



Article

Testing a New Approach to Monitor Mild Cognitive Impairment and Cognition in Older Adults at the Community Level

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Abstract

Dementia and mild cognitive impairment (MCI) are growing health concerns in Canada's aging population. Over 700,000 Canadians currently live with dementia, and this number is expected to rise. As the older adult population increases, coupled with an already strained healthcare system, there is a pressing need for innovative tools that support aging in place. This study explored the feasibility and acceptability of using a Digital Human (DH) conversational agent, combined with AI-driven speech analysis, to monitor cognitive function, anxiety, and depression in cognitively healthy community-dwelling older adults (CDOA) aged 65 and older. Sixty older adults participated in up to three in-person sessions over six months, interacting with the DH through journaling and picture description tasks. Afterward, 51 of the participants completed structured interviews about their experiences and perceptions of the DH and AI more generally. Findings showed that 84% enjoyed interacting with the DH, and 96% expressed interest in learning more about AI in healthcare. While participants were open and curious about AI, 67% voiced concerns about AI replacing human interaction in healthcare. Most found the DH friendly, though reactions to its appearance varied. Overall, participants viewed AI as a promising tool, provided it complements, rather than replaces, human interactions.

Keywords: digital human; mild cognitive impairment; dementia; healthcare; older adults; AI literacy; remote health monitoring



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1. Introduction

Dementia is a chronic condition affecting over 700,000 Canadians [1], and more than 50 million people globally [2]. Although less severe than dementia, mild cognitive impairment (MCI) also afflicts a significant portion of the population [3]. As the older adult population grows, the prevalence of MCI and dementia is expected to rise, increasing the demand for healthcare services and support [4]. Canada's population is projected to grow by 36% over the next 20 years [5], with older adults comprising approximately a quarter of the total population [6].

Currently, the Canadian healthcare system is under strain, grappling with overcrowded emergency rooms, a shortage of family doctors, and overburdened healthcare workers [7]. By 2040, over half of individuals aged 65 and older are projected to live with a major illness [5]. These demographic trends are expected to present significant challenges for the healthcare system. The aging population coupled with the challenges

faced by the healthcare system underscores the urgent need for innovative health-related tools and technologies that enable timely care and support aging in place. In response, the Government of Canada has committed close to \$200 billion CAD over 10 years to improve health services, with a focus on modernizing healthcare through digital tools [7].

AI is increasingly integrating into daily life, including for use in healthcare monitoring. Increased accessibility to smartphones, coupled with Wi-Fi and artificial intelligence (AI), more generally, has transformed the way that individuals monitor their health [8,9]. Remote patient monitoring (RPM) technologies, such as wearable devices, are digital technologies that utilize AI to monitor and record real-time physiological data, such as vital signs, from a remote location, such as one's home [10]. These tools enable healthcare workers to collect real-time, non-urgent medical data, and monitor changes in health over time [10–13], while also empowering patients to manage their health from the comfort of their own home [14]. The benefits of RPM technologies are multifaceted, including, but not limited to offering patients some autonomy over their health, reducing transportation barriers, side-stepping long-wait times at hospitals and clinics, offering cost-saving benefits for the end-user, and alleviating some pressure on the healthcare system [14–18]. Despite the growing promise of RPM technologies, their full potential remains unrealized due to limited real-world studies and insufficient co-creation with end users. Without meaningful engagement and feedback from those who would use these technologies, their effectiveness in practical settings is not fully understood.

Given the aging population, the projected increases in MCI and dementia, and inefficiencies and challenges within the healthcare system, the demand for effective technologies to maintain and support cognitive health in older adults will continue to grow. Specifically, there is a growing need to develop non-invasive, engaging, and acceptable tools and technologies to assess and monitor cognitive function and mental health in older adults receiving aged care services with commercial potential. This need for innovative tools and technologies would facilitate timely healthcare delivery to older adults, mitigate barriers related to healthcare access, and support aging in place. As a first step, conducting a feasibility study with cognitively healthy community-dwelling older adults (CDOA) allows for the evaluation of the initial usability and acceptability of the technology before extending its use to more vulnerable clinical populations living with MCI and dementia.

This feasibility study, using a mixed-methods observational design, aimed to address this need through two primary objectives: (1) to investigate the feasibility, acceptability and performance of a Digital Human (DH) conversation agent combined with an AI-driven speech analysis algorithm for monitoring cognitive function, anxiety, and depression in cognitively healthy CDOA, and (2) to collect qualitative data on participants' experiences with the DH and their AI-literacy.

2. Materials and Methods

2.1. Participants

Seventy-two CDOA were recruited from the research database maintained by the Centre for Elder Research (CER) at Sheridan College in Ontario, Canada, and recruitment notices distributed by community organizations. Twelve participants withdrew or dropped-out prior to the initial in-person visit due to various reasons, including time commitment ($n = 1$), discomfort with audio/video recording ($n = 1$), transportation or distance challenges ($n = 1$), lack of response to follow-up communications ($n = 7$), or undisclosed reasons ($n = 2$). As a result, 60 older adults were enrolled for the baseline (visit 1) in-person assessment. Participant demographics are summarized in Table 1. Eligibility criteria included: (1) being aged 65 or older; (2) feeling comfortable maintaining a conversation in English; and (3) being able to reasonably commit to multiple in-person visits to CER, spaced approximately three

months apart over the course of six months. All participants provided written or electronic informed consent using REDCap and were compensated for their participation in the study. The study was approved by Sheridan’s Research Ethics Board (SREB No. 2002-06-005-007).

Table 1. Participant demographics.

	In-Person Assessments (<i>n</i> = 60)	Follow-Up Phone Interview (<i>n</i> = 51)
Age (Years)	75.0 ± 6.2	74.8 ± 6.4
Gender (%)		
Male	30	28
Female	70	72
Intersex	0	0
Prefer not to say	0	0
Ethnicity (%)		
Arabic (Middle East, North Africa)	2	1.9
Black (e.g., African, American, Caribbean, etc.)	1.7	1.9
Latin American (e.g., Mexican, Chilean, Costa Rican, etc.)	1.7	1.9
South Asian (e.g., East Indian, Pakistani, Sri Lankan, Bangladeshi, etc.)	3.3	3.7
White	86.7	85.2
I would like to specify an identity not listed	5	5.6
Education (%)		
High school	6.7	7.4
College diploma	31.7	27.8
University degree	35.0	38.9
Post graduate degree	20.0	18.5
Other	6.7	7.4

2.2. In-Person Assessments Overview

Over the six-month study period, participants completed up to three visits at CER, occurring at baseline (visit 1), three months (visit 2), and 6 months (visit 3), with intervals of approximately three months between assessments. Each visit was approximately 30 min.

