Factors Influencing Digital Health Engagement of Older Adults with Multimorbidity during a Longitudinal Trial

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Abstract

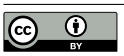
Older adults with multimorbidity remain under-served by digital health self-management interventions, despite being among the highest users of healthcare. Their engagement with such technologies is poorly understood, particularly in real-world, longitudinal contexts. This paper presents a mixed-methods analysis of engagement with the ProACT self-management platform during a six-month trial involving older adults with multimorbidity. Drawing on quantitative usage data and qualitative interviews, we examine patterns of engagement with symptom and wellbeing monitoring and management, and explore the influence of age, gender, and triage nurse support. Findings reveal that engagement is non-linear, highly individualised, and shaped by clinical support, motivation, usability, and life context. Participants developed personalised routines, adjusting use based on symptom variability and life disruptions. Triage nurse support played a key role in sustaining engagement, offering reassurance, guidance and motivation. We offer implications for designing digital health technologies that support episodic, meaningful, and contextually adaptive use in later life.

CCS Concepts

• **: Human-centered computing Human computer interaction (HCI) Empirical studies in HCI**;

Keywords

Engagement, Digital health, Older adults, Self-management, Multimorbidity, Clinical support



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1 Introduction

Life expectancy has increased dramatically over the last 50 years [33], yet people are not necessarily living well for longer, with global healthy life expectancy estimated at just 63.3 years in 2016 [74]. The rising prevalence of chronic health conditions, particularly multimorbidity - the co-occurrence of two or more conditions – poses major challenges for ageing populations. In developed countries, over 25% of adults and 50% of people aged 65+ live with multimorbidity [23], which significantly affects physical, mental and social wellbeing. Multimorbidity is associated with functional decline, high rates of polypharmacy, increased healthcare utilisation and reduced quality of life [35, 75].

Self-management, defined as the tasks and decisions individuals undertake to manage symptoms, emotions, and lifestyle changes [3], is a crucial aspect of multimorbidity care. Yet managing multimorbidity is inherently complex, requiring navigation of overlapping symptoms, multiple medications, and fragmented care systems [39]. Digital health technologies are increasingly proposed as tools to support self-management, offering potential to monitor symptoms, track progress and prompt positive health behaviours. However, engagement with digital interventions remains problematic [37]. Many users withdraw early, with more than 25% abandoning health apps after one use [28] and attrition is particularly high among older adults [40, 77].

Older adults often lack technical and clinical support to sustain engagement with digital health tools [73]. Physical and cognitive limitations, low digital literacy and poorly designed interfaces create additional barriers to use [5, 15, 36]. Despite this, older

adults with multimorbidity are under-represented in digital health research, and few studies have examined how they engage with self-management technologies in longitudinal contexts [17].

Human support is increasingly recognised as a critical factor for promoting and sustaining digital health engagement [76]. Models such as supportive accountability [47] suggest users engage more consistently when supported by a trusted human. Proactive, personalised support, whether technical, motivational or clinical, has been shown to improve user retention, perceived value and health outcomes [16, 17, 34]. However, delivering ongoing human support at scale remains difficult, leading to growing interest in hybrid models that combine automated and human-led approaches, tailored to users' needs [41].

This paper examines the factors influencing longitudinal engagement of older adults with multimorbidity using the ProACT digital self-management platform during a six-month Effectiveness-Implementation Hybrid (EIH) trial [14]. The trial adopted a 3-Arm pragmatic randomised controlled design. Arm 1 participants used ProACT with triage nurse support; Arm 2 used ProACT without clinical support; and Arm 3 received standard care. This paper focuses on Arms 1 and 2 and reports a mixed-methods analysis of objective engagement data and qualitative interviews. While the quantitative analysis examined engagement patterns by age, gender, and clinical support, the qualitative analysis combined deductive coding based on a pre-defined framework with inductive coding to capture unanticipated, participant-led insights. This approach supported identification of additional motivational and contextual factors, including health status, perceived benefit, and daily life demands, providing a more comprehensive picture of what shaped engagement.

This paper offers three contributions. First, it provides a comprehensive view of how and why older adults with multimorbidity engage with a digital health platform over time, integrating objective usage data with in-depth qualitative insights. Other research to date has focused on either the use of questionnaires or usage logs to assess engagement [45], both of which fail to capture why and how users engage. Second, it provides rare evidence on engagement patterns in an ageing population with complex health conditions, examining the influence of age and gender on digital self-management. Finally, this paper compares engagement of those with and without clinical support. Together, our findings reveal how the realities of multimorbidity, including fluctuating symptoms, medication routines, and caregiving responsibilities, produce highly conditional, dynamic engagement patterns not well accounted for in existing digital health literature.

2 Related work

Engagement is a critical, yet complex, construct in digital health, encompassing not only initial uptake but also sustained, meaningful interaction with technologies over time. Milne-Ives et al. [45] highlight that engagement remains inconsistently defined and measured, varying from simple logins to multifaceted indicators such as frequency, duration, depth, and subjective experience. This conceptual ambiguity poses challenges for evaluating digital interventions, particularly among populations with complex health needs. Older adults and people with multimorbidity represent key user groups for digital health, yet their engagement trajectories are often shaped by distinct barriers, needs, and contextual factors. The following review examines the current evidence on digital health engagement in these populations, with attention to demographic moderators, and the influence of human support models.

2.1 Digital health engagement in older adults and people with multimorbidity

Older adults with multimorbidity face daily challenges in complex self-management routines. These include symptom monitoring, medication adherence, lifestyle adjustments, and navigating fragmented care systems with overlapping, and sometimes conflicting, advice from multiple healthcare professionals [20, 22, 30, 39]. Symptom fluctuation and the interplay between conditions make self-management unpredictable, with exacerbation in one illness impacting the management of others [9, 12].

Digital health technologies offer potential to support older adults' self-management and autonomy [5]. However, most digital interventions focus on individual conditions, such as diabetes [43], COPD [65], kidney disease [7], or hypertension [29]. These siloed tools often increase burden by requiring engagement with multiple platforms that fail to reflect the inter-related nature of multimorbidity [2, 49]. Phi et al. [53] similarly highlight how disease-specific apps can fragment the user experience for individuals managing multiple conditions.

A growing body of HCI research seeks to address this gap. Doyle et al. [18, 19] examined the design of digital tools that enable integrated self-management and personalisation across multiple conditions. These studies highlight the importance of simplifying data, coordinating inputs, and enabling cross-condition insights. Others call for features that reflect the lived realities of multimorbidity, including support for values-based decision-making and care prioritisation [11, 50, 79]. Others have explored digital tools that facilitate shared decision making and care trade-offs [4], while [66] co-designed a dashboard with older adults to help track multiple conditions using visual summaries.

Despite these developments, real-world evaluation of such tools is limited. While design requirements are well established [9], long-term, in-the-wild studies remain rare. Research has argued that people with multimorbidity are unlikely to use digital health tools unless they reduce burden, integrate into daily routines, and offer clear value [2, 4]. These challenges are amplified for older adults, who may experience reduced digital literacy, age-related impairments, and privacy concerns [36, 67, 71, 78].

Recent work has begun to explore lived experiences and engagement patterns with digital self-management platforms tailored for older adults with multimorbidity. Doyle et al. [17], report on a platform offering condition monitoring and nurse support. Quantitative data showed that older adults engaged over several months, while interviews revealed that drops in usage were often due to health improvements rather than disengagement, a finding echoed in lived informatics research [21, 38]. User diversity is a consistent theme. [54] developed a user typology distinguishing between groups such as the 'Independently Empowered,' who integrated a digital self-management platform into daily routines with minimal support, and the 'Socially Activated,' who engaged with external

encouragement. Similarly, a recent scoping review highlighted that benefits (e.g. better symptom tracking and autonomy), barriers (e.g. privacy concerns, digital burden, and motivation challenges), and socio-demographic factors were associated with engagement for individuals with multimorbidity [63]. This highlights the need for flexibility and personalisation in design.

However, sustaining engagement remains a challenge. Nunes and Fitzpatrick [49] argue that self-management technologies must better accommodate changing capacities and goals. Several studies report that initial high usage declines over time unless tools adapt to ongoing needs or offer continued value [2, 4]. Wang et al. [69] confirm these mixed experiences, citing both value and frustration with digital tools.

In summary, while research on digital self-management for multimorbidity remains under-explored, HCI research has made key contributions through co-design, user typologies and longitudinal studies. Yet, more work is needed to evaluate real-world use of these tools and to develop systems that can adapt to the complex, fluctuating realities of multimorbidity in older age.

2.2 The role of human support in enhancing engagement with digital health interventions

Human support is widely recognised as a critical factor in enhancing engagement with digital health interventions. Several studies have demonstrated that involving professionals, such as nurses, coaches, or trained peers, can increase adherence and bolster users' confidence in managing their health [16, 34, 41, 70]. The supportive accountability model posits that users persist longer with digital interventions when accountable to a trusted human supporter [47]. Recent research reinforces this: even minimal personal interaction, such as check-ins or encouragement from a coach, can improve user retention and self-efficacy [68].

