a certain lifestyle activity (e.g. physical activity) prior to the exacerbation? After an exacerbation, did they re-engage and did that consequently lead to stabilisation of symptoms?

A larger scale trial with a larger number of participants with each type of chronic condition is needed to confirm the findings from the three studies presented in this thesis, as well as to assess what levels of engagement are required for the ProACT platform to be effective in terms of improving health outcomes and reducing unscheduled healthcare utilisation. Future work could explore which types of notifications and prompts are most effective for promoting effective engagement in certain situations or for certain cohorts, through conducting a series of micro-randomised experiments, with the goal of developing an optimised intervention. As noted in the recommendations above, there is also scope for researchers to explore how best to design a smarter, more contextually-relevant self-reporting feature that maximises engagement. An optimised digital health intervention could then be evaluated in a larger randomised controlled trial to assess a range of outcomes.

Finally, a customized questionnaire to assess participants' technical proficiency in relation to digital health self-management activities, could be developed, tested and validated. Based on an individual's responses to the questionnaire, specific training programmes could be developed to help participants use and understand digital self-management technologies. Such training could remove barriers such as low technology acceptance and low technology proficiency wherever possible.

7.9 Conclusion

Ageing demographics, the increase in the number of chronically ill patients and the increase in the workload of care by healthcare professionals has led to a growing demand for structural reform within health care systems to drive care to the community, providing individuals with opportunities to better self-manage their health and well-being from home, through the use of digital health technologies. Effective self-management can only be achieved if people engage with self-management tasks and activities, however, and this can be particularly challenging for older adults with multimorbidity who may have limited technical proficiency and who face complex self-management routines.

The aim of this PhD project was to explore patterns of engagement of older adults with multimorbidity with digital self-management over a longitudinal period, in particular with monitoring their symptoms (e.g., BP) and well-being (e.g., activity, self-reported mood). The findings revealed the potential of a digital health platform, such as ProACT, to empower older adults with multimorbidity to engage in digital self-management. Several contributions to the field of digital health were made. Firstly, this thesis provides an understanding of the patterns of engagement with digital self-management technologies and behaviours of older adults with multimorbidity – an understudied cohort in the field of digital health research. The findings presented in this thesis indicate that this cohort engaged in digital self-management for a period of approximately one year, with high levels of user retention and frequent and regular digital self-management routines.

The second contribution is that findings from the analysis presented in this thesis have led to the development of recommendations for researchers, designers and developers of digital health technologies to help maximise engagement and therefore potential impact of such technologies. For example, the analysis found that digital health devices with fewer manual operations are higher utilised than those with more manual operations while fixed daily routines using different digital health devices can help increase engagement among older adults with multimorbidity. Notifications are a useful way to help older adults with their daily routines and mornings are a good time to send them.

Higher levels of engagement with digital health monitoring may result in better outcomes, such as symptom stabilisation and increased levels of PA for older adults with multimorbidity. The analysis found a non-linear positive correlation between the frequency of use of digital health devices and the physical condition of participants.

Mobile device proficiency, as evaluated through the Mobile Device Proficiency Questionnaire, designed specifically for older adults, does not predict engagement with digital health technologies. Even though participants of the study had low levels of mobile device proficiency, they engaged with digital self-management throughout the 12-month trial period. However, consideration should be given to the development of a questionnaire to assess an older adult's digital health technology proficiency or literacy prior to them engaging in digital self-management, so that targeted, individualised training programmes can be developed with a view to maximising effective engagement.

The final contribution is that this thesis outlines several potential implications of this research, including health outcomes, healthcare system efficiencies and healthcare policy. For example, empowering older adults with multimorbidity to engage in digital self-management can lead to better healthcare outcomes, which ultimately could result in less unscheduled healthcare utilisation, lower healthcare costs for both patients and healthcare systems and new reimbursement models that provide healthcare organisations with incentives to integrate digital health technologies into their practice.

Bibliography

ABDI, H. & WILLIAMS, L. J. 2010. Principal component analysis. *Wiley interdisciplinary reviews: computational statistics,* 2**,** 433-459.

ABEDJAN, Z., GOLAB, L. & NAUMANN, F. 2015. Profiling relational data: a survey. *The VLDB Journal,* 24**,** 557-581.

ABEL, E. A., SHIMADA, S. L., WANG, K., RAMSEY, C., SKANDERSON, M., ERDOS, J., GODLESKI, L., HOUSTON, T. K. & BRANDT, C. A. 2018. Dual use of a patient portal and clinical video telehealth by veterans with mental health diagnoses: retrospective, cross-sectional analysis. *Journal of Medical Internet Research,* 20**,** e11350.

ABRAHAM, W. T. & PERL, L. 2017. Implantable hemodynamic monitoring for heart failure patients. *Journal of the American College of Cardiology,* 70**,** 389-398.

ABROMS, L. C., BOAL, A. L., SIMMENS, S. J., MENDEL, J. A. & WINDSOR, R. A. 2014. A randomized trial of Text2Quit: a text messaging program for smoking cessation. *American journal of preventive medicine,* 47**,** 242-250.

ACADEMY OF MEDICAL SCIENCES. 2018. *Multimorbidity: a priority for global health research* [Online]. Available: https://acmedsci.ac.uk/file-download/82222577 [Accessed 11th May 2022].

ACHTYES, E. D., BEN-ZEEV, D., LUO, Z., MAYLE, H., BURKE, B., ROTONDI, A. J., GOTTLIEB, J. D., BRUNETTE, M. F., MUESER, K. T. & GINGERICH, S. 2019. Off-hours use of a smartphone intervention to extend support for individuals with schizophrenia spectrum disorders recently discharged from a psychiatric hospital. *Schizophrenia research,* 206**,** 200-208.

ADELUYI, O. & LEE, J.-A. 2015. Medical virtual instrumentation for ambient assisted living: part 1 concepts. *Measurement and Control,* 48**,** 167-177.

ADIKARAM, K. L. B., HUSSEIN, M. A., EFFENBERGER, M. & BECKER, T. 2015. Data transformation technique to improve the outlier detection power of Grubbs' test for data expected to follow linear relation. *Journal of applied mathematics,* 2015**,** 1-9.

AGARWAL, S. Data mining: Data mining concepts and techniques. 2013 international conference on machine intelligence and research advancement, 2013. IEEE, 203-207.

AHMAD, P., QAMAR, S. & RIZVI, S. Q. A. 2015. Techniques of data mining in healthcare: a review. *International Journal of Computer Applications,* 120.

AJIBADE, S. S. & ADEDIRAN, A. 2016. An overview of big data visualization techniques in data mining. *International Journal of Computer Science and Information Technology Research,* 4**,** 105-113.

AKOGLU, H. 2018. User's guide to correlation coefficients. *Turkish journal of emergency medicine,* 18**,** 91-93.

AL-DURRA, M., TORIO, M.-B. & CAFAZZO, J. A. 2015. The use of behavior change theory in Internet-based asthma self-management interventions: a systematic review. *Journal of medical Internet research,* 17**,** e89.

AL-FAIZ, M. Z., IBRAHIM, A. A. & HADI, S. M. 2018. The effect of Z-Score standardization (normalization) on binary input due the speed of learning in back-propagation neural network. *Iraqi Journal of Information and Communication Technology,* 1**,** 42-48.

ALANZI, T. 2018. mHealth for diabetes self-management in the Kingdom of Saudi Arabia: barriers and solutions. *Journal of Multidisciplinary Healthcare,* 11**,** 535.

ALFONSSON, S., OLSSON, E. & HURSTI, T. 2016. Motivation and treatment credibility predicts dropout, treatment adherence, and clinical outcomes in an internet-based cognitive behavioral relaxation program: a randomized controlled trial. *Journal of medical Internet research,* 18**,** e5352.

ALHUSSEIN, G. & HADJILEONTIADIS, L. 2022. Digital health technologies for long-term self-management of osteoporosis: systematic review and meta-analysis. *JMIR mHealth and uHealth,* 10**,** e32557.

ALI, P. J. M., FARAJ, R. H., KOYA, E., ALI, P. J. M. & FARAJ, R. H. 2014. Data normalization and standardization: a technical report. *Mach Learn Tech Rep,* 1**,** 1-6.

ALLOGHANI, M., AL-JUMEILY, D., MUSTAFINA, J., HUSSAIN, A. & ALJAAF, A. J. 2020. A systematic review on supervised and unsupervised machine learning algorithms for data science. *Supervised and unsupervised learning for data science***,** 3-21.

ALPAYDIN, E. 2020. *Introduction to machine learning*, MIT press.

ALSAYAT, A. & EL-SAYED, H. Efficient genetic K-means clustering for health care knowledge discovery. 2016 IEEE 14th International Conference on Software Engineering Research, Management and Applications (SERA), 2016. IEEE, 45-52.

AMERICAN DIABETES ASSOCIATION 2018. Economic costs of diabetes in the US in 2017. *Diabetes Care,* 41**,** 917-928.

AMORIM, A. B., PAPPAS, E., SIMIC, M., FERREIRA, M. L., JENNINGS, M., TIEDEMANN, A., CARVALHO-E-SILVA, A. P., CAPUTO, E., KONGSTED, A. & FERREIRA, P. H. 2019. Integrating Mobile-health, health coaching, and physical activity to reduce the burden of chronic low back pain trial (IMPACT): a pilot randomised controlled trial. *BMC musculoskeletal disorders,* 20**,** 1-14.

ANDALIBI, N. & FLOOD, M. K. 2021. Considerations in designing digital peer support for mental health: Interview study among users of a digital support system (Buddy Project). *JMIR mental health,* 8**,** e21819.

ANDERSEN, T. O., LANGSTRUP, H. & LOMBORG, S. 2020. Experiences With Wearable Activity Data During Self-Care by Chronic Heart Patients: Qualitative Study. *Journal of Medical Internet Research,* 22**,** e15873.

ANDROUS, A. B. 2023. *Here's How Much Your Healthcare Costs Will Rise as You Age* [Online]. Available: https://www.registerednursing.org/articles/healthcare-costs-by-age/#:~:text=By%20the%20time%20you%20reach,as%20high%20as%20for%20men. [Accessed Oct 19 2023].

AREF-ADIB, G., MCCLOUD, T., ROSS, J., O'HANLON, P., APPLETON, V., ROWE, S., MURRAY, E., JOHNSON, S. & LOBBAN, F. 2019. Factors affecting implementation of digital health interventions for people with psychosis or bipolar disorder, and their family and friends: a systematic review. *The Lancet Psychiatry,* 6**,** 257-266.

ARMSTRONG, J. J., ZHU, M., HIRDES, J. P. & STOLEE, P. 2012. K-means cluster analysis of rehabilitation service users in the home health care system of Ontario: Examining the heterogeneity of a complex geriatric population. *Archives of physical medicine and rehabilitation,* 93**,** 2198-2205.

ÅRSAND, E., TATARA, N., ØSTENGEN, G. & HARTVIGSEN, G. 2010. Mobile phone-based self-management tools for type 2 diabetes: the few touch application. *Journal of diabetes science and technology,* 4**,** 328-336.

ASIMAKOPOULOS, S., ASIMAKOPOULOS, G. & SPILLERS, F. 2017. Motivation and User Engagement in Fitness Tracking: Heuristics for Mobile Healthcare Wearables. *Informatics,* 4**,** 5.

ATKINSON JR, R. L., BUTTERFIELD, G., DIETZ, W., FERNSTROM, J., FRANK, A., HANSEN, B. & MOORE, B. 2003. Weight management: State of the science and opportunities for military programs. *National Academy of Sciences*.

ATTIG, C. & FRANKE, T. 2020. Abandonment of personal quantification: A review and empirical study investigating reasons for wearable activity tracking attrition. *Computers in Human Behavior,* 102**,** 223-237.

AUDULV, Å. 2013. The over time development of chronic illness self-management patterns: a longitudinal qualitative study. *BMC public health,* 13**,** 1-15.

AYESHA, S., HANIF, M. K. & TALIB, R. 2020. Overview and comparative study of dimensionality reduction techniques for high dimensional data. *Information Fusion,* 59**,** 44-58.

AZEVEDO, A. & SANTOS, M. F. 2008. KDD, SEMMA and CRISP-DM: a parallel overview. *IADS-DM*.

BäHLER, C., HUBER, C. A., BRüNGGER, B. & REICH, O. 2015. Multimorbidity, health care utilization and costs in an elderly community-dwelling population: a claims data based observational study. *BMC health services research,* 15**,** 1-12.

BAKER, L., RIDEOUT, J., GERTLER, P. & RAUBE, K. 2005. Effect of an Internet-based system for doctor-patient communication on health care spending. *Journal of the American Medical Informatics Association,* 12**,** 530-536.

BALAPOUR, A., REYCHAV, I., SABHERWAL, R. & AZURI, J. 2019. Mobile technology identity and self-efficacy: Implications for the adoption of clinically supported mobile health apps. *International Journal of Information Management,* 49**,** 58-68.

BAND, R., BRADBURY, K., MORTON, K., MAY, C., MICHIE, S., MAIR, F. S., MURRAY, E., MCMANUS, R. J., LITTLE, P. & YARDLEY, L. 2017. Intervention planning for a digital intervention for self-management of hypertension: a theory-, evidence-and person-based approach. *Implementation Science,* 12**,** 1-13.

BANDODKAR, A. J., JIA, W., YARDıMCı, C., WANG, X., RAMIREZ, J. & WANG, J. 2015. Tattoo-based noninvasive glucose monitoring: a proof-of-concept study. *Analytical chemistry,* 87**,** 394-398.

BANDURA, A. & WESSELS, S. 1994. *Self-efficacy*, na.

BARLOW, J., WRIGHT, C., SHEASBY, J., TURNER, A. & HAINSWORTH, J. 2002. Self-management approaches for people with chronic conditions: a review. *Patient Education and Counseling,* 48**,** 177-187.

BARNETT, M. 2005. Chronic obstructive pulmonary disease: a phenomenological study of patients' experiences. *Journal of clinical nursing,* 14**,** 805-812.

BARTLETT, S. J., LAMBERT, S. D., MCCUSKER, J., YAFFE, M., DE RAAD, M., BELZILE, E., CIAMPI, A., DI CARLO, M. & LYDDIATT, A. 2020. Self-management across chronic diseases: Targeting education and support needs. *Patient education and counseling,* 103**,** 398-404.

BAUER, S. & MOESSNER, M. 2013. Harnessing the power of technology for the treatment and prevention of eating disorders. *International Journal of Eating Disorders,* 46**,** 508-515.

BAUMEL, A., MUENCH, F., EDAN, S. & KANE, J. M. 2019. Objective user engagement with mental health apps: systematic search and panel-based usage analysis. *Journal of medical Internet research,* 21**,** e14567.

BEATTY, L., KEMP, E., BINNION, C., TURNER, J., MILNE, D., BUTOW, P., LAMBERT, S., YATES, P., YIP, D. & KOCZWARA, B. 2017. Uptake and adherence to an online intervention for cancer-related distress: older age is not a barrier to adherence but may be a barrier to uptake. *Supportive Care in Cancer,* 25**,** 1905-1914.

BENGTSSON, U., KJELLGREN, K., HALLBERG, I., LINDWALL, M. & TAFT, C. 2016. Improved Blood Pressure Control Using an Interactive Mobile Phone Support System. *J Clin Hypertens (Greenwich),* 18**,** 101-8.

BENIS, A., BANKER, M., PINKASOVICH, D., KIRIN, M., YOSHAI, B.-E., BENCHOAM-RAVID, R., ASHKENAZI, S. & SEIDMANN, A. 2021. Reasons for utilizing telemedicine during and after the COVID-19 pandemic: an internet-based international study. *Journal of Clinical Medicine,* 10**,** 5519.

BENTLEY, C. L., POWELL, L., POTTER, S., PARKER, J., MOUNTAIN, G. A., BARTLETT, Y. K., FARWER, J., O'CONNOR, C., BURNS, J. & CRESSWELL, R. L. 2020. The use of a smartphone app and an activity tracker to promote physical activity in the management of chronic obstructive pulmonary disease: randomized controlled feasibility study. *JMIR mHealth and uHealth,* 8**,** e16203.

BENTLEY, F. & TOLLMAR, K. The power of mobile notifications to increase wellbeing logging behavior. Proceedings of the SIGCHI conference on human factors in computing systems, 2013. 1095-1098.

BERNELL, S. & HOWARD, S. W. 2016. Use your words carefully: what is a chronic disease? *Frontiers in public health,* 4**,** 159.

BERRY, E., DAVIES, M. & DEMPSTER, M. 2017. Illness perception clusters and relationship quality are associated with diabetes distress in adults with Type 2 diabetes. *Psychology, health & medicine,* 22**,** 1118-1126.

BERRY, N., LOBBAN, F. & BUCCI, S. 2019. A qualitative exploration of service user views about using digital health interventions for self-management in severe mental health problems. *BMC psychiatry,* 19**,** 1-13.

BHATIA, N. 2010. Survey of nearest neighbor techniques. *arXiv preprint arXiv:1007.0085*.

BINDRA, K. & MISHRA, A. A detailed study of clustering algorithms. 2017 6th international conference on reliability, infocom technologies and optimization (trends and future directions)(ICRITO), 2017. IEEE, 371-376.

