Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Designing for healthy ageing: Lessons learned from engaging pre-frail older adults in the development of digital self-monitoring health technologies

Alex Dallman-Porter
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Tori Simpson
victoria.simpson22@imperial.ac.uk

Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Andrew Watt
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Tricia Tay
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Souradip Mookerjee
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Shuang Wu
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Gianpaolo Fusari
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Matthew Harrison
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
David Sunkersing
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Kate Grailey
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Jonathan J Gregory
Pivotal Health and Clinical Advisor, Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Michael Fertleman
Cutrale Perioperative & Ageing Group, Department of Bioengineering, Faculty of Engineering, Imperial College London
Ara Darzi
Pivotal Health and Clinical Advisor, Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London
Leila Shepherd
Helix Centre, Institute of Global Health Innovation, Department of Surgery and Cancer, Imperial College London

Research Article

Keywords:

Posted Date: August 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10548546/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

Mobile health (mHealth) technology, including wearable monitoring devices and mobile applications displaying personal health and fitness data, is increasingly ubiquitous. Its use is limited outside of consumer, non-clinical applications among younger adults. However, there is potential for this technology to support preventative healthcare programs for older adults to maintain their independence and extend their healthy lifespan. There is evidence to show the efficacy of self-monitoring interventions using mobile health technology in this group in a study setting, but adherence, engagement and real-world uptake remain a challenge. This demonstrates the need to consider how we might tailor these consumer mHealth offerings to be more accessible for this group among whom digital literacy is often a barrier, in turn increasing uptake and engagement.

Here, we discuss qualitative insights from a group of 30 older adults trialling a prototype mHealth intervention designed to improve frailty outcomes through self-monitoring. While acceptance of the hardware (smartwatch, sleep analyser, and passive environmental sensors) and accompanying application was high and reports of usability and utility were generally positive, the depth of engagement with the sensor data was limited. In addition, scepticism surrounding data accuracy contributed to a reluctance to make behavioural changes. Furthermore, the participant's expectations of the system's technical capabilities and degree of personalisation were not entirely met. Based on these findings, we present recommendations for further investigation, including alternative design approaches that may improve accessibility of mHealth applications for older adults and increase their engagement with self-monitoring healthy ageing interventions.

1- Introduction

1.1 The rise of mHealth and its current usage

Mobile Health (mHealth) is defined as 'medical or public health practice that is delivered with supports of mobile phones, patient monitoring devices, and other wireless devices' (World Health Organization, 2011)[1]. It is increasingly ubiquitous in a range of healthcare settings, including remote patient monitoring, disease prevention and management, treatment adherence, and health education (Marcolino et al. 2018[2], Pérez-Jover et al. 2019[3], Hall et al. 2015[4]).

Self-monitoring is the use of mHealth tools by an individual to observe and respond to changes in health related to a condition or illness; for example, the management of blood sugar in diabetes. Increasingly mHealth is being explored as an avenue to promote healthy behavioural change in preventative rather than disease treatment use cases (Lynch & Cohn, 2016[5]). Possible advantages of self-monitoring include the provision of health information to remote or underserved groups, encouragement of active health management by patients, increased uptake of preventative interventions, complementing existing services with enhanced data collection, provision for more personalised healthcare, and finally the cost savings associated with all (Maita et al. 2024[6], Tong et al. 2021[7]). However, there is concern as to whether it can successfully scale and integrate into existing healthcare systems (Peyroteo et al. 2021[8]) and the technology has significant potential for inequity by excluding those who are less digitally literate and/or educated (van de Weken et al. 2025[9]).

1.2 The case for preventative age-related health interventions at the pre-frail stage

It is well established that the elderly proportion of the global population is growing (United Nations, 2024[10]). While global life-expectancy has increased by an average of 20 years since 1960, the proportion of life spent in good health has not kept pace, resulting in, on average, 10 more years spent in poor to medium health per individual (Dewhurst et al. 2022[11]). Frailty, defined as a reduced capacity to tolerate physiological stressors, is closely correlated with age (WHO, 2017[12]) and is associated with numerous age-related adverse health outcomes (Chu et al. 2021[13]). Frailty is a continuum from robust health through pre-frailty to increasingly severe frailty. The Fried Frailty Scale used in this study assesses five health domains; individuals scoring 0 are deemed robust, while those scoring 1-2 are prefrail, 3 are mildly frail, and 4-5 are frail (Fried et al. 2001[14]). Wang et al. 2021[15] estimate that pre-frailty affects 54.1% and frailty 26.3% of the global population over 65 years of age. However, there is evidence to show that interventions, particularly multicomponent interventions incorporating exercise, may prevent or reverse frailty, and are more impactful when administered to pre-frail than frail individuals (da Silva Sobrinho et al. 2025[16]).

1.3 The potential of mHealth for older adults

The implementation of scalable, preventative health interventions for the growing population of older adults is a national priority. There is an opportunity to address this with mHealth technologies. However, older adults (defined here as over 65) are currently underserved these technologies. Whilst few studies have investigated the attitudes to self-monitoring using mHealth tools to promote frailty-preventative behavioural change among older adults, it is well established that older adults have not been adopting mHealth technologies as quickly as other age groups (van Acker et al. 2023[17]). Though it is well documented that older adults are interested in engaging with mHealth technologies, this group faces a variety of challenges to accessing their benefits (Batsis et al. 2019[18]). Technological confidence, varied user needs compared to the average user, lack of motivation, need for support, and privacy concerns are cited as barriers to adoption (van Acker et al. 2023, Suh & Li, 2022[19], Huh et al. 2014[20]). There is evidence to show that high user engagement with digital sensors leads to better health outcomes (O'Connor et al. 2016)[21], and that a lack of engagement correlates with higher levels of frailty (Kwan et al. 2023)[22]. More research is needed to understand the factors influencing engagement with digital self-monitoring technologies among older adults. Identification of opportunities to design these technologies to foster more equitable outcomes is needed to realise its potential as a scalable, home-based path to preventative care for older adults.

