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# "How do I compare to the other people?": Older Adults' Perspectives on Personal Smart Home Data for Self-Management


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Research on smart home monitoring for older adults has predominantly focused on systems whose data and alerts are directed towards family members, caregivers, or healthcare providers. Older adults have expressed interest in engaging with these systems by seeing and using their data, but they are often limited to a passive role as subjects of monitoring. This paper presents qualitative results of a longitudinal smart home project with older adults living independently in the community. Based on interviews conducted throughout the 2.5-year study with 12 participants, we report on their lived experiences of having the monitoring system in their homes and on how they reflected on the data collected by the system. The results show how participants were able to extract meaningful information from the monitoring data without finding the system invasive or intrusive. Specifically, older adults exhibited interest in data that they found indicative of living an active lifestyle, such as time spent outside the home. Drawing from critical literature on active aging, we discuss implications for incorporating peer comparisons to support reflection on personal health data without reinforcing a deficit narrative of aging.



CCS Concepts: • **Human-centered computing** → **Empirical studies in ubiquitous and mobile computing**; • **Social and professional topics** → **Seniors**; • **Applied computing** → *Consumer health.*

Additional Key Words and Phrases: older adults, aging in place, smart home, personal informatics

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## 1 INTRODUCTION

Monitoring to support older adults' quality of life is a common application for smart home technology. Smart home systems are well-suited for assisting older adults (ages 65+) to live in their homes because they can be used to continuously monitor health and behavior in the residences where they are installed, potentially delaying the need for moving in with a caregiver [6]. A recent U.S. survey has shown that 3 in 4 adults over 50 would like to stay in their homes [1]. Indeed, living at home is vital to older adults' autonomy, privacy, self-identity, and purpose of living [121].

Prior work has primarily focused on monitoring where healthcare providers, caregivers, or family members have access to the resident's data or receive alerts when the system detects a potential health issue (e.g., [115, 107]). In this case, the monitoring is intended to facilitate the work of the caregiver while minimizing disruptions for the older adult. While this research has presented promising results, these systems tend to be asymmetric (i.e., there is no monitoring reciprocity with caregivers) [73]. As a result, they are unfavored by older adults who live independently [19], limiting their use as a proactive rather than reactive tool.

Smart home data could be used by older adult residents themselves for their self-management, similarly to other personal health data collected by wearable devices or self-report (e.g., [106]). As reflected by HCI research over the last several years, health and well-being are the main applications of self-tracking [39]. In the case of older adults, this approach is proactive, promoting their agency as technology users and independence in everyday life. Reactive approaches are needed to support older adults who need present caregivers, whereas proactive systems have the potential to provide health benefits to extend independence. Personal health data can be used by the individual, healthcare providers, family members, or peers for various purposes such as behavior change, awareness of habits, and managing chronic conditions. Given that reflection on data through visualizations is a key part of the process of accomplishing the intended purpose of tracking [70], prior work has investigated how to support users to make sense of their data (e.g., [41, 37]). There remains a gap about how to support older adults to make sense of their smart home monitoring data.

In this paper, we present qualitative findings from a longitudinal in situ smart home study with older adults living alone in the community. We analyzed data from over 70 interviews with 12 participants to understand their experience of living with the sensors installed in their homes and their perspectives on the data collected by the system. The results show that the system was unobtrusive, did not raise substantial privacy concerns, and that the participants found meaningful information in the collected data. Specifically, by reflecting on visualizations on retrospective data from their homes, they interpret measures such as time spent outside of the home as indications of living an active life, something that they value and strive for. Their interpretation process involved social aspects because they often made comparisons with other participants' data. To the best of our knowledge, this is the first in longitudinal study of home monitoring with independent older adults, addressing a known research gap [97]. We report on its rich results [50] that capture the context of use due to taking place in real life settings [114, 96]. Additionally, we discuss how many specific findings from prior short-term studies remain valid in the long-term.

## 2 RELATED WORK

In this section, we discuss prior work examining smart home monitoring systems and the use of personal data collected through monitoring and tracking systems.

## 2.1 Smart Homes for Older Adults

Smart homes leverage ubiquitous ecosystems of sensors and devices to monitor activities and automate tasks in domestic settings [48]. Smart home systems provide a non-intrusive and passive way to monitor older adults, which allow them to lead an independent life in their homes (i.e., aging in place) longer [29, 13]. Prior research on smart home monitoring has explored various ways to collect and share information about older adults' status to interested parties (e.g., healthcare providers, caregivers, and family members) on a regular basis via ambient sensing technologies and displays [29, 24, 35]. Conveyed information about older adults' status has included notifications of potential problem or crisis situations (e.g., fall [86]), or "peace of mind" [24].

Most prior studies on smart home systems have focused on assisting caregiving tasks by allowing caregivers to watch over older adults' remotely [115], coordinate necessary caregiving activities among a set of caregivers [24], or interact with the care recipients [105]. For instance, the Digital Family Portrait allowed a remote family member to have a qualitative sense of an older adult's daily activities while visualizing home-based sensor information [115]. Intel researchers extended the system and developed the CareNet Display, including more detailed information of important events, such as eating behaviors, medications, and outings [24]. While the Digital Family Portrait targets distant family members, the CareNet targets local members of an older adult's care network to support coordination and information sharing among multiple caregivers. Although these smart home systems promoted independence, assisting older adults to live in their homes longer, older adults often feel disempowered because of the unidirectional nature of monitoring [18, 129].

To address these concerns, researchers have explored provisions for smart home systems to allow older adults to become equal actors in the system (i.e., two-way monitoring) [53]. For instance, the Presence Clock [53] is a pair of analog clocks with embedded LEDs to share two-way presence information (e.g., activity levels) between older adults and caregivers. Although the design of two-way monitoring system promotes empowerment through reciprocity, the caregiver and care recipient relationships still remains unbalanced. Prior research has shown that older adults are more inclined to exchange support among their peers rather than family members [21, 110, 7]. Hence, researchers have explored a number of approaches to incorporate peer-care based monitoring for smart home systems. For instance, Arreola et al. [7] introduced a peer-care-based monitoring system, Check-in Tree, which allows older adults to check in with their peers through a tree-shaped artifact with LED-enabled picture frames hanging on each branch.

While these smart home monitoring systems promote peace of mind and crisis preparedness, allowing older adults to remain independent in their homes, there are concerns about the adoption of these systems by older adults. Older adults fear that these monitoring systems will impact their social relationships by replacing human contact with their formal and informal caregivers [113, 75]. In addition, there are growing tensions around the perceived usefulness and privacy risks of monitoring systems [26]. Existing research found that the values and assumptions guiding the design of these technological interventions are not always shared by the older adults [134]. Hirsch et al. [51] explored social and psychological factors that might trigger rejection from older adults. They found that assistive technologies may be rejected if they fail to be a part of the existing ecology of their homes, lead to a sense of being spied upon, and create a feeling of shame and burden over the need for assistance. Therefore, we need to investigate how we can design smart home technologies that support older adults' active engagement, directly benefiting them. Towards that goal, in this paper, we explored older adults' experiences and perspectives on the sensor data collected through a smart home monitoring system.

## 2.2 Personal Data from Tracking and Monitoring Systems

As of 2020, 21% of U.S. adults use systems that track health data such as smart watches or fitness trackers [131]. These systems can be used for health management in various ways, including obtaining self-knowledge, pursuing specific health goals, monitoring for adverse health events, and encouraging daily habits [39]. These uses rely on reviewing and reflecting on short-term or long-term personal health data [70].

However, such data do not always make sense to users. How to provide meaningful information to people through self-tracked data is a challenge that has been identified repeatedly in prior work [74, 57]. Qualitative studies involving visualizations have described how making sense of personal health data involves generating hypotheses and evaluating specific features to derive insights [78, 23], similarly to interpreting visualizations of other kinds of data [68]. There is a need to assign specific health-related meanings to numbers, if they are not integrated into the tool design [104]. Establishing those meanings can be a social process, involving comparisons or communication with peers [130]. For example, to understand if what they are experiencing is normal [65], or to find a reference range [41].

Older adults self-track health-related data more than other age groups [43, 125], using both paper and digital means to collect data [124, 18]. Indeed, several chronic conditions that can be managed using personal health data, such as hypertension and Parkinson's [126], are more common in late life. Past research has shown that older adults display interest in visualizations of their personal health data [17, 34, 3, 132] and may also benefit from the reflection involved in manually inputting data in self-tracking systems [40]. Monitoring systems for older adults also collect potentially useful data [81]. There are numerous examples of data from home monitoring being used to identify health-related trends. For example, home sensors can detect early signs of Alzheimer disease from changes in the resident's circadian rhythm [88]. Monitoring home activity can also identify patterns of health changes such as mental illness symptoms [32, 44, 133] and changes in mobility [87].