Support can be delivered through proactive or reactive models. Proactive supp≤ort involves regular, scheduled outreach (e.g. weekly calls or messages), whereas reactive models rely on users to seek help. Research indicates proactive support is more effective for sustaining engagement. Boucher and Raiker [6] reported that users with scheduled support had higher adherence than those using on-demand support, even if clinical outcomes were similar. Likewise, a recent HCI case study with older adults with multimorbidity [44] found that adding regular nurse-initiated check-ins improved engagement on a health management platform. Frequency and intensity also matter - moderate check-ins are well-received, but too much contact can cause user fatigue or dependence [44, 76].

Despite the benefits of human support, resource constraints challenge the scalability of fully human-led interventions. Hybrid models that integrate automated features with selective human input have therefor gained prominence. These approaches provide scalable support while preserving the relational benefits of human contact. A recent review of coaching models - human, AI, and hybrid - concluded that hybrid approaches best balance scalability and user experience [41]. Designing such hybrid systems requires combining AI's efficiency with human empathy. For instance, digital systems can automate reminders and monitoring, while human coaches provide personalised feedback or intervene when disengagement is detected. Users often express appreciation for knowing a human is available, even if most interactions are automated [16, 41].

The effectiveness of support also depends on user characteristics. Individuals with low digital or health literacy benefit more from guided interventions, including 'digital navigators' who provide technical and motivational support [8]. Similarly, users with low intrinsic motivation or high anxiety may respond better to structured, frequent support, while more confident or autonomous users may prefer minimal contact. Peer support features such as forums or group chats can enhance engagement, particularly for users seeking social connection, though not all users benefit [13, 25, 26]. Consequently, support strategies must be aligned with user preferences, as poorly matched support can hinder engagement. Recent HCI work on digital coaching [60] similarly finds that adapting support content, communication style and the coach's persona to individual needs is essential. Our research contributes further nuance to this discourse, exploring how proactive triage support interacts with user characteristics to shape longitudinal patterns of digital health use.

3 Methods

3.1 Participant recruitment

The EIH trial recruited 240 participants aged 65 and over in Ireland, each living with at least two of the following conditions: diabetes, chronic respiratory disease (CRD), chronic heart failure (CHF), or chronic heart disease (CHD). The sample size was determined to ensure sufficient statistical power for evaluating the trial's primary outcomes (which are outside the scope of this paper). Based on a desired power of 0.80, an error variance of 2, and a Type I error rate of 0.05, and accounting for an anticipate attrition rate of 30%, a minimum of 76 participants per trial Arm was required to detect a small-to moderate effect size (Cohen's d = 0.25). This was rounded up to 80 per Arm to ensure robustness, resulting in a total target sample size of 240. Participants were enrolled via convenience sampling through local media advertisements, primary care, condition support groups, and a home care organisation. Participants were randomised via block randomisation, using Redcap[1], into one of three Arms:

- Arm 1 - digital health platform use with clinical triage nurse support.
- Arm 2 – platform use without triage support.
- Arm 3 – standard care (no platform access and therefore no included in this paper).

Blinding was not feasible due to intervention visibility. Ethical approval was obtained from two academic committees and a regional health service. All participants provided written informed consent.

3.2 Trial procedures and data collection

Arm 1 and 2 participants received a suite of connected devices, including a blood pressure monitor, weight scale, smartwatch, and a tablet preloaded with the custom-built ProACT App (Figure 1, Figure 2, Figure 3, Figure 4). Those with diabetes or respiratory

[1]https://project-redcap.org/

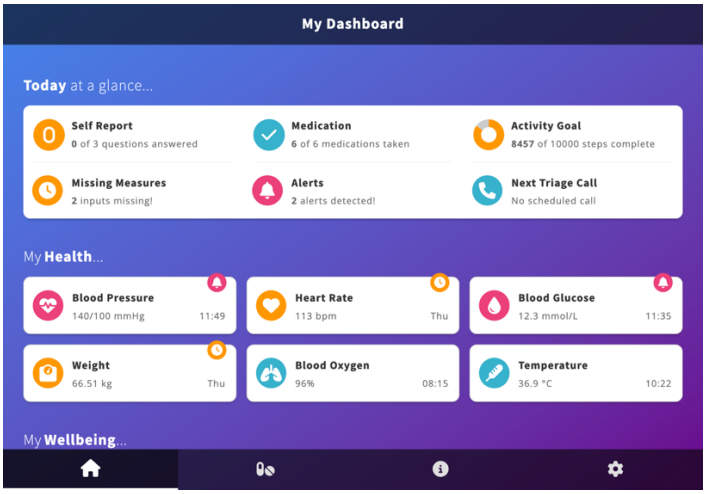

Figure 1: Dashboard of the ProACT App

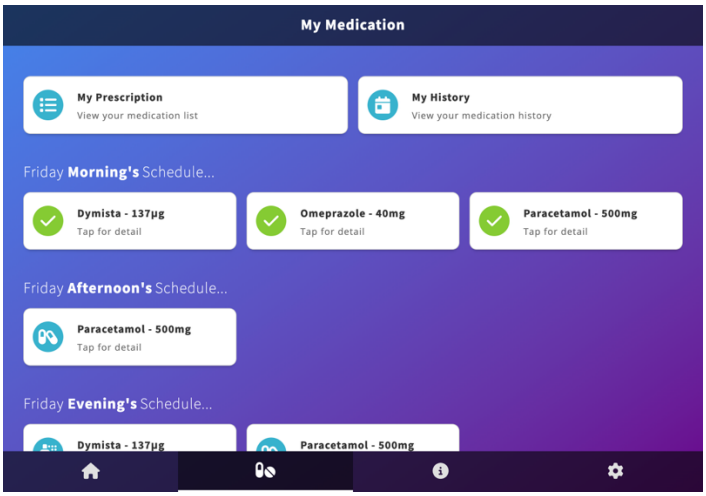

Figure 2: Medication management section of the App

conditions also received a blood glucose monitor or pulse oximeter, respectively. The App, co-designed with older adults with multimorbidity, informal carers and healthcare professionals [17, 66] comprised three main sections:

- A dashboard presenting physiological data trends, self-report inputs (e.g., mood, breathlessness), activity goal setting and progress, and tailored education.
- Medication management (digital prescription, schedule and adherence tracking).
- An educational library covering chronic conditions, self-management strategies and platform training.

A researcher visited participant homes at trial onset to set up the technology and provide training. The trial period was six months. As participants used the platform, device and App interactions were logged. A subset of participants completed interviews at baseline and post-trial. A mixed-methods approach was chosen to enable a comprehensive understanding of engagement. In Arm 1, four nurses provided triage support (Monday to Friday 9:00 to 17:00), using a custom-built interface to monitor alerts (health readings falling outside an individual's normal range), follow up with participants and advise on appropriate actions. Participants were also provided with a technical helpdesk phone number, whereby they could contact the research team if they were having any difficulties.

3.3 Platform engagement data analysis

While there is no standardised approach to measuring digital health engagement, frequency of interaction is a widely used indicator [45, 72]. In digital health research, this is often assessed in terms of how frequently users log data or interact with features such as symptom monitoring [52, 72]. For the purposes of this paper, interaction data with the devices and the ProACT App were aggregated into weekly intervals to enable longitudinal tracking. Data from trial Arms 1

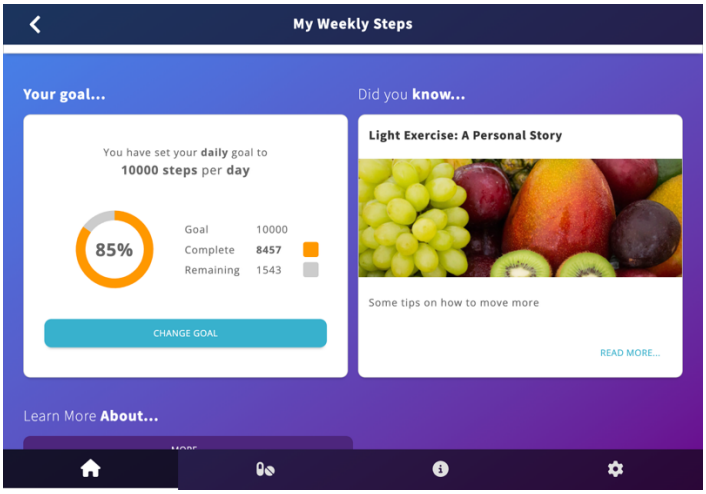

Figure 3: Setting an activity goal and contextualised education

and 2 were analysed for weeks 2 to 26, excluding onboarding and completion weeks to reduce variability.