1.4 Applying wellbeing-supportive design guidelines to support older adults' adoption and engagement with mHealth

The barriers to mHealth adoption amongst older adults identified in the literature point to a need not just for good usability, but to design for the psychological conditions that support sustained motivation and meaningful engagement. Positive computing as a field - acknowledging the vast impact technology has had on individuals and society - has the primary aim of designing technology that supports wellbeing[23]. A range of psychological frameworks, including self-determination theory (SDT) provide the theoretical basis within positive computing for supporting wellbeing through the design of technology. It identifies three basic psychological needs, positioning them as foundational to wellbeing[24]:

1. Autonomy: a sense of willingness/endorsement, acting in accordance with one's goals and values
2. Competence: feeling able and effective
3. Relatedness: feeling connected to and involved with others

In the context of mHealth for older adults, the barriers to adoption identified in section 1.3, can potentially be understood as arising from basic psychological needs identified by SDT not being met, rather than purely technical or demographic considerations. This paper applies the lens of positive computing, underpinned by SDT, to its findings as a way of examining where mHealth interventions can support or frustrate the psychological needs of older adults; building on the research-through-design approach described in the following section[25].

1.5 The case for a research-through-design approach to design mHealth technologies tailored to the needs of older adults

Research-through-design is "an approach to scientific inquiry that takes advantage of the unique insights gained through design practice to provide a better understanding of complex and future-oriented issues in the design field" (Godin & Zahedi, 2014[26]). Research-through-design's goal is the generation of knowledge and understanding resulting from the making of an artefact rather than the completion of the artefact itself. Through this it enables the investigation of research questions through practical rather than theoretical means, with participants responding to tangible designs and situations rather than imagined scenarios. There is evidence that the involvement of older adults in the development of physical activity interventions leads to greater engagement (Cazza et al. 2017[27], Boulton et al. 2020[28]). To create mHealth accessible interventions that meet the unique needs of older adults, whilst utilising the potential of digital technologies, it is essential to take such a human-centred design approach (Nimmanterdwong et al. 2022[29], Vargemidis et al. 2020 [30]).

The work presented here took an iterative, research-through-design approach to address the research question "What are the attitudes of older adults towards self-monitoring of their health and fitness using digital technology?". We aimed to identify factors influencing older adults' engagement with mHealth data and propensity to act on it. As well as having implications for other practitioners working on mHealth interventions for older adults, the lessons learned from this study will inform the continued development of the intervention.

2 - Methods

2.1 Study design

This study is part of the Healthy Ageing Design & Feasibility Project, led by the Helix Centre at Imperial College London (SETREC **6875521)**, with the goal to co-design, iterate, and evaluate a self-monitoring mHealth intervention for pre-frail older adults. The intervention aims to encourage the adoption of healthy activity habits to improve age-related health outcomes and ultimately delay or prevent the progression of frailty.

Recruitment

The target group was pre-frail and mildly frail adults over 65 years old. 30 participants were recruited via in-person distribution of flyers, electronic newsletters, local newspapers and paid social media advertisements. In-person locations included community centres, libraries, public health screening events and supermarkets. Participants were offered to keep the Sleep Analyser on completion and were compensated with £50 after six weeks and a further £10 for each month of participation thereafter.

Applicants completed an online Qualtrics XM screening form (assisted via telephone if required) to collect age, ethnicity, neurodivergence, highest education level, and digital literacy and to assess eligibility via self-report questions related to inclusion-exclusion criteria (listed in Table 1). Enriched convenience sampling was used whereby eligible individuals were invited to the study on a first-come-first-serve basis. The sample was reviewed by the research team intermittently to ensure demographic diversity.

Intervention

The intervention was developed using an iterative, research-through-design approach. It featured a range of commercial wearables and passive environmental mHealth sensors. They were accompanied by a tablet application for participants to view their sensor data, activity guidance, and "Healthy Habits" recommendations. Participants were enrolled in four consecutive cohorts from April 2024 to February 2025, with each receiving an iteration of the intervention (see Appendix 1 for a detailed description of the iterations).

Data collection

Qualitative feedback was gathered about the acceptability of, and attitudes towards the intervention. Data were gathered (by ADP, TS, AW and TT with technical and logistical support from SW, SM, DL, and JS) throughout participation. Further details of the data collection are given in Appendix 1.

2.2 Qualitative analysis

Qualitative data was organised by participant ID in NVivo 14 (Lumivero, 2023[31]). The approach to thematic analysis was informed by Braun & Clarke (2006)[32]. A code book was established inductively through discussion between two key coders (ADP and TS) after a period of familiarisation with the entire dataset addressing the research question. Following this, 10% of the dataset (3 of the 30 participants, chosen by random number generator) was coded independently by each key coder. This coded data was assessed for intercoder reliability (ICR) using the in-built Coder Query function in the NVivo software to produce an Overall Unweighted Kappa coefficient. The interpretation of the codes was then refined via discussion between the two coders based on the Kappa coefficients for each code (where a Kappa coefficient below 0.4 signalled a disagreement on that code and potential need for refinement or removal), and the code book was updated accordingly. Another round of independent coding, with the updated code book, followed by an ICR assessment was then performed to achieve the final result for ICR. The remaining portion of the full dataset was then coded by a single key coder for efficiency (ADP). On completion of coding, draft themes and subthemes based on the codes were generated by a single key coder (ADP). The draft themes were discussed with the second key coder (TS) and refined.