2.3. In-Person Baseline Assessment—Month 0

After providing informed consent, participants were assigned a unique study code to ensure that all data were linked to a code rather than to personal identifiers. Two weeks prior to the baseline in-person assessment (month 0), participants received a secure REDCap link to complete the demographics questionnaire, the Patient Health Questionnaire-8 (PHQ-8) and the Generalized Anxiety Disorder questionnaire-7 (GAD-7). Participants who had not completed these questionnaires in advance were given the opportunity to do so during their initial visit to CER. During the in-person baseline assessment, the Mini Mental State Exam (MMSE) was administered by the Research Coordinator. Following the MMSE, participants were seated in front of a computer where they interacted with the Digital Human (DH) for several minutes, which guided them through a series of vocal tasks. During the interaction, participants completed a journaling task administered by the DH, which is an open-ended prompting question asking participants to describe what they did the day before for up to two minutes. They also answered a one-item general mental health question, rating their current mental health on a scale from “poor” to “excellent”. Next, the DH asked participants to complete two picture description tasks. Participants were presented with two black-and-white drawings depicting a scenario (i.e., living room scene, kitchen scene, restaurant scene) and were asked to describe everything that they saw in the picture for up to two minutes. Audio and video data was collected passively during the entire interaction with the DH.

2.4. In-Person Assessments—Month 3 and Month 6

Within two weeks prior to each subsequent in-person visit, participants were asked to complete the PHQ-8 and the GAD-7 questionnaires. Participants who had not completed these questionnaires in advance were able to do so during their visit to CER. Similar to the baseline assessment, the MMSE was administered by the Research Coordinator at the start of the visit. Following the MMSE, participants again were seated in front of a computer where they interacted with the DH for several minutes, which guided them through a series of vocal tasks. During each interaction, participants completed a journaling task administered by the DH. They also answered a one-item general mental health question, rating their current mental health on a scale from “poor” to “excellent”. Similar to the baseline assessment, at the six-month visit, participants additionally completed two picture description tasks. Throughout each interaction, audio and video data were collected passively.

2.5. Final Interview Overview

Approximately six weeks after completing their final in-person visit, participants were invited to take part in a one-hour structured interview conducted via video or phone call. Participants were informed in advance of the duration of the interview and topics of discussion, and participation was entirely voluntary. These interviews collected qualitative data on participants’ experiences and feedback regarding the DH, their familiarity with AI, their level of AI literacy, and their concerns about the use of AI, specifically within healthcare.

2.6. Data Analysis

Quantitative data was collected during the in-person visits from the MMSE, GAD-7, and PHQ-8. Descriptive statistics such as the mean, standard deviation, minimum and maximum values were calculated. PHQ-8 and GAD-7 data is summarized in Table 2 and PHQ-8 and GAD-7 mean total scores across all three visits are visualized in Figures 1 and 2.

Table 2. PHQ-8 and GAD-7 Summary Data.

		Patient Health Questionnaire (PHQ-8) Total Score	Generalized Anxiety Disorder Questionnaire (GAD-7) Total Score
Visit 1	Minimum	0	0
	Maximum	16	21
	Mean	3.25	2.79
	Standard Deviation	3.26	3.94
Visit 2	Minimum	0	0
	Maximum	16	18
	Mean	3.11	2.60
	Standard Deviation	3.11	3.31
Visit 3	Minimum	0	0
	Maximum	7	6
	Mean	2.67	1.53
	Standard Deviation	2.26	1.92

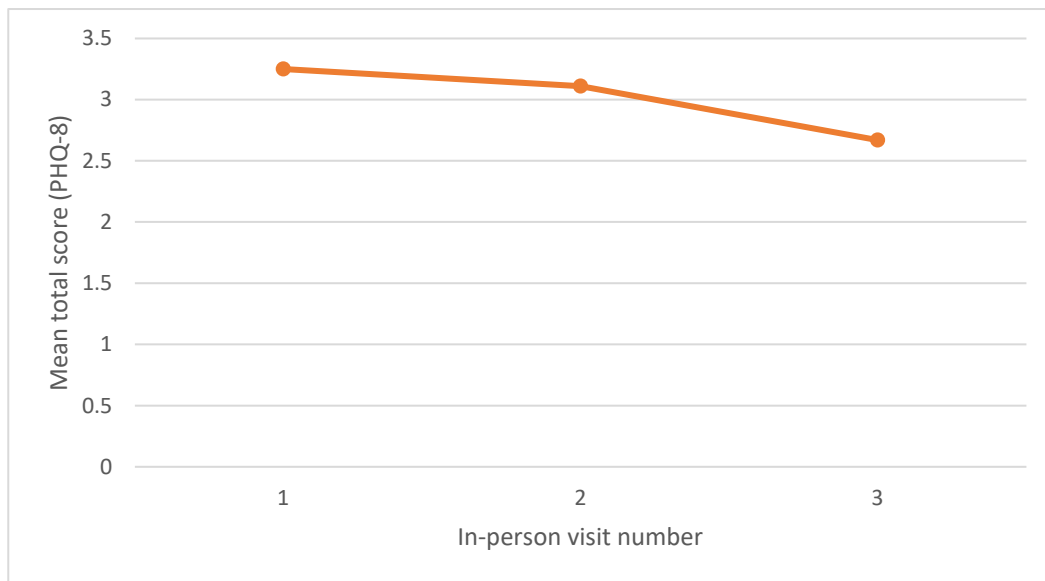


Figure 1. Changes in mean PHQ-8 total scores for the entire cohort across three in-person visits.