Older adults prefer to be engaged users of monitoring systems, rather than only being observed passively [27, 119]. They have expressed interest in engaging with monitoring technology by using smart home data to obtain information about their health [55, 33, 129, 67]. These data could be useful for supporting their self-management work, similarly to tracked personal health data. Nevertheless, interpreting smart home data is notoriously difficult. Because sensor data are opaque in isolation, interpretation requires situated reasoning and knowledge of the activities and spatial configuration of the home for contextualization [123, 42, 62, 31]. When there are multiple residents, this process is inherently collaborative. There is a need for additional research to understand how to provide valuable insights to older adults through smart home data [109, 17, 95]. Prior work has found that data such as time spent away from home, activities, and sleep would be useful for this purpose [33].

A recurring challenge in smart homes for older adults is obtaining data that are relevant for their health [97], understandable and actionable [49]. Most commonly, smart home systems are designed to identify specific activities of daily living (e.g., eating, getting dressed). However, because it is difficult to detect such high level activities in real life settings, these studies are often run in the lab and focus on low level activities [92]. In this study, we focus on indoor location data, as these measurements can be enough to detect changes in activity patterns in the home [94].

Older adults value technology that provide positively framed health information [15], something that could be done by highlighting their strengths in comparison with peers using similar systems [136]. This approach is aligned with *Active Aging*.

### 2.3 Active, Positive, or Successful Aging

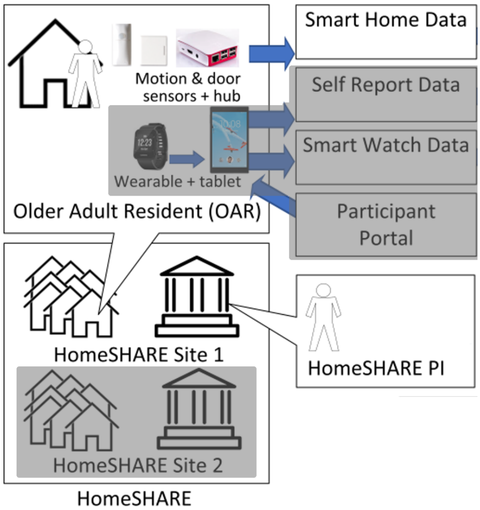
The concepts of Active, Positive, and Successful Aging are common in gerontology and related fields, including aging research in HCI [90]. These concepts are similarly defined as assets-based (i.e., leveraging the community's existing assets and resources [138, 61]), focusing on aging with quality of life and strengths of old age, such as wisdom, as opposed to portraying aging as a period of decline. Evidence from prior research indicates that this perspective has a measurable positive impact on older adults: those who have better self-perception of aging live longer, taking into account age, gender, functional health, SES, and loneliness [69]. More positive subjective age or self-identity, based on perceptions of age-related changes, are linked with well-being [137, 140] and better health outcomes [9, 141].

Older adults commonly construct their identities of active aging through downward comparisons with peers who are less active or more frail [11] to distance themselves from ageist images of old age [135]. Older adults also perform active aging both online and offline. Even in spaces for this group, there is a social stigma in being seen as *really old* (i.e., not active) that is not about chronological age but cognitive ability and social behaviors [28]. To distance themselves from the identity of being old, they present themselves as busy, healthy, and productive [47, 36], while discussing issues such as pain or needing assistance only privately with close friends. They grapple with the contradictions of the positive image of the active older adult, realities in the experience of aging, and aging stereotypes [54].

HCI researchers have described how research in technologies for aging too often focus on older adults' limitations, for example by assuming that users are homebound [2], contradicting the ideals of active aging it should support. Recent publications have argued for engaging with positive aging narratives [98, 60], focusing not only on physical health, but enjoyment and well-being [46], providing positive feedback [15, 27], and promoting downward comparisons through design by emphasizing instances when users are doing "better" than their peers [136]. Providing positive feedback through downward comparisons just one time makes people feel significantly younger [120].

There is a recurring criticism of the concept of active or successful aging regarding its neoliberal undertones. Successful aging is portrayed as an accomplishment of the individual, where youthfulness is achievable through personal effort, erasing the role of systematic marginalization and the myriad of other factors that shape the aging experience [52, 82]. Following this perspective, those who do not conform to the youthful *normality* are irregular and need an intervention [102]. Despite being common and beneficial to older adults, downward comparisons have the same problem identified in these criticisms. It relies on ageist ideas to position the person as different and better than those who are *really old* or inactive.

Health technology promoting physical activity is at the same time an anti-aging strategy and a tool that differentiates the active and the inactive [58], as older adults feel pressure to measure up, particularly when held to the same standards as younger people [128]. However, when systems are designed to provide more age-appropriate standards, such as situating the user's data in the context of their peers, older adults tend to engage in downward comparisons. Users need to have a frame of reference to extract meaning from their data. How to provide this resource to older adults without promoting inappropriate standards or downward comparisons is an open challenge. In this study, we investigate how older adults engage with their home sensor data with minimal comparative information.




(a) Diagram for the full deployment project. In this paper, we focus on home sensor data from site 1: Bloomington, IN, USA. Parts of the project outside the scope of this paper are obscured.

(b) A motion sensor installed on the wall of a home, by a light switch. Similar sensors were used for the ceiling.

Fig. 1. Overview for the full project, including a diagram (a) and a picture of a sensor (b).

## 3 METHODS

This study is part of a larger project on home monitoring with older adults. In this section, we first describe the project and then we provide details on the specific methods for the study presented in this paper.

### 3.1 Project Background

The project consists of a multi-site longitudinal deployment of a home monitoring system for older adults. The system was designed to capture the movements of a single person in their home through motion sensors placed in each room. The project has collected data from 2018 to 2021 in two different U.S. sites (Bloomington, IN and Denver, CO) with a total of 29 participants (Figure 1a). These sites were selected due to feasibility, as each was local to at least one Principal Investigator, and diversity, as their populations differed in density, ethnicity, and social-economic status.

All participants were older adults (65 years old and older) who lived independently alone in the community. In other words, they lived in ordinary houses or apartments, rather than at retirement communities or eldercare facilities. Therefore, the size and layout of their homes varied from small one-bedroom apartments to large three-level houses. The system was designed to be flexible enough so that it could be installed to these different residences. In each home, one motion sensor was installed per room (e.g., bedroom, living room, bathroom) and labeled accordingly. These sensors were placed close to the entrance of the room, adjacent to a light switch (Figure 1b). Door sensors were placed on external doors (e.g., front door, garage door) to capture instances of leaving the home and returning. The system also included an array of 4 motion sensors to measure walking speed, placed on a straight line equally spaced on the ceiling over a hallway. The number of sensors per participant is provided in Table 2.

During the deployment, the system stored a log of sensor activity from each home. The sensor data consist of timed sensor events (i.e., turning on and off) corresponding to whether there was movement detected in that room at a specific time. These logs provided a continuous measurement of movement inside of the home over several months for each participant. We processed these raw data into a continuous estimate of indoor *location*. In summary, the resulting data contains the estimated location of the person in the home, continuously in 30-second intervals. The location is indicated as one of the rooms in the home (e.g., kitchen) or as "outside the home" based on data from door sensors. Since each participant lived alone, there is an assumption that no more than one room is occupied at a given time.

Based on the location data, we calculated several metrics such as how much time the person spent in a specific room or outside the home per day and how many times they walked from one room to another in the home. Outliers in these metrics identify outlier days, where the movements in the home deviated from the normal routine.

While project participants also used a tablet and a wearable device that collected data on physical activity, sleep, and heart rate, these components are not included in the scope of this paper.

### 3.2 Qualitative study

This paper presents qualitative findings from several interviews with participants from one of the two U.S. sites of the deployment study. We describe the participants' experiences with having the sensors in their homes over a period of multiple years and their perspectives about the data collected by the monitoring system.

*3.2.1 Participants.* For this study, we recruited 12 participants from one site, a small city in the U.S. Midwest with a population of approximately 80,000 people. As with the larger project, all participants are older adults living alone in the community. Not every person participated in all interviews, since they were not required. The interview participants are listed in Table 1. Their ages ranged from 65 to 78 at the start of the study. All participants were retired, with one exception (P12). One participant was male (P7), while the others were female. All of them were non-hispanic white, reflecting the demographics of the study location, where more than 90% of adults over 65 are non-hispanic white. They reported having good or excellent health and using the internet at least once a day. They were proficient users of smartphones and tablets, but they reported needing help for setting up or troubleshooting a device. Most participants had at least an undergraduate degree. Half of the participants reported an yearly income below $30,000. According to the Pew Research Center, taking into account household size and cost of living of the study site, income under $25,000 corresponds to the lower income bracket and income over $77,000 corresponds to the higher income bracket [12]. Therefore, study participants had low to middle income.

*3.2.2 Interviews.* We ran three sets of interviews with study participants: monthly interviews, activity interviews, and data interviews. In total, we facilitated 77 interviews over the course of two and a half years to inquire about participants' experiences with the home monitoring system used in the project and about their opinions and perspectives towards the data collected by the system. Table 2 includes details about the number of interviews and sensors for each participant.