Researcher characteristics and reflexivity

The wider research team combined clinical, research, design, and technical expertise. ADP and TS are human-centred designers with previous experience of co-design and qualitative feedback collection. TT is a clinician and PhD candidate in age-related health. AW is an undergraduate psychology student. As designers of the intervention being studied, it was acknowledged that ADP and TS may have a bias towards positive feedback. As such, any differences in coding were discussed collectively, and decisions were agreed as a group to reduce the influence of any single researcher's biases.

3 - Results

Participants were required to take part in the study for a minimum of six weeks but were given the option to extend their participation further. One participant withdrew before six weeks due to a bereavement. Of the remaining 29, participation periods ranged from 6 weeks (42 days) to 374 days. Their demographic make-up is shown in Table 2. The average completion rate across all feedback collection points was 92%. Inductive analysis of the qualitative data resulted in the discovery of 19 codes, shown in Appendix 2. The ICR test resulted in an initial Kappa coefficient of 0.56. This increased to 0.69 after refinement of the codes and coding approach by discussion between the two key coders, and subsequent re-coding. The coded data were grouped into four themes shown in Table 3 and described in this section. Grammatical or spelling errors present in the raw data have been corrected and notes recorded in third person by researchers have been converted to first-person for clarity when quoting.

3.1 Acceptance of sensing equipment and data collection

The data collected here show that there was a high degree of acceptance of the digital sensors amongst the study cohort. In addition to generally positive feedback, 79.3% (23 of 29) participants who completed the required six-week study period volunteered to extend their participation, resulting in an average participation period of 28.4 weeks. Many commented that the presence of digital sensors did not trouble them and that they largely forgot about them:

"I feel I have been able to take to the system like duck to water. I have not even been conscious about any of the sensors in the house. The only slight eyesore has been the hanging wires from the wall in my hallway." – ***Female, 73***

Minor objections were made against the visual incursion of one red environmental sensor that required mains power (necessitating a trailing wire), repetitive and frequent manual measurements (such as taking grip strength and weight twice a week), slight physical discomfort in relation to wearing the smartwatch continuously, occasional mental discomfort induced by dwelling on one's health (weight and sleep in particular), and not being able to see data recorded by the passive environmental sensors.

"I wonder why all the tasks have to be completed so frequently? If it's for just testing the equipment - I understand. If it's for actually monitoring someone's health - such frequent readings is enough to make anyone paranoid about their health" – ***Female, 80***

"*Weight is a metric I'd rather not see so frequently - I never have scales at my house before this, and I'm much more conscious about weight now than before"* – ***Female, 76***

"[smartwatch] strap is a little irritating, little itchy, not breathable" – ***Male, 76***

3.2 Shallow engagement with data

Participants typically engaged with the sensor data available in the tablet application frequently but superficially, often checking the basic daily homepage data without assessing changes over time. Many perceived that they had improved, but did not seek to quantify this with the historical data available in the app. Three subthemes may account for this: curiosity as a motivator without intention, fear of error, and disinterest in detailed historical data.

Subtheme - Curiosity as a motivator without intention

When discussing reasons for joining the study, participants often alluded to a general curiosity about their state of health, occasionally with a specific area of interest due to existing circumstances;

"I'm interested in my sleep - sometimes wake up for the loo and it's hard to get back to sleep. Has got worse as getting older. Would be interested in tracking this to see if I can reduce the amount I need to get up in the night" – ***Female, 66***

or to benchmark or prove their fitness levels;

"Particularly interested in steps because [I] believes [I'm] pretty active for someone of [my] age and wanted proof!" – ***Male, 79***

Another notable motivator for many was the participation in research;

"I want to use it because it's helping you… I'm interested in research but it's not actually affected the way that I do anything" – ***Female, 80***

However, the data suggest that beyond this curiosity, participants had limited intention to engage with their health data and change their behaviour. Some stated this explicitly;

"So what interested me about the program was about being aware if anything changes maintaining my health but not necessarily improving it" – ***Female, 76***

while others said that they were more "aware" of their health, but did not necessarily change their behaviour in response to this increased awareness;

"I feel more informed about my health - it's good to be aware of your health. Haven't really acted on this information though – haven't really made any changes to daily life" -***Male, 71***

Thus, the question many participants had in relation to their health, it seems, was 'Am I doing alright?', rather than 'How can I do better?'. Nonetheless, many participants described their experience positively, and some expressed that they had made active changes in their lifestyle thanks to seeing their health data;

"Most interested in steps. [I've] changed [my] behaviour, [I] walk more often than taking the bus now" – ***Female, 77***

"I was aware beforehand that I wasn't taking enough exercise, and the walking data collected gave me the push I needed to do something about it" – ***Female, 74***

Subtheme - Fear of error

A common concern of participants was making a mistake. Some wanted to ensure they were correctly fulfilling their role as a study participant;

"[I was a] bit worried about messing something up with the study – press[ing] the wrong thing" – ***Male, 71***

while others lacked confidence with the technology or feared breaking it in some way;

"I'm a bit worried about touching things… worried that I've made the watch go wrong" – ***Female, 76***

and for others it was a matter of pride;

"don't want to be "silly", don't want to get things wrong for us; don't like not having any way of knowing if things are going ok." – ***Male, 79***

The barrier created by fear of error was compounded by the design of the application interface. Both applications tested displayed only the day's most recent data on the homepage, requiring users to navigate further to reach more detailed data.