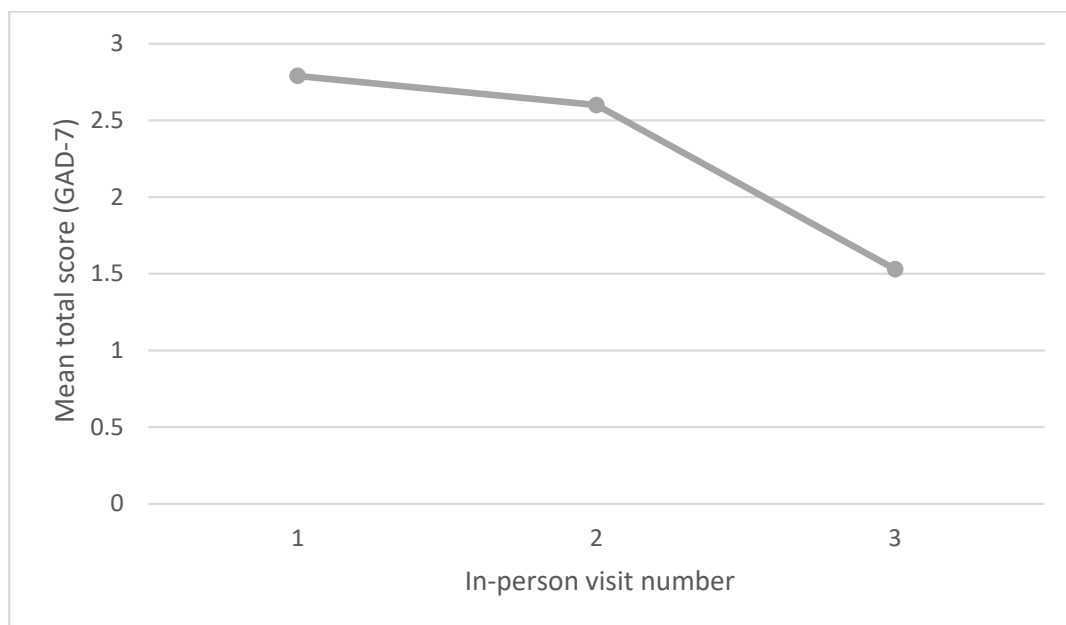


Figure 2. Changes in mean GAD-7 total scores for the entire cohort across three in-person visits.

Quantitative and qualitative data was collected during the final video/phone interviews. Descriptive statistics, such as percentages, were used to summarize participant responses.

3. Results

3.1. In-Person Assessments

Sixty CDOA completed the baseline in-person assessment. Following this, three participants withdrew from the study without providing a reason. Of the remaining participants, 54 completed the second assessment, and 13 completed the third assessment.

After the initial interaction with the DH, approximately 70% of participants responded positively to the DH (i.e., “DH was pleasant and had kind eyes”), 13% had a neutral reaction (i.e., “DH was fine”), and 17% had a negative reaction (i.e., “DH was creepy and disconcerting”).

3.2. Final Interview Outcomes

Fifty-one participants completed the final phone interview about their experience with and opinions of the DH and AI technology, more generally. Participants were asked to rate their answers on a scale from 1 to 5, with 1 meaning the least and 5 meaning the most. Approximately 84% at least somewhat enjoyed interacting with the DH, the entire cohort (100%) felt at least somewhat comfortable interacting with the DH, almost all (96%) found the DH to be at least a little likeable, almost all (92%) are interested in learning to use new technologies, almost all (98%) felt at least a little confident with learning to use new technologies, all (100%) are at least a little interested in AI-related technologies and their applications, while almost all (96%) are interested in learning more about the uses of AI, specifically in healthcare.

When asked to give more detailed answers about their opinions of AI in healthcare, more than half of the cohort (55%) stated they felt a mix of excitement and concern about the increasing use of AI in daily life, while 23% felt more excited than concerned, and 22% felt more concerned than excited. More than half (53%) stated that they would feel uncomfortable if their healthcare provider relied on AI for their medical care, while 27% said they would feel comfortable, and 20% would feel a mix of both. In total, 67% of the cohort think that AI in healthcare would lead to better outcomes for patients, 10% think it would lead to worse outcomes, and 10% think it would not make much of a difference, while 13% felt unsure about the outcomes. A third (35%) of the cohort thinks that AI in healthcare would worsen the personal connection between a patient and their healthcare provider, while 18% believe that personal connection would get better. However, 47% said the connection would either stay the same, or the quality of the connection would depend more on the healthcare provider than on AI. In addition, 92% stated that they were interested in learning to use new technologies, with 8% failing to provide a definitive answer. Almost all (96%) stated they were interested in learning more about the uses of AI in fields like healthcare, with 4% failing to provide a definitive answer. These results are summarized in Figures 3–8.

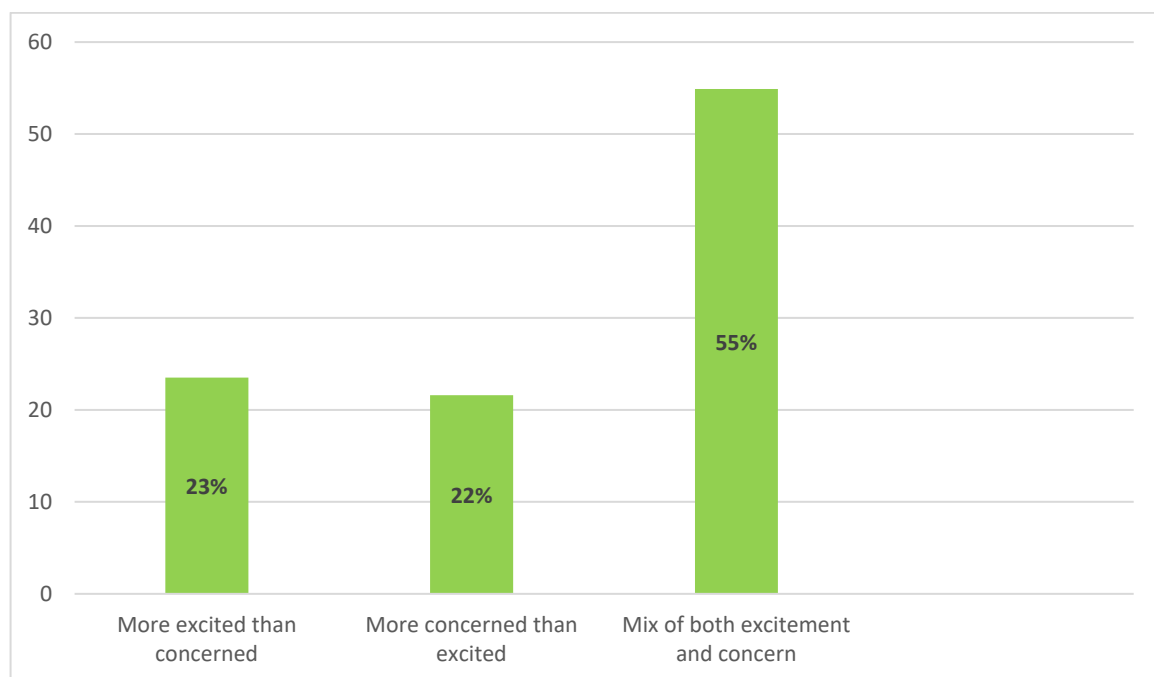


Figure 3. Participant responses to the phone interview question: “Would you say you are more excited than concerned about the increasing use of AI in daily life, more concerned than excited, or a mix of both? Why do you feel that way?”.