*Monthly* interviews consisted of seven short sessions for the first six months of the study, starting with a baseline session when the system was set up in the person's home. In these interviews, we checked with participants about their overall experience with the system. We also discussed with them any issues they may have faced with the sensors. For example, participants answered the following questions: "what do you think about the sensors installed in your home?" and "did having the sensors and the watch impact how you carry out daily activities at all?" These interviews were quite short, unless participants had issues to report or asked open ended questions. We had all seven

Table 1. Demographics of the participants

| P | Age | Health (self-rated) | Internet use | Education | Income |
|---|---|---|---|---|---|
| 1 | 71 | Good | Most of the day | Bachelor's Degree | $10,000 to $19,999 |
| 3 | 72 | Good | Several times a day | Master's Degree | $50,000 to $59,999 |
| 4 | 74 | Good | Several times a day | Some college | $30,000 to $39,999 |
| 6 | 65 | Excellent | Most of the day | Bachelor's Degree | $20,000 to $29,999 |
| 7 | 75 | Good | Several times a day | Associate Degree | $20,000 to $29,999 |
| 8 | 76 | Good | Several times a day | Master's Degree | $20,000 to $29,999 |
| 9 | 65 | Excellent | Several times a day | Master's Degree | $20,000 to $29,999 |
| 10 | 66 | Excellent | Most of the day | Bachelor's Degree | $20,000 to $29,999 |
| 12 | 66 | Excellent | Most of the day | Bachelor's Degree | $50,000 to $59,999 |
| 13 | 78 | Excellent | Several times a day | Doctorate Degree | $70,000 to $79,999 |
| 14 | 73 | Good | Most of the day | Some college | $40,000 to $49,999 |
| 15 | 69 | Good | About once a day | Some college | $30,000 to $39,999 |

interviews (baseline + monthly) for nine participants, for a total of 63 short interview sessions. The baseline and 6-month follow up interviews were longer than the others, as the baseline interview asked questions about participants' initial impressions and expectations of the system, and the same questions were repeated after 6 months to assess how those impressions had changed after that amount of time.

In the *activity* interviews, we talked about their opinions on the system data and also discussed their daily routines. These interviews took place approximately four months before the end of the deployment, when participants were in the study between one and a half to two years. The data collected from these interviews were intended to understand the participants' regular routines and how they used each room of their homes. We discussed for those rooms whether people would have any interest in the data and for what purposes. Questions included: "where in the house are you usually using your computer or your tablet?" and "would you want to have access to data about how much time you spend in your living room or is that not of interest to you?" We had a total of eight activity interviews with participants.

Lastly, in the *data* interviews, we discussed with each participant in-depth about the data collected by the system installed in their homes. We created a range of visualizations of the participants' own data to investigate what aspects they found interesting in the data collected and what preferences they had for visualizations. We used a talk-aloud approach in these sessions, as participants were asked to voice their thought process as they saw the data visualizations, one by one, with minimal prompting from the researchers. We talked with six participants in total for the data interviews. Interview sessions lasted between 60 and 90 minutes and included approximately 30 visualizations.

For the monthly and activity interviews, the participants had not yet seen the data collected by the home sensors, so their responses are based on what they would expect the data to look like. For the data interviews, we provided participants with visualizations of their own data, so that they could discuss more extensively and base their responses on what they could see.

*3.2.3 Data visualizations.* The data interview visualizations focused primarily on two kinds of data collected by the system: time spent in the kitchen and time spent outside the home. We chose these two kinds of data because we expected that they might be relevant for activities related to health and well-being. We anticipated that kitchen data might reflect eating patterns, as preparation time could be different for certain kinds of meals, while time outside could include exercise (e.g., hiking) and also socializing activities, such as visiting others and attending events. Additionally, prior work has found that time spent outside the home would be of interest to older adults [33]. The system had collected other health-related data, such as time spent in the bedroom overnight, indicating sleep patterns. However, we deprioritized such data for the interviews because most participants had shown little interest in sleep data collected by the study smartwatch during prior interviews. Since we expected that collecting diary data would not be feasible for a longitudinal study, the visualizations did not include contextual information such as diary entries from participants.

We created several detailed graphs showing patterns in those two kinds of data from different perspectives, including time series, calendar, and comparison with other participants. Additionally, we showed participants a graph of room changes, a measurement of indoor activity based on how many times the person moves between rooms in a day. Lastly, two visualizations consisted of overviews with data from all rooms (e.g., Figure 6). We sought to balance both breadth (data from all rooms) and depth (data for kitchen and time spent outside the home) in the interviews.

We used Tableau, MS Excel, Matplotlib, and Photoshop to create the visualizations. Because all but one participant chose to have the interview remotely, they saw digital versions of the visualizations. For the participant whose interview was in person, all of their materials were printed in color. The different charts were created to be diverse both in design and data shown, to display more detailed or more summarized data, and use number oriented or whimsical (i.e., illustration style, as in [72]) representations. Most charts were specific to each participant, displaying their monitoring data, with the exception of a few comparative plots (e.g., Figure 3). Several examples of the different visualizations are presented along with quotes in the findings section.

*3.2.4 Qualitative data analysis.* We qualitatively analyzed each set of interviews as separate data sets following a thematic analysis approach [14]. For these analyses, two researchers first coded the interviews from 1-2 participants separately, then discussed the resulting initial set of codes to create a single code book for that data set. Then, one researcher coded all interviews using the corresponding data set code book and four researchers discussed the codes and emerging themes over multiple synchronous meetings. Analysis for each data set was a collaborative and iterative process. After all three data sets had been analyzed following these steps, one researcher identified cross cutting themes for the data sets and read all interviews for each participant, in the order they were conducted, making annotations on how answers evolved over time.

## 4 FINDINGS

Older adult participants found the smart home monitoring system to be unobtrusive. They easily forgot it was there and it did not affect their daily activities. They also did not have privacy concerns about the data being collected.

When examining their data through visualizations, they went through a sensemaking process that included asking questions and creating hypotheses. Participants were interested in smart home data that they associated with an active lifestyle, such as time spent outside of the home.

### 4.1 Experience with home monitoring system

Participants reported having a neutral perspective towards the sensors installed in their homes throughout the study. This perspective did not shift substantially over time. They consistently reported that they did not notice most of the sensors and that the monitoring did not affect their daily behaviors. Although they disliked seeing the sensors, particularly in more private spaces such as bathrooms, very few expressed having privacy concerns.

*4.1.1 Sensor perception and impact.* In the baseline interviews, shortly after having the sensors installed (Figure 1b), older adults in the study said that they expected to forget about the sensors in a short amount of time. As soon as the next interview, one month into the study, people claimed to not notice them anymore. As P8 stated, the presence of sensors did not lead to any change in behaviors:

> "[The sensors] are totally easy to ignore and unobtrusive in any way. They don't interfere or impact my life in any way, and they're just there and I assume they're gathering data." (P8)

This answer was consistent across participants, as they did not report any impact of having the system installed, positive or negative. In another example, P15 said in the fourth monthly interview:

> "I actually very often forget about the sensors." (P15)

Participants who reported changes in their activity referred to what they did outside the home, such as taking longer walks, and attributed the changes to step data collected by the smartwatch rather than by the home sensors.

There were only two exceptions to this pattern of low noticeability: ceiling sensors and bathroom sensors. The sensors installed on the ceiling to measure walking speed were noticeable to people even after several months. This awareness led to thoughts about what the sensors were measuring. Still, as shown in the following quote, people were not bothered by the sensors on the ceiling:

> "So when I go under the gait ones I think 'oh, [researcher] is watching how fast I'm going.' But I don't... It's a short little hallway and it doesn't really affect me, but yeah, I notice. But the rest of it, not so much." (P9)

Visitors also did not notice or ask about the sensors, except for the ones installed on the ceiling, as P14 explained:

> "It's the ceiling [sensors]. Yeah, no one ever seems to see the other ones, because they're pretty hidden. [...] But a lot of people don't seem to even notice them, and if I mention something then they'll say 'oh, I wondered what those were.' " (P14)

The second exception was in the case of bathroom sensors. While participants were not opposed to the presence of those sensors in their bathrooms, a few of them mentioned disliking seeing them and being reminded of their presence. For example, P9 said:

> "I still do sort of think about [sensors] as being an eye looking at me because they have a little eye. The bathroom ones are really the only ones that bothered me in that way." (P9)

In one case, a participant moved the sensor so that it would be less visible during their daily activities. P8 talked about doing this in the beginning of the study, in their first monthly interview:

> "I just moved the location of the one sensor in the bathroom. Because it was staring me in the eyes when I was brushing my teeth and it bugged me." (P8)

P8 and P9 were the only participants who mentioned being bothered by the bathroom sensors. Among other people, only the ceiling sensors were noticeable. In both situations, seeing the sensors increased awareness of the monitoring, but that awareness was described as neutral in the case of the ceiling sensors. Ceiling sensors were noticeable because the way they were installed made them stand out. Bathroom sensors were installed on the wall, similarly to the other rooms. The higher awareness about their presence likely is due to the bathroom being a more private space of the home.