Subtheme - Disinterest in detailed historical data

Participants also had little interest or incentive to engage with data beyond their most recent daily values. Although accompanying guidance encouraged the consideration of one's average values against a recommended target, as opposed to stochastically checking current daily values, this was either missed or ignored by many;

"If I look at too much detail it doesn't interest me, I just look at the high level data like sleep score, steps" – ***Female, 73***

3.3 Expectations were not met

Although it is clear from the data and the level of study adherence that participants found the experience acceptable and beneficial to some extent, there were many cases where their expectations were not met. This may have contributed to scepticism of the technology and acted as a barrier to engagement and behavioural change. The shortfall fell into three broad categories; the technology was not smart enough, perceived irrelevance, and wanting more human guidance.

Subtheme – the technology was not smart enough

Participants reported dissatisfaction with the capabilities of hardware and software to accurately reflect their lived experiences. Almost every participant questioned the accuracy of the readings reported by their sensors. Reasons included the following: when data did not align with other personal sensors;

"Withings watch is still undercounting steps compared to fitbit for today fitbit is 9600 steps while Withings is only 5600" – ***Male, 70***

When data did not reflect reality;

"sleep mat says [I've] woken up lots when [I've] not" – ***Female, 72***

When data was unexpectedly variable;

"Variability of readings... is an indication of inaccuracy" – ***Female, 68***

and when activities were reported incorrectly;

"[the smartwatch] recorded 17mins of cycling yesterday despite [me] not having done anything yesterday" – ***Male, 76***

Additionally, there were complaints that certain activities were not recognised by the sensors;

"[the Watch] doesn't measure all the different kinds of activity, e.g., yoga and pilates" – ***Female, 72***

Furthermore, the system could not account for confounding circumstances, such as injury, weather, or needing rest;

"It was pointless being told to walk more as I have had pain in my right leg post tripping on a raised paving stone. Walking around is/was painful at the time or caused me not to sleep due to the throbbing in the right knee. Why would I want to put myself in more pain?" – ***Female, 65***

Perhaps because of the knowledge they were testing a prototype, some participants were more comfortable with these issues than others. However, it is likely that these perceived inadequacies reduced trust in the system and decreased participants' inclination to engage with and act on the data;

"If it picks up things you're not doing, then can you trust it's not failing to pick up things you are doing?" – ***Female, 78***

Subtheme – Perceived Irrelevance

For many, an attraction of at-home or wearable sensors is the promise of personalised healthcare. This expectation possibly contributed to many participants' dismissal of the information, guidance and recommendations as uninteresting or irrelevant to their circumstances;

"Lots of recommendations on active minutes need to be more age-related - some people do play tennis at 80 but not many. I don't have a garden so no mowing the lawn… Like the idea of the recommendations to choose from, don't want to come up with them myself, but most just aren't relevant to me… I already know all the intro info on active mins" – ***Female, 80***

Similarly, a strong theme was the complaint that standardised health questionnaires used in the study (e.g. Lawton-Brody IADLs) had questions that were phrased inappropriately;

"I do object (as I suspect others may also) however, to the fact that it is taken from an American source and asks questions relating to US dollars" – ***Female, 78***

Or, more commonly, had a limited choice of answers that could not adequately describe participants' genuine feelings;

"I felt that for a number of questions the answers available weren't applicable to me" – ***Male, 72***

Subtheme – wanting more human guidance

Despite the data above, there were various requests from participants for more information or guidance. Notably, this information was sometimes present in the written manual provided. Comments suggested participants were reluctant to independently read 'instructions' and relate them to their data, and preferred discussion with the researchers;

"I haven't really looked much at the data and it would only be useful if a professional explained it to me and advised on any changes I should make." – ***Female, 80***

"[I] like to talk things through and ask people rather than read instructions because [I] can find the solution to [my] questions quicker" – ***Male, 79***

3.4 Reluctance to act on data

As shown in section 3.2, some participants felt the intervention prompted them to adopt healthier behaviours. However, others described reasons why they hadn't acted on their data, which fell into the following subthemes: acceptance of current state, struggle to change, and need for clearer instruction.

Subtheme – acceptance of current state

For some, there was not sufficient impetus to change. Some struggled to "see the point" of making changes if they already felt sufficiently well, or if the benefits of the suggested behaviours were not obvious;

Appreciates the value of health but isn't obsessed with the recording, would rather enjoy the activity. Knows she's done a lot of walking today, whether it's recorded or not. "Who will know or care about these records? I'm not accountable to anyone, my doctor isn't looking, I'm not paid, I don't have health issues and my natural lifestyle is quite robust and healthy, I walk intentionally a lot" – ***Female, 67***

Subtheme – struggle to change

Others knew they should change, but did not believe that they could;

"inwardly I know if I set those goals it might not work - I am a very routine person. I suppose I could go twice around the block instead of once, but I have some health issues that means I don't like to push myself" – ***Male, 71***

For some this, took the form of avoidance or denial of potential issues evidenced by their mHealth data;

"Was reluctant to research it anymore and did not want to see a doc about it because [I] didn't want to have to worry about "oh god I could never be someone with a 'condition'". Wilfully ignoring it." – ***Female, 74***

Subtheme – need for clearer instruction

For some the act of setting a target value and aiming to reach that goal was sufficient to incite behavioural change, but these individuals were usually highly activated and self-motivated. For example, one participant, who was highly engaged with the data, felt strongly that the program was beneficial;

set a goal of steps - has been following it closely since starting the study and making sure he gets the number of steps he is aiming for… app is like "having a training coach in the house - especially when you are living alone you need the motivation which the app is providing me with that its great!" – ***Male, 74***

For less activated participants, placing the burden of data investigation, interpretation and response planning was perhaps too much, and resulted in some requests for clearer instruction;

"disappointed as she was hoping more (electronic personal trainer)" – ***Female, 65***

"Accountability is important - if you told me to do it I would, but totally on my own there's too many distractions" – ***Female, 74***

Interestingly, this feedback is in tension with criticisms of the guidance being too generic, and with negative reactions to reminders that featured in the system participants were testing.

