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

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Augmenting K-means Clustering with Qualitative Data to Discover Engagement Patterns of Older Adults with Multimorbidity when using Digital Health Technologies: Findings from a Proof-of-Concept Trial

Abstract

Background: Multiple chronic conditions (multimorbidity) are becoming more prevalent among ageing populations. Digital health technologies have the potential to assist in the self-management of multimorbidity, improving the awareness and monitoring of health and well-being, supporting a better understanding of the disease, and encouraging behaviour change.

Objectives: The aim of this study is to analyse how 60 older adults (average age=74 ± 6.4 [65-92 years]) with multimorbidity engaged with digital symptom and well-being monitoring when using a digital health platform over a period of approximately 12 months.

Methods: 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.

Results: Three clusters were identified; the typical user, the least engaged user, and the highly engaged user. Our findings show that gender, the types of chronic conditions and age 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, increase physical activity).

Conclusions: The findings indicate potential factors that influence older adult engagement with digital health technologies for home-based multimorbidity self-management. The least engaged user groups showed decreased health and well-being outcomes related to multimorbidity self-management. Addressing the factors highlighted in this study in the design and implementation of home-based digital health

technologies may improve symptom management and physical activity outcomes for older adults self-managing multimorbidity.

Keywords: Ageing; digital health; multimorbidity; chronic disease; engagement; k-means clustering

Introduction

According to the United Nations, the number of people aged 65 and older is growing faster than all other age groups [1]. From 2000 to 2030, the worldwide population of people aged 65 and older will increase from approximately 550 million to 973 million [2]. Furthermore, by 2050, 16% of the world's population will be over 65 years old, while 426 million people will be over 80 years old [1]. Living longer is a great benefit to today's society. However, it can introduce several challenges. Ageing can be associated with many health problems, including multimorbidity, i.e. the presence of two or more chronic conditions [3]. The prevalence rate of multimorbidity amongst older adults is estimated to be between 55% and 98%, and the factors associated with multimorbidity are older age, female gender, and low socioeconomic status [4]. In the United States, almost 75% of older adults have multimorbidity [5], and it was estimated that 50 million people in the European Union were living with multimorbidity in 2015 [6]. Likewise, the prevalence rate of multimorbidity is 69.3% among older adults in China [5].

Home-based self-management for chronic conditions involves actions and behaviours that protect and promote good healthcare practices comprising the management of physical, emotional and social care [7]. Engaging in self-management can help older adults understand and manage their conditions, prevent illness, and promote wellness [7, 8]. However, self-management for older adults with multimorbidity is a long-term, complex and challenging mission [9, 10]. There are numerous self-care tasks to engage in, which can be very complicated, especially for people with multiple chronic conditions. Furthermore, the severity of the disease can negatively impact a person's ability to engage in self-management [10].

Digital home-based health technologies have the potential to support better engagement with self-management interventions, such as monitoring of symptom and well-being parameters and medication adherence [10, 11]. Such technologies can help older adults understand their disease(s), respond to changes, and communicate with healthcare providers [12-14]. Furthermore, digital health technologies can be tailored to individual motivations and personal needs [13], which can improve sustained use [15] and result in people feeling supported [16]. Digital self-management can also create better opportunities for adoption and adherence in the long term compared with paper booklet self-management [16]. Moreover, digital health technologies, such as small wearable monitoring devices, can increase the frequency of symptom monitoring for patients with less stress than manual notifications [17].

A large body of research implements data mining and/or machine learning algorithms using data acquired from home-based healthcare data sets. Data mining techniques, such as data visualisation, clustering, classification and prediction etc., can help researchers understand users, behaviours and healthcare phenomena by identifying novel interesting patterns. These techniques can also be used to build predictive models [18-21]. In addition, data mining techniques can help in designing healthcare management systems and tracking the state of a person's chronic disease resulting in appropriate interventions and a reduction in hospital admissions [18] [22]. Vast amounts of data can be generated when users interact with digital health technologies, which provides an opportunity to understand chronic illnesses as well as elucidate how users engage with technologies in the real world. Armstrong et al. [23] used the k-means algorithm to identify previously unknown patterns of clinical characteristics in homecare rehabilitation services. 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 led to more appropriate rehabilitation services for home care clients. Madigan et al. [22] used CART (Classification and Regression Trees) to investigate a home-based healthcare data set that comprised 580 patients who had three specific conditions, i.e. chronic obstructive pulmonary disease (COPD), heart failure (HF) and hip replacement. 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 [22]. Other research [24] has developed a flow diagram of a proposed platform by using machine learning methods to analyse multiple healthcare data sets, including medical images, diagnostic and voice records. The authors believe that the system could help people in less developed areas, with lower ratios of doctors and hospitals, to diagnose diseases such as breast cancer, heart disease, diabetes and liver disease at a lower cost and in less time than local hospitals. In that study, the accuracy of disease detection was over 95% [24].

There are many different approaches to clustering analysis of healthcare data sets, such as k-means, DBSCAN (Density-Based clustering), agglomerative hierarchical clustering, self-organising maps, partitioning around medoids algorithm, hybrid hierarchical clustering, etc. [25-28]. K-means clustering is one of the most commonly used clustering/unsupervised machine learning algorithms [19, 29], and it is relatively easy to implement and relatively fast [30-32]. In addition, k-means has been used in research studies related to chronic conditions, such as diabetes [33], COPD [34, 35] and heart failure [36]. For example, a cloud-based framework with k-means clustering technique has been used for the diagnosis of diabetes and was found to be more efficient and suitable for handling extensive datasets in cloud computing platforms when compared to hierarchical clustering [32]. Violán et al. [37] analysed data from 408,994 patients aged 45 to 64 years with multimorbidity using k-means clustering to ascertain multimorbidity patterns. The authors stratified the k-means clustering analysis by gender, and six multimorbidity patterns were found for each gender. 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.

The majority of data mining studies on chronic conditions focus on the diseases themselves and their symptoms; there is less exploration of the patterns of engagement of those with multimorbidity with digital health technologies. However, data mining and machine learning are excellent ways to understand users' engagement patterns with digital health technologies. A study by McCauley et al. [38] compared clustering analysis of the user interaction event log data from a reminiscence mobile app which was designed for people living with dementia. In addition to quantitative user interaction log analysis, McCauley et al. also gathered data on the qualitative experience of users. The study showed the benefits of using data mining to analyse the user log data with complementary qualitative data analysis [38]. This is a research challenge where both quantitative and qualitative methods can be combined to fully understand users. For example, the quantitative analysis of the user event data can tell us about usage patterns, the preferred times of day to use the app and the feature use etc., but qualitative data (e.g. user interviews) are necessary to understand 'why' those usage patterns exist.

The aim of this study was to analyse how older adults with multimorbidity engage with digital symptom and health monitoring over a period of approximately 12 months using a digital health platform. In this article, user log data of engagement with digital health technology and user interview qualitative data are examined to explore the patterns of engagement. K-means clustering was used to analyse the user log data in this study. 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 by analysing the weekly submissions of every parameter and the interviews of participants? (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?

Methodology

The study was a proof-of-concept trial with an action research design and mixed methods approach. Action research is a period of investigation that *describes, interprets, and explains social situations while executing a change intervention aimed at improvement and involvement* [39]. An action research approach supports the generation of solutions to practical problems, while using methods to understand contexts of care, needs and experiences of participants.

Recruitment and sample

While 120 participants consented to take part across Ireland and Belgium, this article reports on data from 60 Irish older adults with multiple chronic conditions (two or more of the following: chronic obstructive pulmonary disease (COPD), heart failure (HF), heart disease (HD), diabetes). Participants were recruited through purposive sampling, and were recruited from multiple sources including through healthcare organisations (general practitioner clinics, specialist clinics), relevant older person networks, chronic disease support groups, social media, and local newspaper advertising. Recruitment strategies included the user of study flyers, advertisements and giving talks and platform demonstrations.

Sources of Data

The dataset was collected during the ProACT project proof-of-concept trial. As the trial was a proof-of-concept of a novel digital health platform, the main goal was to understand how the platform worked or did not work, rather than whether it worked. Thus, to determine sample size, a pragmatic approach was taken in line with two important factors: (1) is the sample size large enough to provide a reliable analysis of the ecosystem and (2) is it small enough to be financially feasible? The literature suggests that overall sample size in proof-of-concept digital health trial is low. A review of 1030 studies on technical interventions for management of chronic disease focused on heart failure (436 studies), stroke (422 studies) and COPD (172 studies) suggested that robust sample sizes for each condition were 17 for COPD, 19 for heart failure and 21 for stroke [40]. Full details on the study protocol can be found in [41].

Participants used a suite of sensor devices (i.e. blood pressure monitors, weight scales, glucometers, pulse oximeters, activity watches) and a tablet app to monitor their conditions and well-being. All participants received a smartwatch to measure activity levels and sleep, and a blood pressure monitor to measure blood pressure and pulse, and a weight scale. A blood glucose meter was provided to those with diabetes, and a pulse oximeter was provided to those with COPD to measure blood oxygen levels (SpO2). In addition, all participants received an iPad with a custom-designed application, the ProACT CareApp, which allowed users to: view their data; self-report on symptoms that could not be easily captured through a sensor (for example, breathlessness, oedema) and well-being (for example, mood, satisfaction with social life); 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 healthcare professionals, took part in this process. Findings from the user-centred design process have been published elsewhere [42, 43]. More detailed information about the full ProACT platform and CareApp used by participants can be found in [44].