As the total vitals measures recorded per week comprised unbounded, over-dispersed count data with an inflated number of zeros (8.39%), Bayesian zero-inflated negative binomial regression analysis was used to examine how participants' recording frequency changed over time, and how intervention Arm, age, and gender impacted upon this. As the App usage data comprised bounded count data (how many days per week each participant used the App) with an inflated number of minimum and maximum values (i.e., 24.6% and 29.5% of data points reflected App usage on zero and seven days per week, respectively), Bayesian ordinal regression analysis was employed to examine how the probability of participants using the App each day per week changed over time, and how Arm assignment, age, and gender impacted upon this. The data were analysed in R Studio [55, 56], using the BRMS package [8]. All models were estimated using the Markov Chain Monte Carlo algorithm (two chains, 10,000 iterations, with first 5,000 iterations discarded as burn-in).

For each outcome, a progressive model building process was used to identify the most parsimonious model with reliable parameter estimates. Simpler models (e.g., fixed intercept/slope) were compared with more complex ones (e.g., random intercept/slopes/quadratic terms) using differences in expected log predictive density (ELPD); posterior predictive check plots, trace plots, R-hat statistics, effective sample sizes, autocorrelation function and partial autocorrelation function plots, and pareto k values were also checked. Model diagnostics and comparisons are provided in Tables S1-S4 of the Supplementary Materials, along with justification for the analysis approach taken and R code.

Initial models included the predictor variables of 'ZTime' (the week number z-standardised) and 'Arm' to capture overall usage patterns and Arm differences. Best-fitting models included:

- For vitals: random intercept and slope
- For App use: random intercept, slope and quadratic term.

Age (z-standardised) and gender were then added to examine their effects. For interpretation, final models were re-run using unstandardised variables:

- TimeZero (ranging from 0-24 to reflect weeks 2-26) allowed estimation of initial usage (i.e., the intercept would reflect usage during participants' first full week [following the onboarding week] rather than middle week of participation)
- AgeZero (range from 0-30 to reflect ages 65-95) allowed comparison of youngest through oldest age.

3.4 Interview data analysis

Interviews were conducted primarily in-person (with some by phone), audio-recorded and transcribed verbatim. Interview topics explored participants' self-management routines during the trial, how they interpreted and acted on data, their perceptions of their health and wellbeing during the trial, the support they received to self-manage and their experiences of using the technology. Analysis followed a Collaborative Qualitative Analysis (CQA) approach, drawing on an interdisciplinary team (HCI, health psychology, social science) and employing reflexive practices to ensure participant-centred interpretation while accounting for researcher personality [58]. A hybrid thematic analysis was used [24], combining a deductive approach (based on the literature, study aims and interview guide) to create an initial codebook, and an inductive approach to identify themes during coding. The initial deductive codebook is available in the Supplementary Materials. NVivo v12 [42] was used to organize and analyse the data. Multiple coders worked collaboratively, with consensus meetings to refine codes and themes. This ensured analytical rigour, reduced bias, and enhanced the richness of the findings.

4 Results

4.1 Participant demographics

A total of 240 participants consented to participate in the trial, randomised into three trial Arms (n=82 Arm 1, n=78 Arm 2, n=80

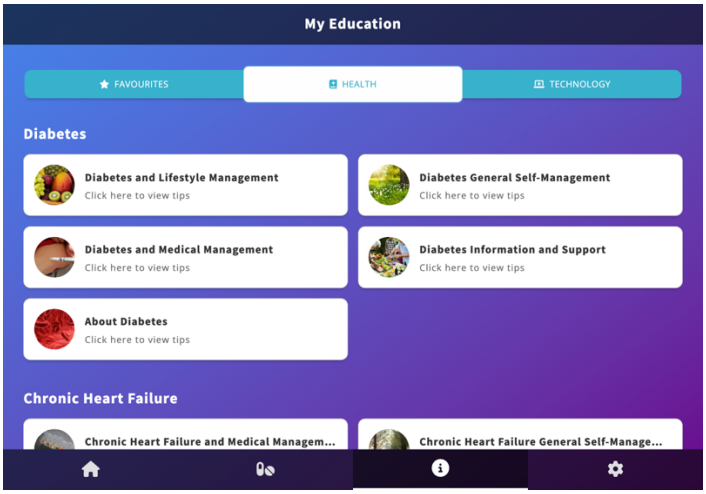

Figure 4: Educational library

Arm 3). For the engagement data analysis, 146 were included: 76 in Arm 1 and 70 in Arm 2. They included 67 and 79 male and female participants, respectively, aged between 65 and 95 ($M_{age} = 73.51$). Further demographic details for these participants are reported in Table 1. A subset of 43 participants were interviewed (n=23 Arm 1, n=20 Arm 2). Their mean age was 72.56 years (SD = 6.27), age range was 65-87 years and n=20 were female.

4.2 Attrition

Of the 240 individuals who consented to participate, a total of 204 completed the trial across the three trial Arms. Twenty-four participants signed a consent form but never started their trial periods, as they were not content with their assigned Arm, experienced significant deterioration in their health, and/or were unavailable for further contact. Another 12 participants started their trial periods but did not complete six months, due to personal reasons (e.g., illness, death, or caring for their family), trial burden (e.g., dissatisfaction with the technology), or non-stated reasons. This represents an overall dropout rate of 15% – 10% of whom dropped out pre-trial and 5% of whom dropped out having started the trial. This 5% included five participants in Arm 1, four in Arm 2 and three in Arm 3.

4.3 Engagement with vitals monitoring

The participants recorded 19.35 vitals measures per week on average, ranging from 0 to 85; more details are provided in Table 2. Of 3,650 potential datapoints (i.e., with 146 participants potentially recording vitals measures each week for 25 weeks), 76 (2.08%) were missing due to the removal of one outlier (i.e., one participant experienced a technical problem with the App and entered a single blood glucose reading repeatedly) and participant withdrawal during the trial period, the earliest of whom withdrew during their tenth week of participation.

Overall, there was a statistically significant decrease in the number of vitals measures that participants recorded each week over time (-0.02 (95% CI: -0.04, -0.01)). At the beginning of their trial periods, participants in Arm 2 recorded significantly fewer vitals measures than participants in Arm 1 (-0.25 (95% CI: -0.48, -0.01)). There was then no statistically significant difference between Arms in how their vitals measures recording each week changed over time (-0.01 (95% CI: -0.02, 0.01)).

At the beginning of their trial periods, older participants recorded significantly fewer vitals measures than younger participants (-0.03 (95% CI: -0.05, -0.01)). There was then no statistically significant difference between older and younger participants in how their vitals measures recording each week changed over time (0.00 (95% CI: -0.00, 0.00)).

Finally, at the beginning of their trial periods, there was no statistically significant difference between female and male participants in vitals measures recorded (-0.15 (95% CI: -0.39, 0.09)). There was also no statistically significant difference between female and male participants in how their vitals measures recording each week changed over time (0.01 (95% CI: -0.02, 0.01)). More details are provided in Table 3.

4.4 Engagement with the ProACT App

The participants used the App 3.72 days per week on average, ranging from 0 to 7 days per week; more details are provided in Table 4. The data points demonstrated inflation at the minimum and maximum values: 24.64% and 29.48% comprised zeros and sevens, respectively, indicating the presence of 'non-users' and 'hyper-users'. Of 3,650 potential datapoints (i.e., with 146 participants potentially using the App each week for 25 weeks), 75 (2.06%) were missing due to participant withdrawal.

Overall, there was a statistically significant initial decrease in the number of days per week of App usage over time (-0.25 (95% CI: -0.42, -0.08)). However, there was also a statistically significant reduction in this decline (i.e., the decline slowed down or stabilised) over time (0.01 (95% CI: 0.00, 0.01)).

The Arms did not statistically significantly differ in how many days per week they used the App at the beginning of their trial periods, albeit Arm 2 trended lower (-0.91 (95% CI: -2.12, 0.29)).

Table 1: Participant demographics (engagement data)

Arm	
Arm 1	76 (52.05%)
Arm 2	70 (47.95%)
Age Mean (SD), range	
73.51 years (SD = 6.25), 65-95	
Gender N (%)	
Female	67 (45.89%)
Male	79 (54.11%)
Highest Education Level N (%)	
None	1 (0.68%)
Some primary (not complete)	5 (3.43%)
Primary complete (approx. age 11 / 12)	37 (25.34%)
Secondary school complete (approx. age 17/18)	27 (18.49%)
Diploma / certificate	30 (20.55%)
Undergraduate degree	8 (5.48%)
Postgraduate / higher degree	19 (13.01%)
Not reported	19 (13.01%)
Condition Combinations N (%)	
CHD & Diabetes	40 (27.40%)
CHD & COPD	29 (19.86%)
CHD & Chronic Asthma	19 (13.01%)
CHD & CHF	15 (10.27%)
CHD, Diabetes, & COPD	14 (9.59%)
CHD, CHF, & COPD	5 (3.42%)
CHD, COPD, & Chronic Asthma	5 (3.42%)
Diabetes & COPD	4 (2.74%)
CHD, Diabetes, & Chronic Asthma	4 (2.74%)
CHF & Diabetes	3 (2.05%)
Diabetes & Chronic Asthma	2 (1.37%)
CHD, CHF, & Chronic Asthma	2 (1.37%)
CHF & Chronic Asthma	1 (0.68%)
CHD, CHF, & Diabetes	1 (0.68%)
CHD, CHF, Diabetes, & COPD	1 (0.68%)
CHD, CHF, COPD, & Chronic Asthma	1 (0.68%)

There was also no statistically significant difference between the Arms in how their use of the App changed over time, either initially as represented by the linear slope (0.07 (95% CI: -0.10, 0.23)), or subsequently as represented by the quadratic term (-0.00 (95% CI: -0.01, 0.01)).