"The "Withings man" tells me to be active but I ignore him because I take care to get up and move around." – ***Female, 78***

"I was excited to have wearable tech to help me to work towards a more active lifestyle before having the tech. Since having the watch it just annoys me [to] have tech 'nag' me. I am well aware of my lifestyle." – ***Female, 65***

There were some suggestions to better contextualise the users' health data by comparing it to an average for the user's age, or to introduce a peer support element, but this was not universally popular;

"Would also like to be able to have friends on app, 'only if I'm doing well though!'" – ***Female, 78***

"Don't want to compare with others, but wants to know what healthy range of each metric is" – ***Female, 76***

4 - Discussion and Implications

4.1 Discussion

The data reported here demonstrate that the cohort studied was highly amenable to the installation of diverse self-monitoring hardware in their homes for an extended period. Participants were able to use the hardware and software (described fully in Appendix 1), and gave positive feedback in relation to the experience, with some reporting improvements in their behaviour, fitness, and health. Previous literature highlights physical limitations (sight, hearing, dexterity) as a significant barrier to older adults' use of mHealth technologies (van Acker et al. 2023, Wilson et al.[33]). This was not true of the cohort studied here, perhaps due to the focus on pre-frailty rather than more advanced frailty. Similarly, concerns of data privacy and issues of trust like those reported in other studies of eHealth use among older adults (Wilson et al.) were absent in this cohort. This could have been due to the personal installation of the equipment and rapport built between participants and researchers.

Reports of increased awareness of health in response to the intervention observed here corroborate those identified by Brickwood et al. (2020) when assessing a similar intervention. Fear of error as a barrier to engagement was also a replicated finding, likely owing to navigational difficulty influenced by the design of the application interface.

Curiosity about mHealth data has been previously identified as motivator (Batsis et al. 2019). However, our data indicate that this motivation extends only to shallow engagement with data. For example, participants variably took advantage of the goal setting features in the intervention, shown to be effective in promoting behavioural change (Kampmeijer et al. 2016[34]), but rarely checked it against their historical or average data, instead referring to current daily readings and relying on memory to assess whether they had met their goal. This difference in engagement with daily (shallow) data and historical (deep) data has not been previously discussed.

Data inaccuracy causing erosion of trust and disengagement emerged as a prominent theme. While the inaccuracy of wrist worn step counters (Nelson et al. 2017[35], Huang et al. 2016[36]) and the impact of perceived accuracy on engagement have been demonstrated previously (Kononova et al. 2019[37]), the impact of inaccurate activity recognition has not. Here, the incorrect reporting of activities (cycling, swimming etc.) greatly reduced trust. Participants also expressed frustration that recognition of important activities like gardening, yoga and tai chi was absent, replicating the finding of Vargemidis et al. 2020 that interventions should align with such activities. The exclusion of activity recognition should be considered in future interventions to mitigate this loss of trust.

Vargemidis et al. 2020 recommend that physical activity interventions for older adults should actively guide users with relevant examples of activity, rather than passively monitor disembodied metrics. The interventions studied here attempted to address this with the provision of activity suggestions. However, participants still found the guidance generic or irrelevant and often ignored it. Despite this, themes emerged around requests for clearer instruction and prompts to help overcome the struggle to change. This highlights a design challenge – interventions must provide sufficient data and guidance to support older adults to change their behaviour, but maintain freedom of choice to foster self-determination and account for user heterogeneity (see Cazza et al.

2017) while also avoiding overwhelming data complexity. The importance of autonomy and freedom of choice has been demonstrated previously (Pettersson et al. 2021[38]). Pusey et al. (2019)[39] propose a model where older adults ask questions and doctors facilitate discussion, providing options and advice. This aligns with the themes that emerged here around preference for human-delivered information, expert guidance and learning through conversation.

To consider how wellbeing supportive design has been applied within the project, specifically SDT, we must examine how participants basic psychological needs of autonomy, competence, and relatedness, were either supported or frustrated. In SDT 'needs frustration' refers to instances where a design does not support one or more of a user's basic psychological needs. In line with the idea that supporting a user's three basic psychological needs increases their motivation, engagement, and wellbeing; the converse is true that when a user's basic psychological needs are not met there are negative consequences for their motivation, engagement, and wellbeing. Firstly, From an SDT perspective, the high acceptance of self-monitoring hardware suggests that the hardware itself did not actively undermine any of the three basic psychological needs, and likely the personal installation of the equipment and rapport built between participants and researchers supported relatedness. Meanwhile, the pattern of shallow engagement can be understood as a competence frustration. The interface showed participants their health data but did not meaningfully help them interpret or act on it – placing the burden of understanding, interpreting, and changing their behaviour in response to the data on the user, who may not have the confidence or motivation to do so. Fear of error, a related finding, compounds this: if users are not sure how to use the interface, or what to do with the information it provides to them, then the technology is not supporting their competence. When it comes to data inaccuracy, this is an example of an autonomy frustration: if data is inaccurate, and activities that are meaningful to users go unrecognised – users cannot make informed decisions that align with their own goals and motivations. Finally, balancing providing clear guidance and support with avoiding overwhelming data should be seen as a balance between supporting competence for the users without undermining autonomy. Guidance given in these circumstances should inform and suggest rather than direct, so that participants feel both that they are capable of making changes to their behaviour relating to their health and are choosing to change their behaviour.