The study took place between April 2018 and June 2019. On average, participants in the trial typically participated for 12 months, though some stayed on for 14 months and others for nine months (in the case of those who entered the trial later). It was one of the trial objectives to understand real-world engagement. Therefore, participants were asked to take readings with the devices and self-report in the ProACT CareApp whenever they wished (not necessarily daily). As part of the trial, participants were assisted by a technical help desk that responded to questions about the technology and home visits were conducted as needed to resolve issues. Additionally, a clinical triage service monitored participant readings and contacted them in instances of abnormal parameter values (e.g. high blood pressure, low SpO2) [45]. Participants also received a monthly check-in phone call from one of the triage nurses.

Table 1 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 healthcare 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 [42]. Off-the-shelf digital devices by two providers, Withings and iHealth, were used during the trial. Data from these providers were extracted into a custom platform called 'CABIE-SIMS', which includes a data aggregator for storing health and well-being data. All devices require the user to interact with them in some way. However, some devices needed more interaction than others (Taking a blood glucose reading, for example, took several steps, but physical activity and sleep only required opening the activity watch app to sync the data. The activity watch was supposed to synchronise automatically without user interaction. However, inconsistencies with syncing meant that users were advised to open the Withings app to sync their data. CABIE-SIMS would display the readings in 'near' real-time, apart from activity data, which was collected at regular intervals throughout the day, while sleep data was gathered every morning. Table *1* lists the types of data that were collected and the number of participants who collected them. In addition, semi-structured interviews were conducted with all participants at four-time points throughout the trial to understand their experience of using the ProACT platform. While a full qualitative thematic analysis was outside the scope of this article and was reported on elsewhere (e.g., [44]), interview transcripts for participants of interest to the analysis presented in this article were reviewed as part of the present study to provide an enhanced understanding of the results.

Table 1. Types of data, collection methods, and number of participants collecting that data

Data Type	**Collection Method**	**Number of participants (at start of trial)**
Blood pressure	Place device on arm and turn on device, which opens Withings HealthMate 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. Prepare the lancing device by inserting a new lancet and setting the puncture depth. Wash hands thoroughly. Insert a test strip into the device. Take a blood sample from the finger. Apply the blood sample to the test strip and wait for the result to display. Discard the test strip and lancet.	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 is automatically transferred via Wi-Fi to app	60 (as lifestyle parameter) including 11 (as symptom parameter for HF)
Physical activity	Participants advised to open Withings Healthmate app at least once per day to ensure syncing of data.	60
Sleep	Participants advised to open Withings Healthmate app 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

Data analysis methods

The original dataset in CABIE-SIMS was formatted using the JavaScript object notation (JSON) format. As a first step, a JSON to CSV file converter was used to make the dataset more accessible for data analysis. The main focus was on dealing with duplicate data and missing data during the data cleaning phase. Duplicate data might occur when 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. As for missing data, the dataset file comprised of 'N/A' values for all missing data.

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 (blood pressure (BP), pulse, blood oxygen level (SpO2), blood glucose (BG), weight, physical activity (PA), self-report (SR), sleep). All following analysis was implemented in the R programming language and R studio (including correlation analysis, principal component analysis, k-means clustering, T-test and one-way ANOVA).

After performing Shapiro-Wilk normality tests on the data submitted each week, we found that the data were not normally distributed. Therefore, Spearman's correlation was used to check the correlation between the parameters. 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. Similarly, the Shapiro-Wilk test was conducted to check the normality of the variables in each group. It was found that most of the variables in each group were normally distributed and only the weight submission records of Cluster3, the physical activity submission record of Cluster2, the self-report submission record of Cluster3, and the sleep submission record of Cluster1 were not normally distributed. Therefore, 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 [46].

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 is to understand the impact of digital healthcare technology, specific questions will be focussed on, such as ' Has it had any impact on the management of your health?' in the second interview.

Ethical Considerations

Ethical approval was received from three ethical committees, including the Health Service Executive northeast research ethics committee, the school of health and science research ethics committee at Dundalk Institute of Technology and the Faculty of Health Sciences Research Ethics Committee, Trinity College Dublin. All procedures were in line with the EU's General Data Protection Regulation (GDPR) for research projects, with the platform and trial methods and procedures undergoing data protection impact assessments in both countries. Written informed consent was obtained on an individual basis from participants in accordance with legal and ethical guidelines in each trial region, following a careful explanation of the study and provision of patient information and informed consent forms in plain language. All participants were informed of their right to withdraw from the study at any point without having to provide a reason for this. Participants were not compensated for their time. Data stored within the Cabie-SIMS platform was identifiable, as this data (with the participant's consent) was shared with the clinical triage teams and healthcare professionals. This was clearly outlined in the participant information leaflet and consent form. The dataset that was extracted for the purpose of the analysis presented in this paper was pseudonymised.

Results

Participants

A total of 60 older adults were enrolled in the study. 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; n=55 had HD; n=22 had COPD, and n=31 had diabetes. Over the course of the trial, 8 participants withdrew, and three 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.

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 1 shows the correlation matrix for all parameter weekly submissions (days). In this study, a moderate correlation (correlation coefficient between 0.3 to 0.7 and -0.7 to -0.3) [47, 48] is chosen as the standard for selecting parameters. First, 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. Thus, SpO2 was not selected for clustering. Likewise, the correlation coefficient between BG and weight (0.19), PA (0.2), SR (-0.06), and Sleep (0.25) are weak. Therefore, BG was not selected for clustering, and BP, weight, PA, SR and sleep were selected for clustering.

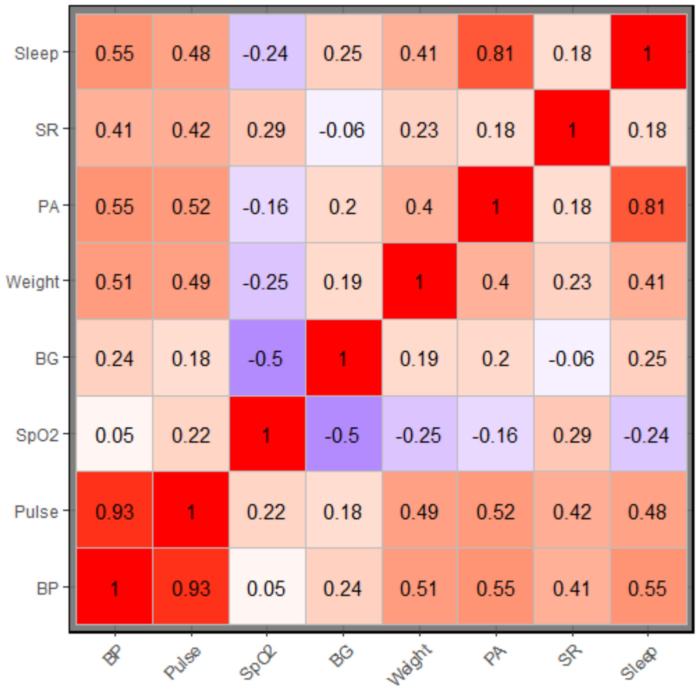

Figure 1. Correlation matrix for weekly submissions(days) of all parameters.

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 Principal Component Analysis (PCA). As can be seen from Figure 2, the first two principal components explain 73.6% of the variation, which is an acceptably large percentage. However, after a check of individual contributions, 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.

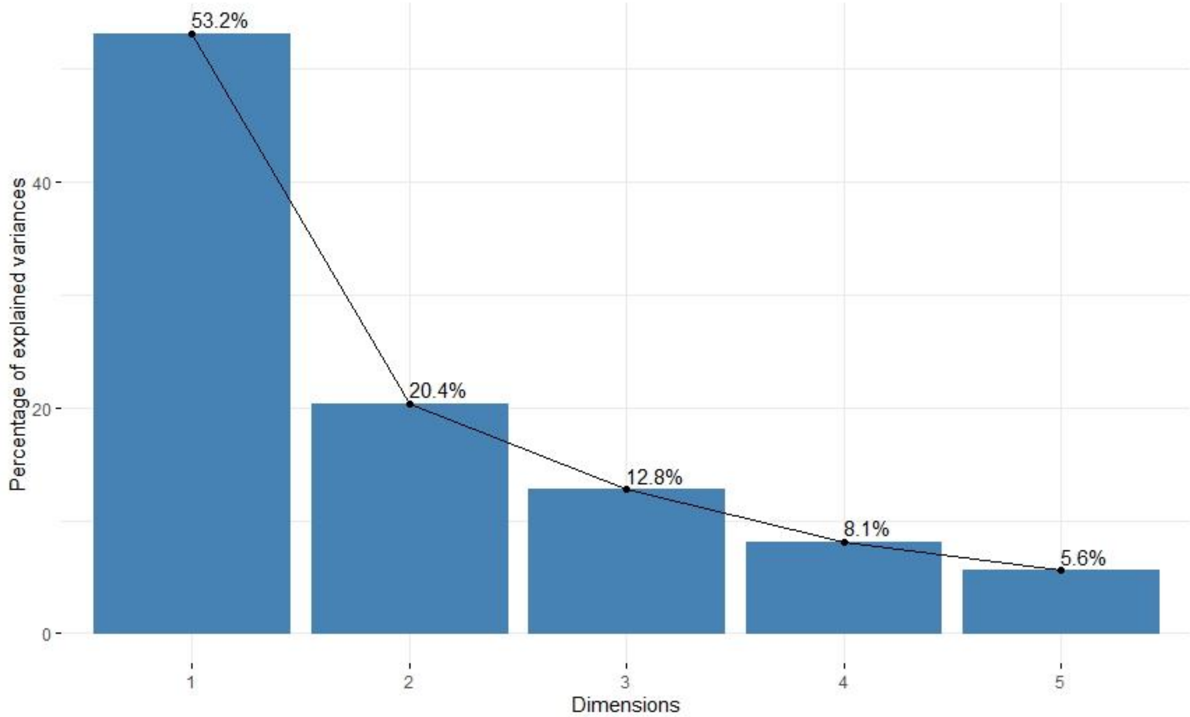

Figure 2. The scree plot of every dimension by Principal Components Analysis

After removing the outliers (P038 and P016), as Figure 3 shows the first two principal components explain 70.5% of the variation which is an acceptably large percentage.