Participants' experiences and attitudes did not change substantially over time. Most participants required some kind of maintenance in the system during the six month period (e.g., replacing a broken sensor), but those incidents did not seem to substantially impact people's overall opinions of the system. Throughout the study, participants predominantly expressed neutral opinions about it.

*4.1.2 Privacy.* When asked about privacy concerns, several participants explicitly mentioned that they did not mind the motion sensors, comparing them with more invasive alternatives, such as video recording. Participants indicated that they would be concerned if the data being collected were richer, as P15 said:

> "I was a little apprehensive but I'm okay knowing it's just motion. So I feel okay about it." (P15)

We asked participants if they would like to have tools to control the data collection to protect their privacy, such as turning off the system temporarily as needed, but they consistently did not see a need for it. To them, there were not enough privacy concerns to warrant this kind of functionality.

When visitors asked about the sensors, participants explained that the data being collected were not detailed enough to be concerning. P10 discussed this kind of interaction in their fourth monthly interview:

> "People have questions. I had company over the weekend. It's like, 'are those cameras or what?' 'No, no. That's movement only.' " (P10)

Still, there were a few instances of friends or visitors showing more privacy concerns than the residents. According to the participants, this did not happen frequently. One example was described by P1, in the following quote:

> "I was not worried about being monitored. I had friends that said, 'how can you have that in every room so they know what you're doing.' And I said, 'well, it's just monitors, so you can go in and out and they can see how much time I spend.' And some people like my age are terrified of anybody monitoring them." (P1)

This difference in attitude might be influenced by trust in the researchers' university, information about protections provided upon joining the study, or people who are open to participating in this kind of study being less privacy-conscious than average. For example, the informed consent process included a description how their data would be stored, accessed, and used and how their anonymity would be protected. There were no additional questions about data protection.

In short, participants predominantly did not notice the smart home sensors in their homes and did not exhibit privacy concerns. They also preferred not to notice the sensors, particularly in more private spaces, as that would increase awareness of their presence.

### 4.2 Reflections on home monitoring data

Participants were interested in seeing their data throughout the study. In this section, we describe how they made sense of their data visualizations, what insights they were most interested in, and the feedback they provided during the data interviews.

*4.2.1 Interests and expectations before seeing the data.* We asked participants about their opinions and potential interest in the data being collected through the home sensors throughout the study. Before they had access to that data, they generally were uncertain about what the data would show. As they did not know if the data would provide any meaningful information, they were most often unsure if seeing it would be useful in any way. As P9 said:

> "I still don't have an understanding of what it's for. [...] Of what that data would look like." (P9)

Although they did not know what to expect from the data collected, participants did have questions and showed curiosity, mentioning that they would like to see it. A few times, people asked about the data directly, as P15 did in the following example:

> "I was wondering, do [the researchers] compare how the participants are doing? I mean, I've just wondered how do I compare maybe to the other people." (P15)

Although they did not know what the data would show, participants answered questions about their interest in the data by discussing possible uses for home monitoring broadly.

In the short term, they considered using the data for self-knowledge or validation. They expected that knowing more about how they were spending their time might be useful for improving their habits, such as being more active.

For example, P8 speculated that the home monitoring data could be used to manage exercise, considering her chronic pain and depressive symptoms:

> "I guess I'd try to evaluate whether I'm moving around less because of pain in my feet or the concurrent depression that I have often because I'm in pain. So much of the time and I could evaluate [...] you know, if it's just depression, then you'd get up and move." (P8)

A few participants considered that the data would be particularly meaningful during the more restrictive periods of the COVID-19 pandemic, since they were spending more time at home. P9 shared this perspective, as she discussed using the data for validation:

> "I don't think I need an electronic report of what I'm doing in the day. I know, although I do have to say there are some days, especially during COVID, when I think I didn't accomplish anything. [...] But then I realized. Oh yes, I did. I did a lot, you know. I did the laundry for example. That was three trips up and down the stairs, whatever. So maybe it could be useful in that and that you would say like you know you did accomplish things today. " (P9)

In a few cases, people displayed curiosity about the time they spent in hobbies or crafts. This information would be more interesting than measurements about their regular daily activities, such as chores, as P1 explained:

> "Probably the only room might be interested in knowing how much time I spend in is my studio. [...] Because I'd like to know how much time I spend on my artwork. The other thing is like very routine. I have a very routine schedule. [...] I never know when I'm gonna, when the inspiration strikes me." (P1)

Similarly, P7 talked about wanting to see the time he spent on collecting and building Legos, his main hobby:

> "I often wonder you know how many hours do I spend doing this, doing that. Just like building the [Lego] set I did yesterday." (P7)

Only a couple of participants explicitly mentioned wanting to see long-term information about their health and well-being. One of them was P6, who expressed interest in seeing gradual changes in health as she aged:

> "You know at this age I'm keenly aware of how my physical abilities are changing. So it would be interesting to note what's happening." (P6)

As shown in the examples above, participants did not know what to expect from the home monitoring data. Still, they were curious about the data and speculated about several different ways that information could be useful for them.

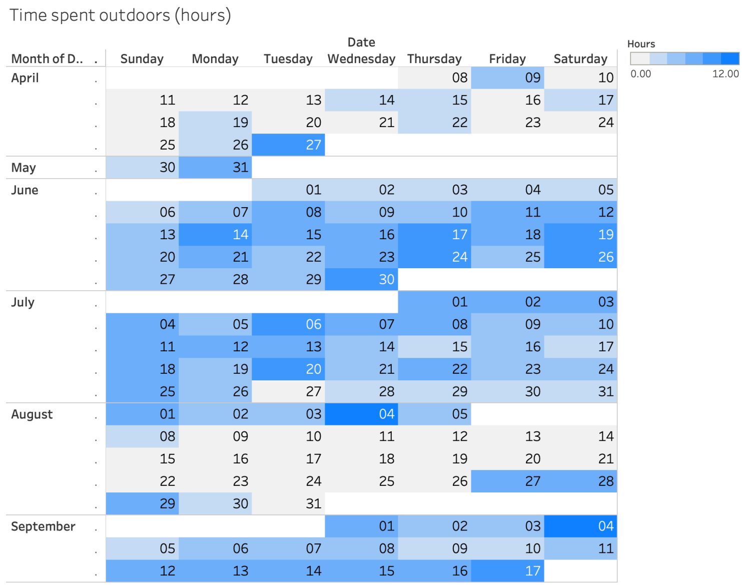



Fig. 2. Calendar visualization displaying the time spent outside the home for P8, between April and September of 2021. The data range from 0 to 12 hours, indicated by color. This visualization format was used for all participants to display time spent outside the home and time spent in the kitchen.

*4.2.2 Sensemaking.* When we showed data visualizations to the participants, they underwent a similar process of making sense of their home monitoring data. They formed hypotheses, asked questions about the data, made comparisons, and discussed the role of context in interpreting the visualizations. These activities were not prompted by the researchers, rather they were part of the talk-aloud process of the interview.

When looking at a data visualization, participants often asked questions to clarify different aspects of what the data might have measured. The questions referred both to the visualization itself and to how the system functions.

Questions about the system revolved around how and when the sensors were activated and how the indoor location was determined based on those activations. These questions helped people to understand how a specific activity or movement in the home would show up in the data collected. For example, while examining a histogram of time spent outside the home (see Figure 4), P6 asked what would happen if the doors were open while she was at home:

> "And does it sense like my passage through? Because I keep the doors open in the summer. So if I just open the door and leave it open it might not know that I've gone outside." (P6)

Questions about the visualizations were more about understanding details such as scale and legend. In other words, people asked about whether they were interpreting the graphs correctly. P8 asked this question about a specific day on a calendar graph (Figure 2):

> "What does that mean? That nothing happened, right? I wasn't there... but that would seem to indicate. Well, let me ask you. This, does July 27th indicate I was not outside at all?" (P8)

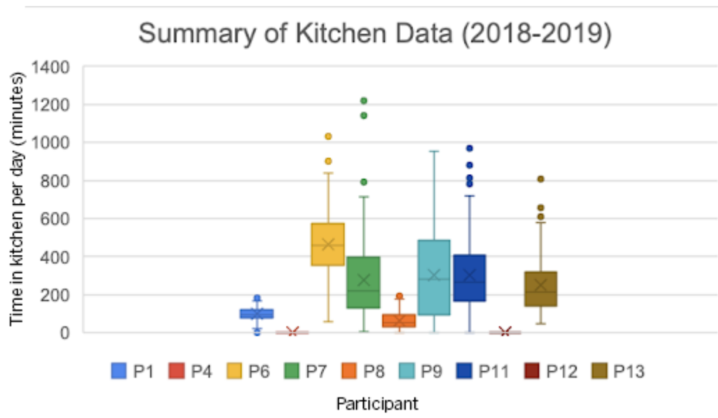



Fig. 3. Box and whisker plot of the time spent in the kitchen per day, in minutes, for nine participants. Data collected between 2018 and 2019. We showed this visualization to each participant during the data interviews and a similar visualization for comparison of time spent outside the home.