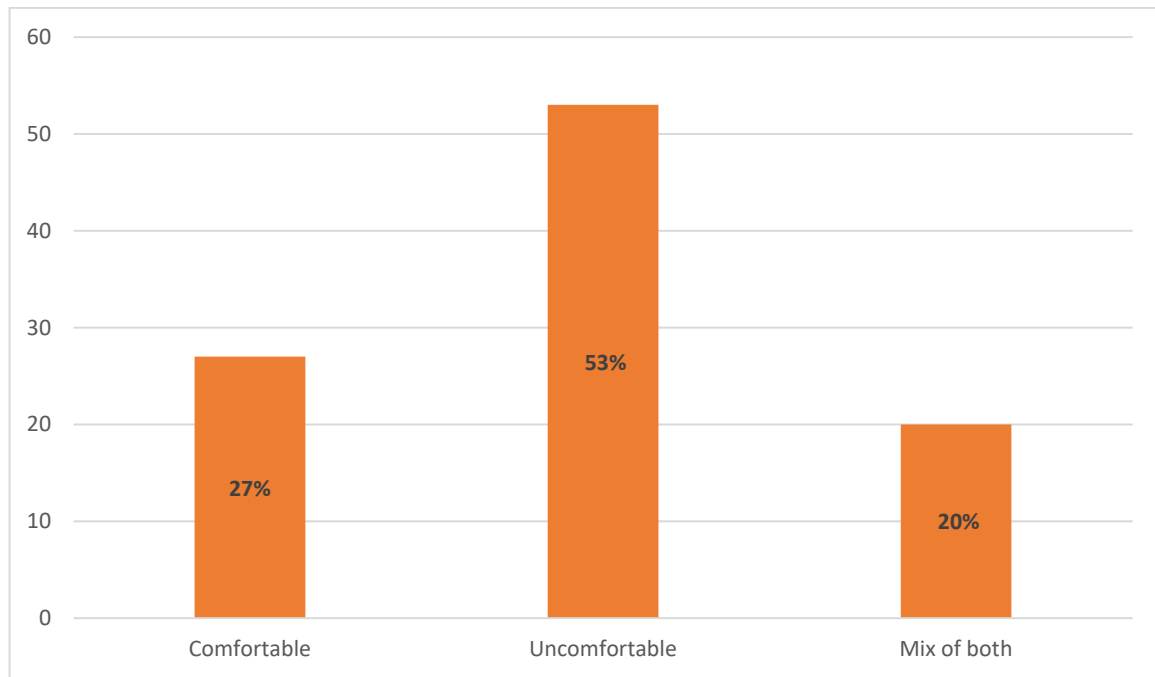


Figure 4. Participant responses to the phone interview question: “Would you feel comfortable if your healthcare provider relied on AI for your medical care, or would you say you would be uncomfortable? Why do you feel that way?”.

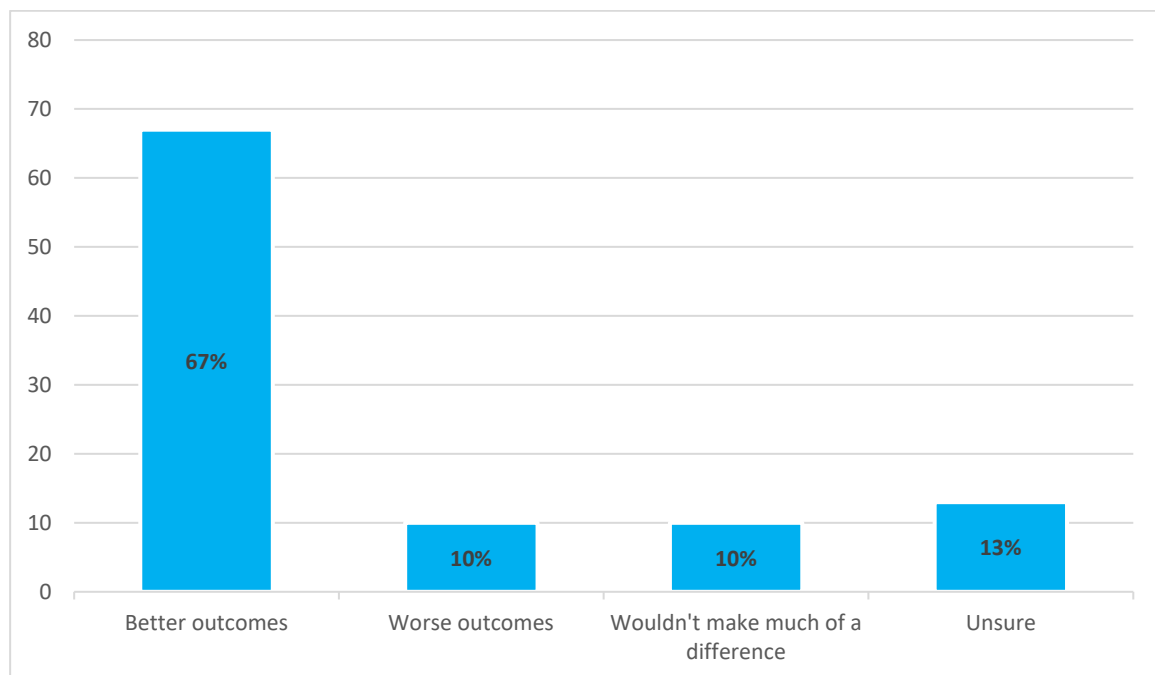


Figure 5. Participant responses to the phone interview question: “Do you think AI in health care would lead to better outcomes for patients, worse outcomes, or it wouldn't make much difference? Why do you feel that way?”.