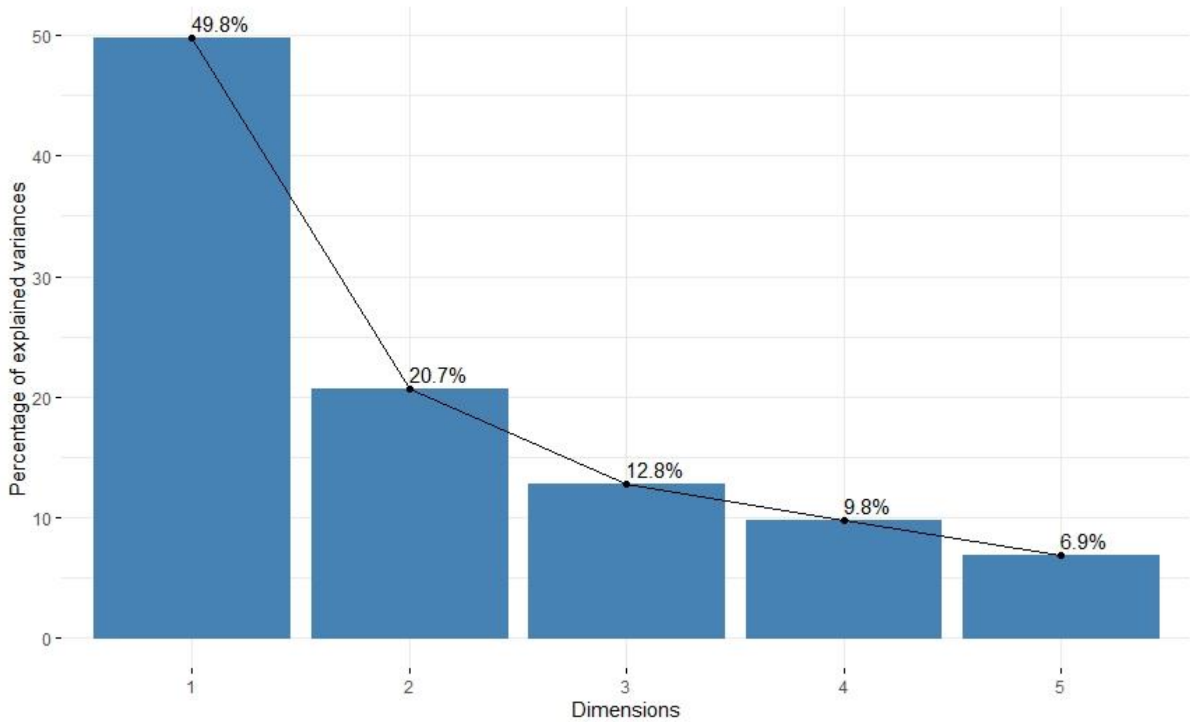

Figure 3. The scree plot of every dimension by Principal Components Analysis (without outliers)

The clusters were projected into two dimensions as shown in Figure 4. Each sub-figure in Figure 4 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 5 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).

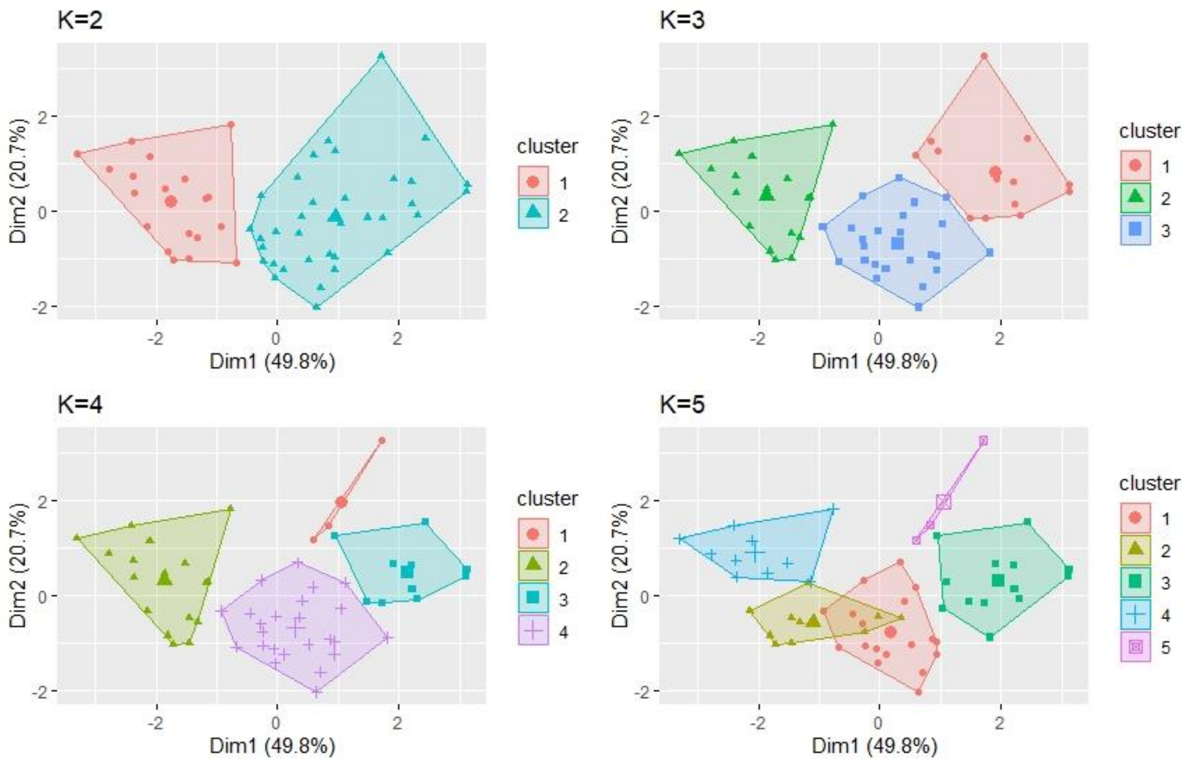

Figure 4. the visualisation of clustering with the number of clusters ranging from 2 to 5

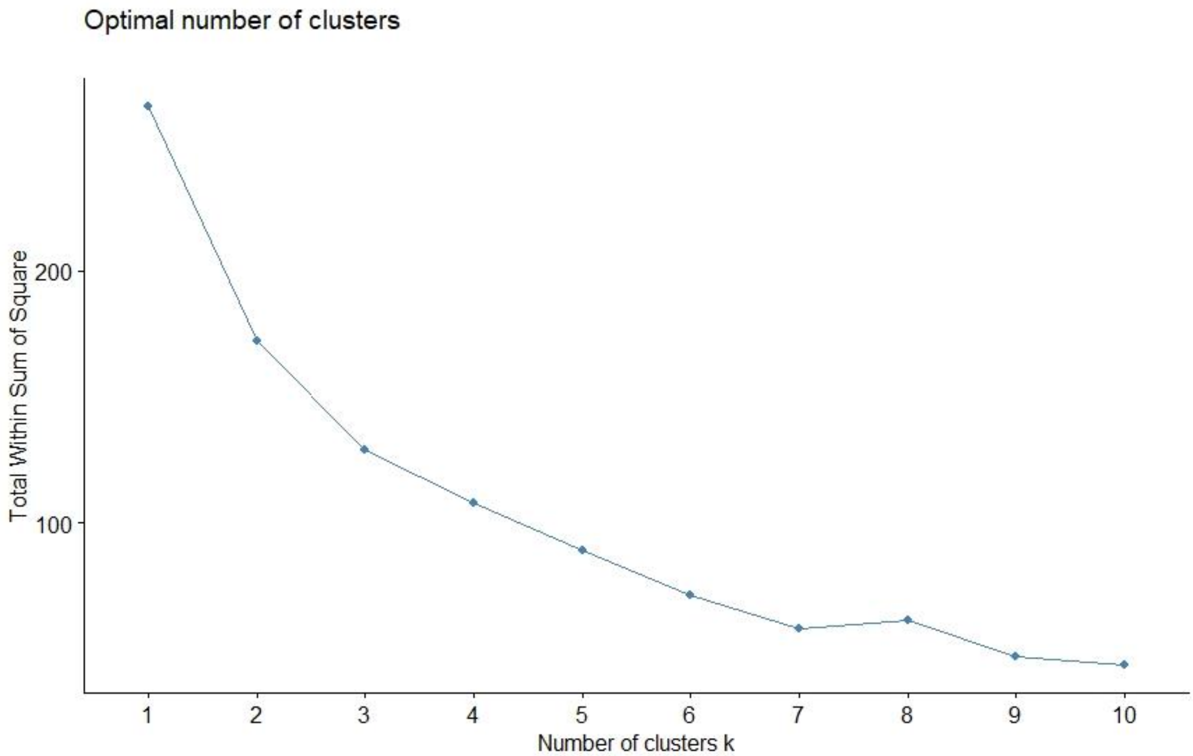

Figure 5. the optimal number of clusters by elbow method

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.