BIRD, R., ÖZER-ERDOGDU, I., ASLAN, M. & TEZCAN-GüNTEKIN, H. 2022. Healthcare provider perspectives on digital and interprofessional medication management in chronically ill older adults of Turkish descent in Germany: A qualitative structuring content analysis. *Frontiers in Public Health,* 10**,** 838427.

BIRK, J. L., KRONISH, I. M., MOISE, N., FALZON, L., YOON, S. & DAVIDSON, K. W. 2019. Depression and multimorbidity: Considering temporal characteristics of the associations between depression and multiple chronic diseases. *Health Psychology,* 38**,** 802.

BISIO, I., DELFINO, A., LAVAGETTO, F. & SCIARRONE, A. Enabling smartphone-centric platforms for in-home rehabilitation: a comparison among movement recognition approaches. 2016 IEEE International Conference on Communications (ICC), 2016. IEEE, 1-6.

BLASIAK, A., SAPANEL, Y., LEITMAN, D., NG, W. Y., DE NICOLA, R., LEE, V. V., TODOROV, A. & HO, D. 2022. Omnichannel Communication to Boost Patient Engagement and Behavioral Change With Digital Health Interventions. *Journal of Medical Internet Research,* 24**,** e41463.

BLOCK, G., AZAR, K. M., ROMANELLI, R. J., BLOCK, T. J., HOPKINS, D., CARPENTER, H. A., DOLGINSKY, M. S., HUDES, M. L., PALANIAPPAN, L. P. & BLOCK, C. H. 2015. Diabetes prevention and weight loss with a fully automated behavioral intervention by email, web, and mobile phone: a randomized controlled trial among persons with prediabetes. *Journal of medical Internet research,* 17**,** e240.

BOCKTING, C. L., KOK, G. D., KAMP, L. V. D., SMIT, F., VAN VALEN, E., SCHOEVERS, R., VAN MARWIJK, H., CUIJPERS, P., RIPER, H. & DEKKER, J. 2011. Disrupting the rhythm of depression using Mobile Cognitive Therapy for recurrent depression: randomized controlled trial design and protocol. *BMC psychiatry,* 11**,** 1-9.

BOERSMA, P., BLACK, L. I. & WARD, B. W. 2020. Peer reviewed: prevalence of multiple chronic conditions among US adults, 2018. *Preventing chronic disease,* 17.

BOHM, A. K., JENSEN, M. L., SORENSEN, M. R. & STARGARDT, T. 2020. Real-World Evidence of User Engagement With Mobile Health for Diabetes Management: Longitudinal Observational Study. *JMIR Mhealth Uhealth,* 8**,** e22212.

BOL, N., HELBERGER, N. & WEERT, J. C. 2018. Differences in mobile health app use: a source of new digital inequalities? *The Information Society,* 34**,** 183-193.

BOOTH, F. G., R BOND, R., D MULVENNA, M., CLELAND, B., MCGLADE, K., RANKIN, D., WALLACE, J. & BLACK, M. 2021. Discovering and comparing types of general practitioner practices using geolocational features and prescribing behaviours by means of K-means clustering. *Scientific Reports,* 11**,** 1-15.

BORGHOUTS, J., EIKEY, E., MARK, G., DE LEON, C., SCHUELLER, S. M., SCHNEIDER, M., STADNICK, N., ZHENG, K., MUKAMEL, D. & SORKIN, D. H. 2021. Barriers to and facilitators of user engagement with digital mental health interventions: systematic review. *Journal of medical Internet research,* 23**,** e24387.

BOUTAYEB, A. & BOUTAYEB, S. 2005. The burden of non communicable diseases in developing countries. *International journal for equity in health,* 4**,** 1-8.

BRACHMAN, R. J. 1996. The process of knowledge discovery in databases. *Advances in knowledge discovery and data mining***,** 37-57.

BRANCH, O. H., GRAHAM, S. A., MOORE, R. C. & AREáN, P. A. 2022. Aging-related factors in digital health: Design, uptake, engagement, and outcomes. *Frontiers in Digital Health,* 4.

BRECKNER, A., ROTH, C., GLASSEN, K. & WENSING, M. 2021. Self-management perspectives of elderly patients with multimorbidity and practitioners-status, challenges and further support needed? *BMC Family Practice,* 22**,** 1-13.

BRIEN, S. B., LEWITH, G. T. & THOMAS, M. 2016. Patient coping strategies in COPD across disease severity and quality of life: a qualitative study. *NPJ primary care respiratory medicine,* 26**,** 1-7.

BRILLEMAN, S. L., PURDY, S., SALISBURY, C., WINDMEIJER, F., GRAVELLE, H. & HOLLINGHURST, S. 2013. Implications of comorbidity for primary care costs in the UK: a retrospective observational study. *British Journal of General Practice,* 63**,** e274-e282.

BRITISH HEART FOUNDATION. 2023. *High blood pressure - symptoms and treatment* [Online]. Available: https://www.bhf.org.uk/informationsupport/risk-factors/high-blood-pressure/symptoms-and-treatment [Accessed Feb 15 2023,].

BRODLEY, C. E. & UTGOFF, P. E. 1992. *Multivariate versus univariate decision trees*, Citeseer.

BROOKE, J. 1996. Sus: a "quick and dirty'usability. *Usability evaluation in industry,* 189**,** 189-194.

BROWN, J. C., YUNG, R. L., GOBBIE-HURDER, A., SHOCKRO, L., O'CONNOR, K., CAMPBELL, N., KASPER, J., MAYER, E. L., TOLANEY, S. M. & PARTRIDGE, A. H. 2018. Randomized trial of a clinic-based weight loss intervention in cancer survivors. *Journal of Cancer Survivorship,* 12**,** 186-195.

BUIS, L. R., DAWOOD, K., KADRI, R., DAWOOD, R., RICHARDSON, C. R., DJURIC, Z., SEN, A., PLEGUE, M., HUTTON, D. & BRODY, A. 2019. Improving blood pressure among African Americans with hypertension using a mobile health approach (the MI-BP App): protocol for a randomized controlled trial. *JMIR research protocols,* 8**,** e12601.

BUREAU, R., BEMMOUNA, D., FARIA, C. G. F., GOETHALS, A.-A. C., DOUHET, F., MENGIN, A. C., FRITSCH, A., ZINETTI BERTSCHY, A., FREY, I. & WEINER, L. 2021. My health too: investigating the feasibility and the acceptability of an internet-based cognitive-behavioral therapy program developed for healthcare workers. *Frontiers in Psychology,* 12**,** 760678.

CADMUS-BERTRAM, L., TEVAARWERK, A. J., SESTO, M. E., GANGNON, R., VAN REMORTEL, B. & DATE, P. 2019. Building a physical activity intervention into clinical care for breast and colorectal cancer survivors in Wisconsin: a randomized controlled pilot trial. *Journal of Cancer Survivorship,* 13**,** 593-602.

CALDEIRA, C., GUI, X., REYNOLDS, T. L., BIETZ, M. & CHEN, Y. 2021. Managing healthcare conflicts when living with multiple chronic conditions. *International Journal of Human-Computer Studies,* 145**,** 102494.

CALDERóN-LARRAñAGA, A., VETRANO, D. L., FERRUCCI, L., MERCER, S., MARENGONI, A., ONDER, G., ERIKSDOTTER, M. & FRATIGLIONI, L. 2019. Multimorbidity and functional impairment–bidirectional interplay, synergistic effects and common pathways. *Journal of internal medicine,* 285**,** 255-271.

CAO, L. 2006. Singular value decomposition applied to digital image processing. *Division of Computing Studies, Arizona State University Polytechnic Campus, Mesa, Arizona State University polytechnic Campus***,** 1-15.

CAPRANZANO, P., FRANCAVIGLIA, B., SARDONE, A., AGNELLO, F., VALENTI, N., FRAZZETTO, M., LEGNAZZI, M., OCCHIPINTI, G., SCALIA, L. & CALVI, V. 2021. Suitability for elderly with heart disease of a QR code-based feedback of drug intake: Overcoming limitations of current medication adherence telemonitoring systems. *International Journal of Cardiology,* 327**,** 209-216.

CARROLL, J. K., MOORHEAD, A., BOND, R., LEBLANC, W. G., PETRELLA, R. J. & FISCELLA, K. 2017. Who uses mobile phone health apps and does use matter? A secondary data analytics approach. *Journal of medical Internet research,* 19**,** e5604.

CARTER, M. C., BURLEY, V. J., NYKJAER, C. & CADE, J. E. 2013. Adherence to a smartphone application for weight loss compared to website and paper diary: pilot randomized controlled trial. *Journal of medical Internet research,* 15**,** e32.
CEBECI, Z. & YILDIZ, F. 2015. Comparison of k-means and fuzzy c-means algorithms on different cluster structures. *Journal of Agricultural Informatics,* 6.
CEFALU, W. T., PETERSEN, M. P. & RATNER, R. E. 2014. The alarming and rising costs of diabetes and prediabetes: a call for action! : Am Diabetes Assoc.
CENTERS FOR DISEASE CONTROL AND PREVENTION. 2021. *High Blood Pressure Symptoms and Causes* [Online]. Available: https://www.cdc.gov/bloodpressure/about.htm [Accessed Feb 15 2023,].
CENTERS FOR DISEASE CONTROL AND PREVENTION. 2022a. *COPD: Symptoms, Diagnosis, and Treatment* [Online]. Available: https://www.cdc.gov/copd/features/copd-symptoms-diagnosis-treatment.html [Accessed Feb 20 2023,].
CENTERS FOR DISEASE CONTROL AND PREVENTION. 2022b. *Diabetes* [Online]. Available: https://www.cdc.gov/diabetes/basics/index.html [Accessed Feb 15 2023,].
CHAMORRO-KOC, M., PEAKE, J., MEEK, A. & MANIMONT, G. 2021. Self-efficacy and trust in consumers' use of health-technologies devices for sports. *Heliyon,* 7**,** e07794.
CHAN, N.-Y. & CHOY, C.-C. 2017. Screening for atrial fibrillation in 13 122 Hong Kong citizens with smartphone electrocardiogram. *Heart,* 103**,** 24-31.
CHARLTON, J., RUDISILL, C., BHATTARAI, N. & GULLIFORD, M. 2013. Impact of deprivation on occurrence, outcomes and health care costs of people with multiple morbidity. *Journal of health services research & policy,* 18**,** 215-223.
CHAU, M. M., BURGERMASTER, M. & MAMYKINA, L. 2018. The use of social media in nutrition interventions for adolescents and young adults—A systematic review. *International journal of medical informatics,* 120**,** 77-91.
CHEN, K., LOU, V. W.-Q., TAN, K. C.-K., WAI, M. Y. & CHAN, L. L. 2020. Changes in technology acceptance among older people with dementia: the role of social robot engagement. *International journal of medical informatics,* 141**,** 104241.
CHEN, Y., LU, B., CHEN, Y. & FENG, X. 2015. Breathable and stretchable temperature sensors inspired by skin. *Scientific reports,* 5**,** 11505.
CHI, Y., VELARDO, C., ALLEN, J., ROBINSON, S., RIGA, E., JUDGE, D., TARASSENKO, L. & FARMER, A. J. 2021. System architecture for" Support Through Mobile Messaging and Digital Health Technology for Diabetes"(SuMMiT-D): design and performance in pilot and randomized controlled feasibility studies. *JMIR formative research,* 5**,** e18460.
CHU, X., ILYAS, I. F., KRISHNAN, S. & WANG, J. Data cleaning: Overview and emerging challenges. Proceedings of the 2016 international conference on management of data, 2016. 2201-2206.
CHUNG, J. E. 2014. Social networking in online support groups for health: how online social networking benefits patients. *Journal of health communication,* 19**,** 639-659.
CIKES, M., SANCHEZ-MARTINEZ, S., CLAGGETT, B., DUCHATEAU, N., PIELLA, G., BUTAKOFF, C., POULEUR, A. C., KNAPPE, D., BIERING-SØRENSEN, T. & KUTYIFA, V. 2019. Machine learning-based phenogrouping in heart failure to identify responders to cardiac resynchronization therapy. *European journal of heart failure,* 21**,** 74-85.
COLLIER, S. R., MCCRAW, C., CAMPANY, M., LUBKEMANN, A., STCLAIR, P., JI, H., SANDBERG, K., MORGAN, J. W. & SMITH, C. J. 2020. Withings body cardio versus gold standards of pulse-wave velocity and body composition. *Journal of personalized medicine,* 10**,** 17.
COMON, P. 1994. Independent component analysis, a new concept? *Signal processing,* 36**,** 287-314.
COMPERNOLLE, S., CARDON, G., VAN DER PLOEG, H. P., VAN NASSAU, F., DE BOURDEAUDHUIJ, I., JELSMA, J. J., BRONDEEL, R. & VAN DYCK, D. 2020. Engagement, Acceptability, Usability, and Preliminary Efficacy of a Self-Monitoring Mobile Health Intervention to Reduce Sedentary Behavior in Belgian Older Adults: Mixed Methods Study. *JMIR Mhealth Uhealth,* 8**,** e18653.

COOK, J. D., PRAIRIE, M. L. & PLANTE, D. T. 2017. Utility of the Fitbit Flex to evaluate sleep in major depressive disorder: a comparison against polysomnography and wrist-worn actigraphy. *Journal of affective disorders,* 217**,** 299-305.

COVER, T. & HART, P. 1967. Nearest neighbor pattern classification. *IEEE transactions on information theory,* 13**,** 21-27.

CRISP, D. A. & GRIFFITHS, K. M. 2014. Participating in online mental health interventions: who is most likely to sign up and why? *Depression research and treatment,* 2014.

CROOKS, R. E., BELL, M., PATTEN, S. B., WIEBE, S., HOLROYD-LEDUC, J., BULLOCH, A. G., MACRODIMITRIS, S., MACKIE, A., SAURO, K. M. & FEDERICO, P. 2017. Mind the gap: exploring information gaps for the development of an online resource hub for epilepsy and depression. *Epilepsy & Behavior,* 70**,** 18-23.

CUNNINGHAM, P. & DELANY, S. J. 2021. k-Nearest neighbour classifiers-A Tutorial. *ACM computing surveys (CSUR),* 54**,** 1-25.

CZAJA, S., BEACH, S., CHARNESS, N. & SCHULZ, R. 2013. Older adults and the adoption of healthcare technology: Opportunities and challenges. *Technologies for active aging***,** 27-46.

CZAJA, S. J., BOOT, W. R., CHARNESS, N., ROGERS, W. A. & SHARIT, J. 2018. Improving social support for older adults through technology: Findings from the PRISM randomized controlled trial. *The Gerontologist,* 58**,** 467-477.

DALGAARD, L. G., GRöNVALL, E. & VERDEZOTO, N. MediFrame: a tablet application to plan, inform, remind and sustain older adults' medication intake. 2013 IEEE International Conference on Healthcare Informatics, 2013. IEEE, 36-45.

DALIGADU, J., POLLOCK, C. L., CARLAW, K., CHIN, M., HAYNES, A., THEVARAAJAH KOPAL, T., TAHSINUL, A., WALTERS, K. & COLELLA, T. J. 2018. Validation of the Fitbit Flex in an acute post–cardiac surgery patient Population. *Physiotherapy Canada,* 70**,** 314-320.

DALLAS, G. 2013. *Principal Component Analysis 4 Dummies: Eigenvectors, Eigenvalues and Dimension Reduction* [Online]. Available: https://georgemdallas.wordpress.com/2013/10/30/principal-component-analysis-4-dummies-eigenvectors-eigenvalues-and-dimension-reduction/ [Accessed March 21, 2023 2023].

DANCEY, C. P. & REIDY, J. 2007. *Statistics without maths for psychology*, Pearson education.

DANG, S., KARANAM, C. & GóMEZ-MARíN, O. 2017. Outcomes of a mobile phone intervention for heart failure in a minority county hospital population. *Telemedicine and e-Health,* 23**,** 473-484.

DE MARCHI, F., LOPES, S. & PETIT, J.-M. Efficient algorithms for mining inclusion dependencies. Advances in Database Technology—EDBT 2002: 8th International Conference on Extending Database Technology Prague, Czech Republic, March 25–27, 2002 Proceedings 8, 2002. Springer, 464-476.

DECI, E. L., EGHRARI, H., PATRICK, B. C. & LEONE, D. R. 1994. Facilitating internalization: The self-determination theory perspective. *Journal of personality,* 62**,** 119-142.

DELIAS, P., DOUMPOS, M., GRIGOROUDIS, E., MANOLITZAS, P. & MATSATSINIS, N. 2015. Supporting healthcare management decisions via robust clustering of event logs. *Knowledge-Based Systems,* 84**,** 203-213.

DEMARK-WAHNEFRIED, W., SCHMITZ, K. H., ALFANO, C. M., BAIL, J. R., GOODWIN, P. J., THOMSON, C. A., BRADLEY, D. W., COURNEYA, K. S., BEFORT, C. A. & DENLINGER, C. S. 2018. Weight management and physical activity throughout the cancer care continuum. *CA: a cancer journal for clinicians,* 68**,** 64-89.

DENNISON, L., MORRISON, L., CONWAY, G. & YARDLEY, L. 2013. Opportunities and challenges for smartphone applications in supporting health behavior change: qualitative study. *Journal of medical Internet research,* 15**,** e2583.

DEVORE, A. D., WOSIK, J. & HERNANDEZ, A. F. 2019. The future of wearables in heart failure patients. *JACC: Heart failure,* 7**,** 922-932.