All participants asked questions during their interview sessions. These questions helped the participants to better understand the system as well as the data. They adjusted their expectations for what the system can and cannot measure, its accuracy, and potential sources of noise (e.g., pets). This process was part of establishing a mental model of the system and what level of detail to expect of the measurements.

Most older adults showed interest in comparisons of their data with data from others in the study and they were open to sharing anonymized data with other participants for this purpose. These comparisons provided additional information about how to interpret the data in question, such as knowing if the time spent in a room is longer or shorter than average. These comparisons often had a perspective of competition, as people wanted to do better than others. For example, P8 negatively interpreted having spent less time in the kitchen in comparison with others (Figure 3).

> "I'm so competitive, I'm kind of pissed that I'm way down there in the bottom ranks. It's like, what? Do I not do anymore in the kitchen in that tiny little bit? What is the matter with me? But I don't. I mean, I'm not unhappy. and aside from seeing a graph that says you're not in the kitchen very much, I'm not the least bit unhappy with the results." (P8)

There was one participant who did not show any interest in this comparative perspective. P7 expected the data to show that he was very active, regardless of the data collected in others' homes. P7 stated:

> "I'm probably much more active than most. People my age. [...] Compared to somebody else, is really not very important to me. Yeah, it's not a competition, it's called life." (P7)

The identity of being an active older person was consistently seen as important and desirable by the participants. We discuss this finding in greater depth in the next subsection.

A few of the visualizations, such as Figure 3, enabled comparison by showing the data from several participants side by side. Additionally, most visualizations showed variations of a measurement over a period of time, such as Figure 2. These images allowed comparisons of specific days against the person's own average. Therefore, they highlighted outlier days, such as when the person spent much longer than usual in a particular room. In these cases, participants came up with hypotheses about what had happened on that day.

Hypotheses were very common, as all participants raised several of them during the interview. As was the case with questions, they were not prompted by the researchers. Instead, they came up naturally in the talk-aloud process as we discussed each visualization. Participants tended to raise possible explanations for what they were seeing by mentioned aspects of their daily lives that could have caused an outlier day or recounting something different that happened around the time shown in the visualization. For example, P1 described a lengthy cooking process to explain a period of spending long hours in the kitchen:

> "I think I do know what it is. I was making an emphasis on cooking and freezing Indian dishes and preparing spices in the kitchen and making ghee in the kitchen. I can remember in July spending a lot of time in the kitchen because I had to make two batches of ghee because I burnt the first batch. [...] I think yeah, that's what I was doing. I was making Indian food." (P1)

Another participant explained how his girlfriend would spend time on her computer on the kitchen table. P7 said the following, referring to a day where the data reflected more time spent in the kitchen than usual, by several hours:

> "I would almost make a bet that [girlfriend's name] was here visiting and was sitting at the kitchen table working on a book." (P7)

Although they formed these hypotheses, most of the time participants were not able to confirm or disprove them due to lack of enough contextual information. Because the data displayed in the visualizations had been collected months or even years earlier, people did not remember what actually caused outliers. We asked participants to bring their calendars to the interviews, and the calendars were often useful to provide explanations for the patterns in the data. For example, P4 checked the calendar to see when there was someone in her kitchen working on renovations:

> "They redid my kitchen countertops and my sink. There was a guy that was in there every day from say 10 o'clock to four. [...] I forgot about him, but I think that was last April or May. My calendar might tell me. [...] I see some of the darker ones, and it has to be when he was here. [...] No, he was at my place in March, looks like, the most hours. And that must be when he did my kitchen because he was in there, like I said, all day long." (P4)

However, their calendar did not provide enough information to confirm a hypothesis the majority of the time. In those situations, participants tended to mention several possible explanations for the outlier day. P8 talked about factors that lead to spending more time in the kitchen, such as cooking or baking for a birthday party:

> "Sometimes if there's birthdays, I spend more time in the kitchen fiddling around, but I don't know. I can't give you a good explanation. [...] Sometimes we don't know if something is actually different. Or maybe there's some just some issue with the sensors." (P8)

Overall, participants paid attention to outliers in their data visualization and came up with hypotheses for what might have caused them. They also asked questions about the system itself and the visualizations to understand how different activities would be reflected in the collected data.

*4.2.3 Participants' perceptions about their data.* As they examined their data visualizations, participants showed the most interest in data that they associated with a reflection of living an active life. While this concept of an active life encompassed physical activity, it included being social, busy, and active in their community (e.g., volunteering or traveling). Overall, having an active life was seen as the ideal, or something to strive towards. We observed that being active is something that they value as part of their self-identity and that they believed that the home monitoring data could reflect it through measuring their activities.

Time spent outside the house was the main measure that participants interpreted as an indication of being active. Accordingly, they described how they considered spending more time outside of the house would be better.

One participant, P4, described numerous valued or enjoyable activities that take place outside the home, even during the COVID-19 pandemic. These examples included volunteering, socializing, and engaging in hobbies, as the following quote illustrates:

> "I think [spending time outside] makes me healthy and I just need the fresh air. [...] I worked at the university club, which I still do. and I'm also a volunteer at the hospital. [...] I live in a cul-de-sac, and when there were nice days, we would all meet with our chairs six feet apart. and sit out and have a beer or a cup of coffee or whatever. we wanted just to get out to see other people. [...] In May, and that's when all the gardening of our stuff goes in. I have a neighbor who is always sharing stuff so she's down here, bringing me more stuff all the time." (P4)

Additionally, most participants were outside the home when they engaged in physical activities, such as walking and hiking. Therefore, they saw the measure of time spent outside the home as a proxy measure to how much they were exercising. For example, when looking at data on how much time they spent out of the home, P6 and P13 talked about their exercise habits:

> "All summer I was outside a whole lot, so I think on balance, in the long run, it works out, but it always makes me kind of nervous. You haven't been outside, gotta exercise." (P6, comparative plot, see Figure 3)

> "Almost every day, unless it's raining quite hard. I walk from 6:30 to about 7:20 every morning with my neighbor. And that might be the most time that I spend outside of the house." (P13, histogram, see Figure 4)

Other kinds of data measured by the system were also seen as reflecting on being active or inactive. For example, the count of room changes in a day was a measure of being active indoors. Higher values were seen as better, indicating higher level of activity. P8 expressed how seeing a high number of room changes (Figure 4) was validating:

> "I think the thing that this tells me. Is that I'm not as sedentary as I sometimes think I am, and that's good. 'cause sometimes I feel like I do tons of sitting which I do. But obviously I'm also getting up and moving around." (P8)

Certain data, namely time spent in rooms associated with rest or sedentary activities, such as the living room, were interpreted by the participants as indicators of lower activity. As shown in the following quote, P15 explained that seeing a lot of time spent in the living room was not ideal:

> "It scares the everloving tar out of me what the answer would be. But yes, I think it would be kind of interesting. But I can tell you right now, the majority of the time is spent right here. As I talk to you, sitting on my couch. [...] I would like to think that it would make me move a little more 'cause I think sometimes I get too carried away with sitting in one spot, either watching TV or whatever." (P15)

When data, such as time spent outside or room changes, indicated lower levels of activity, participants showed more skepticism about the measurements. In these cases, they questioned the accuracy of the data or talked about limitations, i.e., what it could not measure.

For example, P7 was active outside of the home, something that the measure of indoor activity (i.e., room changes) did not capture. When at home, activities such as working with Legos did

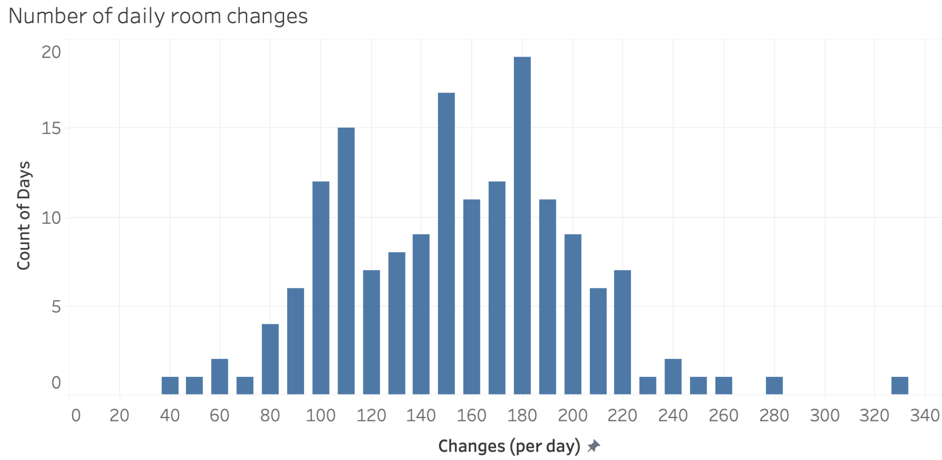



Fig. 4. Histogram of the number of room changes per day for P8. Count of room changes is a measure of activity inside the home. In this case, room changes most often are in the 80-220 range. P8 had 15 days with room changes in the 100-110 range. All participants were shown this visualization, along with the median value for all participants, 100 changes, as a reference for interpretation.