Participant characteristics

As seen in Figure 6, 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 2). As Table 2 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 which are 10 out of 31 (32%) and Cluster3 which are 14 out of 31 (45%) represent higher proportions of total male participants than female participants in Cluster2 which are 7 out of 23 (30%) and Cluster3 which are 10 out of 23 (43%). Figure 7 shows the proportion of the four chronic conditions within the three clusters. Cluster1 has the largest proportion of participants with COPD and the smallest proportion of participants with diabetes. Moreover, Cluster3 has the smallest proportion of participants with HF which are 3 out of 24 (13%) (Table 2).

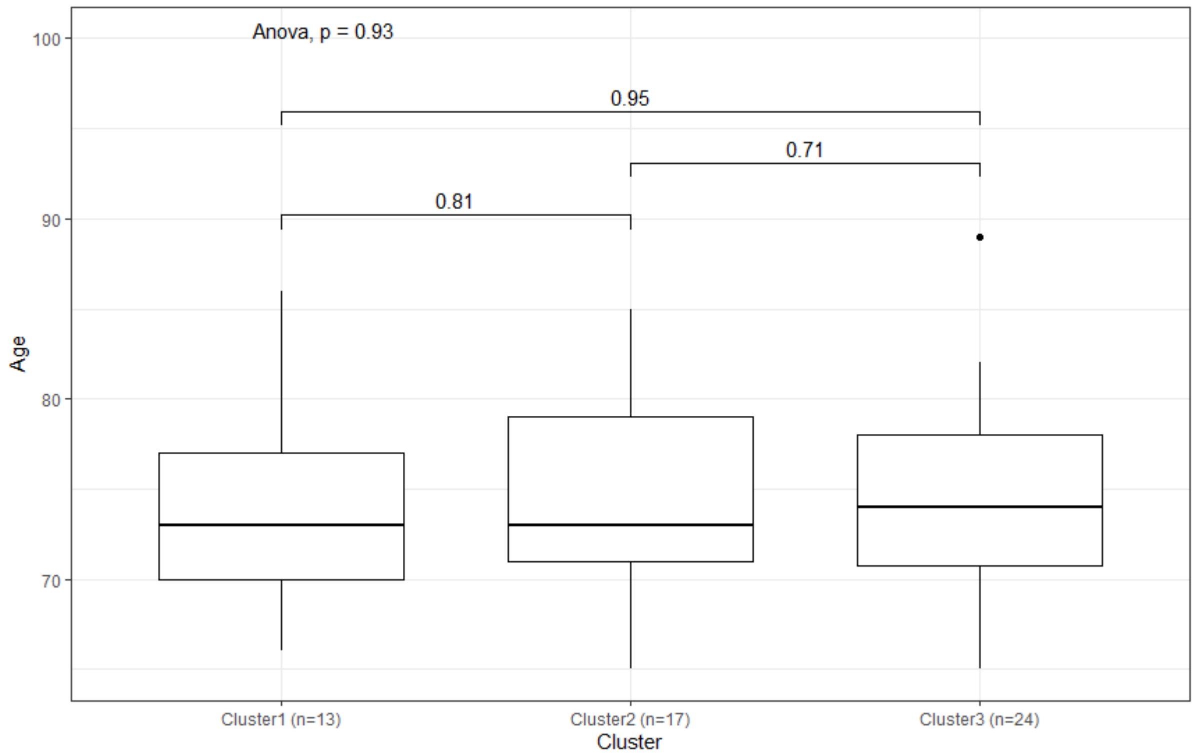

Figure 6. The variation of age within the three clusters based on the weekly submissions

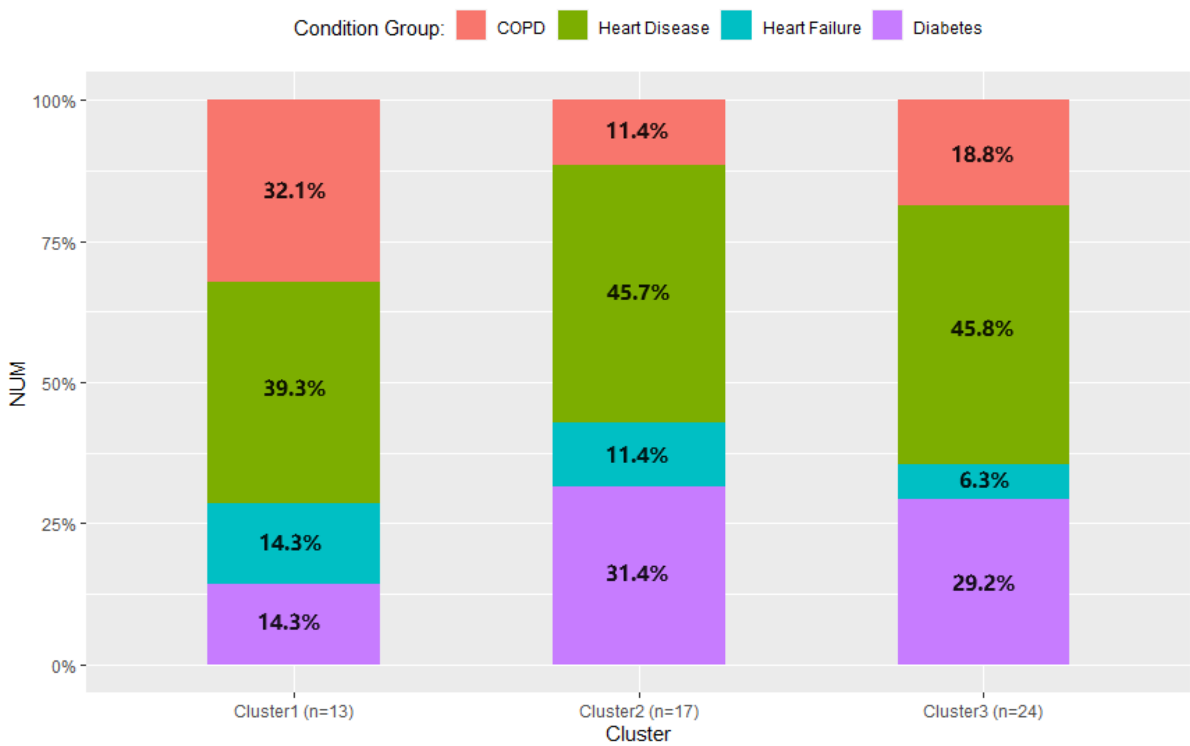

Figure 7. The variation of conditions within the three clusters. Each bar presents the percentage of each condition out of all conditions in the cluster (bearing in mind that participants can have multiple conditions). For example, there are 13 participants, and 28 records under the 4 condition groups 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 2).

Table 2. 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 (23)	10 (32)	14 (45)
Female	6 (26)	7 (30)	10 (43)
Chronic Conditions, n (%)			
COPD	9 (69)	4 (24)	9 (38)
Heart Disease	11 (85)	16 (94)	22 (92)
HF	4 (31)	4 (24)	3 (13)
Diabetes	4 (31)	11 (65)	14 (58)

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 8, 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 3, 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).

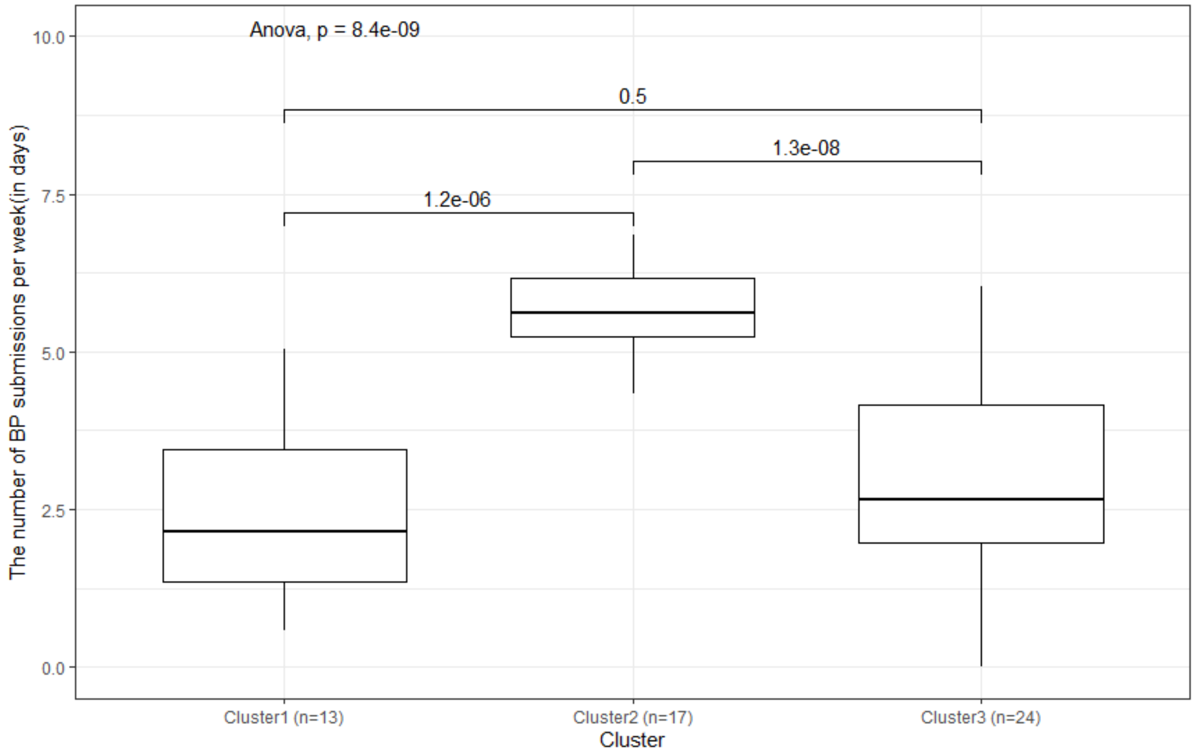

Figure 8. The variation of weekly submissions (days) for blood pressure (BP) data within the three clusters