DICARLO, L., MOON, G., INTONDI, A., DUCK, R., FRANK, J., HAFAZI, H., BEHZADI, Y., ROBERTSON, T., COSTELLO, B. & SAVAGE, G. 2012. A digital health solution for using and managing medications: wirelessly observed therapy. *IEEE pulse,* 3**,** 23-26.

DINSMORE, J., HANNIGAN, C., SMITH, S., MURPHY, E., KUIPER, J. M., O'BYRNE, E., GALVIN, M., JACOBS, A., SMITT, M. S. & VAN LEEUWEN, C. 2021. A Digital Health Platform for Integrated and Proactive Patient-Centered Multimorbidity Self-management and Care (ProACT): Protocol for an Action Research Proof-of-Concept Trial. *JMIR research protocols,* 10**,** e22125.

DOBSON, R., WHITTAKER, R., JIANG, Y., MADDISON, R., SHEPHERD, M., MCNAMARA, C., CUTFIELD, R., KHANOLKAR, M. & MURPHY, R. 2018. Effectiveness of text message based, diabetes self management support programme (SMS4BG): two arm, parallel randomised controlled trial. *Bmj,* 361.

DöĞER, E., BOZBULUT, R., ACAR, A. Ş. S., ERCAN, Ş., UĞURLU, A. K., AKBAŞ, E. D., BIDECI, A., ÇAMURDAN, O. & CINAZ, P. 2019. Effect of telehealth system on glycemic control in children and adolescents with type 1 diabetes. *Journal of clinical research in pediatric endocrinology,* 11**,** 70.

DONDERS, A. R. T., VAN DER HEIJDEN, G. J., STIJNEN, T. & MOONS, K. G. 2006. A gentle introduction to imputation of missing values. *Journal of clinical epidemiology,* 59**,** 1087-1091.

DONTJE, M. L., VAN DER WAL, M. H., STOLK, R. P., BRüGEMANN, J., JAARSMA, T., WIJTVLIET, P. E., VAN DER SCHANS, C. P. & DE GREEF, M. H. 2014. Daily physical activity in stable heart failure patients. *Journal of Cardiovascular Nursing,* 29**,** 218-226.

DOULAMIS, N. Iterative motion estimation constrained by time and shape for detecting persons' falls. Proceedings of the 3rd International Conference on PErvasive Technologies Related to Assistive Environments, 2010. 1-8.

DOYLE, J., MCALEER, P., VAN LEEUWEN, C., SMITH, S., MURPHY, E., SILLEVIS SMITT, M., GALVIN, M., JACOBS, A., TOMPKINS, L. & SHEERIN, J. 2022. The role of phone-based triage nurses in supporting older adults with multimorbidity to digitally self-manage–Findings from the ProACT proof-of-concept study. *Digital health,* 8**,** 20552076221131140.

DOYLE, J., MURPHY, E., GAVIN, S., PASCALE, A., DEPARIS, S., TOMMASI, P., SMITH, S., HANNIGAN, C., SMITT, M. S. & VAN LEEUWEN, C. 2021. A digital platform to support self-management of multiple chronic conditions (ProACT): Findings in relation to engagement during a one-year proof-of-concept trial. *Journal of medical Internet research,* 23**,** e22672.

DOYLE, J., MURPHY, E., HANNIGAN, C., SMITH, S., BETTENCOURT-SILVA, J. & DINSMORE, J. Designing digital goal support systems for multimorbidity self-management: insights from older adults and their care network. Proceedings of the 12th EAI International Conference on Pervasive Computing Technologies for Healthcare, 2018. 168-177.

DOYLE, J., MURPHY, E., KUIPER, J., SMITH, S., HANNIGAN, C., JACOBS, A. & DINSMORE, J. Managing Multimorbidity: Identifying Design Requirements for a Digital Self-Management Tool to Support Older Adults with Multiple Chronic Conditions. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 2019. 1-14.

DOYLE, J., MURPHY, E., SMITH, S., HANNIGAN, C., KUIPER, J., JACOBS, A. & DINSMORE, J. Addressing medication management for older people with multimorbidities: a multi-stakeholder approach. Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare, 2017. 78-87.

DURICK, J., ROBERTSON, T., BRERETON, M., VETERE, F. & NANSEN, B. Dispelling ageing myths in technology design. Proceedings of the 25th Australian Computer-Human Interaction Conference: Augmentation, Application, Innovation, Collaboration, 2013. 467-476.

EBERLE, C. & STICHLING, S. 2021. Clinical improvements by telemedicine interventions managing type 1 and type 2 diabetes: systematic meta-review. *Journal of medical Internet research,* 23**,** e23244.

EBERLY, L. E. 2007. Multiple linear regression. *Topics in Biostatistics***,** 165-187.

ECHEVARRIA, C., STEER, J., WASON, J. & BOURKE, S. 2021. Oxygen therapy and inpatient mortality in COPD exacerbation. *Emergency Medicine Journal,* 38**,** 170-177.

EFFING, T. W., BOURBEAU, J., VERCOULEN, J., APTER, A. J., COULTAS, D., MEEK, P., VALK, P. V. D., PARTRIDGE, M. R. & PALEN, J. V. D. 2012. Self-management programmes for COPD: moving forward. *Chronic respiratory disease,* 9**,** 27-35.

EISNER, E., DRAKE, R. J., BERRY, N., BARROWCLOUGH, C., EMSLEY, R., MACHIN, M. & BUCCI, S. 2019. Development and long-term acceptability of ExPRESS, a mobile phone app to monitor basic symptoms and early signs of psychosis relapse. *JMIR mHealth and uHealth,* 7**,** e11568.

EKSTEDT, M., KIRSEBOM, M., LINDQVIST, G., KNECK, Å., FRYKHOLM, O., FLINK, M. & WANNHEDEN, C. 2021. Design and development of an eHealth service for collaborative self-management among older adults with chronic diseases: a theory-driven user-centered approach. *International Journal of Environmental Research and Public Health,* 19**,** 391.

EL MORR, C., ALI-HASSAN, H., EL MORR, C. & ALI-HASSAN, H. 2019. Descriptive, predictive, and prescriptive analytics. *Analytics in healthcare: a practical introduction***,** 31-55.

ELBAEVA, A. D., ELBAEVA, R. I., SENOV, K. M., BOLGOV, Y. V. & ELBAEV, A. D. Automatic Blood Glucometer-Tonometer to Control Diabetes Mellitus. 2019 International Conference" Quality Management, Transport and Information Security, Information Technologies"(IT&QM&IS), 2019. IEEE, 330-332.

ELBATTAH, M. & MOLLOY, O. Data-Driven patient segmentation using K-Means clustering: the case of hip fracture care in Ireland. Proceedings of the Australasian Computer Science Week Multiconference, 2017. 1-8.

ELIAN, A., SADA, N., ELFADEL, I., SAEED, M. & SHABRA, A. A preliminary evaluation of continuous, shoe-integrated weight measurements for heart failure patients. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016. IEEE, 4768-4771.

ERHUNMWUNSEE, L., BHANDARI, P., SOSA, E., SUR, M., ITUARTE, P. & LUI, N. S. 2020. Socioeconomic, rural, and insurance-based inequities in robotic lung cancer resections. *Video-Assist Thorac Surg,* 5**,** 13.

EUROPEAN COMMISSION. 2018. *Overview of eHealth : Digital health and care* [Online]. Available: https://health.ec.europa.eu/ehealth-digital-health-and-care/overview_en#communication [Accessed Sep 6, 2023 2023].

EUROPEAN COMMISSION. 2021. *Cost of Non-Communicable Diseases in the EU* [Online]. Available: https://knowledge4policy.ec.europa.eu/health-promotion-knowledge-gateway/cost-non-communicable-diseases-eu_en#:~:text=CVD%20cost%20EU%20health%20care%20systems%20almost%20%E2%82%AC111,than%20%E2%82%AC20%20billion%20due%20to%20stroke%20%28EHN%202017%29. [Accessed Oct 20th 2023].

FANNING, J., BROOKS, A. K., IP, E., NICKLAS, B. J., REJESKI, W. J., NESBIT, B. & FORD, S. 2020. A mobile health behavior intervention to reduce pain and improve health in older adults with obesity and chronic pain: the MORPH pilot trial. *Frontiers in digital health,* 2**,** 598456.

FARAWAY, J. J. 2002. *Practical regression and ANOVA using R*, University of Bath Bath.

FARWATI, M., RIAZ, H. & TANG, W. 2021. Digital health applications in heart failure: a critical appraisal of literature. *Current Treatment Options in Cardiovascular Medicine,* 23**,** 1-11.

FAUX-NIGHTINGALE, A., PHILP, F., CHADWICK, D., SINGH, B. & PANDYAN, A. 2022. Available tools to evaluate digital health literacy and engagement with eHealth resources: A scoping review. *Heliyon*.

FAYYAD, U., PIATETSKY-SHAPIRO, G. & SMYTH, P. 1996. The KDD process for extracting useful knowledge from volumes of data. *Communications of the ACM,* 39**,** 27-34.

FEIJT, M. A., DE KORT, Y. A., BONGERS, I. M. & IJSSELSTEIJN, W. A. 2018. Perceived drivers and barriers to the adoption of eMental health by psychologists: the construction of the levels of adoption of eMental health model. *Journal of medical Internet research,* 20**,** e153.

FINK, E. L. 2009. The FAQs on data transformation. *Communication Monographs,* 76**,** 379-397.
FISCHER, J. E., YEE, N., BELLOTTI, V., GOOD, N., BENFORD, S. & GREENHALGH, C. Effects of content and time of delivery on receptivity to mobile interruptions. Proceedings of the 12th international conference on Human computer interaction with mobile devices and services, 2010. 103-112.
FLOCKE, S. A. & STANGE, K. C. 2004. Direct observation and patient recall of health behavior advice. *Preventive medicine,* 38**,** 343-349.
FLODGREN, G., RACHAS, A., FARMER, A. J., INZITARI, M. & SHEPPERD, S. 2015. Interactive telemedicine: effects on professional practice and health care outcomes. *Cochrane Database of Systematic Reviews*.
FOGG, B. J. A behavior model for persuasive design. Proceedings of the 4th international Conference on Persuasive Technology, 2009. 1-7.
FORSTER, A. J., MURFF, H. J., PETERSON, J. F., GANDHI, T. K. & BATES, D. W. 2003. The incidence and severity of adverse events affecting patients after discharge from the hospital. *Annals of internal medicine,* 138**,** 161-167.
FORTIN, M., LAPOINTE, L., HUDON, C., VANASSE, A., NTETU, A. L. & MALTAIS, D. 2004. Multimorbidity and quality of life in primary care: a systematic review. *Health and Quality of life Outcomes,* 2**,** 1-12.
FORTUNA, K. L., BROOKS, J. M., UMUCU, E., WALKER, R. & CHOW, P. I. 2019. Peer support: A human factor to enhance engagement in digital health behavior change interventions. *Journal of Technology in Behavioral Science,* 4**,** 152-161.
FRANCE, E. F., WYKE, S., GUNN, J. M., MAIR, F. S., MCLEAN, G. & MERCER, S. W. 2012. Multimorbidity in primary care: a systematic review of prospective cohort studies. *British Journal of General Practice,* 62**,** e297-e307.
FRAZE, T., JIANG, H. J. & BURGESS, J. 2011. Hospital stays for patients with diabetes, 2008: Statistical Brief# 93.
FRIE, K., HARTMANN-BOYCE, J., JEBB, S., OKE, J. & AVEYARD, P. 2020. Patterns in Weight and Physical Activity Tracking Data Preceding a Stop in Weight Monitoring: Observational Analysis. *Journal of medical Internet research,* 22**,** e15790.
FRIEDMAN, N. & GOLDSZMIDT, M. Discretizing continuous attributes while learning Bayesian networks. ICML, 1996. 157-165.
FUKUOKA, Y., GAY, C. L., JOINER, K. L. & VITTINGHOFF, E. 2015. A novel diabetes prevention intervention using a mobile app: a randomized controlled trial with overweight adults at risk. *American journal of preventive medicine,* 49**,** 223-237.
FUKUOKA, Y., LINDGREN, T. & JONG, S. 2012. Qualitative exploration of the acceptability of a mobile phone and pedometer‐based physical activity program in a diverse sample of sedentary women. *Public Health Nursing,* 29**,** 232-240.
GAL, M. S. & RUBINFELD, D. L. 2019. Data standardization. *NYUL Rev.,* 94**,** 737.
GARCIA, S., LUENGO, J., SáEZ, J. A., LOPEZ, V. & HERRERA, F. 2012. A survey of discretization techniques: Taxonomy and empirical analysis in supervised learning. *IEEE transactions on Knowledge and Data Engineering,* 25**,** 734-750.
GARG, S. K., LYLES, C. R., ACKERMAN, S., HANDLEY, M. A., SCHILLINGER, D., GOURLEY, G., AULAKH, V. & SARKAR, U. 2015. Qualitative analysis of programmatic initiatives to text patients with mobile devices in resource-limited health systems. *BMC medical informatics and decision making,* 16**,** 1-12.
GATWOOD, J., SHUVO, S., ROSS, A., RIORDAN, C., SMITH, P., GUTIERREZ, M. L., CODAY, M. & BAILEY, J. 2020. The Management of Diabetes in Everyday Life (MODEL) program: development of a tailored text message intervention to improve diabetes self-care activities among underserved African-American adults. *Translational Behavioral Medicine,* 10**,** 204-212.

GELLIS, Z. D., KENALEY, B. L. & HAVE, T. T. 2014. Integrated telehealth care for chronic illness and depression in geriatric home care patients: The integrated telehealth education and activation of mood (I‐TEAM) Study. *Journal of the American Geriatrics Society,* 62**,** 889-895.
GGPLOT2. 2023. *ggplot2* [Online]. Available: https://ggplot2.tidyverse.org/index.html [Accessed Sep 23, 2023 2023].
GIVERTZ, M. M., STEVENSON, L. W., COSTANZO, M. R., BOURGE, R. C., BAUMAN, J. G., GINN, G., ABRAHAM, W. T. & INVESTIGATORS, C. T. 2017. Pulmonary artery pressure-guided management of patients with heart failure and reduced ejection fraction. *Journal of the American College of Cardiology,* 70**,** 1875-1886.
GJEKA, R., PATEL, K., REDDY, C. & ZETSCHE, N. 2021. Patient engagement with digital disease management and readmission rates: the case of congestive heart failure. *Health Informatics Journal,* 27**,** 14604582211030959.
GOLSTEIJN, R. H., PEELS, D. A., EVERS, S. M., BOLMAN, C., MUDDE, A. N., DE VRIES, H. & LECHNER, L. 2014. Cost-effectiveness and cost-utility of a Web-based or print-delivered tailored intervention to promote physical activity among adults aged over fifty: an economic evaluation of the Active Plus intervention. *International Journal of Behavioral Nutrition and Physical Activity,* 11**,** 1-17.
GOMES, R. D. S., BARBOSA, A. R., MENEGHINI, V., CONFORTIN, S. C., D'ORSI, E. & RECH, C. R. 2020. Association between chronic diseases, multimorbidity and insufficient physical activity among older adults in southern Brazil: a cross-sectional study. *Sao Paulo Medical Journal,* 138**,** 545-553.
GOODFELLOW, D., ZHI, R., FUNKE, R., PULIDO, J. C., MATARIC, M. & SMITH, B. A. 2018. Predicting infant motor development status using day long movement data from wearable sensors. *arXiv preprint arXiv:1807.02617*.
GRAHAM, S., IRVING, J., CANO, I. & EDWARDS, M. 2018. Participation with online recovery specific groups-findings from the UK Life in Recovery survey 2015. *Alcoholism Treatment Quarterly,* 36**,** 459-481.
GREENWALD, P., STERN, M. E., CLARK, S. & SHARMA, R. 2018. Older adults and technology: in telehealth, they may not be who you think they are. *International journal of emergency medicine,* 11**,** 1-4.
GROENEWEGEN, A., RUTTEN, F. H., MOSTERD, A. & HOES, A. W. 2020. Epidemiology of heart failure. *European journal of heart failure,* 22**,** 1342-1356.
GRöNVALL, E. & VERDEZOTO, N. Beyond self-monitoring: understanding non-functional aspects of home-based healthcare technology. Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing, 2013. 587-596.
GUPTA, A., SHARMA, A. & GOEL, A. 2017. Review of regression analysis models. *Int. J. Eng. Res. Technol,* 6**,** 58-61.
GUROVICH, Y., HANANI, Y., BAR, O., NADAV, G., FLEISCHER, N., GELBMAN, D., BASEL-SALMON, L., KRAWITZ, P. M., KAMPHAUSEN, S. B. & ZENKER, M. 2019. Identifying facial phenotypes of genetic disorders using deep learning. *Nature medicine,* 25**,** 60-64.
GUSTAFSON, D. H., MCTAVISH, F., MAHONEY, J. E., JOHNSON, R. A., LEE, J. D., QUANBECK, A., ATWOOD, A. K., ISHAM, A., VEERAMANI, R. & CLEMSON, L. 2015. The effect of an information and communication technology (ICT) on older adults' quality of life: study protocol for a randomized control trial. *Trials,* 16**,** 1-12.
GUSTAFSON, D. H., MCTAVISH, F. M., CHIH, M.-Y., ATWOOD, A. K., JOHNSON, R. A., BOYLE, M. G., LEVY, M. S., DRISCOLL, H., CHISHOLM, S. M. & DILLENBURG, L. 2014. A smartphone application to support recovery from alcoholism: a randomized clinical trial. *JAMA psychiatry,* 71**,** 566-572.
GUSTAFSON SR, D. H., KORNFIELD, R., MARES, M.-L., JOHNSTON, D. C., CODY, O. J., YANG, E. F., GUSTAFSON JR, D. H., HWANG, J., MAHONEY, J. E. & CURTIN, J. J. 2022. Effect of an eHealth