Older participants used the App significantly fewer days per week than younger participants at the beginning of their trial periods (-0.15 (95% CI: -0.25, -0.05)). There was then no statistically significant difference in how their use of the App changed over time, either initially (0.00 (95% CI: -0.01, 0.02)) or subsequently (-0.00 (95% CI: -0.00, 0.00)).

Finally, there was no statistically significant difference between females and males in how many days per week they used the App at the beginning of their trial periods (-0.68 (95% CI: -1.93, 0.57)). There was also no statistically significant difference between females and males in how their use of the App changed over time, either initially (-0.01 (95% CI: -0.18, 0.16)), or subsequently (-0.00 (95% CI: -0.01, 0.01)). More details are provided in Table 5.

4.5 Theme 1 – engagement behaviours

Participants described a wide range of engagement behaviours that reveal the complex and multi-layered nature of self-management among older adults with multimorbidity. Beyond routine tracking, participants engaged with the platform in ways that reflected shifting health priorities, interactions between conditions, and the practical realities of daily life. This adaptability, reflected in how participants shifted between routine tracking, trend-checking, and symptom-driven monitoring, illustrates a dynamic and context-responsive pattern of engagement. These varied approaches correspond with the wide week-to-week differences observed in the quantitative data, where engagement ranged from non-use to sustained daily monitoring.

Table 2: Participants' mean (and range) of Total Vitals Measures recorded per week

All Participants		
19.35 (0 – 85)		
By Arm		
Arm 1		Arm 2
20.70 (0 – 70)		17.88 (0 – 85)
By Age(with Age categorised as 65-74, 75-84, and 85+ for greater insight here; please note, however, Age was treated as a continuous variable in the analysis)		
65-74 years	75-84 years	85+ years
20.05 (0 – 76)	19.33 (0 – 85)	12.19 (0 – 44)
By Gender		
Female		Male
20.51 (0 – 78)		18.38 (0 – 85)

Table 3: Inferential statistics parameter estimates

	Estimate	**Standard Error**	**Lower & Upper 95% CI**
Intercept	3.42	0.13	3.17, 3.67
TimeZero	-0.02	0.01	-0.04, -0.01
Arm 2 (vs. Arm 1)	-0.25	0.12	-0.48, -0.01
AgeZero	-0.03	0.01	-0.05, -0.01
Male (vs. Female)	-0.15	0.12	-0.39, 0.09
TimeZero * Arm 2	-0.01	0.01	-0.02, 0.01
TimeZero * AgeZero	0.00	0.00	-0.00, 0.00
TimeZero * Male	-0.01	0.01	-0.02, 0.01
SD (Intercept)	0.71	0.05	0.62, 0.82
SD(TimeZero)	0.05	0.00	0.04, 0.05
Cor(Intercept, TimeZero)	0.15	0.09	-0.03, 0.33

Table 4: Participants' mean days (and range) of ProACT App usage per week

All Participants		
3.72 (0 – 7)		
By Arm		
Arm 1		Arm 2
3.97 (0 – 7)		3.46 (0 – 7)
By Age(with Age categorised as 65-74, 75-84, and 85+ for greater insight here; please note, however, Age was treated as a continuous variable in the analysis)		
65-74 years	75-84 years	85+ years
4.15 (0 – 7)	3.38 (0 – 7)	1.18 (0 – 7)
By Gender		
Female		Male
4.19 (0 – 7)		3.34 (0 – 7)

Table 5: Inferential statistics parameter estimates

	Estimate	Standard Error	Lower & Upper 95% CI
Intercept (1)	-6.61	0.67	-7.94, -5.32
Intercept (2)	-5.43	0.66	-6.76, -4.15
Intercept (3)	-4.65	0.66	-5.97, -3.37
Intercept (4)	-3.81	0.66	-5.13, -2.53
Intercept (5)	-3.06	0.66	-4.38, -1.80
Intercept (6)	-2.15	0.65	-3.47, -0.89
Intercept (7)	-1.15	0.65	-2.45, 0.11
TimeZero	-0.25	0.09	-0.42, -0.08
Arm 2 (vs. Arm 1)	-0.91	0.61	-2.12, 0.29
AgeZero	-0.15	0.05	-0.25, -0.05
Male (vs. Female)	-0.68	0.63	-1.93, 0.57
TimeZero * Arm 2	0.07	0.08	-0.10, 0.23
TimeZero * AgeZero	0.00	0.01	-0.01, 0.02
TimeZero * Male	-0.01	0.09	-0.18, 0.16
$TimeZero^2$ (Quadratic Term)	0.01	0.00	0.00, 0.01
$TimeZero^2$ * Arm 2	-0.00	0.00	-0.01, 0.00
$TimeZero^2$ * AgeZero	-0.00	0.00	-0.00, 0.00
$TimeZero^2$ * Male	-0.00	0.00	-0.01, 0.01
SD (Intercept)	3.45	0.28	2.94, 4.03
SD(TimeZero)	0.42	0.04	0.35, 0.51
SD($TimeZero^2$)	0.01	0.00	0.01, 0.02
Cor(Intercept, TimeZero)	-0.42	0.10	-0.60, -0.22
Cor(Intercept, $TimeZero^2$)	0.47	0.10	0.27, 0.65
Cor(TimeZero, $TimeZero^2$)	-0.94	0.02	-0.97, -0.90

4.5.1 Patterns of engagement. Participants developed personalised self-management routines, adjusting their engagement with the platform based on health status, symptoms, and daily routines. While some prioritised symptom monitoring, others engaged in additional behaviours, such as reviewing data trends, setting goals, and tracking medication. These varying levels of engagement reflect individual needs and the perceived utility of specific platform features. This variability also mirrors the quantitative spread in vitals recording (0-85 measures per week), and the range of App use from non-use to hyper-use.

Most participants reported using monitoring devices regularly, integrating them into their daily routines. This structured approach supported self-management and provided reassurance: *"My routines and everything changed... In a good way. I was using it, and... I was getting benefit out of it, and I was getting ease of mind about my symptoms... And with the information going to the [triage] and getting the alerts, it made me more aware of what was happening to me"* (IES0069, M, 67, COPD, Diabetes/CHD, Arm1). Such embedded routines help explain why participants recorded, on average, 19.35 vitals per week, with Arm 1 showing higher baseline recording than Arm 2.

While many engaged with both the devices and the App, usage frequency varied. Some used the App occasionally, to review trends: "There's no point in looking at it [the App] day by day. It's to see trends that were useful" (IES0080, M, 82, Diabetes/CHD, Arm2). Others used the App more frequently, for daily medication tracking and self-reporting. Some used it to plan their day, check step goals, and track medication schedules: "I weigh myself before breakfast, take my blood pressure and oxygen levels. Then, with the watch, I could track my steps. So I was checking what steps I needed, and in the evening, I had to put my medication in again. It was good for me to keep track of everything like that" (IES0079, F, 65, COPD/Asthma/CHD, Arm1). A regular, structured daily routine aligns closely with the hyper-user pattern observed in the quantitative data (29.48% of weeks with seven days of use).

Participants prioritised monitoring based on their most pressing health concerns. Those with hypertension or diabetes focused on blood pressure or glucose monitoring to support structured routines: *"My heart rate and blood pressure are my main concerns... This gave me a great way to control everything because I had it all in front of me. Before this, I hadn't a clue.. Now, I stuck to the routine much better... "* (IES0072, F, 70, Diabetes/CHD, Arm1). Others used the App as a reference when uncertain about changes in their condition: *"If I wasn't sure about something that happened in the last few days, I'd open the app and just have a look and see the differences... I'm managing everything a lot better"* (IES0080, M, 82, Diabetes/CHD, Arm2). Collectively, the examples help account for both the high average level of vitals recording and the selective use of the App seen in the quantitative data, where participants engaged intensively when they saw clear purpose and less frequently when they did not.

4.5.2 Fluctuations in engagement. Engagement patterns varied, with some participants adjusting their frequency of use based on health status, motivation, or perceived need. Those with stable conditions often reduced monitoring over time, while others with more variable symptoms maintained daily use: *"I only take my blood pressure once a week normally. During the trial, I was compelled to do it daily. But… I'm back to once a week now because my blood pressure is fine. I do understand why some people with more variability might need to check daily"* (IES0055, F, 66, Asthma/CHF/CHD, Arm1). Similarly, others noted that daily monitoring was only necessary when readings were inconsistent or described reducing frequency of monitoring after initial intensive use: *"In the first week, I did it every day. Then, I reduced it to every three or four days. I tried to stick to that routine, twice a week worked well for me"* (IES0062, F, 68, Asthma/CHD, Arm1). This shift aligns with the quantitative patterns of a decline in vitals recording over time.