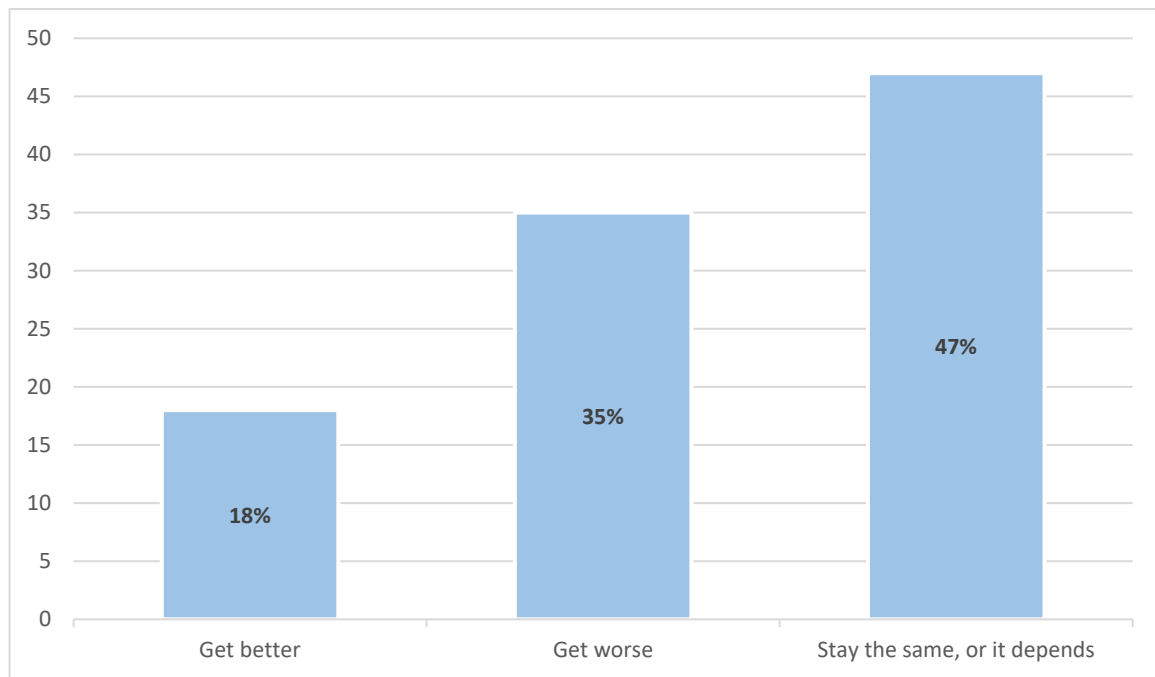


Figure 6. Participant responses to the phone interview question: “How do you think AI would impact the personal connection between a patient and their healthcare provider? Would it get worse, get better or stay the same? Why do you feel that way?”.

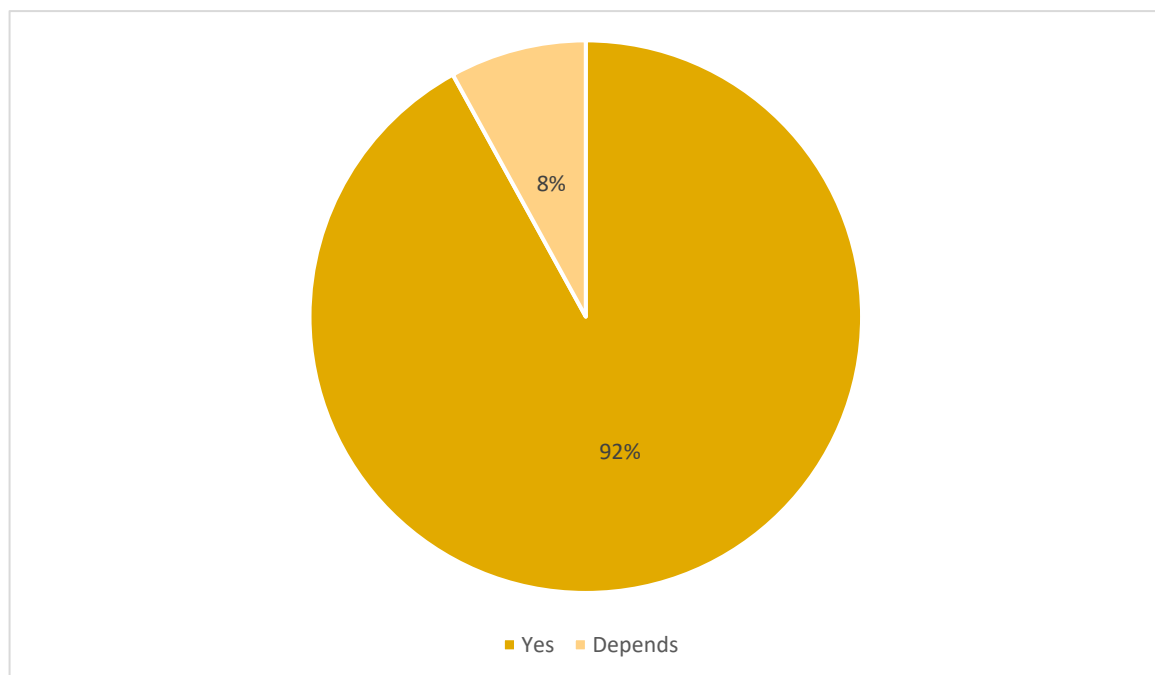


Figure 7. Participant responses to the phone interview question: “Are you interested in learning to use new technologies?”.