intervention on older adults' quality of life and health-related outcomes: a randomized clinical trial. *Journal of general internal medicine,* 37**,** 521-530.
HAGGERTY, J. L. 2012. Ordering the chaos for patients with multimorbidity. British Medical Journal Publishing Group.
HAIJUN, X., FANG, P., LING, W. & HONGWEI, L. Ad hoc-based feature selection and support vector machine classifier for intrusion detection. 2007 IEEE International Conference on Grey Systems and Intelligent Services, 2007. IEEE, 1117-1121.
HAKOBYAN, L., LUMSDEN, J., SHAW, R. & O'SULLIVAN, D. A longitudinal evaluation of the acceptability and impact of a diet diary app for older adults with age-related macular degeneration. Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services, 2016. 124-134.
HALL, S., SATTAR, S., AHMED, S. & HAASE, K. R. Exploring perceptions of technology use to support self-management among older adults with cancer and multimorbidities. Seminars in oncology nursing, 2021. Elsevier, 151228.
HAMIDEH, D. & NEBEKER, C. 2020. The digital health landscape in addiction and substance use research: will digital health exacerbate or mitigate health inequities in vulnerable populations? *Current Addiction Reports,* 7**,** 317-332.
HANSEN, A. H., BRADWAY, M., BROZ, J., CLAUDI, T., HENRIKSEN, Ø., WANGBERG, S. C. & ÅRSAND, E. 2019. Inequalities in the use of eHealth between socioeconomic groups among patients with type 1 and type 2 diabetes: cross-sectional study. *Journal of medical Internet research,* 21**,** e13615.
HARDINGE, M., RUTTER, H., VELARDO, C., SHAH, S. A., WILLIAMS, V., TARASSENKO, L. & FARMER, A. 2015. Using a mobile health application to support self-management in chronic obstructive pulmonary disease: a six-month cohort study. *BMC medical informatics and decision making,* 15**,** 1-10.
HARJUMAA, M., HALTTU, K., KOISTINEN, K. & OINAS-KUKKONEN, H. User experience of mobile coaching for stress-management to tackle prevalent health complaints. Scandinavian Conference on Information Systems, 2015. Springer, 152-164.
HARRISON, S., ROBERTSON, N., GRAHAM, C., WILLIAMS, J., STEINER, M., MORGAN, M. & SINGH, S. J. 2014. Can we identify patients with different illness schema following an acute exacerbation of COPD: a cluster analysis. *Respiratory medicine,* 108**,** 319-328.
HAWKINS, R. P., KREUTER, M., RESNICOW, K., FISHBEIN, M. & DIJKSTRA, A. 2008. Understanding tailoring in communicating about health. *Health education research,* 23**,** 454-466.
HAZRA, N. C., RUDISILL, C. & GULLIFORD, M. C. 2018. Determinants of health care costs in the senior elderly: age, comorbidity, impairment, or proximity to death? *The European journal of health economics,* 19**,** 831-842.
HE, Z., BIAN, J., CARRETTA, H. J., LEE, J., HOGAN, W. R., SHENKMAN, E. & CHARNESS, N. 2018. Prevalence of multiple chronic conditions among older adults in Florida and the United States: comparative analysis of the OneFlorida data trust and national inpatient sample. *Journal of Medical Internet Research,* 20**,** e8961.
HEART, T. & KALDERON, E. 2013. Older adults: are they ready to adopt health-related ICT? *International journal of medical informatics,* 82**,** e209-e231.
HEERDEN, A. V., TOMLINSON, M. & SWARTZ, L. 2012. Point of care in your pocket: a research agenda for the field of m-health. *Bulletin of the World Health Organization,* 90**,** 393-394.
HEISE, A., QUIANé-RUIZ, J.-A., ABEDJAN, Z., JENTZSCH, A. & NAUMANN, F. 2013. Scalable discovery of unique column combinations. *Proceedings of the VLDB Endowment,* 7**,** 301-312.
HELLERSTEIN, J. M. 2008. Quantitative data cleaning for large databases. *United Nations Economic Commission for Europe (UNECE),* 25**,** 1-42.
HERPICH, M., RIST, T. & ANDRé, E. Co-designing a recommender system for the elderly. Proceedings of the 10th international conference on pervasive technologies related to assistive environments, 2017a. 52-55.

HERPICH, M., RIST, T., SEIDERER, A. & ANDRé, E. Towards a gamified recommender system for the elderly. Proceedings of the 2017 International Conference on Digital Health, 2017b. 211-215.
HIGHTON-WILLIAMSON, E., PRIEBE, S. & GIACCO, D. 2015. Online social networking in people with psychosis: a systematic review. *International Journal of Social Psychiatry,* 61**,** 92-101.
HOLMEN, H., TORBJøRNSEN, A., WAHL, A. K., JENUM, A. K., SMåSTUEN, M. C., ÅRSAND, E. & RIBU, L. 2014. A mobile health intervention for self-management and lifestyle change for persons with type 2 diabetes, part 2: one-year results from the Norwegian randomized controlled trial RENEWING HEALTH. *JMIR mHealth and uHealth,* 2**,** e3882.
HUCH, M. & STRESE, H. 2005. Ambient Assisted Living-Preparing an Article 169 Measure. *MST NEWS,* 5**,** 8.
HUNTING, G., SHAHID, N., SAHAKYAN, Y., FAN, I., MONEYPENNY, C. R., STANIMIROVIC, A., NORTH, T., PETROSYAN, Y., KRAHN, M. D. & RAC, V. E. 2015. A multi-level qualitative analysis of Telehomecare in Ontario: challenges and opportunities. *BMC health services research,* 15**,** 1-15.
INAMDAR, A. A. & INAMDAR, A. C. 2016. Heart failure: diagnosis, management and utilization. *Journal of clinical medicine,* 5**,** 62.
ISLAM, M. S., LIU, D., WANG, K., ZHOU, P., YU, L. & WU, D. A case study of healthcare platform using big data analytics and machine learning. Proceedings of the 2019 3rd High Performance Computing and Cluster Technologies Conference, 2019. 139-146.
ISLAM, S. M. S., LECHNER, A., FERRARI, U., FROESCHL, G., ALAM, D. S., HOLLE, R., SEISSLER, J. & NIESSEN, L. W. 2014. Mobile phone intervention for increasing adherence to treatment for type 2 diabetes in an urban area of Bangladesh: protocol for a randomized controlled trial. *BMC health services research,* 14**,** 1-9.
ISMAIL, A., ABDLERAZEK, S. & EL-HENAWY, I. M. 2020. Development of smart healthcare system based on speech recognition using support vector machine and dynamic time warping. *Sustainability,* 12**,** 2403.
IYENGAR, V., WOLF, A., BROWN, A. & CLOSE, K. 2016. Challenges in diabetes care: can digital health help address them? *Clinical Diabetes,* 34**,** 133-141.
JADHAV, A., PRAMOD, D. & RAMANATHAN, K. 2019. Comparison of performance of data imputation methods for numeric dataset. *Applied Artificial Intelligence,* 33**,** 913-933.
JAIN, A. K. & DUBES, R. C. 1988. *Algorithms for clustering data*, Prentice-Hall, Inc.
JAMES, G., WITTEN, D., HASTIE, T. & TIBSHIRANI, R. 2013. *An introduction to statistical learning*, Springer.
JARMAN, A. M. 2020. Hierarchical cluster analysis: Comparison of single linkage, complete linkage, average linkage and centroid linkage method. *Georgia Southern University*.
JARVIS, M.-A., SARTORIUS, B. & CHIPPS, J. 2020. Technology acceptance of older persons living in residential care. *Information Development,* 36**,** 339-353.
JIAN, A. K. 2009. Data Clustering: 50 Years beyond K-Means, Pattern Recognition Letters. *Corrected Proof*.
JIANG, S., FANG, S., BLOOMQUIST, S., KEIPER, J., PALAKAL, M. J., XIA, Y. & GRANNIS, S. J. Healthcare Data Visualization: Geospatial and Temporal Integration. VISIGRAPP (2: IVAPP), 2016. 214-221.
JIAWEI, H., MICHELINE, K. & JIAN, P. 2016. *Data mining concepts and techniques (3rd Edition)*.
JOHN P. CUNHA. 2021. *What Is a Good Oxygen Rate by Age?* [Online]. Available: https://www.emedicinehealth.com/what_is_a_good_oxygen_rate_by_age/article_em.htm [Accessed September 20, 2022 2022].
JOLLIFFE, I. 2005. Principal component analysis. *Encyclopedia of statistics in behavioral science*.
JONES, J. R., KARAHALIOS, A., PUTHUCHEARY, Z. A., BERRY, M. J., FILES, D. C., GRIFFITH, D. M., MCDONALD, L. A., MORRIS, P. E., MOSS, M. & NORDON-CRAFT, A. 2023. Responsiveness of Critically Ill Adults With Multimorbidity to Rehabilitation Interventions: A Patient-Level

Meta-Analysis Using Individual Pooled Data From Four Randomized Trials. *Critical Care Medicine*, 10.1097.

JOUBERT, M., BENHAMOU, P.-Y., SCHAEPELYNCK, P., HANAIRE, H., CATARGI, B., FARRET, A., FONTAINE, P., GUERCI, B., REZNIK, Y. & JEANDIDIER, N. 2019. Remote monitoring of diabetes: a cloud-connected digital system for individuals with diabetes and their health care providers. *Journal of diabetes science and technology,* 13**,** 1161-1168.

KADAM, V. S., KANHERE, S. & MAHINDRAKAR, S. 2020. Regression techniques in machine learning &applications: a review. *International Journal for Research in Applied Science and Engineering Technology,* 8**,** 826-830.

KAMBHATLA, N. & LEEN, T. K. 1997. Dimension reduction by local principal component analysis. *Neural computation,* 9**,** 1493-1516.

KAMEI, T., KANAMORI, T., YAMAMOTO, Y. & EDIRIPPULIGE, S. 2020. The use of wearable devices in chronic disease management to enhance adherence and improve telehealth outcomes: A systematic review and meta-analysis. *J Telemed Telecare***,** 1357633X20937573.

KANJO, E., YOUNIS, E. M. & ANG, C. S. 2019. Deep learning analysis of mobile physiological, environmental and location sensor data for emotion detection. *Information Fusion,* 49**,** 46-56.

KANNISTO, K. A., KORHONEN, J., ADAMS, C. E., KOIVUNEN, M. H., VAHLBERG, T. & VäLIMäKI, M. A. 2017. Factors associated with dropout during recruitment and follow-up periods of a mHealth-based randomized controlled trial for Mobile. Net to encourage treatment adherence for people with serious mental health problems. *Journal of medical Internet research,* 19**,** e6417.

KAPLAN, A. L., COHEN, E. R. & ZIMLICHMAN, E. 2017. Improving patient engagement in self-measured blood pressure monitoring using a mobile health technology. *Health information science and systems,* 5**,** 1-9.

KAPPEN, D. L., MIRZA-BABAEI, P. & NACKE, L. E. Gamification through the application of motivational affordances for physical activity technology. Proceedings of the Annual Symposium on Computer-Human Interaction in Play, 2017. 5-18.

KARAVIDAS, M., LIM, N. K. & KATSIKAS, S. L. 2005. The effects of computers on older adult users. *Computers in human behavior,* 21**,** 697-711.

KARIO, K. 2020. Management of hypertension in the digital era: small wearable monitoring devices for remote blood pressure monitoring. *Hypertension,* 76**,** 640-650.

KATSIS, Y., BALAC, N., CHAPMAN, D., KAPOOR, M., BLOCK, J., GRISWOLD, W. G., HUANG, J., KOULOURIS, N., MENARINI, M. & NANDIGAM, V. Big data techniques for public health: a case study. 2017 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), 2017. IEEE, 222-231.

KAUR, M. & GARG, S. K. 2014. Survey on clustering techniques in data mining for software engineering. *International Journal of Advanced and Innovative Research,* 3**,** 238-243.

KAVAKIOTIS, I., TSAVE, O., SALIFOGLOU, A., MAGLAVERAS, N., VLAHAVAS, I. & CHOUVARDA, I. 2017. Machine learning and data mining methods in diabetes research. *Computational and structural biotechnology journal,* 15**,** 104-116.

KEIM, D. A., HAO, M. C., DAYAL, U., JANETZKO, H. & BAK, P. 2010. Generalized scatter plots. *Information Visualization,* 9**,** 301-311.

KELDERS, S. M., BOHLMEIJER, E. T. & VAN GEMERT-PIJNEN, J. E. 2013. Participants, usage, and use patterns of a web-based intervention for the prevention of depression within a randomized controlled trial. *Journal of medical Internet research,* 15**,** e2258.

KESAVARAJ, G. & SUKUMARAN, S. A study on classification techniques in data mining. 2013 fourth international conference on computing, communications and networking technologies (ICCCNT), 2013. IEEE, 1-7.

KHAN, A., MUKHTAR, H., AHMAD, H. F., GONDAL, M. A. & ILYAS, Q. M. Improving usability through enhanced visualization in healthcare. 2017 IEEE 13th International Symposium on Autonomous Decentralized System (ISADS), 2017. IEEE, 39-44.

KHAN, M. & KHAN, S. S. 2011. Data and information visualization methods, and interactive mechanisms: A survey. *International Journal of Computer Applications,* 34**,** 1-14.

KIM, S. & CHOUDHURY, A. 2020. Comparison of older and younger adults' attitudes toward the adoption and use of activity trackers. *JMIR mHealth and uHealth,* 8**,** e18312.

KIM, S. H. & UTZ, S. 2019. Effectiveness of a social media–based, health literacy–sensitive diabetes self‐management intervention: a randomized controlled trial. *Journal of Nursing Scholarship,* 51**,** 661-669.

KIM, S. S. & MALHOTRA, N. K. 2005. A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. *Management science,* 51**,** 741-755.

KINCADE, K. 1998. Data mining: digging for healthcare gold. *Insurance & Technology,* 23**,** 2-7.

KIRWAN, M., VANDELANOTTE, C., FENNING, A. & DUNCAN, M. J. 2013. Diabetes self-management smartphone application for adults with type 1 diabetes: randomized controlled trial. *J Med Internet Res,* 15**,** e235.

KITT, J., FOX, R. & TUCKER, K. L. 2020. Digital health: new approaches in hypertension management. *Journal of Cardiology and Cardiovascular Sciences,* 4.

KLASNJA, P., KENDALL, L., PRATT, W. & BLONDON, K. Long-term engagement with health-management technology: a dynamic process in diabetes. AMIA Annual Symposium Proceedings, 2015. American Medical Informatics Association, 756.

KLASNJA, P. & PRATT, W. 2012. Healthcare in the pocket: mapping the space of mobile-phone health interventions. *J Biomed Inform,* 45**,** 184-98.

KLONOFF, D. C. & KERR, D. 2018. Overcoming barriers to adoption of digital health tools for diabetes. SAGE Publications Sage CA: Los Angeles, CA.

KOH, H. C. & TAN, G. 2011. Data mining applications in healthcare. *Journal of healthcare information management,* 19**,** 65.

KOLLER, D., SCHöN, G., SCHäFER, I., GLAESKE, G., VAN DEN BUSSCHE, H. & HANSEN, H. 2014. Multimorbidity and long-term care dependency—a five-year follow-up. *BMC geriatrics,* 14**,** 1-9.

KöNIG, T., PIGLIAUTILE, M., ÁGUILA, O., ARAMBARRI, J., CHRISTOPHOROU, C., COLOMBO, M., CONSTANTINIDES, A., CURIA, R., DANKL, K. & HANKE, S. 2022. User experience and acceptance of a device assisting persons with dementia in daily life: a multicenter field study. *Aging clinical and experimental research,* 34**,** 869-879.

KREBS, P., PROCHASKA, J. O. & ROSSI, J. S. 2010. A meta-analysis of computer-tailored interventions for health behavior change. *Preventive medicine,* 51**,** 214-221.

KREUTER, M. W., OSWALD, D. L., BULL, F. C. & CLARK, E. M. 2000. Are tailored health education materials always more effective than non-tailored materials? *Health education research,* 15**,** 305-315.

KRUSE, C. S., ATKINS, J. M., BAKER, T. D., GONZALES, E. N., PAUL, J. L. & BROOKS, M. 2018. Factors influencing the adoption of telemedicine for treatment of military veterans with post-traumatic stress disorder.

KRUSKAL, J. B. & WISH, M. 1978. *Multidimensional scaling*, Sage.

KUMBHARE, T. A. & CHOBE, S. V. 2014. An overview of association rule mining algorithms. *International Journal of Computer Science and Information Technologies,* 5**,** 927-930.

KUSUMASARI, T. F. Data profiling for data quality improvement with OpenRefine. 2016 international conference on information technology systems and innovation (ICITSI), 2016. IEEE, 1-6.