Some participants reported increased engagement over time as they recognised the platform's value. One initially skeptical participant reflected: *"Well, I was skeptical… Would it help me, would it be useful? In actual fact, it was"* (IES0070, F, 70, Diabetes/CHD, Arm2). Others described growing in confidence: *"At the beginning, it was all new, and I was afraid I'd do something wrong… But as I got used to it, it became a daily habit"* (IES0079, F, 65, COPD/Asthma/CHD, Arm1).

4.5.3 Engagement in response to health concerns. Some participants increased self-monitoring when experiencing symptoms or changes in health status. They used the devices and App to identify possible causes or track deviations from normal readings: *"If I got a bursting headache, I would check to see if my blood pressure was up. And it was"* (IES0072, F, 70, Diabetes/CHD, Arm1). Others checked real-time heart rate using the smartwatch when concerned about fluctuations: *"I was always wearing it, and I was always pressing it to see what my heart was doing"* (IES0082, F, 74, Diabetes/CHD, Arm1). Participants also adjusted the timing of readings during the day, often around medication schedules: *"I'd always give the medication time to work before I took things like my blood pressure. There was no point in taking it too early, because the medication might not have kicked in yet… I might also check before meals or after meals"* (IES0086, F, 68, COPD/Diabetes/CHD, Arm2). In line with the quantitative findings, these behaviours illustrate a pattern of high overall engagement coupled with marked variability in both vitals recording and App use, indicating that participants often increased monitoring during periods of symptom change or health uncertainty.

4.6 Theme 2 – facilitators of engagement

Participants described a range of factors that supported their engagement with the platform, revealing facilitators that extended beyond typical accounts of digital self-management. Alongside recognising health benefits and finding the technology easy to use, many participants highlighted the value of reassurance, encouragement, and practical guidance offered through the triage nurses in Arm 1, particularly when readings were unexpected or when they were unsure about device use. For some, engagement was also motivated by a desire to contribute meaningful data to the research project, adding an additional layer of purpose beyond personal health management. These facilitators reflect a multifaceted set of supports shaped by participants' health priorities and by the practical and motivational resources available to them.

4.6.1 Perceived benefits. Participants consistently described perceived benefits as a major driver of sustained engagement with the platform. Many highlighted improvements in health and self-management behaviours, with regular use enabling them to track key parameters. Access to real-time health data reinforced the value of daily monitoring, empowering informed lifestyle adjustments, including increased activity, dietary changes, and better medication adherence, ultimately fostering a greater sense of control. Some saw platform use as directly contributing to improved outcomes, including stabilisation or even reversal of conditions. One participant reflected: *"I'm not a diabetic anymore, with my tests… it's probably my eating habits since… So, [now] I only have one main meal. And this is how I'm managing things a lot better. This is how I've reversed my diabetes"* (IES0080, M, 82, Diabetes/CHD, Arm2).

Others linked engagement to weight loss and enhanced mobility: *"Changing my diet. Losing weight. I was 13 stone… Could be like 10 now. The loss of weight is going to help me do more walking"* (IES0082, F, 74, Diabetes/CHD, Arm1). For some, daily tracking itself became a source of motivation: *"I'm fitter now.. I'm making an effort more… It kind of made you say, 'I have to move, I have to keep going', it gives you the incentive to do more"* (IES0048, F, 71, COPD/CHD, Arm2).

The emphasis participants placed on feeling healthier or more in control resonates with the quantitative pattern showing that, across the cohort, many individuals engaged frequently with the platform, reflected in higher-vitals weeks and complete weeks of use, indicating that sustained engagement often occurred when participants found the system meaningful or useful.

4.6.2 Usable and useful technology. Many participants found the technology easy to use and a valuable tool for self-management, which supported sustained engagement. Several described focusing on specific health parameters based on individual needs or condition status. The automated nature of certain devices was particularly appreciated, reducing manual input and simplifying the process. For users with limited digital experience, the platform was described as intuitive and accessible: *"I found it easy enough, now for me because I'm not a whizz kid at computers or anything like that"* (IES0072, F, 70, Diabetes/CHD, Arm1).

Others acknowledged an initial learning curve but found it manageable: *"Initially I found it frustrating… I must have phoned you [the helpdesk] nearly every day. But once I got the hang of it and learned how to do it, I was using it"* (IES0184, F, 71, COPD/CHD, Arm2).

Some relied on trial and error to build confidence, identifying small adjustments that improved accuracy: *"Once I got used to them, it was easy enough to use [blood pressure monitor]. Once you got it in the right position, the arm like and you had to be on the bare arm. I found with the jumper, it wasn't getting as good a reading"* (IES0198, M, 76, COPD/CHF/CHD, Arm2).

This sense of ease and growing confidence helps illustrate why overall vitals monitoring remained relatively high, despite fluctuations in other aspects of engagement.

4.6.3 Contribution to research and helping others. For some participants, the motivation to use the platform extended beyond personal benefits, as contributing to research emerged as a significant facilitator of engagement. Some were driven by a desire to support scientific advancement and digital health research, perceiving their involvement as an opportunity to inform future healthcare solutions: *"I was interested in the technology part of it, how it was measuring things and looking at things, yes. And that it was, I was interested that it was contributing to a bigger project. Apparently, that was your theme because I would be very wont to support all things Europe"* (IES0012, M, 85, CHD/CHF, Arm1).

Some participants expressed a combination of motivations, balancing self-interest with a desire to contribute meaningful data to the study: *"Well, partly so you could have the information that I was passing... And then kind of time for me to look after myself and take an interest in myself"* (IES0048, F, 71, COPD/CHD, Arm2). These findings suggest that engagement with digital health interventions is not purely driven by personal health benefits but can also be reinforced by a sense of purpose, contribution to a greater cause, and commitment to the research process. Participants' motivations to contribute to research offer one explanation for the steady contribution of data observed in the quantitative dataset, even as individual engagement levels varied week to week.

4.6.4 Support from triage nurses. Arm 1 participants frequently described triage nurse support as reassuring and motivating, reinforcing a sense of accountability and progress: *"They were like cheerleaders... just keep doing what you're doing because everything is on track"* (IES0079, F, 65, COPD/Asthma/CHD, Arm1). Support was especially valued at moments of clinical uncertainty or perceived risk. For example, one participant described how prompt follow-up to abnormal readings reduced anxiety and enabled appropriate action: *"It was reassuring. You know, when you take your blood pressure and... it's terrible low, terrible high. And the next thing [the nurse] rings me 'well, you have an alert here... I think you might have to go to the hospital straight away. What way do you feel, this, that and the other?' And next thing, bang, everything is ok"* (IES0069, M, 67, COPD/Diabetes/CHD, Arm1).

Across these accounts, triage nurse support extended beyond reassurance to actively shape how participants engaged with the platform. Guidance from nurses helped participants interpret unexpected or ambiguous readings, reducing uncertainty that might otherwise have led to frustration or disengagement. Timely explanations, such as clarifying cuff placement, medication timing, or whether a reading warranted concern, enabled participants to continue monitoring rather than abandoning the devices. As one participant noted, when technical difficulties arose, nurse support facilitated continued use: *"Well, yes, I would have said to them, I am not able to use such and such, when it broke down twice for me and they were able to sort that out for me. Yes"* (IES0082, F, 74, Diabetes/CHD, Arm1).

Participants also described the motivational role of triage support in reinforcing health behaviours and self-management practices. Several reported that positive feedback from nurses validated their efforts and encouraged ongoing engagement: *"Yeah it did [motivate me]... I felt like I was on the right track"* (IES0079, F, 65, COPD/Asthma/CHD, Arm1). Others emphasised the importance of the "human side" in sustaining use, contrasting it with the technological aspects of the platform: *"She was always positive... being positive helps to encourage you to keep going. ... It's the human side. Whereas these are all technology"* (IES0088, M, 72, COPD/CHD, Arm1). In some cases, this support directly prompted appropriate healthcare-seeking behaviour. One participant described how nurse feedback led them to consult their GP and adjust medication: *"I wouldn't have known that it was that bad... I was able to go to the doctor and he put me on stronger medication. They were fantastic"* (IES0072, F, 70, Diabetes/CHD, Arm1).

This interpretive and motivational support appeared to build confidence over time. Participants described increased trust in their data, greater confidence in device use, and a growing willingness to integrate monitoring into their self-management routines. For example, one participant explained how nurse feedback helped them identify and correct improper cuff use, reinforcing both confidence and continued engagement: *"It was good to know that the nurse was there and they were able to see these things"* (IES0079, F, 65, COPD/Asthma/CHD, Arm 1).

These experiences help explain the quantitative finding that, while Arm 1 and Arm 2 showed similar patterns of change in engagement over time, participants with access to triage support often perceived this support as enabling sustained and consistent use of the platform – particularly during moments of uncertainty, confusion or perceived risk.