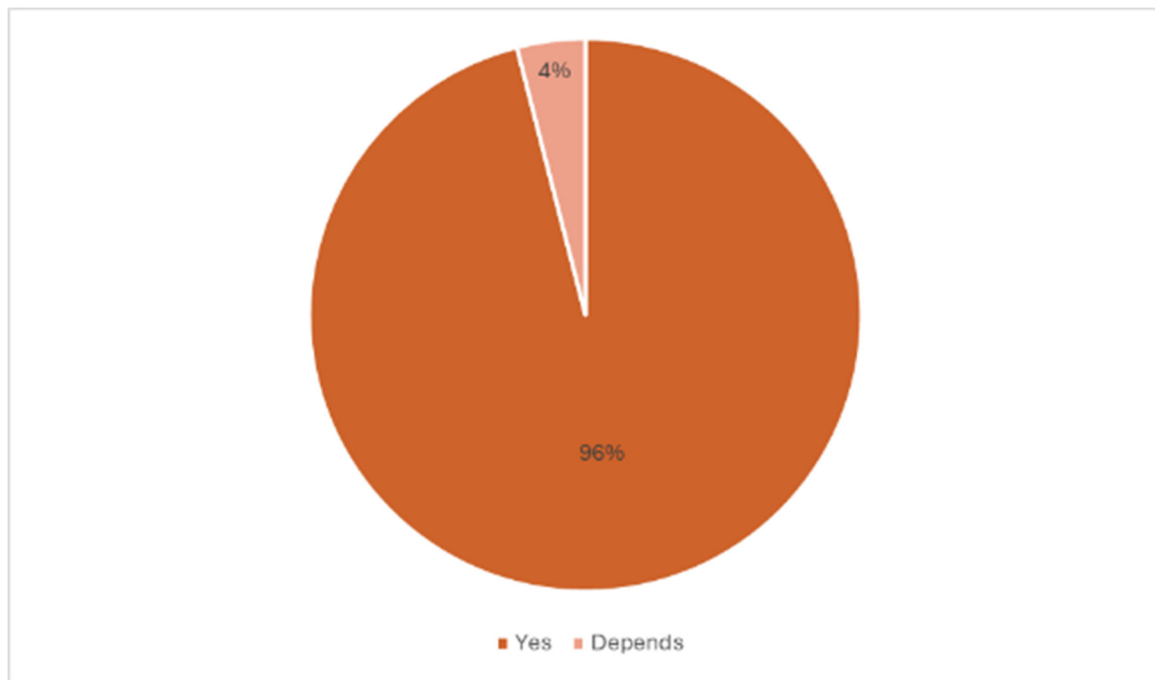


Figure 8. Participant responses to the phone interview question: “Are you interested in learning more about the uses of AI in fields like healthcare?”.

3.3. Study Termination

The decline in participation rates, specifically between Visit two ($n = 54$) and Visit three ($n = 13$), was primarily due to the early termination of the study, a decision made on 27 February 2024, that was outside the researchers’ control. This decision occurred only a few weeks before the final allowable assessment of 31 March 2024. This limited timeframe, coupled with restricted team resources, including research team availability and computers with the appropriate setups, made it challenging to complete Visit 3 for more participants. Additionally, the need to space visits approximately three months apart and participants’ own availability further constrained participation. External factors related to transportation challenges, weather conditions, and participants’ personal commitments and appointments, compounded these challenges, as they were required to visit the CER for in-person assessments. The limited assessment time slots and short notice for scheduling also contributed to the drop-off. In sum, the decline in participation was primarily driven by study termination timing, resource limitations, scheduling constraints, and external factors beyond the researchers’ control.

4. Discussion

Canada’s population demographics are shifting, with individuals aged 65 and older outpacing those 20 and younger [19]. This aging population is driving an evolving demand for healthcare services, especially with the projected rise in chronic conditions such as MCI and dementia. This demographic shift underscores the increasing need for targeted healthcare solutions that are non-invasive, engaging and user-friendly to monitor mental health and cognition in older adults. Involving older adults in the design and development of these tools and technologies will help to ensure that they are trustworthy, widely accepted, and tailored to their unique needs.

Public knowledge and acceptance of AI in healthcare is evolving. However, older adults exhibit mixed levels of trust in these technologies, and there is limited research on AI literacy among this demographic. Kaur and Chen addressed this gap and found significant variability in AI literacy [20]. Not unlike ethical concerns identified by previous

studies [20,21], two-thirds (67%) of our cohort voiced concerns about AI replacing human interaction in healthcare potentially diminishing empathy and increasing social isolation and feelings of loneliness [20]. Roughly 35% of participants believed that AI would worsen the personal connection between patients and doctors, citing distrust in AI, concerns about over-reliance on technology, and the importance of empathy in healthcare interactions. Trust emerged as a central theme influencing perceptions of remote health monitoring (RHM) technologies [22]. RHM includes both wearable and mountable devices that utilize the medical Internet of Things to collect and evaluate behavioural and physiological information about a person, and can generate recommendations or warnings [23–25]. As noted by Feldberg [22], concerns around privacy, security, and misuse of personal data were prevalent, with participants noting fears about third-party access, data breaches, and the misuse of data. Similarly, the 2022 Pew Research Center survey found that 37% of American adults believe AI in healthcare could worsen the security of patient information [26]. These findings highlight that trust plays a significant emotional role in the acceptance and perceptions of RHM and AI-related technology, like our DH [27]. This suggests that developers of these technologies should prioritize transparency of functions and security of data to build consumer confidence and trust in novel technologies. Despite these reservations, optimism regarding AI's potential in healthcare persists. Two-thirds (67%) in our cohort believed that AI in healthcare could lead to better patient outcomes, by alleviating some of the burden on healthcare workers, increasing efficiency, and enhancing diagnostic accuracy. This optimism exceeds the 34% of American adults aged 65 and older who shared similar views in the Pew survey [26]. On the other hand, 10% of our cohort thinks AI in healthcare would worsen outcomes, citing concerns about AI's inability to interpret human nuances in body language and facial expressions, and a preference for human judgement over technology.

Both our study and the Pew survey [26] identified fears that increased reliance on AI might reduce face-to-face interactions, leading to feelings of disconnection and depersonalized care. These concerns align with those expressed by users of RHM for chronic conditions, who worry about being “lost in data” and losing personalized healthcare [28]. Some participants in our study expressed strong opposition to interacting with a DH when it relates to their healthcare. For example, when asked for their views on interacting with a DH for the purpose of RHM, Participant 025 shared, “I am getting close to 70 years old, and I am dealing with health issues. I want to talk to a real human. I want personal care. I am not interested in AI healthcare. Maybe I would feel differently if I was 20 or 30.” To improve acceptance and perceived usefulness of DH platforms, public education and awareness of AI in healthcare must be enhanced, especially if they are to be adopted into daily life or home use.