not involve a lot of movement. However, he did a lot of manual labor elsewhere. While looking a visualization of these data, he emphasized his active self-identity:

> "I spend long, long, long hours sorting Legos, building Lego sets. When I'm not doing that, I'm out building other things. [Girlfriend]'s new house, we put 265 feet of fence in there. I put shelving in. I did a $68,000 rebuild of her condominium. So, I'm active." (P7)

Several participants claimed that the data about time spent outside of the home were not accurate, substantially underestimating the actual time they were out. In the quote below, P13 discussed how the estimated time did not even account for the duration of her daily morning walk:

> "Okay, if it says, I only spent 35 minutes outside of the House, then I guess that's true. But I say it's not true, I say that even in May, I was outside the house at least an hour and a half, every day." (P13)

We believe that the participants were correct in this assessment, as a few participants had unreasonably low average time spent outside the home (e.g., 2 minutes per day). Still, it is notable that this questioning was much more common when the participants saw the data as unfavorable. We have found that the noise caused by pets can lead to underestimating the time spent outside the home and overestimating room changes. Participants almost exclusively thought it was an issue when examining data about time spent outside the home, as the following quote illustrates:

> "It's always better to spend more time outside the house, but if the monitors are picking up activity in the house. Other people or animals that could be in the house, it can cannot be a an accurate representation of going in and out." (P1)

There were two measures related to health and exercise that were mentioned as potentially interesting. P13 talked about being interest in measuring climbing stairs, while P1 saw bathroom data as potentially useful:

> "I do go up and down stairs quite a few times, every day, especially when I go upstairs and forget what I wanted and then come back down and then remember it and go

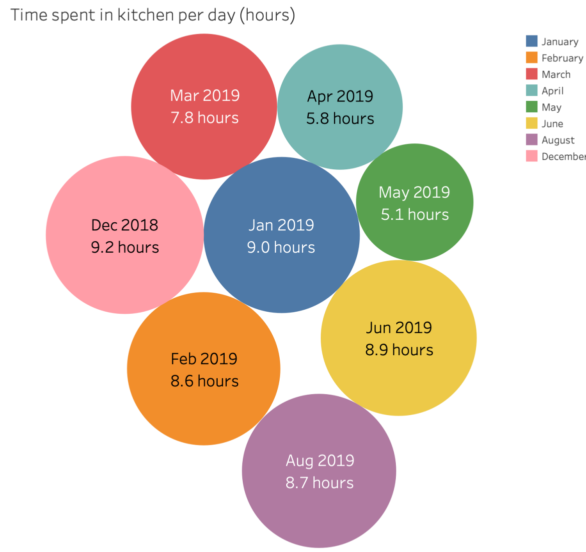



Fig. 5. Bubble chart of the median time spent in the kitchen per day, by month, for P6. All participants were shown this visualization for time spent in the kitchen and outside of the home.

> again. It's not very common [to climb stairs this much] in people over 70 I think, and i'm well over 70." (P13)

> "It would be useful for me to know, like the bathroom visits. Because I have to use the bathroom a lot. because when you get older. You urinate more. Or you know, like, I have to get up during the night to urinate, and so I could kind of tell how much time I spend in the bathroom from that." (P1)

Other data were consistently seen as unremarkable or unsurprising. Measurements that were not interpreted as related to health or living an active life, such as time doing chores, did not provide meaningful information to the participants. Even if they did not know what their patterns were already, they expressed that the time spent in the kitchen, for example, is not good or bad. Therefore, there is no reason to want to spend more or less time there. For instance, P6 found her kitchen data unsurprising and not interesting (Figure 5):

> "It doesn't surprise me at all. You know, 'cause, that's where I hang out. But if you get a chart of your life, a lot of it would probably be known. So you go, so, big deal." (P6)

Similarly, P13 did not see any value in her kitchen data, as shown in the following quote:

> "I don't really have any preference I spent time in the kitchen when I want to be there, or need to be there. That's all. I don't think about it, this respect to how much time other people spend in the kitchen. [...] I don't read in the kitchen. I don't visit with friends in the kitchen." (P13, comparative plot, see Figure 3)

Contrary to what we expected, participants did not associate kitchen data with cooking or eating habits (e.g., taking the time to cook a nutritious meal). In contrast, data about time spent outside the home and indoor activity (i.e., room changes) were valued due to its association with living active lives.

*4.2.4 Feedback on visualization design and displayed data.* As they talked about their data visualizations during the interviews, participants often expressed wanting to change something about the visualization or the study to obtain more meaningful insights from their data. These changes included having more contextual information, more granular sensor configurations, or more flexibility to explore the data in their own time.

A few participants talked about the limitations of comparing home monitoring data, since the layout of their homes and sensor placement would lead to different data even if they were engaging in the same activities. For instance, P1 lived in a small apartment and expected that other people would spend more time in the kitchen because they had space for a kitchen table:

> "My kitchen does not have a kitchen table in it, or anything, [...] and I only cooked in there, I didn't sit down and eat. [...] Because I see that I am like miniscule compared to everybody else, and when I see that miniscule rating i'm thinking. that is one of the variables that could lead to that being misinterpreted. [...] But it's just in my instance, maybe everybody else has a kitchen table in their kitchen. Maybe I'm the anomaly." (P1)

Similarly, P13 explained that the sensors did not reflect that what it means to move inside the home can be very different depending on how many levels there are:

> "It seems to me it's different for people who live in an apartment that only has one floor and I have three. I do go up and down stairs quite a few times, every day, especially when I go upstairs and forget what I wanted and then come back down and then remember it and go again" (P13)

Most participants wished to have more contextual information to make sense of their past data. P6 said:

> "I don't remember that day. [...] So I have no context to put it into or say, oh that's because I was always doing this so and so. [...] Unless I had, you know, information attached like you wrote this paper, or you called these people, or you had this meeting right during these hours so I could look back and say, 'Oh yeah, I actually got things done on that day.' " (P6)

When they had to rely on their memory, participants could only recall major factors that influenced their habits, such as the COVID-19 quarantine or changes in seasons. Participant P7 talked about spending *"a lot more [time in the kitchen] when you're quarantined and isolated."* P7 also talked about spending less time outside the home regarding data collected between November of 2020 and April of 2021, because *"you're in winter to start with. There's not much to do outside of the house."*

We asked all participants about which visualizations they found more interesting or easily interpretable. Their answers varied widely, with different people preferring more numeric representations (e.g., Figure 3) or more whimsical options (Figure 7). The only visualization that was favored by all participants was a month-long overview of data from every room of the home (Figure 6). This was the most interesting graph for P4, who commented on how it reflected spending time in the living room and walking through the bedroom:

> "It looks good because I go through the bedroom every time I go to my bathroom. I physically have to go through it. So it looks right. and the sitting, definitely way too much. [...] I like these last [visualizations], where it broke everything down and really showed where I was in my house, the most or in or outside." (P4, Figure 6)

Those who preferred the more pictorial representations appreciated that they were more straightforward and intuitive to understand. For instance, P4 expressed this sentiment when seeing the kitchen illustration (Figure 8).

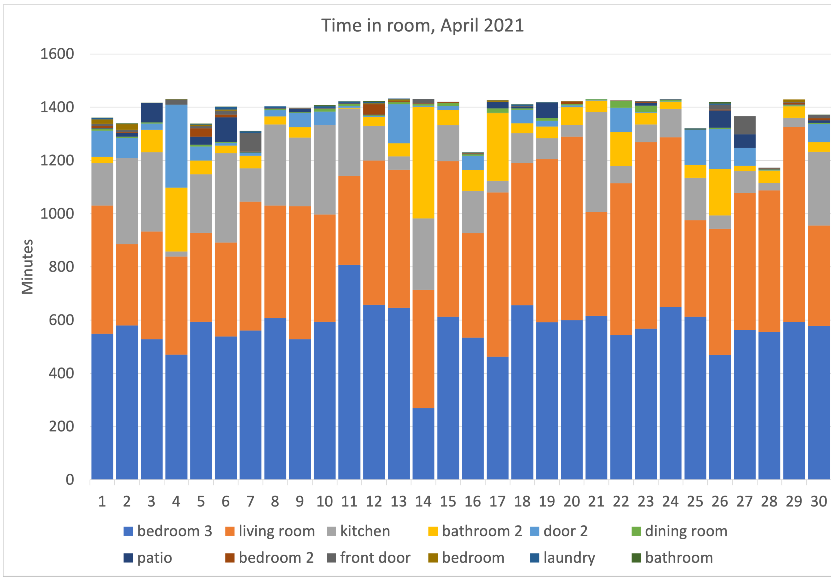



Fig. 6. Stacked bar chart showing an overview of time spent in each room of the home during the month of April 2021 (P4). All participants were shown a similar visualization with their data. The visualization shows that P4 spent most of the time at home either in bedroom 3 or in the living room. Several bars are below a full 24 hours of data (1440 minutes) because they do not include instances where the location could not be determined.