4.7 Theme 3 – barriers to engagement

Participants identified a wide range of barriers that disrupted or limited their engagement with the platform, reflecting the complex realities of managing multiple long-term conditions. Rather than centering on a single issue, the barriers described across this theme span perceptions of limited personal benefit, the competing demands of multimorbidity, the effort required to complete monitoring tasks, and challenges related to the technology itself, as well as life events that made regular self-management difficult. This breadth of barriers highlights a layered and varied set of challenges.

4.7.1 Perceived lack of benefit. While many participants reported positive experiences with the platform, others questioned its value in their self-management practices. Some participants did not perceive a significant benefit from engaging with the technology, either due to a lack of commitment to using it, or because they felt it was more suited to individuals with greater health needs, older adults, or those living in remote areas. For some, pre-existing self-management routines were deemed sufficient, reducing the need to engage with additional monitoring tools. This was particularly evident among participants whose conditions were relatively stable or who already maintained regular contact with healthcare professionals. One participant explained that once their weight stabilised, the platform no longer felt necessary: *"In the weight, yes, [thought it was useful to monitor and see changes over time] but I eventually got to the stage where I thought it's nothing, there's no variation... It told me my weight was very stable. And the triage people picked up this kind of thing as well"* (IES0012, M, 85, CHD/CHF, Arm1). A pattern of disengagement among those who saw little added value is consistent with the quantitative evidence of irregular monitoring, including weeks where no platform use was recorded.

4.7.2 Complexity of health and self-management. The complexity of managing multiple chronic conditions was another barrier to engagement, with some participants reporting that their health conditions interfered with their ability to use the platform effectively. For example, participants experiencing pain or fatigue found that their symptoms often took precedence over self-monitoring. One participant, who struggled with arthritis, described how their condition made it difficult to engage with weight management despite intending to do so: *"I said I'd try harder to lose weight because it was coming up on the scales every day, I didn't really… I got this arthritis in my knee and it just took over"* (IES0096, F, 70, COPD/CHD, Arm2).

Another participant explained that the side effects of their medication, particularly extreme fatigue, impacted their ability to engage in self-management activities: *"I'm tired full stop and I have been since I have been on the [arthritis medication] and it has made me… it has me exhausted"* (IES0184, F, 71, COPD/CHD, Arm2). The way symptoms such as pain and fatigue displaced self-monitoring resonates with the wide week-to-week variation observed in the vitals data, where periods of very low activity were common.

4.7.3 Burden and perceived effort. For some participants, the effort required to engage with the platform outweighed its perceived benefits, even though they acknowledged the potential value of self-monitoring. Some described a preference for passive health monitoring (e.g. through devices such as the smartwatch) over more interactive, hands-on tracking (such as self-reporting symptoms through the App), which was perceived as administratively burdensome. One participant reflected on this difficulty: *"It's no excuse… the programme and the monitoring is of enormous value. And as I get older and even when there are other extra challenges, it's possibly the time when it [the platform] can come into its own, will be most effective.. But as I said, it's the passive monitoring versus the hands-on monitoring, and that's the difficulty. I think the idea of the administration tasks was probably a deterrent"* (IES0003, M, 70, Asthma/Diabetes/CHD, Arm2). Other participants described feeling overwhelmed or annoyed by the volume of data input required, suggesting that simplification of information entry may improve engagement: *"I could say there's not too much wrong with the technology, only maybe looking for too much information at the one time. And it can overpower the person that's putting in the information"* (IES0069, M, 67, COPD/Diabetes/CHD, Arm1). Participant descriptions of administrative effort feeling disproportionate align with quantitative patterns showing uneven engagement, with some weeks marked by complete non-use while others reflected more regular routines.

4.7.4 Technology challenges. Technical issues posed a key barrier to engagement. Participants raised concerns about device accuracy and reliability, particularly when platform data conflicted with their own devices. For example, the smartwatch's step count was frequently questioned: *"It was recording false information. It wasn't recording my steps. It really was recording the amount of times I moved my arms"* (IES0184, F, 71, COPD/CHD, Arm2). Data synchronisation issues, especially with the smartwatch, were also common and frustrating: *"And if it didn't synchronise… I would have a problem and I'd get frustrated with that"* (IES0192, F, 65, COPD/CHD, Arm1).

Hardware challenges, such as difficulty using the tablet or poor internet connectivity, further affected participation: *"I think it's a great idea [the technology]. But I found that iPad didn't work for me"* (IES0138, F, 80, CHF/CHD, Arm2). Furthermore, some participants with physical limitations required carer assistance, affecting their independence: *"I could only use the technology when a carer was helping me, as I only had use of one hand"* (IES0132, M, 75, Diabetes/CHD, Arm1).

While low digital literacy initially hindered some users, most reported comfort over time: *"I think I would have benefited more from the trial if I had better understood the technology"* (IES0184, F, 71, COPD/CHD, Arm2).

Reports of device inaccuracies, syncing problems, and physical access barriers help shed light on the sporadic gaps and inconsistencies present in the quantitative dataset, including missing entries tied to weeks when monitoring was not feasible.

4.7.5 External factors. For a small number of participants, engagement with self-management through the platform was hindered by external life events. Participants described significant personal circumstances, such as hospitalisations, holidays, and caring responsibilities, which disrupted their ability to engage with the technology. One participant, for instance, detailed how caring for a spouse with Alzheimer's disease led to an unpredictable routine, making it difficult to maintain consistent self-management: *"In the beginning, a typical day would be I would get up at 6:00 in the morning… I would stand on the scales. I would get my big bag of heart failure pills… It's been a peculiar six months because my husband had Alzheimer's, so he was getting worse. Progressively through the six months and in March, he went into a nursing home"* (IES0138, F, 80, CHF/CHD, Arm2).

Similarly, another participant described how their partner's declining health and medical treatments took priority over engaging with the platform, illustrating how caring responsibilities often overshadowed personal health management: *"I was a bit of a disaster because I really just didn't throw myself into it, just with various things, [wife] was in a lot of pain, back pain and hobbling, and she was up and down to the sports clinic getting different procedures and stuff… I just, it just wasn't a good time to get into it"* (IES0003, M, 70, Asthma/Diabetes/CHD, Arm2).

Life circumstances such as caring responsibilities or hospitalisation offer a clear explanation for the fluctuating nature of engagement seen in the quantitative data, where some weeks show reduced or absent monitoring.

5 Discussion

This paper presents a mixed-methods examination of digital health engagement among older adults with multimorbidity during a six-month trial of the ProACT digital health platform. Although age, gender, and trial arm were central analytic variables in the quantitative modelling, the qualitative findings highlighted other, sometimes more salient, drivers of engagement. These included symptom burden, perceived self-management benefit, fatigue, and competing life demands. Triage nurse support also played a key role, not only by providing reassurance and motivation, but by helping participants interpret complex, cross-condition health data, thereby

increasing users' confidence in responding to symptoms. Our findings provide encouraging evidence that older adults living with multimorbidity can meaningfully engage with digital health technologies over time. While our findings reveal that engagement is non-linear, highly individual, and deeply influenced by life context, usability, and perceived value, participants used the platform to support complex health routines, track fluctuations across conditions and respond to emerging issues.

This extends the arguments of [2] and [4], who emphasise that people with multimorbidity are unlikely to persist with digital interventions unless they streamline tasks and demonstrate tangible benefit. Our results show that such persistence is possible: participants often remained engaged when the platform fit into their routines, simplified their health monitoring, and provided reassurance. Rather than viewing multimorbidity as a barrier to digital engagement, we suggest it presents an opportunity to design systems that are flexible, integrative, and responsive to the layered realities of managing multiple conditions. Key findings are:

- Participants recorded vitals approximately 19 times per week on average. Engagement decreased slightly over time. Younger participants and those with triage nurse support recorded more readings at the beginning of their trial periods. Furthermore, with younger and older participants, as well as those in Arms 1 and 2, demonstrating non-significant differences in their engagement trajectories over time (i.e., similar declines in engagement), younger participants and those with triage nurse support appeared to maintain their advantage (i.e., recorded more readings) during their trial periods.
- Average usage of the ProACT App was ~3.7 days/week. A substantial proportion were 'hyper-users' or 'non-users'. Usage declined initially but later stabilised. Younger participants used the App more at the beginning of their trial periods; furthermore, with no significant differences emerging between younger and older participants in their engagement trajectories over time, younger participants appeared to maintain their advantage (i.e., more days of App use) during their trial periods. Gender and clinical support had no significant effects on App use.
- Participants used the platform differently (as evident in the quantitative and qualitative data), based on preferences, health status, and routines (as evident in the qualitative data). Some used it daily, others selectively.
- Triage nurse support was highly valued, offering reassurance and motivation. Engagement was also driven by perceived health benefits, ease of use, and contribution to research.
- Participants cited condition-related illness and fatigue, technology burden, and external life stressors as barriers. Technical issues (especially syncing) and device complexity discouraged consistent use.

These insights extend recent HCI literature that calls for more situated, real-world studies of digital health engagement, particularly in under-represented older and chronically ill populations, that reflect their lived experiences [17, 31, 64].