LABOVITZ, D. L., SHAFNER, L., REYES GIL, M., VIRMANI, D. & HANINA, A. 2017. Using artificial intelligence to reduce the risk of nonadherence in patients on anticoagulation therapy. *Stroke,* 48**,** 1416-1419.

LAING, B. Y., MANGIONE, C. M., TSENG, C.-H., LENG, M., VAISBERG, E., MAHIDA, M., BHOLAT, M., GLAZIER, E., MORISKY, D. E. & BELL, D. S. 2014. Effectiveness of a smartphone application for weight loss compared with usual care in overweight primary care patients: a randomized, controlled trial. *Annals of internal medicine,* 161**,** S5-S12.

LAKSHMANAN, M. 2014. Histogram and vertical bar diagram: Often misapprehended concept. *Cardiovascular drugs and therapy,* 28**,** 387-387.

LAWTON, G. 2022. *logistic regression* [Online]. Available: https://www.techtarget.com/searchbusinessanalytics/definition/logistic-regression [Accessed Apr 21, 2023 2023].

LEE, H. Y., KIM, J. Y., NA, K. Y., PARK, H. Y., HAN, J., PAK, Y., NAM, B., PAE, C. H., LEE, J. & LIM, T. H. 2019. The role of telehealth counselling with mobile self-monitoring on blood pressure reduction among overseas Koreans with high blood pressure in Vietnam. *Journal of telemedicine and telecare,* 25**,** 241-248.

LEE, J.-A., EVANGELISTA, L. S., MOORE, A. A., JUTH, V., GUO, Y., GAGO-MASAGUE, S., LEM, C. G., NGUYEN, M., KHATIBI, P. & BAJE, M. 2016. Feasibility study of a mobile health intervention for older adults on oral anticoagulation therapy. *Gerontology and Geriatric Medicine,* 2**,** 2333721416672970.

LEE, J. A., LENDASSE, A. & VERLEYSEN, M. 2004. Nonlinear projection with curvilinear distances: Isomap versus curvilinear distance analysis. *Neurocomputing,* 57**,** 49-76.

LEFèVRE, T., RONDET, C., PARIZOT, I. & CHAUVIN, P. 2014. Applying multivariate clustering techniques to health data: the 4 types of healthcare utilization in the Paris metropolitan area. *PloS one,* 9**,** e115064.

LENNON, M. R., BOUAMRANE, M.-M., DEVLIN, A. M., O'CONNOR, S., O'DONNELL, C., CHETTY, U., AGBAKOBA, R., BIKKER, A., GRIEVE, E. & FINCH, T. 2017. Readiness for delivering digital health at scale: lessons from a longitudinal qualitative evaluation of a national digital health innovation program in the United Kingdom. *Journal of medical Internet research,* 19**,** e6900.

LESTER, R. T., MILLS, E. J., KARIRI, A., RITVO, P., CHUNG, M., JACK, W., HABYARIMANA, J., KARANJA, S., BARASA, S. & NGUTI, R. 2009. The HAART cell phone adherence trial (WelTel Kenya1): a randomized controlled trial protocol. *Trials,* 10**,** 1-10.

LEUNG, Y., ZHANG, J.-S. & XU, Z.-B. 2000. Clustering by scale-space filtering. *IEEE Transactions on pattern analysis and machine intelligence,* 22**,** 1396-1410.

LI, D.-C., LIU, C.-W. & HU, S. C. 2011. A fuzzy-based data transformation for feature extraction to increase classification performance with small medical data sets. *Artificial intelligence in medicine,* 52**,** 45-52.

LI, Q., QIU, Z.-D., SUN, D.-M. & LIU, L.-L. 2005. Online palmprint identification based on improved 2D PCA. *ACTA ELECTONICA SINICA,* 33**,** 1886.

LIPSCHITZ, J., MILLER, C. J., HOGAN, T. P., BURDICK, K. E., LIPPIN-FOSTER, R., SIMON, S. R. & BURGESS, J. 2019. Adoption of mobile apps for depression and anxiety: cross-sectional survey study on patient interest and barriers to engagement. *JMIR mental health,* 6**,** e11334.

LITMAN, L., ROSEN, Z., SPIERER, D., WEINBERGER-LITMAN, S., GOLDSCHEIN, A. & ROBINSON, J. 2015. Mobile exercise apps and increased leisure time exercise activity: a moderated mediation analysis of the role of self-efficacy and barriers. *Journal of medical Internet research,* 17**,** e4142.

LITTLE, R. J. & RUBIN, D. B. 1989. The analysis of social science data with missing values. *Sociological methods & research,* 18**,** 292-326.

LITTLE, R. J. & RUBIN, D. B. 2002. Single imputation methods. *Statistical analysis with missing data***,** 59-74.

LIU, P., LI, G., JIANG, S., LIU, Y., LENG, M., ZHAO, J., WANG, S., MENG, X., SHANG, B. & CHEN, L. 2019. The effect of smart homes on older adults with chronic conditions: a systematic review and meta-analysis. *Geriatric Nursing,* 40**,** 522-530.

LONINI, L., DAI, A., SHAWEN, N., SIMUNI, T., POON, C., SHIMANOVICH, L., DAESCHLER, M., GHAFFARI, R., ROGERS, J. A. & JAYARAMAN, A. 2018. Wearable sensors for Parkinson's disease: which data are worth collecting for training symptom detection models. *NPJ digital medicine,* 1**,** 1-8.

LOPES, A. C., XAVIER, R. F., AC PEREIRA, A. C., STELMACH, R., FERNANDES, F. L., HARRISON, S. L. & CARVALHO, C. R. 2019. Identifying COPD patients at risk for worse symptoms, HRQoL, and self-efficacy: A cluster analysis. *Chronic illness,* 15**,** 138-148.

LOW, S. T., SAKHARDANDE, P. G., LAI, Y. F., LONG, A. D. & KAUR-GILL, S. 2021. Attitudes and perceptions toward healthcare technology adoption among older adults in Singapore: a qualitative study. *Frontiers in public health,* 9**,** 588590.

LOZOYA, S. V. M., GUIRADO, M. A. Z., GONZáLEZ, A. Z. & LóPEZ, A. B. M. 2022. Use of Technologies and Self-Efficacy in Older Adults. *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje,* 17**,** 125-130.

LU, H., PLATANIOTIS, K. N. & VENETSANOPOULOS, A. N. 2008. MPCA: Multilinear principal component analysis of tensor objects. *IEEE transactions on Neural Networks,* 19**,** 18-39.

LUNDGREN, J., JOHANSSON, P., JAARSMA, T., ANDERSSON, G. & KäRNER KöHLER, A. 2018. Patient experiences of web-based cognitive behavioral therapy for heart failure and depression: qualitative study. *Journal of medical Internet research,* 20**,** e10302.

LUQUE, A. E., VAN KEKEN, A., WINTERS, P., KEEFER, M. C., SANDERS, M. & FISCELLA, K. 2013. Barriers and facilitators of online patient portals to personal health records among persons living with HIV: formative research. *JMIR research protocols,* 2**,** e2302.

LUSTRIA, M. L. A., CORTESE, J., GEREND, M. A., SCHMITT, K., KUNG, Y. M. & MCLAUGHLIN, C. 2016. A model of tailoring effects: a randomized controlled trial examining the mechanisms of tailoring in a web-based STD screening intervention. *Health Psychology,* 35**,** 1214.

LUSTRIA, M. L. A., NOAR, S. M., CORTESE, J., VAN STEE, S. K., GLUECKAUF, R. L. & LEE, J. 2013. A meta-analysis of web-delivered tailored health behavior change interventions. *Journal of health communication,* 18**,** 1039-1069.

MADDUX, J. E. & GOSSELIN, J. T. 2012. *Self-efficacy*, The Guilford Press.

MADHUKUMAR, S. & SANTHIYAKUMARI, N. 2015. Evaluation of k-Means and fuzzy C-means segmentation on MR images of brain. *The Egyptian Journal of Radiology and Nuclear Medicine,* 46**,** 475-479.

MADIGAN, E. A. & CURET, O. L. 2006. A data mining approach in home healthcare: outcomes and service use. *BMC health services research,* 6**,** 1-10.

MAHAJAN, S., LU, Y., SPATZ, E. S., NASIR, K. & KRUMHOLZ, H. M. 2021. Trends and predictors of use of digital health technology in the United States. *The American journal of medicine,* 134**,** 129-134.

MAHER, C. A., LEWIS, L. K., FERRAR, K., MARSHALL, S., DE BOURDEAUDHUIJ, I. & VANDELANOTTE, C. 2014. Are health behavior change interventions that use online social networks effective? A systematic review. *J Med Internet Res,* 16**,** e40.

MAHESH, B. 2020. Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet],* 9**,** 381-386.

MAHOTO, N. A., SHAIKH, F. K. & ANSARI, A. Q. 2014. Exploitation of clustering techniques in transactional healthcare data. *Mehran University Research Journal of Engineering & Technology,* 33**,** 77-92.

MAKROUM, M. A., ADDA, M., BOUZOUANE, A. & IBRAHIM, H. 2022. Machine learning and smart devices for diabetes management: Systematic review. *Sensors,* 22**,** 1843.

MAMOSHINA, P., VOLOSNIKOVA, M., OZEROV, I. V., PUTIN, E., SKIBINA, E., CORTESE, F. & ZHAVORONKOV, A. 2018. Machine learning on human muscle transcriptomic data for biomarker discovery and tissue-specific drug target identification. *Frontiers in genetics,* 9**,** 242.

MANSSON, L., LUNDIN-OLSSON, L., SKELTON, D. A., JANOLS, R., LINDGREN, H., ROSENDAHL, E. & SANDLUND, M. 2020. Older adults' preferences for, adherence to and experiences of two self-management falls prevention home exercise programmes: a comparison between a digital programme and a paper booklet. *BMC geriatrics,* 20**,** 1-15.

MARENGONI, A., ANGLEMAN, S., MELIS, R., MANGIALASCHE, F., KARP, A., GARMEN, A., MEINOW, B. & FRATIGLIONI, L. 2011. Aging with multimorbidity: a systematic review of the literature. *Ageing research reviews,* 10**,** 430-439.

MARIANI, F., PéREZ-BARAHONA, A. & RAFFIN, N. 2010. Life expectancy and the environment. *Journal of Economic Dynamics and Control,* 34**,** 798-815.

MARILL, K. A. 2004. Advanced statistics: linear regression, part I: simple linear regression. *Academic emergency medicine,* 11**,** 87-93.

MARQUEZ CONTRERAS, E., MARQUEZ RIVERO, S., RODRIGUEZ GARCIA, E., LóPEZ-GARCíA-RAMOS, L., CARLOS PASTORIZA VILAS, J., BALDONEDO SUAREZ, A., GRACIA DIEZ, C., GIL GUILLEN, V., MARTELL CLAROS, N. & HYPERTENSION, C. G. O. S. S. O. 2019. Specific hypertension smartphone application to improve medication adherence in hypertension: a cluster-randomized trial. *Current Medical Research and Opinion,* 35**,** 167-173.

MARTIS, R. J., ACHARYA, U. R., MANDANA, K., RAY, A. K. & CHAKRABORTY, C. 2012. Application of principal component analysis to ECG signals for automated diagnosis of cardiac health. *Expert Systems with Applications,* 39**,** 11792-11800.

MASTER, A. M., DUBLIN, L. I. & MARKS, H. H. 1950. The normal blood pressure range and its clinical implications. *Journal of the American Medical Association,* 143**,** 1464-1470.

MATTHEW-MAICH, N., HARRIS, L., PLOEG, J., MARKLE-REID, M., VALAITIS, R., IBRAHIM, S., GAFNI, A. & ISAACS, S. 2016. Designing, implementing, and evaluating mobile health technologies for managing chronic conditions in older adults: a scoping review. *JMIR mHealth and uHealth,* 4**,** e5127.

MATTILA, E., LAPPALAINEN, R., VäLKKYNEN, P., SAIRANEN, E., LAPPALAINEN, P., KARHUNEN, L., PEUHKURI, K., KORPELA, R., KOLEHMAINEN, M. & ERMES, M. 2016. Usage and dose response of a mobile acceptance and commitment therapy app: secondary analysis of the intervention arm of a randomized controlled trial. *JMIR mHealth and uHealth,* 4**,** e5241.

MCCALLUM, S. Gamification and serious games for personalized health. pHealth, 2012. 85-96.

MCGINNIS, R. S., MCGINNIS, E. W., HRUSCHAK, J., LOPEZ-DURAN, N. L., FITZGERALD, K., ROSENBLUM, K. L. & MUZIK, M. Wearable sensors and machine learning diagnose anxiety and depression in young children. 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), 2018. IEEE, 410-413.

MCKINSTRY, B., HANLEY, J., WILD, S., PAGLIARI, C., PATERSON, M., LEWIS, S., SHEIKH, A., KRISHAN, A., STODDART, A. & PADFIELD, P. 2013. Telemonitoring based service redesign for the management of uncontrolled hypertension: multicentre randomised controlled trial. *Bmj,* 346.

MCLAUGHLIN, M., NAM, Y., GOULD, J., PADE, C., MEESKE, K. A., RUCCIONE, K. S. & FULK, J. 2012. A videosharing social networking intervention for young adult cancer survivors. *Computers in Human Behavior,* 28**,** 631-641.

MCLEOD, M., STANLEY, J., SIGNAL, V., STAIRMAND, J., THOMPSON, D., HENDERSON, K., DAVIES, C., KREBS, J., DOWELL, A. & GRAINGER, R. 2020. Impact of a comprehensive digital health programme on HbA1c and weight after 12 months for people with diabetes and prediabetes: A randomised controlled trial. *Diabetologia,* 63**,** 2559-2570.

MEAD, S. & MACNEIL, C. 2006. Peer support: What makes it unique. *International Journal of Psychosocial Rehabilitation,* 10**,** 29-37.

MELAKU, T., BAYISA, B., FEKEREMARYAM, H., FEYISSA, A. & GUTASA, A. 2022. Self-care practice among adult hypertensive patients at ambulatory clinic of tertiary teaching Hospital in Ethiopia: a cross-sectional study. *Journal of Pharmaceutical Policy and Practice,* 15**,** 23.

MELCHIORRE, M. G., PAPA, R., RIJKEN, M., VAN GINNEKEN, E., HUJALA, A. & BARBABELLA, F. 2018. eHealth in integrated care programs for people with multimorbidity in Europe: Insights from the ICARE4EU project. *Health policy,* 122**,** 53-63.
MELVILLE, K. M., CASEY, L. M. & KAVANAGH, D. J. 2010. Dropout from Internet‐based treatment for psychological disorders. *British Journal of Clinical Psychology,* 49**,** 455-471.
MENZIES, T., GREENWALD, J. & FRANK, A. 2006. Data mining static code attributes to learn defect predictors. *IEEE transactions on software engineering,* 33**,** 2-13.
MERAI, R., SIEGEL, C., RAKOTZ, M., BASCH, P., WRIGHT, J., WONG, B. & THORPE, P. 2016. CDC grand rounds: a public health approach to detect and control hypertension. *Morbidity and mortality weekly report,* 65**,** 1261-1264.
MIDDLE, R. & WELCH, L. 2022. Experiences of digital exclusion and the impact on health in people living with severe mental illness. *Frontiers in Digital Health,* 4**,** 1004547.
MIKOLASEK, M., WITT, C. M. & BARTH, J. 2018. Adherence to a mindfulness and relaxation self-care app for cancer patients: mixed-methods feasibility study. *JMIR mHealth and uHealth,* 6**,** e11271.
MILANI, R. V., LAVIE, C. J., BOBER, R. M., MILANI, A. R. & VENTURA, H. O. 2017. Improving hypertension control and patient engagement using digital tools. *The American journal of medicine,* 130**,** 14-20.
MILLEY, A. 2000. Healthcare and data mining. *Health Management Technology,* 21**,** 44-45.
MILNE-IVES, M., HOMER, S., ANDRADE, J. & MEINERT, E. 2024. The conceptualisation and measurement of engagement in digital health. *Internet Interventions,* 36**,** 100735.
MINETAKI, K., AKEMATSU, Y. & TSUJI, M. 2011. Effect of e-health on medical expenditures of outpatients with lifestyle-related diseases. *Telemedicine and e-Health,* 17**,** 591-595.
MISHURIS, R. G., STEWART, M., FIX, G. M., MARCELLO, T., MCINNES, D. K., HOGAN, T. P., BOARDMAN, J. B. & SIMON, S. R. 2015. Barriers to patient portal access among veterans receiving home‐based primary care: a qualitative study. *Health Expectations,* 18**,** 2296-2305.
MITCHELL, K. E., JOHNSON-WARRINGTON, V., APPS, L. D., BANKART, J., SEWELL, L., WILLIAMS, J. E., REES, K., JOLLY, K., STEINER, M. & MORGAN, M. 2014. A self-management programme for COPD: a randomised controlled trial. *European Respiratory Journal,* 44**,** 1538-1547.
MITCHELL, T. M. & MITCHELL, T. M. 1997. *Machine learning*, McGraw-hill New York.
MIYAMOTO, A., LEE, S., COORAY, N. F., LEE, S., MORI, M., MATSUHISA, N., JIN, H., YODA, L., YOKOTA, T. & ITOH, A. 2017. Inflammation-free, gas-permeable, lightweight, stretchable on-skin electronics with nanomeshes. *Nature nanotechnology,* 12**,** 907-913.
MOESSNER, M., MINARIK, C., ÖZER, F. & BAUER, S. 2016. Can an internet-based program for the prevention and early intervention in eating disorders facilitate access to conventional professional healthcare? *Journal of Mental Health,* 25**,** 441-447.
MONK, A. F. 2002. Fun, communication and dependability: extending the concept of usability. *People and Computers XVI-Memorable Yet Invisible.* Springer.
MORAN, O., DOYLE, J., SMITH, S., GIGGINS, O. & DINSMORE, J. 2022. Investigating the needs and concerns of older adults with multimorbidity and their healthcare professionals for conceivable digital psychotherapeutic interventions. *Digital Health,* 8**,** 20552076221089097.
MORAWSKI, K., GHAZINOURI, R., KRUMME, A., LAUFFENBURGER, J. C., LU, Z., DURFEE, E., OLEY, L., LEE, J., MOHTA, N. & HAFF, N. 2018. Association of a smartphone application with medication adherence and blood pressure control: the MedISAFE-BP randomized clinical trial. *JAMA internal medicine,* 178**,** 802-809.
MORET-TATAY, C., BENEYTO-ARROJO, M. J., GUTIERREZ, E., BOOT, W. R. & CHARNESS, N. 2019. A spanish adaptation of the computer and mobile device proficiency questionnaires (CPQ and MDPQ) for older adults. *Frontiers in psychology***,** 1165.
MORGENTHALER, S. 2009. Exploratory data analysis. *Wiley Interdisciplinary Reviews: Computational Statistics,* 1**,** 33-44.