(a) Darkened windows indicating more time than usual spent outside the home.

(b) Balanced image, indicating time spent outside the home close to the participant's median.

(c) Bright windows indicating less time than usual spent outside the home.

Fig. 7. Illustration designed to display time spent outside the home. Participants were shown the three versions labeled with specific days from their dataset.

> "I like this. Interesting. It's right there in front of you, you don't have to look at numbers." (P4)

On the other hand, a few participants criticized specific aspects of those representations. In the case of the home illustration (Figure 7), P6 found it to be a patronizing choice for a system designed for older adults:

> "This seems like it's aimed for children. When you do this kind of imagery. [...] There's a lot of infantilizing of seniors." (P6)

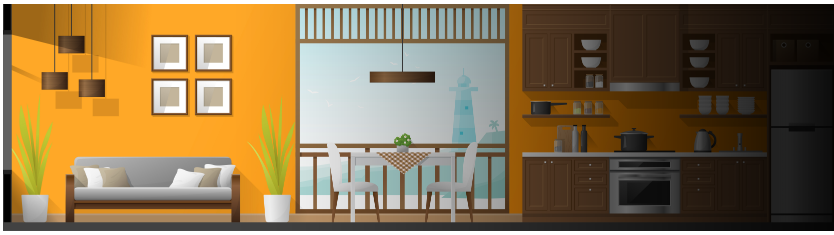


Fig. 8. Illustration designed to display less time than usual spent in the kitchen. Participants were shown this image labeled with a specific day from their dataset.

In the case of the kitchen illustration (Figure 8), P8 saw it as having a negative connotation about the lack of activity in the room:

> "It's sad to see a black kitchen, a darkened kitchen. It seems like it's been abandoned." (P8)

Overall, participants' preferences regarding visualization styles varied widely. They responded particularly well to overview visualizations, such as Figure 6. Pictorial illustrations, namely Figures 7 and 8, were the least favored among all visualizations used in the study.

The results of this study indicate that older adults found certain home data useful, particularly measures that they interpreted as indicators of having an active lifestyle. Time spent outside of the home was the indicator most consistently seen as interesting for this reason, while other kinds of data, such as room changes and time spent in the living room also were seen as relevant. When shown their data, participants often asked questions or created hypotheses to connect outliers to unusual events in their life, such as falling ill or traveling. As such, monitoring the time older adults spend in different parts of their home offers promise for collecting meaningful data for their self-management.

## 5 DISCUSSION

We present qualitative findings about older adults' experiences with a long-term deployment of home monitoring and about their reflections about the data collected by the system's motion sensors. Based on these findings, we conclude that the approach of monitoring indoor location is feasible and useful, given that participants found it unobtrusive, not concerning in terms of privacy, and the data led to meaningful insights among users.

Most findings agree with conclusions from prior studies. This paper's novel contributions lie in confirming that such findings hold *in the long-term.* To our knowledge, this is the first in situ longitudinal study of home sensors with independent older adults. We capture engagement with participants' own long-term data, surpassing limitations of short-term deployments that only reflect the novelty period. In this section, we discuss these conclusions in depth and reflect on opportunities and challenges for future work based on the results.

### 5.1 Privacy and lived experience with smart home monitoring

Because living with motion sensors was not disruptive to residents' daily lives, we show that smart homes could provide insights that help people make sense of their activities without being too obtrusive. Prior work has found that older adults are open to smart home systems that are reliable and not intrusive, as long as they have control over the data and receive support to understand and use them [55]. Even when they are successful in the goal of allowing the resident to remain at home, these systems can deteriorate the experience of living at home in physical, virtual, and emotional levels (e.g., [91], a monitoring system that included motion sensors and cameras). We did not observe this deterioration among our participants, likely because the system was designed for the residents as primary users, preserving their agency, and because users have less privacy concerns about motion sensor data in comparison with cameras [79, 89]. The findings of this study are aligned with past research that reported how people care about the appearance of the sensors [29] and they appreciate when the sensors are placed in a way to not be noticeable, so they quickly forget about them [30]. We confirm that motion sensors remain unobtrusive for residents in the long-term, however visitors might notice the sensors and express privacy concerns. Users might want to have the ability to move sensors, impacting the data collected by the system. Therefore, it might be necessary to account for these changes when processing and displaying data.

Privacy concerns are common barriers to the adoption of smart home technologies by older adults [26, 96, 119, 142], as the data might be important for their self-identity and for how they are perceived by others in their social circles [83]. Willingness to share data with family members and caregivers depends on several factors, such as trust in the individual and perceived need [93]. At the same time, a few studies have reported little or no privacy concerns from older adults about smart home data [108, 33]. As our participants are casual smartphone and tablet users, they likely believed that risks of personal data misuse were low, based on their prior experiences with technology [122] and on expectations that smart home systems include privacy protections by default [10]. In this study, the motion sensor data were not shared with family members or friends, only the researchers had access. This limited data access might explain the low privacy concerns, given that privacy concerns are influenced by the person's relationship with data recipients [119].

Although participants did not express a perceived need for privacy controls (e.g., [16]), they did experience discomfort with motion sensors placed in bathrooms. As these rooms are particular private spaces in the home, people might have heightened privacy concerns regarding data about their use [79, 112]. At the same time, bathroom data could be relevant for health management. For example, a change in bathroom habits could be caused by a urinary tract infection or gastrointestinal symptoms. Interestingly, in the study what bothered participants was not that the motion sensors were present, but that they were visible. Seeing them was an unwelcome reminder of their presence. This finding goes against privacy principles around promoting visibility [20]. For example, smart home visitors often want to be informed about data being collected and to have tools to protect their own privacy [80]. For residents, awareness and an in-depth understanding of privacy risks are necessary for evaluating trade-offs to make informed decisions [84], such as controlling data access in real time [16]. Instead, the dislike of seeing motion sensors could be reflecting an attitude of resignation and fatalism about data privacy [118].

Prior work in this area is diverse in terms of what sensors are part of the monitoring system, a factor that likely influences participants' experiences and privacy concerns. Most studies have included a variety of sensors in addition to motion and door sensors, such as bed sensors [91, 29, 26], fall detection sensors [29, 26], and cameras [16, 91]. These additional data amplify the capabilities of the system, with the trade-off of decreasing privacy. Because people have greater privacy concerns about data collected in their own homes in comparison with other spaces, including public restrooms [89], collecting data users are more comfortable with, such as presence and temperature [79, 89], is a more privacy preserving approach. It is worthwhile investigating the benefits and limitations of more minimalist smart home monitoring so that we understand when they should be used. This paper contributes to this understanding by describing participants' experiences living with the system and reflecting on their data.

## 5.2 Reflecting on smart home monitoring data

The motion sensors in the deployed system measure indoor location, as opposed to the more common approach of monitoring specific activities of daily living (e.g., [67]). While there is evidence that this kind of data can be used to detect changes in health [44, 33] or even early signs of such changes [139], we show how indoor location data also can provide meaningful insights to older adults. Therefore, the system deployed in this study could effectively inform residents about gradual changes in their own habits and health, information that requires long-term tracking. These data could empower users to proactively manage their health while preserving their agency. Most commonly, home monitoring systems are designed to provide information to family members or caregivers instead (e.g., [115]). Researchers have also reported that older adults show interest in seeing their smart home data, particularly time spent inside or outside of the home [30, 33]. We show what meanings they extract from their historical data and describe their reflection process.

Our results support findings from prior work and contribute novel insights to the literature. Prior research has reported that older adults find visualizations helpful to improve health awareness [99, 34], but interpreting smart home data is notoriously difficult. When examining smart home sensor data, people reconstruct behavior and speculate and reflect on data, contextualizing trends [62]. However, this process requires articulation work, such as reasoning about how the home is organized, routines, and activities that take place there [123, 127]. Smart home data are opaque because they make visible where people are, but not what they are doing [123]. In this study, the process of interpreting the data was made simpler by the home only having one resident. However, there is still a social part to this process due to the use of comparisons. Further, despite having their calendars during the interviews, participants expressed the need for more contextual information to better understand the trends they were seeing. Indeed, contextual information is helpful for interpreting and reflecting on past data [4, 106]. However, collecting and connecting such information to the data can be challenging for users in the long term. There is an opportunity to explore how to facilitate this process, for example by connecting to users' existing calendars or personal diaries.