Recognising the limitations of scaling the human support element of this trial, the authors consider future investigation of a large language model (LLM) as an alternative. LLMs facilitate free text or vocal input by users to satisfy the preference for conversation and perhaps ameliorate the fear of error barrier to engagement (Wiratunga et al. 2020[40]). Providing users with narrative summaries, improving accessibility by reducing the burden of data interpretation, might overcome shallow data engagement. Allowing users to "reply" and amend incorrect data or provide contextual information may avoid trust erosion due to inaccuracy and increase perceived personalisation. LLMs tuned for interpretation of sleep and fitness data perform similarly to human experts (Khasentino et al. 2025[41]). A scoping review of studies of LLM use for exercise recommendation and physical activity concluded that LLMs are suited for this purpose, increase engagement and support behaviour change, but that specific tailoring to older adults would be necessary to avoid inappropriate recommendations (Lai et al 2025[42]). Dai (2025)[43] suggests a framework for designing accessible LLM sense-making tools for older adults. The use of LLMs in health coaching is a burgeoning field and more research is required, particularly for their use in interventions for older adults.

4.2 Strengths and Limitations

Strengths of the study included the diverse cohort that resembled the demographics of the Greater London recruitment area[44]. The retention and acceptability were high, and participant feedback indicated frequent, if shallow, engagement with the intervention.

Limitations included the data capture methodology. Verbal feedback was recorded in note form rather than in full transcripts, so it is possible that some bias was introduced by the note-taker. The interviewer and note-taker were not the same person throughout, and so some inconsistency in prompting and recording of feedback was possible (though semi-structured discussion guides were used). The study cohort was likely to have suffered from selection bias towards more motivated and digitally literate older adults. Many also reported some level of engagement with their health or fitness tracking prior to enrolment suggesting higher levels of self-activation than the population average. Initial barriers to adoption and uptake were not deeply investigated in this study, and conclusions may not be valid for a less activated or technologically literate group. Future research will benefit from a focus on marginalised and less technologically literate groups.

4.3 Conclusion

The data presented here indicate that neither the ability to operate digital technology nor concerns over privacy limited access to the intervention among this cohort of older adults, in contrast to previous studies on the acceptability and usability of mHealth self-monitoring systems. While many participants reported a positive experience and perceived improvement in healthy behaviour, the findings also suggest their engagement with data was often shallow and likelihood to act was low. Barriers included scepticism of the data due to inaccuracies, poor reflection of meaningful activities, overly general guidance and difficulty interpreting the raw data, reflecting findings of previous studies. Addressing the inaccessibility of data interpretation may foster improved, more equitable outcomes amongst older adults currently underserved by mHealth interventions.

Declarations

Competing interest

The authors have no competing interests as defined by Nature Portfolio, or other interests that might be perceived to influence the results and/or discussion reported in this paper.

Ethical approval

This study was approved by the Science, Engineering and Technology Research Ethics Committee (SETREC) of Imperial College London (SETREC Ref No. 6875521).

Informed consent

Written informed consent for participation and publication of findings was obtained from all participants prior to enrolment in the study.

Funding Statement

This study was funded by Optum (part of UnitedHealth Group). The funder played no role in study design, data collection, analysis and interpretation of data, or the writing of this manuscript.

Author Contribution

A.D-P. and T.S. wrote the main manuscript. A.D-P., T.S., A.W. and T.T. collected the data during the study. All other authors reviewed the manuscript.

Acknowledgement

We would like to thank Helix Centre team (including Damion Lambert, Brian Quan); Clinical Reference Group (including Simon Dryden, Hutan Ashrafian, Sabaa Gauhar, Ana Luísa Neves, Brendan Delaney, Alison Buttenheim, Louis Koizia, Cerys Morgan, George Peck, Melanie Dani); our interns (Madeline Tatum, Jessica Shields).

Data Availability

All data supporting the findings of this study are available within the paper and its Supplementary Information.

References

1. World Health Organization. mHealth: New Horizons For Health Through Mobile Technologies: Based On The Findings Of The Second Global Survey On eHealth 79–82 (World Health Organization, 2011).
2. Marcolino, M. S. et al. The impact of mHealth interventions: systematic review of systematic reviews. *JMIR mHealth and uHealth*. **6(1)**, e8873; 10.2196/mhealth.8873 (2002).
3. Pérez-Jover, V., Sala-González, M., Guilabert, M., & Mira, J. J. Mobile apps for increasing treatment adherence: systematic review. *Journal of medical Internet research*. **21(6)**, e12505; 10.2196/12505 (2019).
4. Hall, A. K., Cole-Lewis, H., & Bernhardt, J. M. Mobile text messaging for health: a systematic review of reviews. *Annual review of public health*. **36(1)**, 393–415; 10.1146/annurev-publhealth-031914-122855 (2015).
5. Lynch, R., & Cohn, S. In the loop: Practices of self-monitoring from accounts by trial participants. *Health (London)*. **20(5)**, 523–538; 10.1177/1363459315611939 (2016).
6. Maita, K. C. et al. The impact of digital health solutions on bridging the health care gap in rural areas: a scoping review. *Perm J*. **28(3)**; 10.7812/TPP/23.134 (2024)
7. Tong, H. L. et al. Personalized mobile technologies for lifestyle behavior change: a systematic review, meta-analysis, and meta-regression. *Preventive medicine***148**, 106532; (2021)
8. Peyroteo, M., Ferreira, I. A., Elvas, L. B., Ferreira, J. C., & Lapão, L. V. Remote monitoring systems for patients with chronic diseases in primary health care: systematic review. *JMIR mHealth and uHealth*, **9(12)**, e28285; 10.2196/28285 (2021).
9. van de Werken, H. A., Rohrbach, P. J., & Bolman, C. A. Explaining intention and use of Mhealth with the unified theory of acceptance and use of technology. *Acta Psychologica*, **254**, 104819 (2025).
10. United Nations. World Population Prospects 2024: Summary of Results. **UN DESA/POP/2024/TR/NO. 9**. New York: United Nations (2024).
11. Dewhurst, M., Linzer, K., Maud, M., & Sandler, C. Living longer in better health: six shifts needed for healthy aging. *McKinsey Health Institute* https://www.mckinsey.com/mhi/our-insights/living-longer-in-better-health-six-shifts-needed-for-healthy-aging (2022).
12. World Health Organization. WHO clinical consortium on healthy ageing: topic focus: frailty and intrinsic capacity. *Report of consortium meeting, 1–2 December 2016 in Geneva, Switzerland*, **WHO/FWC/ALC/17.2** (2017).
13. Chu, W., Chang, S. F., & Ho, H. Y. Adverse health effects of frailty: Systematic review and meta-analysis of middle-aged and older adults with implications for evidence-based practice. *Worldviews on Evidence-Based Nursing*, **18(4)**, 282–289 (2021).
14. Fried, L. P. et al. Frailty in older adults: evidence for a phenotype. J Gerontol A Biol Sci Med Sci, **56(3)**, M146-156. doi:10.1093/gerona/56.3.m146 (2001)
15. Wang, H. Y., Lv, X., Du, J., Kong, G., & Zhang, L. Age-and gender-specific prevalence of frailty and its outcomes in the longevous population: the Chinese longitudinal healthy longevity study. *Frontiers in medicine*, **8**, 719806 (2021).