MORRISON, L., MOSS-MORRIS, R., MICHIE, S. & YARDLEY, L. 2014. Optimizing engagement with Internet-based health behaviour change interventions: comparison of self-assessment with and without tailored feedback using a mixed methods approach. *Br J Health Psychol,* 19**,** 839-55.

MORRISON, L. G. 2015. Theory-based strategies for enhancing the impact and usage of digital health behaviour change interventions: A review. *Digit Health,* 1**,** 2055207615595335.

MORRISON, L. G., HARGOOD, C., PEJOVIC, V., GERAGHTY, A. W., LLOYD, S., GOODMAN, N., MICHAELIDES, D. T., WESTON, A., MUSOLESI, M. & WEAL, M. J. 2017. The effect of timing and frequency of push notifications on usage of a smartphone-based stress management intervention: an exploratory trial. *PloS one,* 12**,** e0169162.

MORTON, K., DENNISON, L., MAY, C., MURRAY, E., LITTLE, P., MCMANUS, R. J. & YARDLEY, L. 2017. Using digital interventions for self-management of chronic physical health conditions: a meta-ethnography review of published studies. *Patient education and counseling,* 100**,** 616-635.

MORTON, T. A., WILSON, N., HASLAM, C., BIRNEY, M., KINGSTON, R. & MCCLOSKEY, L.-G. 2018. Activating and guiding the engagement of seniors with online social networking: experimental findings from the AGES 2.0 project. *Journal of aging and health,* 30**,** 27-51.

MSHALI, H., LEMLOUMA, T., MOLONEY, M. & MAGONI, D. 2018. A survey on health monitoring systems for health smart homes. *International Journal of Industrial Ergonomics,* 66**,** 26-56.

MUENCH, F. & BAUMEL, A. 2017. More than a text message: dismantling digital triggers to curate behavior change in patient-centered health interventions. *Journal of medical Internet research,* 19**,** e147.

MULVANEY, S. A., RITTERBAND, L. M. & BOSSLET, L. 2011. Mobile intervention design in diabetes: review and recommendations. *Curr Diab Rep,* 11**,** 486-93.

MUñOZ ESQUIVEL, K., GILLESPIE, J., KELLY, D., CONDELL, J., DAVIES, R., MCHUGH, C., DUFFY, W., NEVALA, E., ALAMäKI, A. & JALOVAARA, J. 2023. Factors Influencing Continued Wearable Device Use in Older Adult Populations: Quantitative Study. *JMIR aging,* 6**,** e36807.

MURPHY, E., DOYLE, J., HANNIGAN, C., SMITH, S., KUIPER, J., JACOBS, A., HOOGERWERF, E.-J., DESIDERI, L., FIORDELMONDO, V. & MALUCCELLI, L. Perceptions and Use of Technology to Support Older Adults with Multimorbidity. AAATE Conf., 2017. 160-167.

MURTON, O. M., HILLMAN, R. E., MEHTA, D. D., SEMIGRAN, M., DAHER, M., CUNNINGHAM, T., VERKOUW, K., TABTABAI, S., STEINER, J. & DEC, G. W. 2017. Acoustic speech analysis of patients with decompensated heart failure: a pilot study. *The Journal of the Acoustical Society of America,* 142**,** EL401-EL407.

MYLLYMAKI, P. 2010. Advantages of Bayesian networks in data mining and knowledge discovery. Academy Research Ph. D, Fellow, Complex Systems Computation Group, Helsinki ….

NADAL, C., MCCULLY, S., DOHERTY, K., SAS, C. & DOHERTY, G. The TAC Toolkit: Supporting Design for User Acceptance of Health Technologies from a Macro-Temporal Perspective. CHI Conference on Human Factors in Computing Systems, 2022. 1-18.

NADAL, C., SAS, C. & DOHERTY, G. 2020. Technology acceptance in mobile health: scoping review of definitions, models, and measurement. *Journal of Medical Internet Research,* 22**,** e17256.

NASLUND, J. A., ASCHBRENNER, K. A. & BARTELS, S. J. 2016a. Wearable devices and smartphones for activity tracking among people with serious mental illness. *Mental health and physical activity,* 10**,** 10-17.

NASLUND, J. A., ASCHBRENNER, K. A., MARSCH, L. A. & BARTELS, S. J. 2016b. The future of mental health care: peer-to-peer support and social media. *Epidemiology and psychiatric sciences,* 25**,** 113-122.

NASTESKI, V. 2017. An overview of the supervised machine learning methods. *Horizons. b,* 4**,** 51-62.

NATIONAL HEALTH SERVICE. 2022. *Heart Failure* [Online]. Available: https://www.nhs.uk/conditions/heart-failure/ [Accessed Feb 20 2023,].

NATIONAL INSTITUTE ON AGING. 2017. *Supporting older patients with chronic conditions* [Online]. Available: https://www.nia.nih.gov/health/supporting-older-patients-chronic-conditions [Accessed Dec 20, 2022 2022].

NATIONS, U. 2020. *Ageing* [Online]. Available: https://www.un.org/en/global-issues/ageing [Accessed January 13, 2022 2022].

NAWANGSARI, S., HARAHAP, R. K., AL RASYID, H., HERLINA, N., EKOWATI, E. & ASMARANY, A. I. 2022. Design of Mobile Digital Healthcare Application For Pregnant Women Based on Android. *MATRIK: Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer,* 21**,** 439-450.

NELSON, E. L., YADRICH, D. M., THOMPSON, N., WRIGHT, S., STONE, K., ADAMS, N., WERKOWITCH, M. & SMITH, C. E. 2017. Telemedicine support groups for home parenteral nutrition users. *Nutrition in Clinical Practice,* 32**,** 789-798.

NELSON, L. A., COSTON, T. D., CHERRINGTON, A. L. & OSBORN, C. Y. 2016. Patterns of User Engagement with Mobile- and Web-Delivered Self-Care Interventions for Adults with T2DM: A Review of the Literature. *Curr Diab Rep,* 16**,** 66.

NGUYEN, M. H., BOL, N. & KING, A. J. 2020. Customisation versus personalisation of digital health information: Effects of mode tailoring on information processing outcomes. *European Journal of Health Communication,* 1**,** 30-54.

NICHOLSON, K., MAKOVSKI, T. T., GRIFFITH, L. E., RAINA, P., STRANGES, S. & VAN DEN AKKER, M. 2019. Multimorbidity and comorbidity revisited: refining the concepts for international health research. *Journal of clinical epidemiology,* 105**,** 142-146.

NICK, T. G. & CAMPBELL, K. M. 2007. Logistic regression. *Topics in biostatistics***,** 273-301.

NIZAR, A., DONG, Z. & WANG, Y. 2008. Power utility nontechnical loss analysis with extreme learning machine method. *IEEE Transactions on Power Systems,* 23**,** 946-955.

NOAR, S. M., BENAC, C. N. & HARRIS, M. S. 2007. Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions. *Psychological bulletin,* 133**,** 673.

NORMAN, C. D. & SKINNER, H. A. 2006. eHEALS: the eHealth literacy scale. *Journal of medical Internet research,* 8**,** e507.

NUNES, F., VERDEZOTO, N., FITZPATRICK, G., KYNG, M., GRöNVALL, E. & STORNI, C. 2015. Self-Care Technologies in HCI. *ACM Transactions on Computer-Human Interaction,* 22**,** 1-45.

O'BRIEN, H. L. & TOMS, E. G. 2008. What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American society for Information Science and Technology,* 59**,** 938-955.

O'BRIEN, H. L. & TOMS, E. G. 2010. The development and evaluation of a survey to measure user engagement. *Journal of the American Society for Information Science and Technology,* 61**,** 50-69.

O'CONNOR, Y., O'REILLY, P. & O'DONOGHUE, J. 2013. M-health infusion by healthcare practitioners in the national health services (NHS). *Health Policy and Technology,* 2**,** 26-35.

O'CONNOR, S., HANLON, P., O'DONNELL, C. A., GARCIA, S., GLANVILLE, J. & MAIR, F. S. 2016. Understanding factors affecting patient and public engagement and recruitment to digital health interventions: a systematic review of qualitative studies. *BMC medical informatics and decision making,* 16**,** 1-15.

OEPPEN, J. & VAUPEL, J. W. 2002. Broken limits to life expectancy. American Association for the Advancement of Science.

OH, S. S., KIM, K.-A., KIM, M., OH, J., CHU, S. H. & CHOI, J. 2021. Measurement of digital literacy among older adults: systematic review. *Journal of medical Internet research,* 23**,** e26145.

OHBA, K., YONEDA, Y., KURIHARA, K., SUGANUMA, T., ITO, H., ISHIHARA, N., GOTOH, K., YAMASHITA, K. & MASU, K. 2016. Polynomial regression techniques for environmental data recovery in wireless sensor networks. *Sensors & Transducers,* 199**,** 1.

OKONOFUA, E. C., SIMPSON, K. N., JESRI, A., REHMAN, S. U., DURKALSKI, V. L. & EGAN, B. M. 2006. Therapeutic inertia is an impediment to achieving the Healthy People 2010 blood pressure control goals. *Hypertension,* 47**,** 345-351.

OLSON, J. E. 2003. *Data quality: the accuracy dimension*, Elsevier.

OMRAN, M. G., ENGELBRECHT, A. P. & SALMAN, A. 2007. An overview of clustering methods. *Intelligent Data Analysis,* 11**,** 583-605.

OSKOOEI, A., CHAU, S. M., WEISS, J., SRIDHAR, A., MARTíNEZ, M. R. & MICHEL, B. 2021. DeStress: deep learning for unsupervised identification of mental stress in firefighters from heart-rate variability (HRV) data. *Explainable AI in Healthcare and Medicine.* Springer.

OSTERTAGOVá, E. 2012. Modelling using polynomial regression. *Procedia Engineering,* 48**,** 500-506.

PARK, C., OTOBO, E., ULLMAN, J., ROGERS, J., FASIHUDDIN, F., GARG, S., KAKKAR, S., GOLDSTEIN, M., CHANDRASEKHAR, S. V. & PINNEY, S. 2019. Impact on readmission reduction among heart failure patients using digital health monitoring: feasibility and adoptability study. *JMIR medical informatics,* 7**,** e13353.

PARTRIDGE, S. R., MCGEECHAN, K., HEBDEN, L., BALESTRACCI, K., WONG, A. T., DENNEY-WILSON, E., HARRIS, M. F., PHONGSAVAN, P., BAUMAN, A. & ALLMAN-FARINELLI, M. 2015. Effectiveness of a mHealth lifestyle program with telephone support (TXT2BFiT) to prevent unhealthy weight gain in young adults: randomized controlled trial. *JMIR mHealth and uHealth,* 3**,** e4530.

PATIL, D. D., WADHAI, V. & GOKHALE, J. 2010. Evaluation of decision tree pruning algorithms for complexity and classification accuracy. *International Journal of Computer Applications,* 11**,** 23-30.

PAUWELS, R. A. 2000. National and international guidelines for COPD: the need for evidence. *Chest,* 117**,** 20S-22S.

PEEK, S. T., WOUTERS, E. J., VAN HOOF, J., LUIJKX, K. G., BOEIJE, H. R. & VRIJHOEF, H. J. 2014. Factors influencing acceptance of technology for aging in place: a systematic review. *International journal of medical informatics,* 83**,** 235-248.

PETRELLA, R. J., STUCKEY, M. I., SHAPIRO, S. & GILL, D. P. 2014. Mobile health, exercise and metabolic risk: a randomized controlled trial. *BMC public health,* 14**,** 1-11.

PETTERSSON, B., WIKLUND, M., JANOLS, R., LINDGREN, H., LUNDIN-OLSSON, L., SKELTON, D. A. & SANDLUND, M. 2019. 'Managing pieces of a personal puzzle'—Older people's experiences of self-management falls prevention exercise guided by a digital program or a booklet. *BMC geriatrics,* 19**,** 1-12.

PHAM, X.-L., NGUYEN, T.-H., HWANG, W.-Y. & CHEN, G.-D. Effects of push notifications on learner engagement in a mobile learning app. 2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT), 2016. IEEE, 90-94.

PHYU, T. N. Survey of classification techniques in data mining. Proceedings of the international multiconference of engineers and computer scientists, 2009. Citeseer, 727-731.

PIAU, A., STEINMEYER, Z., CESARI, M., KORNFELD, J., BEATTIE, Z., KAYE, J., VELLAS, B. & NOURHASHEMI, F. 2021. Intrinsic capacitiy monitoring by digital biomarkers in Integrated Care for Older People (ICOPE). *The Journal of frailty & aging,* 10**,** 132-138.

PICKERING, T. G., MILLER, N. H., OGEDEGBE, G., KRAKOFF, L. R., ARTINIAN, N. T. & GOFF, D. 2008. Call to action on use and reimbursement for home blood pressure monitoring: executive summary: a joint scientific statement from the American Heart Association, American Society Of Hypertension, and Preventive Cardiovascular Nurses Association. *Hypertension,* 52**,** 1-9.

PIOTROWICZ, E., PENCINA, M. J., OPOLSKI, G., ZARĘBA, W., BANACH, M., KOWALIK, I., ORZECHOWSKI, P., SZALEWSKA, D., PLUTA, S. & GŁóWCZYŃSKA, R. 2020. Effects of a 9-week hybrid comprehensive telerehabilitation program on long-term outcomes in patients with heart failure: the Telerehabilitation in Heart Failure Patients (TELEREH-HF) randomized clinical trial. *JAMA cardiology,* 5**,** 300-308.

PIOTROWICZ, E., PIEPOLI, M. F., JAARSMA, T., LAMBRINOU, E., COATS, A. J., SCHMID, J.-P., CORRA, U., AGOSTONI, P., DICKSTEIN, K. & SEFEROVIĆ, P. M. 2016. Telerehabilitation in heart failure patients: The evidence and the pitfalls. *International Journal of Cardiology,* 220**,** 408-413.

POLHEMUS, A., NOVAK, J., MAJID, S., SIMBLETT, S., MORRIS, D., BRUCE, S., BURKE, P., DOCKENDORF, M. F., TEMESI, G. & WYKES, T. 2022. Data visualization for chronic neurological and mental health condition self-management: systematic review of user perspectives. *JMIR mental health,* 9**,** e25249.

PORTZ, J. D., MILLER, A., FOSTER, B. & LAUDEMAN, L. 2016. Persuasive features in health information technology interventions for older adults with chronic diseases: a systematic review. *Health and technology,* 6**,** 89-99.

POTTS, C., BOND, R., RYAN, A., MULVENNA, M., MCCAULEY, C., LAIRD, E. & GOODE, D. 2020. Ecological Momentary Assessment Within a Digital Health Intervention for Reminiscence in Persons With Dementia and Caregivers: User Engagement Study. *JMIR Mhealth Uhealth,* 8**,** e17120.

PRESTI, L. L., TESTA, M., MARINO, V. & SINGER, P. 2019. Engagement in healthcare systems: Adopting digital tools for a sustainable approach. *Sustainability,* 11**,** 1-15.

PUNG, A., FLETCHER, S. L. & GUNN, J. M. 2018. Mobile app use by primary care patients to manage their depressive symptoms: qualitative study. *Journal of medical Internet research,* 20**,** e10035.

PYWELL, J., VIJAYKUMAR, S., DODD, A. & COVENTRY, L. 2020. Barriers to older adults' uptake of mobile-based mental health interventions. *Digital health,* 6**,** 2055207620905422.

QUINN, C. C., BUTLER, E. C., SWASEY, K. K., SHARDELL, M. D., TERRIN, M. D., BARR, E. A. & GRUBER-BALDINI, A. L. 2018. Mobile diabetes intervention study of patient engagement and impact on blood glucose: mixed methods analysis. *JMIR mHealth and uHealth,* 6**,** e9265.