5.1 Re-thinking engagement: cycles, routines and meaning

Quantitative data showed a decline in both App use and vitals monitoring, with App use later stabilising, indicating non-linear engagement over time. Despite this variability, attrition from the trial was low: in Arm 1, five of 82 (6%) participants withdrew, while in Arm 2 four of 78 (5%) withdrew. Among those who engaged, most continued using the platform to varying degrees throughout the trial. This reflects prior HCI research showing that people integrate self-tracking technologies into their lives in fits and starts rather than continuously [27, 57]. Rooksby et al. [59] describe self-tracking as a 'lived informatics' practice - adopted and abandoned as needed. While many participants in our study described meaningful, personalised use of the platform, we also recognise that some engagement may have been shaped by the structure of the trial itself. In particular, participants in Arm 1 had access to proactive triage support, and those with diabetes or other high-priority conditions may have engaged out of necessity rather than platform appeal. These contextual factors likely influenced both opportunity and obligation to engage.

The Lived Informatics Model [21] characterises self-tracking as a dynamic cycle of deciding, selecting, tracking, lapsing, and resuming. Our findings align with and extend this model by demonstrating how older adults with multimorbidity moved through these phases in response to changing symptom burden, medication routines, and life circumstances. The observed cycles of engagement, lapse, and resumption mirror the model's recognition that tracking is rarely continuous, but here they are shaped by symptom burden, medication routines, and caring responsibilities. These were not lapses due to failure but deliberate, informed adjustments.

Participants' selective focus on specific conditions (e.g., prioritising blood pressure monitoring because of concern about their heart condition) reflects the 'deciding what to track' phase [21], now complicated by competing demands across conditions and current priorities. For example, some participants monitored daily when symptoms were unstable, but reduced frequency as conditions stabilised or perceived need declined. Patterns of hyper-use and non-use in the quantitative data further suggest a contingent, goal-directed approach to tracking. Sensemaking, another key stage of the model [21], was evident not only in how participants interpreted their data but also in the role others played in that process. Rather than focusing on daily fluctuations, participants typically reviewed broader trends to understand their health trajectory. Triage nurses supported this process by helping to interpret cross-condition symptoms, introducing a socially scaffolded dimension to individual sensemaking.

Finally, the episodic engagement seen in the usage data, including prolonged non-use, aligns with the model's 'lapse' phase [21] but appears more intensive and context-driven than typically described. Together, these patterns position lived informatics in multimorbidity as an adaptive, condition-responsive, and socially supported practice. These patterns, shaped by fluctuating capacity and shifting priorities, also align with broader trends observed in digital self-management, where engagement is often purposeful rather than persistent.

Such variability confirms that one-size-fits-all patterns are rare in digital health engagement [6, 61]. Rather than failure, this reflects pragmatic self-management. Users often engage to meet specific goals, then disengage once needs are met [21]. Similarly, Boucher et al. [6] note that engagement wanes as users' conditions improve. Many participants in our study used the platform to establish health routines or monitor acute changes, then reduced when their vitals stabilised. Importantly, those who perceived clear benefits, such as improved weight management or increased activity, were more likely to integrate the platform into daily routines. Others disengaged when they perceived little value. This suggests that meaningful engagement is tied to goal fulfillment, not constant use [6, 59]. Designing for episodic use, with timely prompts and adaptive content to support re-engagement, may better suit older users managing chronic conditions.

Although this study did not measure clinical outcomes directly, qualitative accounts revealed several ways in which participants modified their self-management behaviours in response to using the platform. Some adopted more structured routines, such as daily vital sign checks aligned with medication timing, or increased physical activity informed by step tracking. Others made dietary changes or became more responsive to early warning signs, using the data to guide decisions like adjusting meal timing or seeking medical input. These examples suggest that, for many, platform engagement extended beyond data entry into meaningful behaviour change, supporting more proactive and personalised self-management over time. This aligns with prior calls for digital health tools that promote autonomy and proactive engagement in multimorbidity [17] and extends the findings of [69], who noted mixed experiences with digital tools, yet did not explore how such tools might prompt concrete behavioural shifts in day-to-day routines.

Patterns of attrition further support this interpretation of engagement as contingent, and context driven. Most pre-trial attrition reflected acute health deterioration or difficulty committing to a structured intervention, highlighting the vulnerability and fluctuating capacity of older adults with multimorbidity. In-trial attrition followed similar patterns, with withdrawal reasons including illness, bereavement, caring responsibilities, or dissatisfaction with the technology. These contextual factors were also identified in the qualitative data as common challenges that shaped fluctuating engagement among those who remained in the trial, such as fatigue, hospitalisation, and caregiving demands. This overlap suggests that attrition and continued use were both mediated by the broader lived realities of managing multimorbidity. Notably, the small number of withdrawals and their even distribution across trial Arms suggest that the platform and triage support did not systematically discourage participation. Instead, attrition appears tied to participants' broader illness trajectories, consistent with prior research showing that lapses and disengagement often result from life instability rather than technology rejection [21, 59]. In this light, attrition itself becomes a meaningful indicator of the contextual complexity of engagement in multimorbidity and signals the need for systems designed to accommodate interruption, re-entry, and adaptive patterns of use.

5.2 Multimorbidity as a driver of complex, conditional engagement

Our qualitative findings show that several distinctive engagement behaviours arose directly from the complexity of managing multiple chronic conditions, an area underexplored in much of the existing HCI and digital health literature, which tends to focus on single-condition self-management or aggregate engagement metrics [2, 16]. While prior studies have acknowledged that multimorbidity adds burden and complexity [2, 18, 53], they rarely examine how this complexity manifests in real-time engagement decisions.

Participants in our study prioritised different monitoring tasks depending on which condition was most salient at a given time, for example, focusing on blood pressure management when cardiovascular symptoms dominated, or adjusting the timing of readings to account for the effects of multiple medications. Symptom interactions, such as fatigue from arthritis medication or breathlessness linked to COPD, often displaced self-monitoring altogether, creating periods of reduced or paused engagement. While other research has qualitatively explored how symptom burden complicates care [9, 20], our findings highlight how these interactions interrupt self-monitoring in real-time. Importantly, participants described how managing one condition could impede or reshape engagement with another - for instance, arthritis-related knee pain preventing intended weight-management routines, or heart-related concerns prompting more frequent checks even when other conditions were stable. This demonstrates that engagement is not simply additive (i.e. that more conditions equate to more monitoring), but *selectively adaptive* based on current needs. External life factors, such as caring responsibilities or acute health events, further compounded this complexity, leading to episodic disengagement even among otherwise motivated users.

These multimorbidity-specific dynamics correspond with several quantitative patterns, including the substantial range in weekly vitals recording (0–85 measures), the inflation of both zero-use and seven-use weeks, and the early decline followed by later stabilisation in engagement. Together, these patterns illustrate that multimorbidity introduces condition-interactive, capacity-fluctuating rationales for engagement, resulting in the variable and non-linear engagement trajectories observed across the trial.

5.3 The role and limits of human support

Triangulating the quantitative and qualitative evidence provides insight into the factors driving the observed engagement patterns. Firstly, Arm 1 participants recorded a greater number of vitals measures at the beginning of their trial periods than Arm 2, and with no significant difference in their engagement trajectories over time (i.e., both Arms demonstrated similar declines in engagement), Arm 1 appeared to maintain their advantage. Similar findings were found regarding App usage, albeit the difference between Arm 1 and 2 participants was non-significant not just throughout their trial periods but at the beginning also. This suggests that the presence of a triage nurse may have influenced initial uptake, the effects of which remained over time. The interviews provide further insight: participants in the triage-supported Arm overwhelmingly valued the 'cheerleading' and reassurance provided by the nurses. This human support offered motivational encouragement and peace of

mind that someone was watching out for them. Several participants described the nurses as a safety net, ready to act if an alert signalled a worrying health reading. This resonates with the concept of supportive accountability: human support can strengthen users' commitment to a digital health intervention by fostering a sense of accountability and care. Mohr's model of supportive accountability [46, 47] posits that users adhere better when they feel a human (coach or clinician) is invested in their success. In fact, recent work has shown that even light-touch personalised support (for example, weekly messages from a coach) can boost engagement and outcomes in digital interventions [1, 34]. Users who receive tailored human prompts are more likely to explore app features and sustain engagement than those without support [34].

Our qualitative findings build on this, suggesting that the value of human support may be highly context dependent. For older adults managing chronic illness, ongoing nurse support offered critical emotional reassurance and helped resolve technical and health-related uncertainties (e.g., correct cuff placement, interpreting readings). Importantly, the nurses' most significant contribution may have been in preventing disengagement during moments of difficulty. For instance, one participant reported that initial frustrations were mitigated through timely guidance, enabling continued use of the platform. A scoping review noted that a lack of support is a major barrier to e-health engagement among older adults, while providing support (to overcome usability concerns and build confidence) is a key facilitator [73]. Older adults with multimorbidity have valued having a nurse guide, educate and encourage them, helping them interpret their health data and feel confident about using technology [16]. From a design perspective, this implies that blending digital platforms with periodic human touchpoints can sustain engagement indirectly by maintaining user trust and motivation, rather than solely by driving usage frequency. Future systems might simulate some of these benefits via virtual coaches or timely automated feedback, a strategy that HCI researchers are actively exploring to achieve scalable support without undermining the personal connection that users value [10, 41, 46, 48].