The differences in attitudes toward AI in healthcare between our study and the Pew survey may speak to the differences in healthcare systems and access to healthcare between Canada and the United States (US). While Canadian healthcare is publicly funded [29], access to timely care remains a significant challenge. In 2023, only 26% of Canadians reported securing same- or next-day appointments with their healthcare provider, and approximately one in five lack a regular primary healthcare provider [30,31]. Wait-times are especially problematic for those 65 and older compared to other Commonwealth countries [32]. Canadians also reported the longest wait times for specialist care among Commonwealth countries, with 62% waiting one month or more to see a specialist [31,33]. Comparatively, the US healthcare system is predominantly privately funded, with the National Medicare program providing coverage for people 65 and older [34]. In 2023, 38% of Americans reported securing a same- or next-day appointment with their healthcare provider [30]. Only 31% reported waiting a month or more for a specialist appointment,

about half the rate reported by Canadians [33]. These differences in healthcare access may influence attitudes towards AI-based technologies in healthcare. Canadians, facing longer wait-times and limited access to primary care, may be more receptive to screening tools, like the DH platform, which could provide more immediate healthcare services and alleviate wait-times. By addressing barriers to healthcare access, AI-related tools could enhance the overall healthcare experience for Canadians. Additionally, Feldberg [22] observed a disconnect between older adults' recognition of the general benefits of RHM technologies and the personal benefits. Perception biases play a role in the adoption of RHM technologies where potential users may fail to see a potential need for the technology. Health status was a key factor in recognizing the personal value of RHM [22,35]. Therefore, the perceived personal benefit of a DH as a screening tool for mental health and cognitive decline may increase acceptance and adoption of the technology in populations with strained access to healthcare, as it addresses immediate healthcare needs.

Kaur and Chen found that many older adults expressed interest in learning more about AI to make informed decisions about AI-enabled products and services [20]. Our findings reflect this trend, with 92% of participants expressing interest in learning to use new technologies, and 96% wanting to explore AI applications in healthcare. Motivations included staying current with technological advancements, maintaining autonomy over their own healthcare, recognizing AI's benefits for aging populations, and general curiosity about AI developments. Contrary to assumptions that older adults' technological concerns would hinder the adoption of home telemedicine services and RHM technologies, our findings suggest otherwise [22,28,36]. Our findings are congruent with those of Feldberg [22], where participants expressed high levels of confidence and trust in learning to use new technologies like the DH platform. Despite the physical and cognitive barriers to technology adoption, such as mobility challenges, unclear instructions, limited customer support, short-term memory changes, and poor interface design, participants maintained a strong interest in adopting new technologies. However, the Dunning-Kruger effect should be considered, as older adults may overestimate their ability to handle novel technologies [37]. Future research should test the DH platform in real-world, uncontrolled environments to better assess the feasibility, usability and acceptance. This approach will help identify unforeseen challenges that may not otherwise be captured in a lab setting and provide more accurate insights into users' experiences and potential barriers in everyday use.

Digital tools, like the DH paired with speech analysis technology, could support aging in place. Although many participants expressed concerns about AI diminishing human interaction with healthcare providers, there already exist numerous health-related tools, technologies and apps to support aging in place. For example, smartphones and mobile health apps, which utilize AI, play an important role in RHM for older adults [38]. A study of CDOA found mixed acceptance of the usefulness of technologies that support aging in place [39]. They preferred technologies that improve mobility and safety, or reduce cognitive decline, whereas others did not perceive such technologies as useful tools to help them remain at home [39]. Three-quarters of our participants indicated they would prefer accessing the DH from home rather than visiting a community testing site already part of their routine, citing privacy, convenience and accessibility. These findings highlight how perceptions of usefulness across groups vary depending on the type of technology and the specific concerns it addresses.

Integrating the DH into RHM could address barriers such as limited access to healthcare professionals, long wait times, and mobility or transportation challenges. A 2015 study on RPM systems for older adults living in rural areas found that perceived usefulness, ease of use and behavioural intention remained stable and high, with acceptance increasing over time [40]. That is, as users became more familiar with the technology, they believed others

in their lives would also benefit from it, highlighting the importance of social factors in technology adoption [40]. This finding was mirrored in our study, where many participants reported that they had never interacted with a DH. Nonetheless, approximately 84% at least somewhat enjoyed interacting with the DH, the entire cohort felt at least somewhat comfortable with the interaction, and 96% found the DH at least a little likeable. These findings suggest that acceptability may increase with repeated exposure. For example, during a phone interview, Participant 002 reflected on how her perception of the DH evolved over time, stating, “either [Sam] changed, or I adapted to Sam. I became more comfortable over the course of the visits [to the Centre]”. This highlights the importance of habituation when understanding how older adults accept and adopt new technologies.

Participants also provided feedback on the appearance of the DH, emphasizing a preference for a DH that closely resembles them in terms of age, gender, and most notably, ethnicity. In particular, Participant 058 highlighted the importance of ethnic concordance, especially when the DH is intended for use within marginalized communities, such as Indigenous populations. This aligns with existing research that has found that when given the choice, patients often prefer healthcare providers who share their racial or ethnic background [41–43]. A growing body of research also supports the race concordance hypothesis with mental health care, whereby racially minoritized patients who are matched with mental health providers of a similar racial or ethnic background report greater satisfaction, perceive higher quality of care, and overall experience better health outcomes [44–48]. These findings suggest that a racially concordant DH may yield similar positive effects. Race concordance, especially among racially minoritized patients, has been associated with improved communication, enhanced perceptions of care, better health outcomes, and increased trust in providers [42,49,50]. Additionally, participant feedback regarding the customizability of the DH is valuable and aligns with prior research indicating that patients find it easier to build a close relationship with racially concordant mental health providers, which fosters greater trust, mutual respect, positive affect, and overall greater satisfaction [42,48–50]. However, in the current iteration, the DH was not customizable. The participant feedback emphasizing ethnic, gender, and age concordance highlights the importance of developing modifiable DHs, that allows the end user to change key characteristics, such as skin tone, facial features and voice. This customizability would enhance perceived relatability and trust, especially among racially and culturally diverse populations. While implementing ethnically or gender-concordant DH avatars introduce additional design and technical challenges, such as avoiding stereotypes, future iterations could explore more feasible approaches to personalization. These insights underscore the importance of incorporating user preferences into the design of a DH to enhance its acceptability. Taken together, allowing the end user to select or customize their DH may foster greater trust and higher adoption rates, particularly among older adults and racially minoritized groups.