As Figure 9 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 9, 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. The other two outliers are participant-051 and participant-053, both of whom mentioned taking their weight as part of their daily routine. 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.

"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)"

"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)"

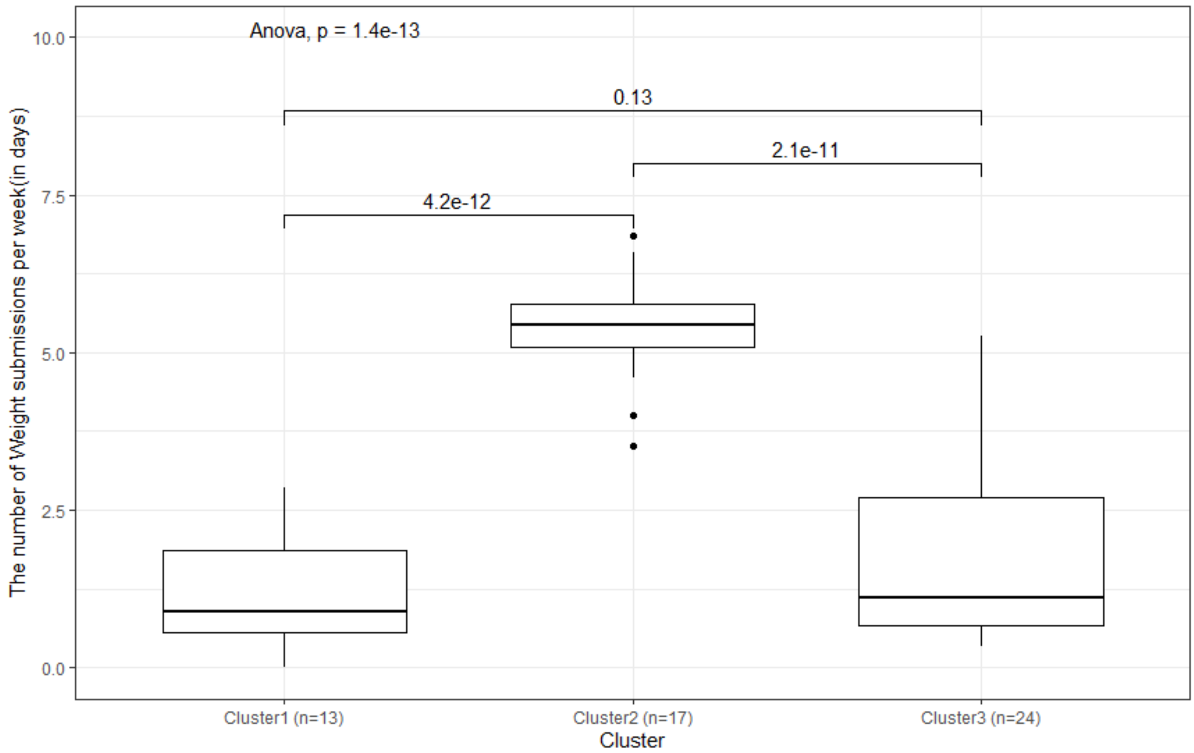

Figure 9. The variation of weekly submission(days) for weight data within the three clusters

In Table 3, 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 10 and Figure 11, as the p-value of the one-way ANOVA are 1.1e-09 and 3.7e-10. Moreover, as Figure 10 and Figure 11 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; 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 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).

"I don't wear it, I told them I wouldn't wear the watch at night, I don't like it" (Participant-030).

Table 3. Weekly submissions (days) of parameters (red = largest submission rate across the clusters and green = lowest)

Parameter, mean±SD	Cluster1 (24.1%)	Cluster2(34.5%)	Cluster3(44.4%)
Blood pressure (BP)	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 (PA)	5.2±0.7	6.7±0.5	6.5±0.4
Self-report (SR)	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

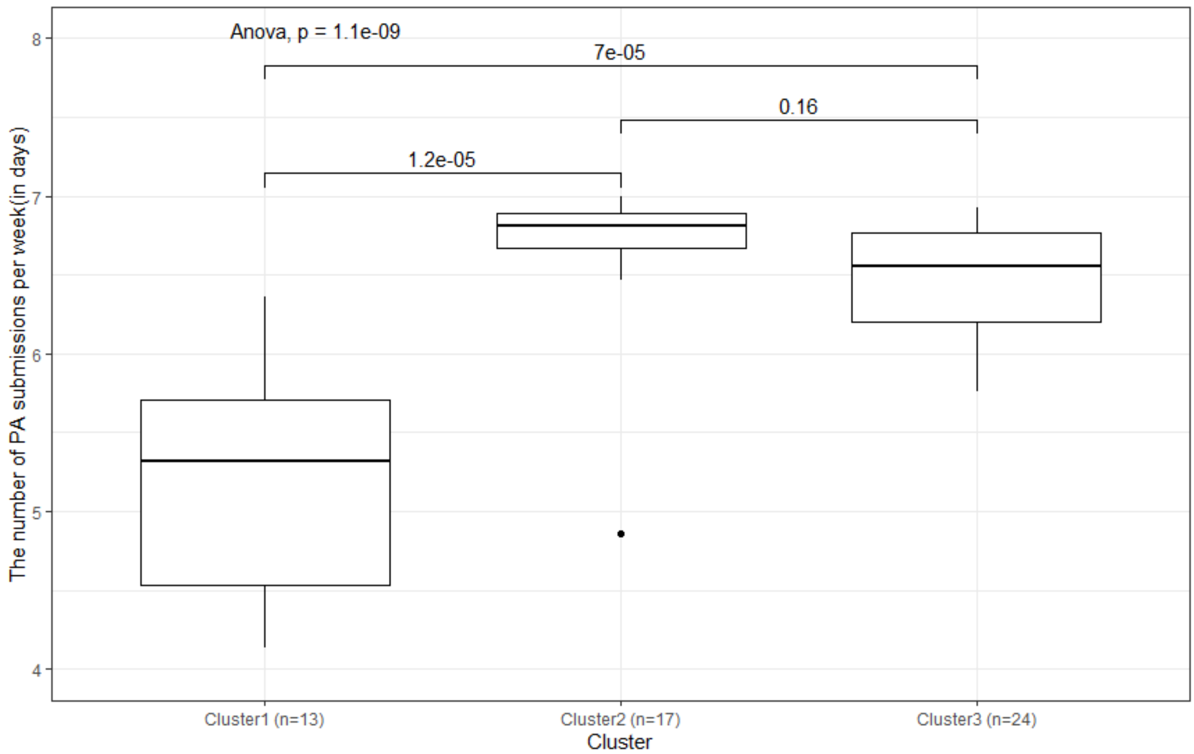

Figure 10. The variation of weekly submission(days) for physical activity (PA) within the three clusters