16. da Silva Sobrinho, A. C. et al. Systematic review of interventions for pre-frail and frail older adults: Evidence from clinical trials on frailty levels. *Archives of gerontology and geriatrics*, **134**, 105851 (2025).
17. Van Acker, J., Maenhout, L., & Compernolle, S. Older adults' user engagement with mobile health: a systematic review of qualitative and mixed-methods studies. *Innovation in Aging*, **7(2)**, igad007 (2023).
18. Batsis, J. A. et al. Technology for behavioral change in rural older adults with obesity. *Journal of nutrition in gerontology and geriatrics*, **38(2)**, 130–148 (2019).
19. Suh, A., & Li, M. How the use of mobile fitness technology influences older adults' physical and psychological well-being. *Computers in Human Behavior*, **131**, 107205 (2022).
20. Huh, J., Le, T., Reeder, B., Thompson, H. J., & Demiris, G. Perspectives on wellness self-monitoring tools for older adults. *International journal of medical informatics*, **82(11)**, 1092–1103 (2013).
21. O'Connor, S. et al. Understanding factors affecting patient and public engagement and recruitment to digital health interventions: a systematic review of qualitative studies. *BMC Med Inform Decis Mak*, **16(1)**, 120 (2016).
22. Kwan, R. Y. C. et al. The association of technology acceptance and physical activity on frailty in older adults during the COVID-19 pandemic period. *European Review of Aging and Physical Activity*, **20(1)**, 24 (2023).
23. Calvo, R. A., & Peters, D. An introduction to positive computing. In *Positive Computing: Technology for Wellbeing and Human Potential* 1–6 (MIT Press, 2014).
24. Ryan, R. M., & Deci, E. L. Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68–78 (2000).
25. Peters, D. Wellbeing supportive design – research-based guidelines for supporting psychological wellbeing in user experience. International Journal of Human–Computer Interaction, 39(14), 2965–2977 (2023).
26. Godin, D., and Zahedi, M. Aspects of Research through Design: A Literature Review. *Design's Big Debates - DRS International Conference 2014, 16–19 June, Umeå, Sweden*. https://dl.designresearchsociety.org/drs-conferencepapers/drs2014/researchpapers/85 (2014)
27. Cozza, M., De Angeli, A., & Tonolli, L. Ubiquitous technologies for older people. Personal and Ubiquitous Computing, **21(3)**, 607–619 (2017).
28. Boulton, E. R., Horne, M., & Todd, C. Involving older adults in developing physical activity interventions to promote engagement: a literature review. *Journal of Population Ageing*, **13(3)**, 325–345 (2020).
29. Nimmanterdwong, Z., Boonviriya, S., & Tangkijvanich, P. Human-centered design of mobile health apps for older adults: systematic review and narrative synthesis. *JMIR mHealth and uHealth*, **10(1)**, e29512: 10.2196/29512 (2022).
30. Vargemidis, D., Gerling, K., Spiel, K., Abeele, V. V., & Geurts, L. Wearable physical activity tracking systems for older adults—a systematic review. *ACM Transactions on Computing for Healthcare*, **1(4)**, 1–37 10.1145/3402523 (2020).
31. Lumivero. NVivo **(Version 14)**www.lumivero.com (2023)
32. Braun, V., & Clarke, V. Using thematic analysis in psychology. *Qualitative research in psychology*, **3(2)**, 77–101 (2006).
33. Wilson, J., Heinsch, M., Betts, D., Booth, D., & Kay-Lambkin, F. Barriers and facilitators to the use of e-health by older adults: a scoping review. *BMC public health*, **21(1)**, 1556 (2021).
34. Kampmeijer, R., Pavlova, M., Tambor, M., Golinowska, S., & Groot, W. The use of e-health and m-health tools in health promotion and primary prevention among older adults: a systematic literature review. *BMC health services research*, **16(Suppl 5)**, 290 10.11
35. Nelson, Rachael K., et al. "Comparison of wrist-and hip-worn activity monitors when meeting step guidelines." *Preventing chronic disease*, **19**, E18 (2022).
36. Huang, Y., Xu, J., Yu, B., & Shull, P. B. Validity of FitBit, Jawbone UP, Nike + and other wearable devices for level and stair walking. *Gait & posture*, **48**, 36–41 (2016).
37. Kononova, Anastasia, et al. "The use of wearable activity trackers among older adults: focus group study of tracker perceptions, motivators, and barriers in the maintenance stage of behavior change." *JMIR mHealth and uHealth*, **7.4**, e9832 (2019).
38. Pettersson, B., Janols, R., Wiklund, M., Lundin-Olsson, L., & Sandlund, M. Older adults' experiences of behavior change support in a digital fall prevention exercise program: Qualitative study framed by the self-determination theory. *Journal of medical internet research*, **23(7)**, e26235 10.2196/26235 (2021).
39. Pusey, E., Tinker, A., & Lucivero, F. The shared decision making of older adults in healthcare. *Working with Older People*, **23(2)**, 77–86 10.1108/WWOP-11-2018-0023 (2019).
40. Wiratunga, N. et al. FitChat: conversational artificial intelligence interventions for encouraging physical activity in older adults. *arXiv preprint arXiv:2004.14067* 10.48550/arXiv.2004.14067 (2020).
41. Khasentino, J. et al. A personal health large language model for sleep and fitness coaching. *Nature Medicine*, **1–10** (2025).
42. Lai, X. et al. Using Large Language Models to Enhance Exercise Recommendations and Physical Activity in Clinical and Healthy Populations: Scoping Review. *JMIR Medical Informatics*, **13(1)**, e59309 10.2196/59309 (2025).
43. Dai, D. Exploring Self-Tracking Practices of Older Adults with CVD to Design LLM-Enabled Data Sense-Making (**Dissertation**). Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-368197 (2025).
44. Office for National Statistics. How life has changed in the City of London: Census 2021 https://www.ons.gov.uk/visualisations/censusareachanges/E09000001/ (2021)