A key limitation of our study was the inclusion of primarily cognitively healthy older adults, which constrained our ability to validate the speech analysis technology as a tool for detecting cognitive decline over time. Nearly all participants scored 26 or higher on the MMSE across all visits indicating no cognitive impairments within the cohort. During the eligibility screening, two participants self-reported an MCI diagnosis. However, both scored within the normal range on the MMSE. Conversely, one participant, who scored 22 on the MMSE during their initial assessment did not self-report an MCI diagnosis during screening. These discrepancies underscore the limitations of the MMSE and highlight that its use in the present study may have reduced sensitivity for detecting early signs or subtle cognitive changes among otherwise cognitively healthy older adults. While widely used as a screening tool [51], the MMSE primarily assesses only basic memory,

attention, language and visuospatial function [52]. It has limited sensitivity to detecting early-stage dementia, especially MCI, or the breadth of cognitive decline experienced by those living with milder forms of cognitive impairments [51,52]. Although the MMSE is the most common screening tool for dementia, and is quick and easy to administer, future studies could explore the use of more robust screening tools for MCI and dementia, such as The Addenbrooke's Cognitive Examination (ACE-III) [53,54], or The Montreal Cognitive Assessment (MoCA). The MoCA is a validated tool, and evaluates eight areas of cognition, including executive function, which the MMSE does not address [55]. It is reliable and has demonstrated higher sensitivity for detecting MCI and is recommended by the Alzheimer's society for clinical use [56,57]. For example, the MoCA was found to be better than the MMSE in the detection of MCI among those 60 and older [55], and it has higher specificity in identifying 87% of healthy controls [55].

Our study was not conducted in a clinical setting and the cohort consisted of cognitively healthy CDOA, which limits the generalizability of our findings to populations with cognitive impairment. Future work should aim to ensure purposive recruitment of participants with diagnosed MCI, which could be verified using more sensitive screening tools, like the MoCA or ACE-III. Considering that the DH was paired with a speech analysis algorithm, future studies should aim to analyze components of speech using the MoCA. Specific scores on the domain of language captured by the MoCA could be cross-validated with speech markers of the speech analysis algorithm to evaluate the accuracy and sensitivity of the speech analysis tool. Additionally, incorporating digital cognitive tasks or longitudinal speech and language markers would allow for ongoing monitoring of cognitive changes over time, providing a more comprehensive assessment of cognitive function. Such approaches could strengthen the alignment between the DH's intended monitoring capabilities and clinically validated cognitive measures, enhancing both the interpretability and clinical relevance of the data collected. Together, this would strengthen the clinical relevance and validation of the speech analysis program as a non-invasive tool for detecting cognitive decline and impairment in older adults.

AI in healthcare holds significant potential for supporting independent living, enhancing autonomy over health, and improving well-being and quality of life for older adults. However, realizing these benefits requires a concerted effort to increase AI literacy within this population. Tailored AI literacy programs, educational initiatives, and supportive resources can bridge this gap. Furthermore, designing user-friendly interfaces can enhance the usability and acceptance of AI-enabled technologies, apps, and services ensuring they meet the specific needs of older adults. While AI literacy was explored conceptually in this study during the semi-structured interviews, it was not assessed using a validated scale. While there are several AI literacy scales that target the general population, students, and teachers, there are lack of validated AI literacy tools specifically tailored to older adults [58]. Given the evolving nature of AI literacy frameworks, particularly in healthcare contexts, future research should incorporate or adapt established measures more precisely assess AI literacy among older adults. Additionally, differentiating between trust in AI systems and trust in healthcare providers using AI may help reveal the determinants shaping user acceptance and confidence, thereby informing efforts to strengthen AI literacy and acceptance among older adults.

While participants generally responded positively to the DH and expressed interest in learning to use new technologies and understanding AI, a few nuanced discrepancies emerged between the quantitative and qualitative data. For example, phone interviews indicated that 100% of the cohort felt at least somewhat comfortable interacting with the DH, yet only 27% reported they would feel comfortable if their healthcare provider relied on AI for their healthcare, with 53% feeling uncomfortable. These discrepancies

may partially reflect gaps in AI literacy. For instance, Participant 043 explained their discomfort by stating, “it feels like doctors are always reading, learning and are up to date. I don’t understand how a robot can do those same things”. This illustrates that participants’ concerns may stem from doubts about AI’s ability to match knowledge and decision-making skills of healthcare providers. Interestingly, despite only 27% feeling comfortable if their healthcare provider relied on AI for their healthcare, 67% believed that AI in healthcare could improve healthcare outcomes. Participant 022 commented, “AI can collect more data, give results more quickly and accurately, which can be used by doctors”. This highlights a disconnect between participants’ trust in AI as a decision-making tool and their recognition of its potential utility. These discrepancies suggest that while older adults may appreciate the benefits of AI in theory, they are hesitant to rely on it in practice, likely due to limited understanding, acceptance, or familiarity. These findings underscore the importance of integrating qualitative insights with quantitative outcomes to capture the nuances in participants’ opinions. Future studies should incorporate validated AI literacy assessment tools and explore targeted educational interventions to address gaps in knowledge. Lastly, systematic mixed-methods approaches, such as convergent designs, could further explain the divergence between quantitative acceptability scores and qualitative perceptions, providing a more comprehensive understanding of older adults’ engagement, understanding, and acceptance of the DH and AI technologies.

Most of the data collection was conducted by a researcher during in-person assessments and telephone/video interviews. As a result, responses may have been influenced by a social desirability bias [59]. Participants may have felt inclined to provide more positive feedback in the presence of a researcher, rather than responses that reflected their true opinions or beliefs. As a result, some discrepancies in responses may be influenced by this social desirability bias, as participants may have responded favourably to the DH and AI when asked by the researcher. Unfortunately, this bias would distort the conclusions made in this study. To minimize the social desirability bias, future studies should consider incorporating self-administered questionnaires or anonymous remote data collection methods.

To further explore the development of a non-invasive, engaging, and acceptable DH tool to assess and monitor cognitive function and mental health in older adults remotely, next steps should involve transitioning from a lab-based to a home-based real-world setting. A phased approach could include (1) pilot testing the DH in participant’s homes under remote researcher supervision, (2) integrating automated tools to capture real-time engagement and feedback data, and (3) assessing longitudinal use, trust and adherence. This progression to more naturalistic settings would enhance the validity of usability and acceptability findings, providing stronger evidence to guide refinements for broader implementation.

5. Conclusions

As chronic conditions like dementia become more prevalent, developing non-invasive, home-based technologies is essential for improving healthcare access, and enabling early interventions. RHM technologies, like the DH platform, offer practical solutions for early detection and intervention to improve patient outcomes, support aging in place, and alleviate pressures on healthcare systems. Designing healthcare technologies that meet the unique needs of older adults, and incorporating end-user feedback is essential in creating tools that are not only effective, but also widely accepted by the population they are designed to serve.

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