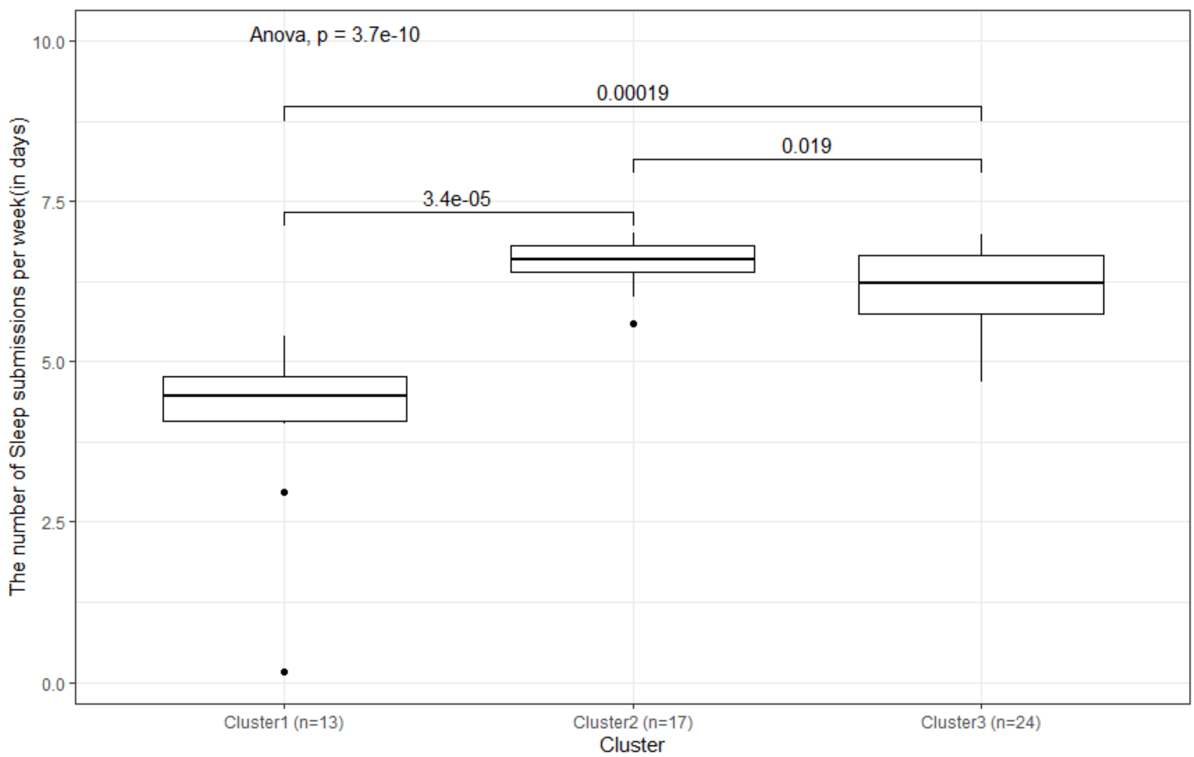

Figure 11. The variation of weekly submission(days) for sleep data within the three clusters

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 Table 3, 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 12 shows, the distribution of SR submissions is different, as the p-value of one-way ANOVA is 0.0013. In Figure 12, 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.

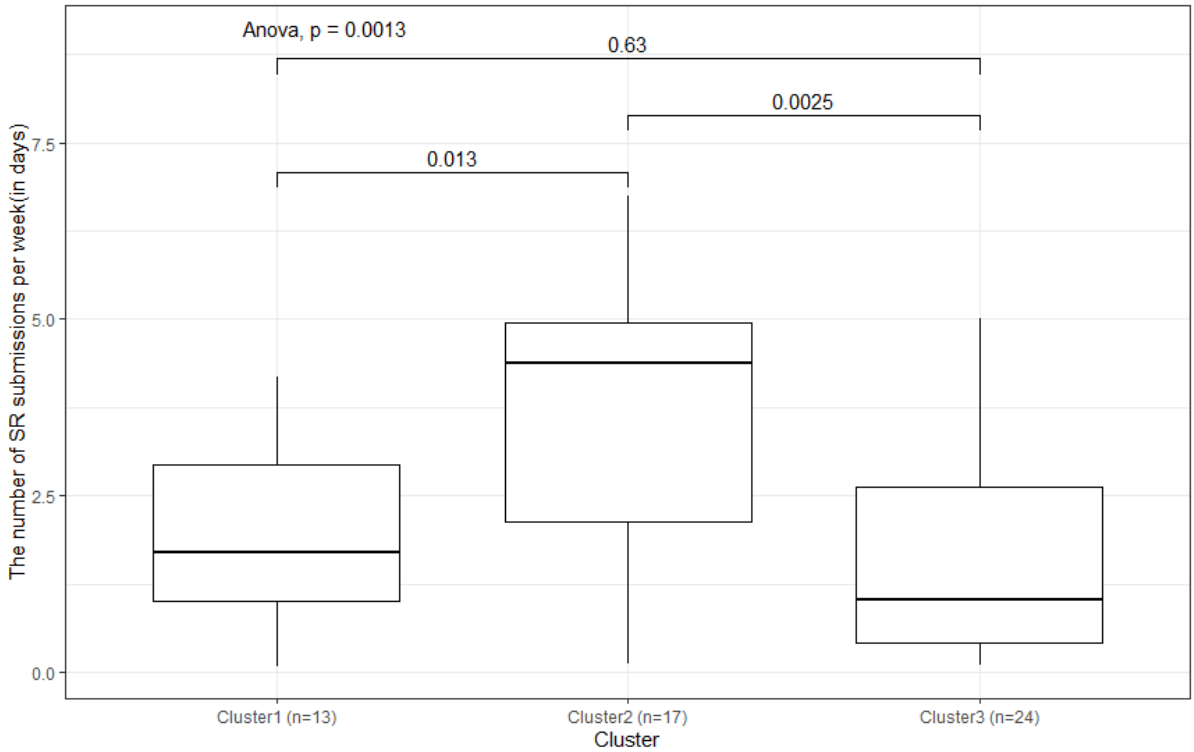

Figure 12. The variation of weekly submission(days) for self-report (SR) within the three clusters

The correlation between the weekly submission of different parameters

As seen in Figure 13, 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 because 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 13, SR has a weak correlation with other parameters, for reasons noted above.

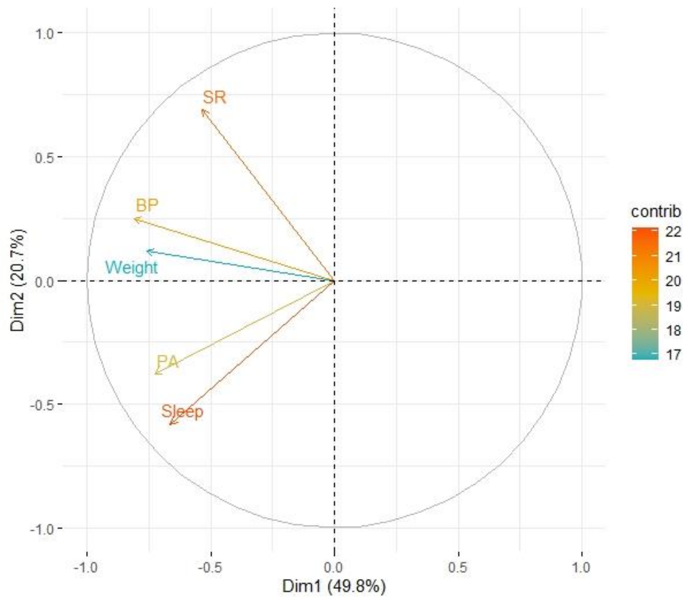

Figure 13. The Principal Component Analysis for variables

Parameter variation over time

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 4 provides a description of each cluster in this regard. As Figure 14 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 [49] (Figure 14 a). As can be seen in Table 5, 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.

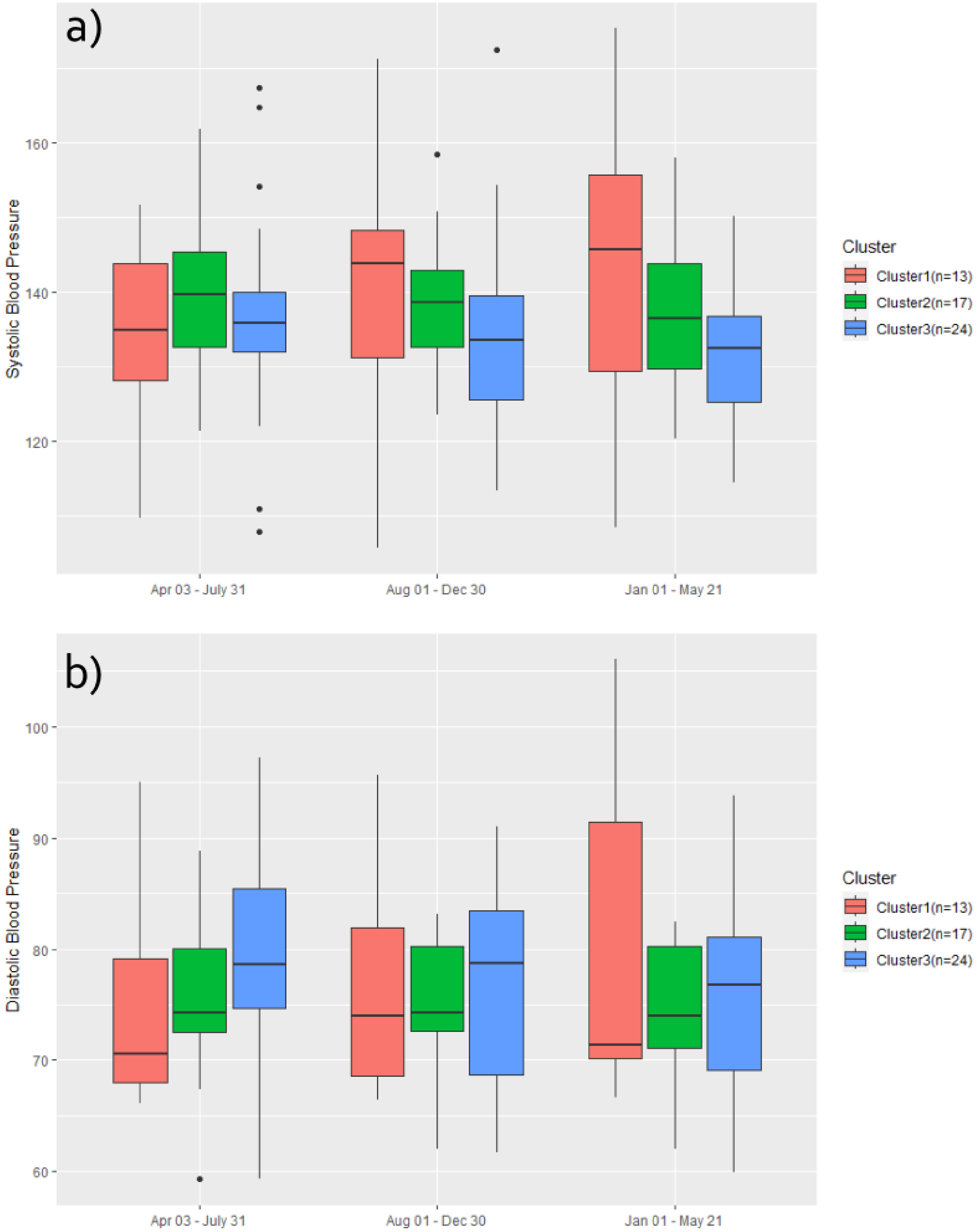

Figure 14. (a) The variation of Systolic Blood Pressure in three clusters between different time periods of the trial (b) The variation of Diastolic Blood Pressure in three clusters between different time periods