Tables

Table 1
Inclusion-exclusion criteria for study eligibility

Inclusion Criteria	Exclusion Criteria
• Community-dwelling;	• taking no medication;
• 65 years old or older;	• have significant cognitive impairment;
• living at home with no more than one other adult;	• have severe limitations in activities of daily living which would prevent active participation in the assessments and physical exercise programme;
• living within the London boroughs;	• unable to safely engage in the exercise component for other health-related reasons such as musculoskeletal or neurological disorders;
• able to mobilise independently and walk 15 minutes unaided;	• have progressive or severe medical illness e.g. acute myocardial infarction in the last 3 months, unstable angina, severe aortic stenosis, uncontrolled orthostatic hypotension, recent bone fracture in the last 3 months, having a life expectancy of less than 24 months, requiring palliative care within the following two years, three or more hospitalisations in the last year;
• willing to engage in an exercise programme for at least six weeks;	• have moderate to severe depression, or psychiatric disorders which may interfere with their participation in the study; were being treated for active cancer;
• capable of informed consent;	• have unstable medical conditions or where clinical optimisation was required e.g., uncontrolled diabetes.
• able to speak and understand written English;	
• score 3 or less on PRISMA-7 frailty assessment	

Table 2
Demographic makeup of the 29 participants who completed at least 6 weeks of the trial. The mean age was 72.6 years (SD = 3.7).

Category	n (%)
Gender	
Male	**13 (45%)**
Female	**16 (55%)**
Ethnicity	
White	**17 (59%)**
Black, British Black, Caribbean, or African	**2 (7%)**
Asian, British Asian, or South Asian	**5 (17%)**
Mixed or Others	**5 (17%)**
Self-reported technology literacy	
High (11–16)	29 (100%)
Low (< 11)	0 (0%)
Education Level	
Bachelor/Graduate/Postgraduate	15 (52%)
Secondary/Sixth form	6 (21%)
None/Primary	1 (3%)
Other	1 (3%)
Unknown	6 (21%)

Table 3
The themes and subthemes generated from the codes and coded data, with codes relevant to each theme and subtheme shown adjacent

Themes	Subthemes	Codes
3.1 Acceptance of sensing equipment and data collection	-	Reactions to monitoring
		Relevance to me
		Anxiety
3.2 Shallow depth of engagement with data	**Curiosity as a motivator without intention**	Motivation to participate
		Relevance to me
		Reassurance
		Engagement with data
		Capacity to change
	Fear of error	Confidence
		Anxiety
	Disinterest in detailed historical data	Engagement with data
		Relevance to me
		Data interpretation
		Information delivery (human)
3.3 Expectations were not met	**The technology was not smart enough**	Data quality/accuracy
		Recognition of effort
		Recommendations for behaviour change
		Confounding factors
		Data interpretation
	Perceived Irrelevance	Relevance to me
		Recommendations for behaviour change
	Wanting more human guidance	Information delivery (human)
		Data interpretation
		Comparison to others
		Confidence
		Anxiety
		Engagement with data
		Peer support
		Recommendations for behaviour change
3.4 Reluctance to act on data	**Acceptance of current state**	Capacity to change
		Engagement with data
		Reactions to monitoring
		Information delivery (human)
		Recommendations for behaviour change
		Obsession
	Struggle to change	Capacity to change
		Confounding factors
		Recommendations for behaviour change
		Anxiety
	Need for clear instruction	Reminders
		Data interpretation

Themes	Subthemes	Codes
		Engagement with data
		Comparison to others
		Peer support

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- DesigningforhealthyageingLessonslearnedfromengagingprefrailolderadultsinthedevelopmentofdigitalselfmonitoringhealthtechnologiesAPPENDICES.pdf