QUINN, C. C., KHOKHAR, B., WEED, K., BARR, E. & GRUBER-BALDINI, A. L. 2015. Older adult self-efficacy study of mobile phone diabetes management. *Diabetes technology & therapeutics,* 17**,** 455-461.

RADHAKRISHNAN, K., JULIEN, C., BARANOWSKI, T., O'HAIR, M., LEE, G., SAGNA DE MAIN, A., ALLEN, C., VISWANATHAN, B., THOMAZ, E. & KIM, M. 2021. Feasibility of a sensor-controlled digital game for heart failure self-management: Randomized controlled trial. *JMIR Serious Games,* 9**,** e29044.

RAHM, E. & DO, H. H. 2000. Data cleaning: Problems and current approaches. *IEEE Data Eng. Bull.,* 23**,** 3-13.

RAHMAN, M. S., KO, M., WARREN, J. & CARPENTER, D. 2016. Healthcare Technology Self-Efficacy (HTSE) and its influence on individual attitude: An empirical study. *Computers in Human Behavior,* 58**,** 12-24.

RAHMAN, Q. A., JANMOHAMED, T., PIRBAGLOU, M., RITVO, P., HEFFERNAN, J. M., CLARKE, H. & KATZ, J. 2017. Patterns of user engagement with the mobile app, Manage My Pain: results of a data mining investigation. *JMIR mHealth and uHealth,* 5**,** e7871.

RASCHE, P., WILLE, M., BRöHL, C., THEIS, S., SCHäFER, K., KNOBE, M. & MERTENS, A. 2018. Prevalence of health app use among older adults in Germany: national survey. *JMIR mHealth and uHealth,* 6**,** e8619.

RAYNER, L., HOTOPF, M., PETKOVA, H., MATCHAM, F., SIMPSON, A. & MCCRACKEN, L. M. 2016. Depression in patients with chronic pain attending a specialised pain treatment centre: prevalence and impact on health care costs. *Pain,* 157**,** 1472.

REDFIELD, M. M., ANSTROM, K. J., LEVINE, J. A., KOEPP, G. A., BORLAUG, B. A., CHEN, H. H., LEWINTER, M. M., JOSEPH, S. M., SHAH, S. J. & SEMIGRAN, M. J. 2015. Isosorbide mononitrate in heart failure with preserved ejection fraction. *New England Journal of Medicine,* 373**,** 2314-2324.

REYCHAV, I., BEERI, R., BALAPOUR, A., RABAN, D. R., SABHERWAL, R. & AZURI, J. 2019. How reliable are self-assessments using mobile technology in healthcare? The effects of technology identity and self-efficacy. *Computers in Human Behavior,* 91**,** 52-61.

REYNOLDSON, C., STONES, C., ALLSOP, M., GARDNER, P., BENNETT, M. I., CLOSS, S. J., JONES, R. & KNAPP, P. 2014. Assessing the quality and usability of smartphone apps for pain self-management. *Pain medicine,* 15**,** 898-909.

RIBEIRO FILHO, J. D. P., DA SILVA E SILVA, F. J., COUTINHO, L. R. & GOMES, B. D. T. P. 2016. MHARS: A mobile system for human activity recognition and inference of health situations in ambient assisted living. *Journal of Applied Computing Research,* 5.

RICKARD, N., ARJMAND, H.-A., BAKKER, D. & SEABROOK, E. 2016. Development of a mobile phone app to support self-monitoring of emotional well-being: a mental health digital innovation. *JMIR mental health,* 3**,** e6202.

RIMER, B. K. & KREUTER, M. W. 2006. Advancing tailored health communication: A persuasion and message effects perspective. *Journal of communication,* 56**,** S184-S201.

ROBROEK, S. J., LINDEBOOM, D. E. & BURDORF, A. 2012. Initial and sustained participation in an internet-delivered long-term worksite health promotion program on physical activity and nutrition. *Journal of medical Internet research,* 14**,** e1788.

RODRíGUEZ, M. D., ROA, J. R., MORáN, A. L. & NAVA-MUñOZ, S. 2013. CAMMInA: a mobile ambient information system to motivate elders to exercise. *Personal and ubiquitous computing,* 17**,** 1127-1134.

ROQUE, N. A. & BOOT, W. R. 2018. A new tool for assessing mobile device proficiency in older adults: the mobile device proficiency questionnaire. *Journal of Applied Gerontology,* 37**,** 131-156.

ROSENBERGER, M. E., BUMAN, M. P., HASKELL, W. L., MCCONNELL, M. V. & CARSTENSEN, L. L. 2016. 24 hours of sleep, sedentary behavior, and physical activity with nine wearable devices. *Medicine and science in sports and exercise,* 48**,** 457.

ROSER, M., ORTIZ-OSPINA, E. & RITCHIE, H. 2013. Life expectancy. *Our world in data*.

ROSS, A. & WILLSON, V. L. 2017. One-way anova. *Basic and advanced statistical tests.* Springer.

RUBIN, D. B. 2004. *Multiple imputation for nonresponse in surveys*, John Wiley & Sons.

RUEHLMAN, L. S., KAROLY, P. & ENDERS, C. 2012. A randomized controlled evaluation of an online chronic pain self management program. *Pain,* 153**,** 319-330.

RUSHAKOFF, R. J., RUSHAKOFF, J. A., KORNBERG, Z., MACMASTER, H. W. & SHAH, A. D. 2017. Remote monitoring and consultation of inpatient populations with diabetes. *Current Diabetes Reports,* 17**,** 1-8.

RUTKOWSKI, L., PIETRUCZUK, L., DUDA, P. & JAWORSKI, M. 2012. Decision trees for mining data streams based on the McDiarmid's bound. *IEEE Transactions on Knowledge and Data Engineering,* 25**,** 1272-1279.

RYAN, A. B. 2006. Post-positivist approaches to research. *Researching and Writing your Thesis: a guide for postgraduate students***,** 12-26.

RYAN, R. M. & DECI, E. L. 2000. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist,* 55**,** 68.

SADIKU, M., SHADARE, A. E., MUSA, S. M., AKUJUOBI, C. M. & PERRY, R. 2016. Data visualization. *International Journal of Engineering Research And Advanced Technology (IJERAT),* 2**,** 11-16.

SAFFORD, M. M., RUSSELL, L., SUH, D.-C., ROMAN, S. & POGACH, L. 2005. How much time do patients with diabetes spend on self-care? *The Journal of the American Board of Family Practice,* 18**,** 262-270.

SAKIB, M. N., SHOOSHTARI, S., ST JOHN, P. & MENEC, V. 2019. The prevalence of multimorbidity and associations with lifestyle factors among middle-aged Canadians: an analysis of Canadian Longitudinal Study on Aging data. *BMC Public Health,* 19**,** 1-13.

SANTOS, A. R., SANTOS, M. A., BAUMBACH, J., MCCULLOCH, J. A., OLIVEIRA, G. C., SILVA, A., MIYOSHI, A. & AZEVEDO, V. A singular value decomposition approach for improved

taxonomic classification of biological sequences. BMC genomics, 2011. BioMed Central, 1-15.
SAUL, L. K. & ROWEIS, S. T. 2000. An introduction to locally linear embedding. *unpublished. Available at: http://www. cs. toronto. edu/~ roweis/lle/publications. html*.
SAVARESE, G., BECHER, P. M., LUND, L. H., SEFEROVIC, P., ROSANO, G. & COATS, A. J. 2022. Global burden of heart failure: a comprehensive and updated review of epidemiology. *Cardiovascular Research*.
SCHALL JR, M. C., SESEK, R. F. & CAVUOTO, L. A. 2018. Barriers to the adoption of wearable sensors in the workplace: A survey of occupational safety and health professionals. *Human factors,* 60**,** 351-362.
SCHIFFER, L., GERTGES, R., NöHRE, M., SCHIEFFER, E., TEGTBUR, U., PAPE, L., DE ZWAAN, M. & SCHIFFER, M. 2021. Use and preferences regarding internet-based health care delivery in patients with chronic kidney disease. *BMC Medical Informatics and Decision Making,* 21**,** 1-8.
SCHöLKOPF, B., SMOLA, A. & MüLLER, K.-R. Kernel principal component analysis. Artificial Neural Networks—ICANN'97: 7th International Conference Lausanne, Switzerland, October 8–10, 1997 Proceeedings, 2005. Springer, 583-588.
SCHRANK, B., SIBITZ, I., UNGER, A. & AMERING, M. 2010. How patients with schizophrenia use the internet: qualitative study. *Journal of medical Internet research,* 12**,** e1550.
SCHUBART, J. R., STUCKEY, H. L., GANESHAMOORTHY, A. & SCIAMANNA, C. N. 2011. Chronic health conditions and internet behavioral interventions: a review of factors to enhance user engagement. *Comput Inform Nurs,* 29**,** 81-92.
SEPAH, S. C., JIANG, L., ELLIS, R. J., MCDERMOTT, K. & PETERS, A. L. 2017. Engagement and outcomes in a digital Diabetes Prevention Program: 3-year update. *BMJ Open Diabetes Research and Care,* 5**,** e000422.
SERRA, A. & TAGLIAFERRI, R. 2019. Unsupervised Learning: Clustering.
SERUMAGA, B., ROSS-DEGNAN, D., AVERY, A. J., ELLIOTT, R. A., MAJUMDAR, S. R., ZHANG, F. & SOUMERAI, S. B. 2011. Effect of pay for performance on the management and outcomes of hypertension in the United Kingdom: interrupted time series study. *Bmj,* 342.
SETIAWAN, I. M. A., ZHOU, L., ALFIKRI, Z., SAPTONO, A., FAIRMAN, A. D., DICIANNO, B. E. & PARMANTO, B. 2019. An adaptive mobile health system to support self-management for persons with chronic conditions and disabilities: usability and feasibility studies. *JMIR Formative Research,* 3**,** e12982.
SEYCHELL, M. 2016. *Towards better prevention and management of chronic diseases* [Online]. Available: https://ec.europa.eu/health/newsletter/169/focus_newsletter_en.htm [Accessed August 16, 2022 2022].
SHAFIQUE, U. & QAISER, H. 2014. A comparative study of data mining process models (KDD, CRISP-DM and SEMMA). *International Journal of Innovation and Scientific Research,* 12**,** 217-222.
SHAILAJA, K., SEETHARAMULU, B. & JABBAR, M. Machine learning in healthcare: A review. 2018 Second international conference on electronics, communication and aerospace technology (ICECA), 2018. IEEE, 910-914.
SHAKEEL, P. M., BASKAR, S., DHULIPALA, V. S. & JABER, M. M. 2018. Cloud based framework for diagnosis of diabetes mellitus using K-means clustering. *Health information science and systems,* 6**,** 1-7.
SHARMA, S., AGRAWAL, J., AGARWAL, S. & SHARMA, S. Machine learning techniques for data mining: A survey. 2013 IEEE international conference on computational intelligence and computing research, 2013. IEEE, 1-6.
SHEA, S., WEINSTOCK, R. S., STARREN, J., TERESI, J., PALMAS, W., FIELD, L., MORIN, P., GOLAND, R., IZQUIERDO, R. E. & WOLFF, L. T. 2006. A randomized trial comparing telemedicine case management with usual care in older, ethnically diverse, medically underserved patients with diabetes mellitus. *Journal of the American Medical Informatics Association,* 13**,** 40-51.

SIEK, K. A., ROSS, S. E., KHAN, D. U., HAVERHALS, L. M., CALI, S. R. & MEYERS, J. 2010. Colorado Care Tablet: the design of an interoperable Personal Health Application to help older adults with multimorbidity manage their medications. *Journal of biomedical informatics,* 43**,** S22-S26.

SILITONGA, P. 2017. Clustering of Patient Disease Data by Using K-Means Clustering. *International Journal of Computer Science and Information Security (IJCSIS),* 15**,** 219-221.

SIMEK, K. 2003. Properties of a singular value decomposition based dynamical model of gene expression data.

SIMS, H., SANGHARA, H., HAYES, D., WANDIEMBE, S., FINCH, M., JAKOBSEN, H., TSAKANIKOS, E., OKOCHA, C. I. & KRAVARITI, E. 2012. Text message reminders of appointments: a pilot intervention at four community mental health clinics in London. *Psychiatric Services,* 63**,** 161-168.

SINGH, S. & SRIVASTAVA, S. 2020. Review of Clustering Techniques in Control System: Review of Clustering Techniques in Control System. *Procedia Computer Science,* 173**,** 272-280.

SINNOTT, C., MC HUGH, S., BROWNE, J. & BRADLEY, C. 2013. GPs' perspectives on the management of patients with multimorbidity: systematic review and synthesis of qualitative research. *BMJ open,* 3**,** e003610.

SLEVIN, P., KESSIE, T., CULLEN, J., BUTLER, M., DONNELLY, S. & CAULFIELD, B. 2020. Exploring the barriers and facilitators for the use of digital health technologies for the management of COPD: a qualitative study of clinician perceptions. *QJM: An International Journal of Medicine,* 113**,** 163-172.

SMAIL-CREVIER, R., POWERS, G., NOEL, C. & WANG, J. 2019. Health-related internet usage and design feature preference for e-mental health programs among men and women. *Journal of Medical Internet Research,* 21**,** e11224.

SMITH, K. A., DENNIS, M. & MASTHOFF, J. Personalizing reminders to personality for melanoma self-checking. Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization, 2016. 85-93.

SOLEY-BORI, M., ASHWORTH, M., BISQUERA, A., DODHIA, H., LYNCH, R., WANG, Y. & FOX-RUSHBY, J. 2021. Impact of multimorbidity on healthcare costs and utilisation: a systematic review of the UK literature. *British Journal of General Practice,* 71**,** e39-e46.

SONAGARA, D. & BADHEKA, S. 2014. Comparison of basic clustering algorithms. *Int. J. Comput. Sci. Mob. Comput,* 3**,** 58-61.

SOOFI, A. A. & AWAN, A. 2017. Classification techniques in machine learning: applications and issues. *J. Basic Appl. Sci,* 13**,** 459-465.

SPADARO, B., MARTIN-KEY, N. A. & BAHN, S. 2021. Building the digital mental health ecosystem: opportunities and challenges for mobile health innovators. *Journal of Medical Internet Research,* 23**,** e27507.

SPARKS, L. & NUSSBAUM, J. F. 2008. Health literacy and cancer communication with older adults. *Patient education and counseling,* 71**,** 345-350.

SPENCE, I. 2005. No humble pie: The origins and usage of a statistical chart. *Journal of Educational and Behavioral Statistics,* 30**,** 353-368.

ST-LAURENT, A., MONY, M., MATHIEU, M. & RUCHAT, S. 2018. Validation of the Fitbit Zip and Fitbit Flex with pregnant women in free-living conditions. *Journal of medical engineering & technology,* 42**,** 259-264.

STADLER, J. G., DONLON, K., SIEWERT, J. D., FRANKEN, T. & LEWIS, N. E. 2016. Improving the efficiency and ease of healthcare analysis through use of data visualization dashboards. *Big data,* 4**,** 129-135.

STAWARZ, K., COX, A. L. & BLANDFORD, A. Beyond self-tracking and reminders: designing smartphone apps that support habit formation. Proceedings of the 33rd annual ACM conference on human factors in computing systems, 2015. 2653-2662.

STELLEFSON, M., CHANEY, B., BARRY, A. E., CHAVARRIA, E., TENNANT, B., WALSH-CHILDERS, K., SRIRAM, P. S. & ZAGORA, J. 2013. Web 2.0 chronic disease self-management for older adults: a systematic review. *J Med Internet Res,* 15**,** e35.

STEVENS, R., POLK, K., MERRILL, C., FENG, F., WEISS, M., BROSNAN, E., GERBER, M. S. & BARNES, L. E. User experience design to enhance the effectiveness of mobile technologies for the treatment of mental health. 2018 Systems and Information Engineering Design Symposium (SIEDS), 2018. IEEE, 135-140.

SULISTYONO, M. T., PANE, E. S., WIBAWA, A. D. & PURNOMO, M. H. Analysis of EEG-Based Stroke Severity Groups Clustering using K-Means. 2021 International Seminar on Intelligent Technology and Its Applications (ISITIA), 2021. IEEE, 67-74.

SUN, H., SAEEDI, P., KARURANGA, S., PINKEPANK, M., OGURTSOVA, K., DUNCAN, B. B., STEIN, C., BASIT, A., CHAN, J. C. & MBANYA, J. C. 2022. IDF Diabetes Atlas: Global, regional and country-level diabetes prevalence estimates for 2021 and projections for 2045. *Diabetes research and clinical practice,* 183**,** 109119.

SUTHAHARAN, S. & SUTHAHARAN, S. 2016. Support vector machine. *Machine learning models and algorithms for big data classification: thinking with examples for effective learning***,** 207-235.

SWITSERS, L., DAUWE, A., VANHOUDT, A., VAN DYCK, H., LOMBAERTS, K. & OLDENBURG, J. 2018. Users' perspectives on mHealth self-management of bipolar disorder: qualitative focus group study. *JMIR mHealth and uHealth,* 6**,** e9529.

TALBOOM-KAMP, E. P., VERDIJK, N. A., HARMANS, L. M., NUMANS, M. E. & CHAVANNES, N. H. 2016. An eHealth Platform to Manage Chronic Disease in Primary Care: An Innovative Approach. *Interact J Med Res,* 5**,** e5.