Table 4. 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 5. The p-value of every cluster among all time slots by one-way ANOVA

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

In Figure 15, 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% [50]. In addition, for patients with COPD, SpO2 levels range between 88% and 92% [51]. 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.

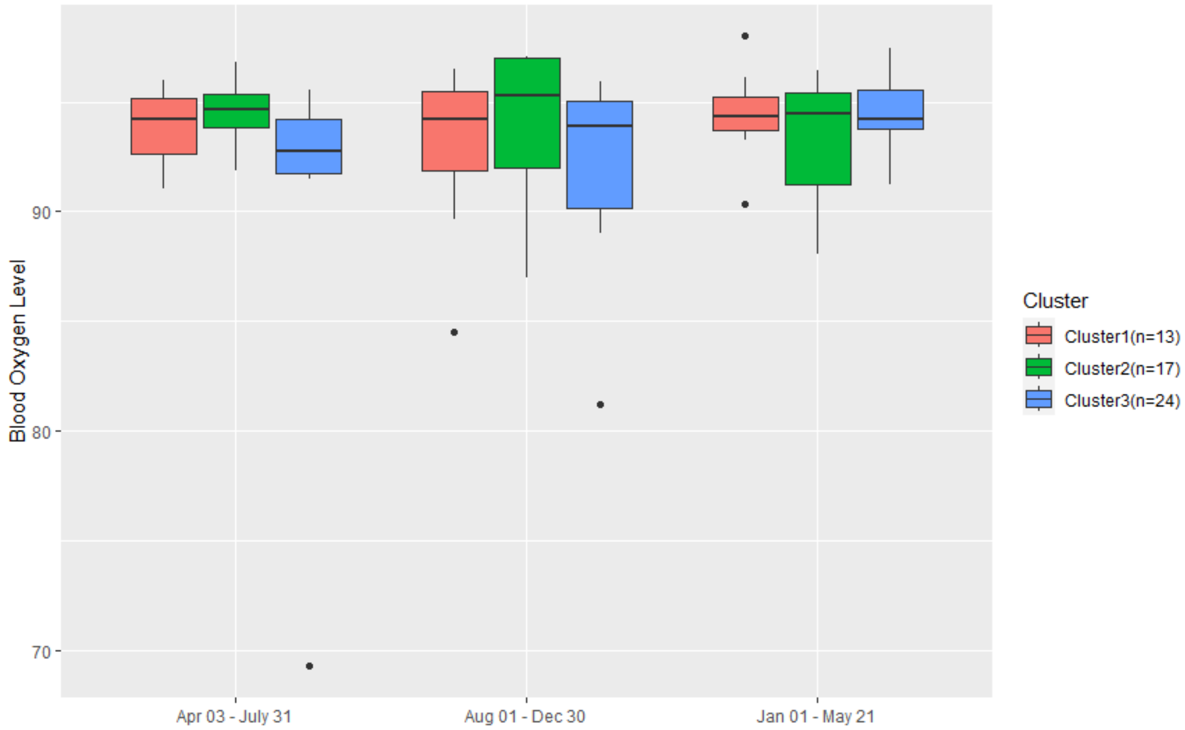

Figure 15.The variation of SpO2 in three clusters between different time periods

In relation to BG, Figure 16 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.

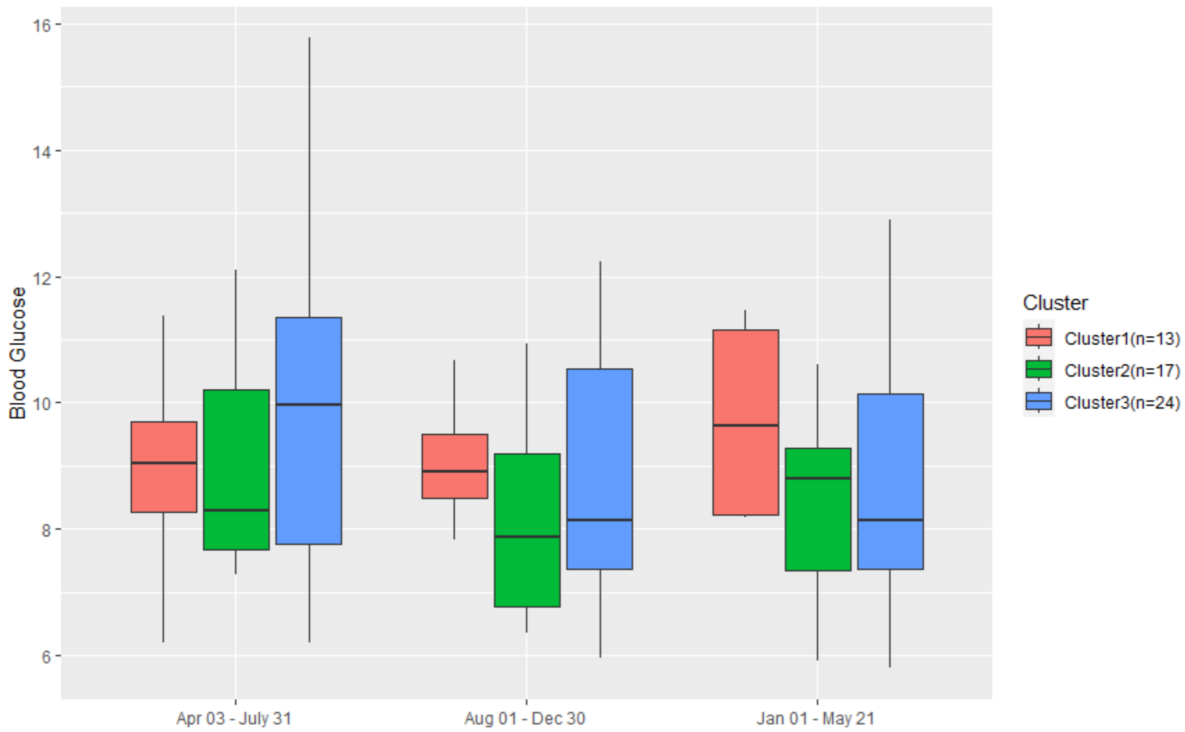

Figure 16.The variation of Blood Glucose in three clusters between different time periods

In relation to weight, Figure 17 shows that the boxplot of Cluster2 is lower than the other two clusters, and comparatively short. As Table 5 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. It is well known that there are many factors that can influence body weight, such as physical activity, diet, environmental factors etc. [52]. In this case, engagement with digital health and well-being monitoring may help control weight but the impact is not significant.

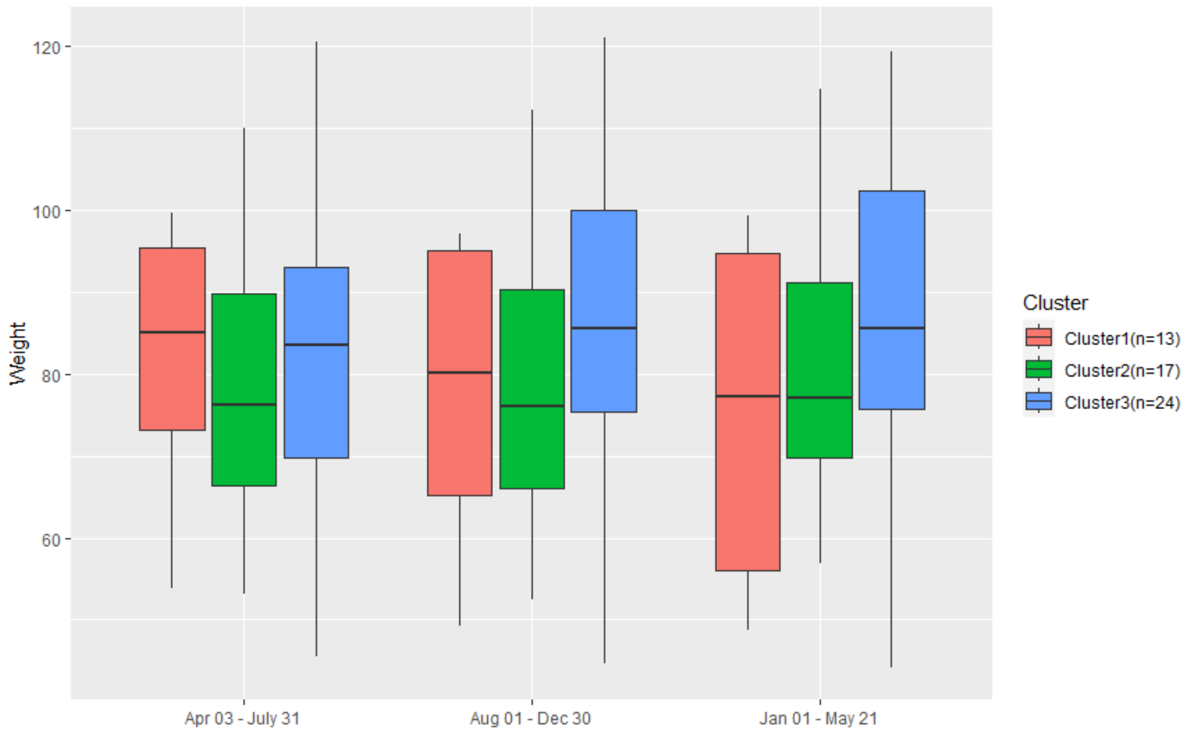

Figure 17. The variation of Weight in three clusters between different time periods

As Table 5 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 18 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 physical activity.