5.4 Demographics and technology fit

Age and gender further contextualise engagement patterns. Quantitative data showed that older participants used the platform less frequently at the outset than younger cohorts. Given the absence of significant differences in engagement trajectories, this suggests that initial age-related differences in usage likely persisted throughout the trial. Prior research confirms that the oldest old often face barriers such as reduced vision, complex interfaces, and lower confidence, all of which can impede engagement [36]. Our qualitative data echoed this: some participants struggled with tablet use or required assistance due to physical impairments. Yet consistent engagement amongst many aligns with prior findings that, with appropriate support, even the oldest adults can use digital tools effectively [15, 17].

Gender did not significantly influence engagement, aligning with recent work suggesting similar usage patterns between older men and women when access is equal [36]. Earlier studies report mixed findings, some showing slightly higher engagement among women [67], others showing no difference in eHealth literacy [78], while others report that older women are less likely to adopt new technologies than men, due to socio-cultural factors or lower prior exposure [32]. Our results indicate that when support is provided, gendered engagement gaps diminish. This is an important insight for designers and researchers, indicating that interventions need not be heavily gender-tailored for basic engagement, though content preferences might still vary.

Platform usability was widely praised, with features like automatic syncing and intuitive interfaces cited as facilitators. Several participants highlighted the ease of automated monitoring and the usefulness of real-time feedback and trend visualisations in integrating tracking into daily routines, supporting structured self-management without feeling burdensome. This aligns with existing design recommendations for older adults [15, 51] highlighting the importance of minimising cognitive and physical demands. However, not all features were equally effective – some participants reported information overload or frustration with manual input tasks, describing the data entry process as too administratively demanding, while issues such as syncing failures or perceived inaccuracy, quickly led to frustration. This reflects earlier work identifying low technology self-efficacy and device complexity as barriers for older users [32, 36]. Yet many participants persisted through trial-and-error, support services, or practice. This highlights the importance of onboarding and early assistance to build confidence. Once users develop a sense of mastery, they are more resilient to setbacks [15, 34, 62].

5.5 Contributions and implications

This study offers several contributions to both digital health and HCI. Methodologically, this study demonstrates the value of longitudinal mixed-methods trials for understanding digital health engagement in later life. Unlike shorter HCI deployments, which typically capture initial reactions or early use, our data reflect how older adults integrate, adapt, abandon, and resume technologies in response to health fluctuations and daily disruptions. This approach surfaces patterns, such as symptom-contingent monitoring, evolving routines, and episodic disengagement, that would be difficult to detect through ethnography alone or through short-term prototype testing. By showing how engagement matures and transforms over time, this work contributes a model for studying complex, real-world digital health use in HCI.

Qualitatively, we contribute new evidence showing how multimorbidity shapes the lived practice of digital engagement. Unlike prior work that identifies general facilitators and barriers, our analysis identifies multimorbidity-specific engagement mechanisms: condition-contingent routines, symptom-triggered monitoring, medication-timed behaviour, and disruptions from interacting illnesses and caring responsibilities. These insights extend lived informatics literature by illustrating how older adults dynamically 'tune' their engagement in response to complex health interactions, offering a richer conceptualisation of episodic and adaptive use.

We demonstrate that sustained engagement is achievable for this cohort, but must account for users' evolving needs, motivations, and life contexts. Our findings support hybrid care models that integrate intuitive technology with optional human support.

Table 6: – Implications for HCI and digital health research

Design Implication	Explanation
Support Episodic Engagement	Allow flexible use patterns and design for drop-off and re-engagement (e.g. 'welcome back' messages, adaptive reminders), reflecting the observed quantitative decline followed by stabilisation of App use and the qualitative accounts of need-driven, non-linear use.
Prioritise Onboarding and Reassurance	Offer tailored early-stage support and address usability concerns to help older adults feel confident with the technology and build trust, as illustrated by Arm 1's higher initial vitals recording and interview accounts of triage nurses resolving early uncertainty and device misuse.
Blend Automation with Human Support	Provide scalable triage through hybrid models that combine digital feedback with human reassurance at key points, grounded in participants' strong valuation of motivational and interpretive support and Arm differences in initial engagement.
Streamline Self-Tracking	Reduce the burden of data entry, automate where possible, and prioritise features based on user needs and symptom relevance, as manual input burden was a driver of reduced or selective engagement.
Adapt to Life Context and Disruptions	Recognise that caring, illness, or life events impact use, and build resilience into platform design, reflecting qualitative accounts of illness flare-ups, hospitalisations, and caring responsibilities that drove 'non-use weeks'.
Align with Self-Management Goals	Emphasise clear benefits to health, routine, and autonomy to sustain meaningful engagement over time, consistent with hyper-user patterns and participants' descriptions of perceived benefit as a major engagement facilitator.
Design for Heterogeneity	Accommodate diverse older adult users by enabling personalisation based on condition, confidence, and motivation, reflecting the highly variable usage patterns (hyper-users vs. non-users) and the role of multimorbidity-specific priorities.

In terms of a contribution to HCI, we extend research on engagement with digital platforms by showing that usage among older adults is cyclical, adaptive, and context-dependent. We contribute empirical support to lived informatics and offer design implications for supporting episodic use, reducing burden, and facilitating re-engagement (summarised in Table 6). By emphasising the experiences of a typically under-represented group - older adults managing multiple chronic conditions - we respond to calls for more inclusive, context-sensitive HCI research [17, 31, 64]. In doing so, we help shift the focus from daily adherence to meaningful, sustained, and contextually appropriate use.

5.6 Limitations

This study has several limitations that should be considered when interpreting the findings. First, while the longitudinal, mixed-methods design strengthens the depth and validity of our insights, the study sample was relatively homogenous (representing individuals from only Ireland), limiting the generalisability of findings to more diverse populations. Engagement patterns may also reflect the structure and expectations of the trial itself. Some participants likely used certain features due to the presence of triage support or the need to fulfil clinical routines (e.g., daily blood glucose monitoring), rather than intrinsic platform motivation Furthermore, the sample consisted exclusively of individuals with multimorbidity who consented to participate in a randomised controlled trial, which may have selected for people more engaged with formal healthcare systems or more willing to adopt structured interventions or digital health tools. This could limit the applicability of findings to those with less formal care engagement or differing attitudes toward digital health. Although attrition was low, those who withdrew early or never began using the technology may represent important perspectives on barriers to engagement that are underrepresented in our analysis. Moreover, while the combination of objective usage data and qualitative interviews allowed for rich triangulation, the interpretation of 'engagement' may still be shaped by implicit assumptions about what constitutes 'successful' use. Finally, the two-arm design enabled a comparison of clinical support versus no support, but future work could explore a broader range of hybrid or adaptive support models to assess their impact on long-term engagement.

6 Conclusion and future work

This paper provides one of the few in-depth, mixed-methods analyses of digital health engagement among older adults with multimorbidity over a longitudinal period. Our findings challenge linear models of engagement, revealing cyclical, episodic use shaped by symptom variability, motivation, perceived value, and life context. Rather than daily adherence, meaningful and adaptive engagement emerged as the more appropriate goal. Participants integrated the ProACT platform into routines when it aligned with their self-management needs and engaged less when the perceived value diminished, without necessarily abandoning the platform altogether. Triage nurse support played a critical role in maintaining motivation, offering reassurance, and preventing disengagement during moments of difficulty. The oldest adults engaged less frequently, yet

many sustained engagement when supported, highlighting the importance of tailored onboarding and confidence-building measures. Engagement was not strongly differentiated by gender, suggesting that inclusive design can support equitable use when access and support are provided.

This study contributes new insights to HCI by demonstrating how lived informatics extends to complex health self-management in later life, and by highlighting the importance of designing for non-linear, personalised, and context-responsive engagement. Our findings also challenge assumptions that multimorbidity is a barrier to digital engagement and instead highlight that older adults with complex health needs can meaningfully and sustainably use digital tools to support self-management. The findings have clear implications for the design of digital health tools: they should support re-engagement, minimise burden, accommodate disruption, and blend automated features with light-touch human support.

Our future work will build on these insights by analysing additional trial data to examine how factors such as platform design, digital skills, health literacy, and baseline psychosocial characteristics shape engagement trajectories. We will explore how engagement evolves in relation to health status, alert frequency, and participants' self-management behaviours over time. This includes a more detailed examination of attrition patterns, disengagement points, and their relationship to health events or perceived benefit. We also aim to develop a nuanced framework for understanding digital health engagement in older adults with chronic conditions, integrating behavioural, emotional, and contextual dimensions to guide the design and evaluation of future interventions. Future research might also examine the potential for agentic AI to scale elements of triage support, enabling personalised yet efficient engagement mechanisms in long-term digital self-management.

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