THARWAT, A., GABER, T., IBRAHIM, A. & HASSANIEN, A. E. 2017. Linear discriminant analysis: A detailed tutorial. *AI communications,* 30**,** 169-190.

TIEU, L., SARKAR, U., SCHILLINGER, D., RALSTON, J. D., RATANAWONGSA, N., PASICK, R. & LYLES, C. R. 2015. Barriers and facilitators to online portal use among patients and caregivers in a safety net health care system: a qualitative study. *Journal of medical Internet research,* 17**,** e275.

TIGHE, S. A., BALL, K., KENSING, F., KAYSER, L., RAWSTORN, J. C. & MADDISON, R. 2020. Toward a Digital Platform for the Self-Management of Noncommunicable Disease: Systematic Review of Platform-Like Interventions. *Journal of medical Internet research,* 22**,** e16774.

TING, Y.-L. 2012. The pitfalls of mobile devices in learning: A different view and implications for pedagogical design. *Journal of Educational Computing Research,* 46**,** 119-134.

TOROUS, J., MICHALAK, E. E. & O'BRIEN, H. L. 2020. Digital health and engagement—looking behind the measures and methods. *JAMA network open,* 3**,** e2010918-e2010918.

TOROUS, J., NICHOLAS, J., LARSEN, M. E., FIRTH, J. & CHRISTENSEN, H. 2018. Clinical review of user engagement with mental health smartphone apps: evidence, theory and improvements. *BMJ Ment Health,* 21**,** 116-119.

TRAN, P. B., KAZIBWE, J., NIKOLAIDIS, G. F., LINNOSMAA, I., RIJKEN, M. & VAN OLMEN, J. 2022. Costs of multimorbidity: a systematic review and meta-analyses. *BMC medicine,* 20**,** 1-15.

TRIANTAFYLLIDIS, A. K., KOUTKIAS, V. G., CHOUVARDA, I., ADAMI, I., KOUROUBALI, A. & MAGLAVERAS, N. 2016. Framework of sensor-based monitoring for pervasive patient care. *Healthcare technology letters,* 3**,** 153-158.

TURNBULL, S., LUCAS, P. J., HAY, A. D. & CABRAL, C. 2021. The role of economic, educational and social resources in supporting the use of digital health technologies by people with T2D: a qualitative study. *BMC Public Health,* 21**,** 1-12.

TWA, M. D., PARTHASARATHY, S., ROBERTS, C., MAHMOUD, A. M., RAASCH, T. W. & BULLIMORE, M. A. 2005. Automated decision tree classification of corneal shape. *Optometry and vision science: official publication of the American Academy of Optometry,* 82**,** 1038.

UK NATIONAL GUIDELINE CENTRE 2016. Multimorbidity: assessment, prioritisation and management of care for people with commonly occurring multimorbidity.

UTTS, J. M. 2014. *Seeing through statistics*, Cengage Learning.

VAN'T RIET, J., CRUTZEN, R. & DE VRIES, H. 2010. Investigating predictors of visiting, using, and revisiting an online health-communication program: a longitudinal study. *Journal of Medical Internet Research,* 12**,** e1345.

VAN DER HEIDE, I., SNOEIJS, S., MELCHIORRE, M. G., QUATTRINI, S., BOERMA, W., SCHELLEVIS, F. & RIJKEN, M. 2015. Innovating care for people with multiple chronic conditions in Europe. *Brussels: ICARE4EU*.

VAN STRALEN, M. M., KOK, G., DE VRIES, H., MUDDE, A. N., BOLMAN, C. & LECHNER, L. 2008. The Active plus protocol: systematic development of two theory-and evidence-based tailored physical activity interventions for the over-fifties. *BMC Public Health,* 8**,** 1-12.

VELARDO, C., SHAH, S. A., GIBSON, O., CLIFFORD, G., HENEGHAN, C., RUTTER, H., FARMER, A. & TARASSENKO, L. 2017. Digital health system for personalised COPD long-term management. *BMC medical informatics and decision making,* 17**,** 1-13.

VENKATESH, V. 2000. Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research,* 11**,** 342-365.

VENKATESH, V. & BALA, H. 2008. Technology acceptance model 3 and a research agenda on interventions. *Decision sciences,* 39**,** 273-315.

VENKATESH, V., MORRIS, M. G., DAVIS, G. B. & DAVIS, F. D. 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly***,** 425-478.

VERDEZOTO, N. & GRöNVALL, E. 2016. On preventive blood pressure self-monitoring at home. *Cognition, Technology & Work,* 18**,** 267-285.

VIEGAS, F. B., WATTENBERG, M., VAN HAM, F., KRISS, J. & MCKEON, M. 2007. Manyeyes: a site for visualization at internet scale. *IEEE transactions on visualization and computer graphics,* 13**,** 1121-1128.

VIEIRA, S., PINAYA, W. H. L. & MECHELLI, A. 2020. Main concepts in machine learning. *Machine learning.* Elsevier.

VILLACAMPA-FERNANDEZ, P., NAVARRO-PARDO, E., TARIN, J. J. & CANO, A. 2017. Frailty and multimorbidity: two related yet different concepts. *Maturitas,* 95**,** 31-35.

VIOLáN, C., ROSO-LLORACH, A., FOGUET-BOREU, Q., GUISADO-CLAVERO, M., PONS-VIGUéS, M., PUJOL-RIBERA, E. & VALDERAS, J. M. 2018. Multimorbidity patterns with K-means nonhierarchical cluster analysis. *BMC family practice,* 19**,** 1-11.

VOLDERS, E., DE GROOT, R. H., COUMANS, J. M., BOLMAN, C. A. & LECHNER, L. 2021. A randomized controlled trial into the cognitive effects of a computer-tailored physical activity intervention in older adults with chronic disease (s). *European Review of Aging and Physical Activity,* 18**,** 1-15.

VOS, T., LIM, S. S., ABBAFATI, C., ABBAS, K. M., ABBASI, M., ABBASIFARD, M., ABBASI-KANGEVARI, M., ABBASTABAR, H., ABD-ALLAH, F. & ABDELALIM, A. 2020. Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019. *The Lancet,* 396**,** 1204-1222.

WALLIN, E. E. K., MATTSSON, S. & OLSSON, E. M. G. 2016. The preference for internet-based psychological interventions by individuals without past or current use of mental health treatment delivered online: a survey study with mixed-methods analysis. *JMIR mental health,* 3**,** e5324.

WANG, S.-C., GAO, R. & WANG, L.-M. 2016. Bayesian network classifiers based on Gaussian kernel density. *Expert Systems with Applications,* 51**,** 207-217.

WANG, T., GU, I. Y. & SHI, P. Object tracking using incremental 2D-PCA learning and ML estimation. 2007 IEEE International Conference on Acoustics, Speech and Signal Processing-ICASSP'07, 2007. IEEE, I-933-I-936.

WANG, Y., LI, M., ZHAO, X., PAN, X., LU, M., LU, J. & HU, Y. 2019. Effects of continuous care for patients with type 2 diabetes using mobile health application: a randomised controlled trial. *The International journal of health planning and management,* 34**,** 1025-1035.

WANG, Y., SONG, Y., ZHU, Y., JI, H. & WANG, A. 2022a. Association of eHealth Literacy with Health Promotion Behaviors of Community-Dwelling Older People: The Chain Mediating Role of Self-Efficacy and Self-Care Ability. *International Journal of Environmental Research and Public Health,* 19**,** 6092.

WANG, Y., ZHANG, P., SHAO, H., ANDES, L. J. & IMPERATORE, G. 2022b. Medical Costs Associated With Diabetes Complications in Medicare Beneficiaries Aged 65 Years or Older With Type 2 Diabetes. *Diabetes Care,* 45**,** 2570-2576.

WATERS, H. & GRAF, M. 2018. The costs of chronic disease in the US. *Santa Monica, CA: The Milken Institute*.

WATERWORTH, J. A., BALLESTEROS, S., PETER, C., BIEBER, G., KREINER, A., WIRATANAYA, A., POLYMENAKOS, L., WANCHE-POLITIS, S., CAPOBIANCO, M. & ETXEBERRIA, I. Ageing in a networked society: social inclusion and mental stimulation. Proceedings of the 2nd International Conference on PErvasive Technologies Related to Assistive Environments, 2009. 1-5.

WEI, J., HOLLIN, I. & KACHNOWSKI, S. 2011. A review of the use of mobile phone text messaging in clinical and healthy behaviour interventions. *Journal of telemedicine and telecare,* 17**,** 41-48.

WEI, K. S., IBRAHIM, N. E., KUMAR, A. A., JENA, S., CHEW, V., DEPA, M., MAYANIL, N., KVEDAR, J. C. & GAGGIN, H. K. 2021. Habits Heart App for Patient Engagement in Heart Failure Management: Pilot Feasibility Randomized Trial. *JMIR Mhealth Uhealth,* 9**,** e19465.

WEI, M., CHOW, T. W. & CHAN, R. H. 2015. Heterogeneous feature subset selection using mutual information-based feature transformation. *Neurocomputing,* 168**,** 706-718.

WEIGEL, F. K. & HAZEN, B. T. 2014. Technical proficiency for IS Success. *Computers in human behavior,* 31**,** 27-36.

WEINSTOCK, R. S., ALEPPO, G., BAILEY, T. S., BERGENSTAL, R. M., FISHER, W. A., GREENWOOD, D. A. & YOUNG, L. A. 2020. The role of blood glucose monitoring in diabetes management. *Compendia,* 2020.

WIEMER-HASTINGS, P., WIEMER-HASTINGS, K. & GRAESSER, A. Latent semantic analysis. Proceedings of the 16th international joint conference on Artificial intelligence, 2004. 1-14.

WIENS, J. & SHENOY, E. S. 2018. Machine learning for healthcare: on the verge of a major shift in healthcare epidemiology. *Clinical Infectious Diseases,* 66**,** 149-153.

WILD, K. V., MATTEK, N. C., MAXWELL, S. A., DODGE, H. H., JIMISON, H. B. & KAYE, J. A. 2012. Computer-related self-efficacy and anxiety in older adults with and without mild cognitive impairment. *Alzheimer's & Dementia,* 8**,** 544-552.

WILKOWSKA, W. & ZIEFLE, M. Which factors form older adults' acceptance of mobile information and communication technologies? Symposium of the Austrian HCI and Usability Engineering Group, 2009. Springer, 81-101.

WILLIAMS, B., MANCIA, G., SPIERING, W., AGABITI ROSEI, E., AZIZI, M., BURNIER, M., CLEMENT, D. L., COCA, A., DE SIMONE, G. & DOMINICZAK, A. 2018. 2018 ESC/ESH Guidelines for the management of arterial hypertension: The Task Force for the management of arterial hypertension of the European Society of Cardiology (ESC) and the European Society of Hypertension (ESH). *European heart journal,* 39**,** 3021-3104.

WILLIS, E. 2016. Patients' self-efficacy within online health communities: facilitating chronic disease self-management behaviors through peer education. *Health Communication,* 31**,** 299-307.

WIRTH, R. & HIPP, J. CRISP-DM: Towards a standard process model for data mining. Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining, 2000. Manchester, 29-39.

WONG, A., YOUNG, A. T., LIANG, A. S., GONZALES, R., DOUGLAS, V. C. & HADLEY, D. 2018. Development and validation of an electronic health record–based machine learning model to estimate delirium risk in newly hospitalized patients without known cognitive impairment. *JAMA network open,* 1**,** e181018-e181018.

WOODWARD, J., CHEN, Y.-P., JURCZYK, K., ROSS, K. M., ANTHONY, L. & RUIZ, J. A Survey of Notification Designs in Commercial mHealth Apps. Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, 2021. 1-7.

WORLD HEALTH ORGANIZATION 2016. Global strategy on human resources for health: workforce 2030.

WORLD HEALTH ORGANIZATION. 2020. *WHO reveals leading causes of death and disability worldwide: 2000-2019* [Online]. Available: https://www.who.int/news/item/09-12-2020-who-reveals-leading-causes-of-death-and-disability-worldwide-2000-2019 [Accessed July 18, 2022 2022].

WORLD HEALTH ORGANIZATION. 2021. *Hypertension* [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/hypertension [Accessed Dec 05, 2022 2022].

WORLD HEALTH ORGANIZATION. 2022a. *Ageing-Demographics* [Online]. Available: https://platform.who.int/data/maternal-newborn-child-adolescent-ageing/ageing-data/ageing---demographics [Accessed April 11, 2022 2022].

WORLD HEALTH ORGANIZATION. 2022b. *Ageing and health* [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health [Accessed Oct 1, 2023 2023].

WORLD HEALTH ORGANIZATION. 2022c. *Chronic obstructive pulmonary disease (COPD)* [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/chronic-obstructive-pulmonary-disease-(copd) [Accessed Dec 12, 2022 2022].

WU, V. X., DONG, Y., TAN, P. C., GAN, P., ZHANG, D., CHI, Y., CHAO, F. F. T., LU, J., TEO, B. H. D. & TAN, Y. Q. 2022. Development of a Community-Based e-Health Program for Older Adults With Chronic Diseases: Pilot Pre-Post Study. *JMIR aging,* 5**,** e33118.

WU, X., KUMAR, V., QUINLAN, J. R., GHOSH, J., YANG, Q., MOTODA, H., MCLACHLAN, G., NG, A., LIU, B. & YU, P. 2007. Top 10 algorithms in data mining Knowledge and Information Systems, vol. 14, no. 1. Dec.

XIE, J., WEN, D., LIANG, L., JIA, Y., GAO, L. & LEI, J. 2018. Evaluating the validity of current mainstream wearable devices in fitness tracking under various physical activities: comparative study. *JMIR mHealth and uHealth,* 6**,** e9754.

XU, S., KIM, J., WALTER, J. R., GHAFFARI, R. & ROGERS, J. A. 2022. Translational gaps and opportunities for medical wearables in digital health. *Science translational medicine,* 14**,** eabn6036.

XU, Z., ZHANG, D., ZHENG, X., LEE, R. C., WONG, S. Y. & WONG, C. K. 2023. Use, satisfaction, and preference of online health services among older adults with multimorbidity in Hong Kong primary care during COVID-19. *BMC geriatrics,* 23**,** 368.

YAO, H. & HAMILTON, H. J. 2008. Mining functional dependencies from data. *Data Mining and Knowledge Discovery,* 16**,** 197-219.

YAO, R., ZHANG, W., EVANS, R., CAO, G., RUI, T. & SHEN, L. 2022. Inequities in health care services caused by the adoption of digital health technologies: scoping review. *Journal of medical Internet research,* 24**,** e34144.

YARDLEY, L., MILLER, S., TEASDALE, E., LITTLE, P. & PRIMIT, T. 2011. Using mixed methods to design a web-based behavioural intervention to reduce transmission of colds and flu. *J Health Psychol,* 16**,** 353-64.

YARDLEY, L., SPRING, B. J., RIPER, H., MORRISON, L. G., CRANE, D. H., CURTIS, K., MERCHANT, G. C., NAUGHTON, F. & BLANDFORD, A. 2016. Understanding and Promoting Effective Engagement With Digital Behavior Change Interventions. *Am J Prev Med,* 51**,** 833-842.

YARDLEY, L., WARE, L. J., SMITH, E. R., WILLIAMS, S., BRADBURY, K. J., ARDEN-CLOSE, E. J., MULLEE, M. A., MOORE, M. V., PEACOCK, J. L. & LEAN, M. E. 2014. Randomised controlled feasibility trial of a web-based weight management intervention with nurse support for obese patients in primary care. *International Journal of Behavioral Nutrition and Physical Activity,* 11**,** 1-11.

YEAGER, C. M. & BENIGHT, C. C. 2018. If we build it, will they come? Issues of engagement with digital health interventions for trauma recovery. *Mhealth,* 4.
YOUNG, H. M., MIYAMOTO, S., DHARMAR, M. & TANG-FELDMAN, Y. 2020. Nurse coaching and mobile health compared with usual care to improve diabetes self-efficacy for persons with type 2 diabetes: randomized controlled trial. *JMIR mHealth and uHealth,* 8**,** e16665.
YUAN, S., MA, W., KANTHAWALA, S. & PENG, W. 2015. Keep using my health apps: Discover users' perception of health and fitness apps with the UTAUT2 model. *Telemedicine and e-Health,* 21**,** 735-741.
ZACHARAKI, E. I., WANG, S., CHAWLA, S., SOO YOO, D., WOLF, R., MELHEM, E. R. & DAVATZIKOS, C. 2009. Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. *Magnetic Resonance in Medicine: An Official Journal of the International Society for Magnetic Resonance in Medicine,* 62**,** 1609-1618.
ZAHI, S. & ACHCHAB, B. Clustering of the population benefiting from health insurance using K-means. Proceedings of the 4th International Conference on Smart City Applications, 2019. 1-6.
ZHENG, T., XIE, W., XU, L., HE, X., ZHANG, Y., YOU, M., YANG, G. & CHEN, Y. 2017. A machine learning-based framework to identify type 2 diabetes through electronic health records. *International journal of medical informatics,* 97**,** 120-127.
ZULMAN, D. M., JENCHURA, E. C., COHEN, D. M., LEWIS, E. T., HOUSTON, T. K. & ASCH, S. M. 2015. How can eHealth technology address challenges related to multimorbidity? Perspectives from patients with multiple chronic conditions. *Journal of general internal medicine,* 30**,** 1063-1070.