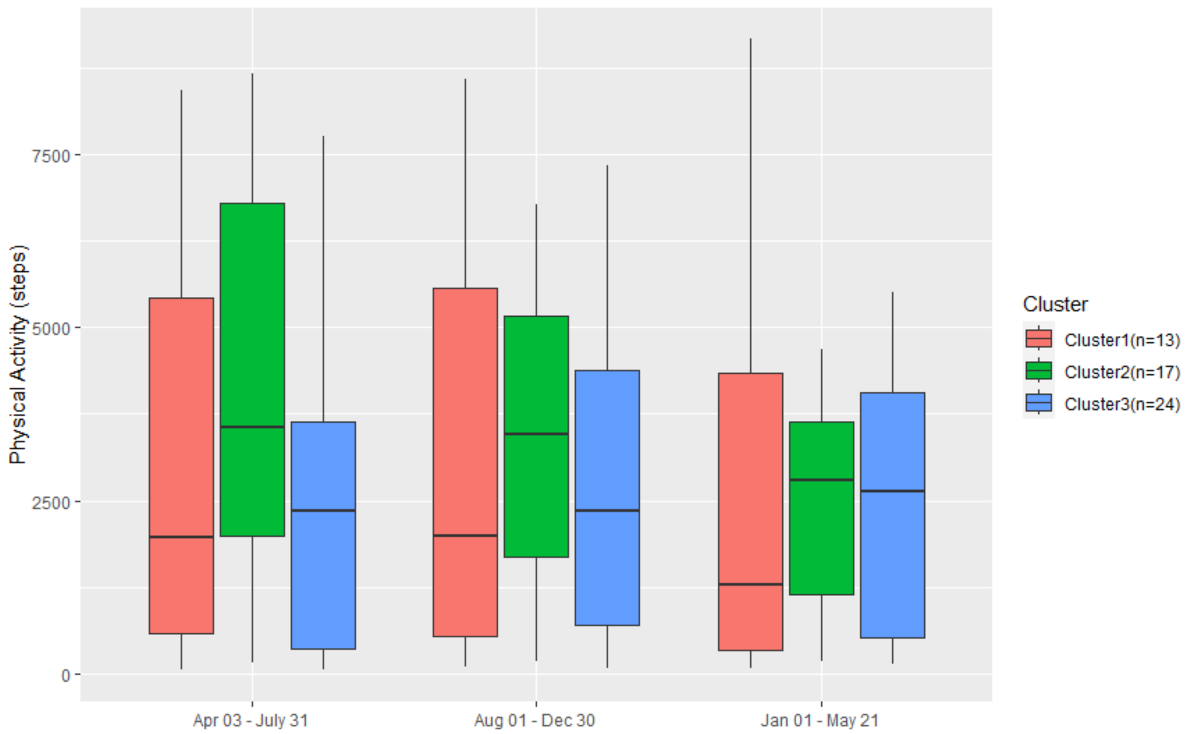

Figure 18.The variation of Physical Activity in three clusters between different time periods

Discussion

Digital health technologies hold great promise to help older adults with multimorbidity to improve health management and health outcomes. However, such benefits can only be realised if users engage with the technology. This article aims to explore patterns of older adults with multimorbidity engaging with digital self-management by using data mining to analyse users' weekly submission data. Three clusters were identified, Cluster1 being the least engaged, Cluster2 being highly engaged, and Cluster3 being the typical user. The subsequent analysis focused on how the clusters differ in terms of participant characteristics, patterns of engagement, stabilisation of condition symptoms and well-being parameters over time, as well as how engagement rates with the different devices correlate with each other.

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 (Table 4) 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.

Each of these findings is discussed in further detail below.

While the findings presented in this article focus on engagement based on usage data by participants of the ProACT trial, the interviews that were carried out as part of the trial identified additional potential factors of engagement. As reported in [44], 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 (Table *1*). These findings supplement the quantitative findings presented in this article.

Age, gender, condition types and engagement

In this study, the difference in engagement with healthcare technologies between genders is not significant. 6 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 which are 7 out of 23 in the highly engaged user group (30%) and typical user group which are 10 out of 23 (43%) compared with male participants (10 out of 31 (32%) & 14 out of 31 (45%) respectively). Other research has found that engagement with mobile health technology for blood pressure monitoring was independent of gender [53]. However, there are also some studies that show female participants are more likely to engage with digital mental healthcare interventions [54, 55]. Therefore, gender cannot be considered as a separate criterion when comparing engagement with healthcare 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 healthcare technologies than older adults [56, 57]. 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 [53] 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 blood glucose and blood pressure 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 [58]. It is also well understood that engaging in blood glucose monitoring can help people with diabetes to better self-manage and make decisions about diet, exercise and medication [59].

Factors influencing engagement

Many research studies use p-values to show the level of similarity or difference between clusters [60-63]. For most of the engagement outcomes, 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, 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 physical activity (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. Our previous research found 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 by P027 in our findings above [64].

Other research that analysed engagement with a diabetes support application found that user engagement was lower when more manual data entry was required [65]. In contrast to the other two groups, BP and Weight are collected using different devices. While measuring blood pressure requires using a blood pressure monitor and manually synchronising the data, measuring weight simply requires standing on the scale, and the data is 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 healthcare device becomes a regular routine, then participants will use it without consciously thinking about it [66]. Likewise, Yuan et al. [67] 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 healthcare 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 [68]. 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.

Relationship between engagement and health and well-being outcomes

Our third finding indicates that higher levels of engagement with digital health monitoring may result in better outcomes, such as symptom stabilisation and increased levels of physical activity. Milani et al. [69] found that digital healthcare 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 [70]. Many studies have shown that as engagement in digital diabetes interventions increases, patients will experience greater reductions in blood glucose than those with lower engagement [71, 72]. However, in our study, blood glucose 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 blood glucose of the typical user group (Cluster3) decreased over time, which could be because the participants of Cluster3 had more physical activity in the later stages of the trial than other time periods, as Figure 18 shows. Cluster2, the highly engaged user group, maintained a relatively high level of physical activity during the trial period, although it continued to decline throughout the trial. Other research shows that more physical activity can also lead to better weight control and management [73, 74], which could be one of the reasons why Cluster2 participants maintained their weight.

Limitations

There are some limitations to the research presented in this paper 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. If more features were included in clustering, such as the intervals of submissions, participants could be grouped differently. It should also be pointed out that correlation is not a causality with respect to analysing engagement rates with outcomes.

Conclusions

This study presents findings following the clustering of a dataset that was generated from a longitudinal study of older adults using a digital health technology platform (ProACT) to self-manage multiple chronic conditions. The highly engaged user group cluster (includes 31.5% of users) has the lowest average age and highest frequency of submissions for every parameter. Engagement with digital healthcare technologies may also influence health and well-being outcomes, for example, symptoms and physical activity levels. The least engaged user group in our study had relatively poorer outcomes. However, the difference between the outcomes of the highly engaged user group and the typical user group is relatively small. There are three possible reasons for the correlations between the submissions of parameters and devices. First, if two parameters are collected by the same device, they usually have a strong correlation and users will equally engage with both. Second, the devices with fewer steps and parameters with less manual data entry will have a weak correlation with those devices that require more manual operations and data entry. Finally, participants' daily routines also influence the correlations between devices. For example, in this study, many participants have a daily routine to weigh themselves after measuring their BP, which leads to a strong correlation between BP and Weight submissions. Future work should explore how to integrate monitoring of additional parameters into a user's routine and whether additional characteristics such as severity of disease or technical proficiency impact engagement.

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Conflicts of Interest

The authors declare no conflict of interest for this work.

Abbreviations

BG – Blood glucose

BP – Blood pressure

CABIE – Context-aware brokering and inference engine

COPD – Chronic obstructive pulmonary disease

EMA – Ecological momentary assessment

EU – European union

JSON - Java script object notation

HD – Heart disease

HF – Heart failure

GDPR – General data protection regulation

ICT – Information and communication technologies

PCA - Principal Component Analysis

SD - Standard deviation

SIMS – Subject information management system

SpO2 – Blood oxygen level

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