The process participants went through to make sense of the data is aligned with findings from prior research about interpreting personal health data [41, 66, 106]. For example, patients with type 1 diabetes and their caregivers found trends in personal health data, considered contextual factors, and created hypotheses to explain changes [106]. In the same study, participants examine data with a pre-existing frame based on their lived experiences. They look for data to fit or extend the frame and either distort or find reason to discard data that contradict the frame [106]. These findings resonate with this study, given the participating older adults' interests and perspectives towards data that they associated with living an active life. They appreciated data that indicated high levels of activity and exhibited skepticism when the data indicated the opposite. This perspective that having an active life is important and good in this phase of life is part of their values. The data provide positive reinforcement, validating traits and behaviors that they consider positive. While interpreting their data, participants also paid attention to outliers, as described in prior work [41, 66]. However, reflecting on their normal habits or long-term trends would likely be more beneficial for purposes of self-awareness and improving their self-management.

The older adults in this study generally did not receive pictorial data representations well. Those visualizations were inspired by prior research with younger participants (e.g., [72]) that achieved better results with this approach. Instead, our results are more aligned with Microsoft Bob, a failed product whose interface included a pictorial representation of a house [85]. Older users are less receptive to this style of illustration, likely because of the harms of infantilizing older adults discussed in prior research [64, 60]. Informed by our results, there is an opportunity for exploring alternative visual metaphors that share the beneficial aspects of pictorial representations without being perceived as infantilizing by older adult users. For example, opting for professional or minimalistic aesthetics, as opposed to more cartoonish designs, should be better received.

### 5.3 Active aging as self-identity

Older adults in the study valued data that they associated with their self-identities of active elders. Data from smart home monitoring can be used for this purpose because participants interpreted time spent outside the home as an indication of living an active life. The data reflect a broad definition of active life, including engaging in hobbies and socializing, being involved in the community such as by volunteering, in addition to just exercise. These characteristics describe fulfilling lives, something that requires more than just independence [5, 71]. This broad definition is also aligned with older adults' understanding of what it means to be active, as described in section 2.3. Therefore, these data can be valuable as a holistic measure of well-being. There is an opportunity for future research to study older adult self-tracking focusing specifically on time spent outside the home. Because it can also be measured in different ways, such as passive GPS location tracking through mobile phones or wearable devices, future research could explore self-tracking this kind of data without the need for home sensors.

Most participants made downward comparisons when looking at their data, even though the visualizations were not designed with that in mind. The comparative charts in the study aimed to provide a frame of reference that is relevant to their age and context [27]. Comparisons with other older adult participants from the same city accounted for factors that influence physical activity, such as weather and major holidays. Downward comparisons were an unintended consequence of this visualization. While these comparisons provide benefits, such as being interpreted positively [120, 136], we must have caution about how we approach providing positive feedback to older adults. Because downward comparisons are based on ageist ideas, they can be harmful to the person's subjective age if or when they no longer have the characteristics highlighted in the comparisons.

Older women are more negatively affected by ageism and anti-aging discourse in comparison with older men, since they live longer and aging discrimination overlaps with gender oppression. For them, at the same time that physical exercise is needed for independent living, it is inherently linked to beauty ideals [103]. Hence, feminist perspectives on self-tracking, body surveillance, and seeking normative ideals can also apply in the case of older adults. For example, women may experience food tracking apps as shaming, guilt inducing tools used in the struggle to conform to societal ideals [76]. To address this issue, scholars have argued for taking subversive approaches in design, promoting non-judgmental mindfulness and open-ended experiences [117]. Similarly, empowering older adults without relying on ageist ideas requires a normalization of diversity in the aging experience, rather than always striving for unattainable or unsustainable fitness [56].

### 5.4 Designing for older adults' personal use of smart home data

To promote positive aging ethically, we need to carefully examine the implications and underlying assumptions in the narrative of activity or positivity in aging discourse and design. Internalized stigma about health and aging causes harm to people, similarly to internalized racism. Effectively reducing the damage requires purposefully deconstructing stigma [111], but that cannot happen by focusing only on the individual, as in the case of downward comparisons. How to provide positive feedback and a positive experiences without an implied hierarchy effectively through design is an open question that warrants further research. In this study, we showed participants' data alongside others to provide them with a frame of reference for interpreting the visualizations, as we did not expect them to have one regarding home monitoring data. Instead, directly providing reference values appropriate for the person's context could support interpretation without leading to downward comparisons. Other approaches such as collaboration [22] and reciprocity [73] could also support positive feedback for older adults.

Additionally, storytelling with personal data is a promising direction for smart home technologies for older adults. For example, stories from people with similar experiences may help people to find validation and relief and construct a new normal [45]. Therefore, sharing stories could support older adults going through health changes to cope, so this process is not viewed and experienced as failure [63]. Such stories may be a form of narrative care, benefiting both the storyteller and the listeners [59, 116]. Providing features that allow users to incorporate different kinds of data (e.g., images, textual accounts, hashtags) to what is captured by home monitoring will facilitate adding contextual information [77] and sharing data through storytelling [38]. As Pichon et al. [101] suggested, users could also benefit from curating their data to share specific aspects of it with others. For example, users might disclose or highlight different aspects of the data depending on who is the recipient.

Time spent outside the home can be an indirect measure of physical activity, particularly for those who do not have a habit of exercising at home (e.g., using a personal treadmill) because it encompasses time spent walking, hiking, gardening, volunteering, running errands, or exercising at a gym. Certainly, such time can also be sedentary. Still, in the case of retired older adults, many sedentary outside activities are beneficial for their well-being. Tracking these data could be done alongside other measurements, such as steps or active minutes, depending on the users' needs and interests.

Time spent outside the home can be meaningful for older adults while encompassing a broad concept of being active, including social events, volunteering, or just spending time around nature. Therefore, this metric is less centered on medical perspectives in comparison with data that directly measures physical activity, such as step counts. This kind of data could be prioritized for self-reflection to move away from overly medicalized narrative, instead focusing on pleasure [100] and social experiences [25]. Incorporating non-numeric data in the form of annotations or images could also help users to reflect on pleasurable aspects of physical activity through documenting it in different ways and focusing on physical sensations the person experiences [100]. For example, when the person goes hiking, they could add pictures of the trail or notes about enjoying the fresh air.

## 6 LIMITATIONS

This study has a few limitations. Participants' privacy attitudes were influenced by this project being conducted by researchers from a local university. They might have felt differently, possibly having more privacy concerns, if they were using a system from a less trusted organization [8]. We did not collect data on privacy attitudes beyond the qualitative interviews reported in this study. There is an opportunity for future work to examine carefully privacy perceptions of motion sensing data, informed by the rich literature on data privacy in HCI.

The association of activity level with time spent outside the home was influenced by the participants' contexts, as their physical activity took place outdoors or at a gym. No participant had a treadmill or similar equipment at home. Their habits outside of the home could be sedentary, but still would be considered part of an "active life" such as volunteering and socializing. At the same time, factors such as the presence of pets in the home limited the accuracy and utility of the data for this purpose.

## 7 CONCLUSION

Moving away from a deficit discourse about aging involves prioritizing older adults' needs and perspectives. In the case of smart home monitoring technologies, we can provide direct benefits to older adults as users by collecting and displaying data that are meaningful to them. In this paper, we provide a detailed account of older adults' experiences of living with smart home monitoring and engaging with their home data. We find that they exhibit interest in data that are perceived as indicators of living an active life. Time spent outside of the home emerged as most common and direct indicator. To make sense of their data, older adults created hypotheses and made comparisons with peers. Although designing to encourage or support these comparisons could provide benefits to this population in the short-term, we draw from critical gerontology literature to reflect on ethical issues to consider in future technology design and research.

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## REFERENCES

[1] AARP. 2019. 2018 home and community preferences: a national survey of adults ages 18-plus.

[2] Juan C Aceros, Jeannette Pols, and Miquel Domènech. 2015. Where is grandma? home telecare, good aging and the domestication of later life. *Technological Forecasting and Social Change*, 93, 102–111.

[3] Ryan Ahmed, Tammy Toscos, Romisa Rohani Ghahari, Richard J Holden, Elizabeth Martin, Shauna Wagner, Carly Daley, Amanda Coupe, and Michael Mirro. 2019. Visualization of cardiac implantable electronic device data for older adults using participatory design. *Applied clinical informatics*, 10, 04, 707–718.

[4] Deemah Alqahtani, Caroline Jay, and Markel Vigo. 2022. Spatio-temporal and contextual cues to support reflection in physical activity tracking. *International Journal of Human-Computer Studies*, 102865.

[5] Aloha Hufana Ambe, Margot Brereton, Alessandro Soro, Laurie Buys, and Paul Roe. 2019. The adventures of older authors: exploring futures through co-design fictions. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–16.

[6] Mohsen Amiribesheli, Asma Benmansour, and Abdelhamid Bouchachia. 2015. A review of smart homes in healthcare. *Journal of Ambient Intelligence and Humanized Computing*, 6, 4, 495–517.

[7] Ingrid Arreola, Zan Morris, Matthew Francisco, Kay Connelly, Kelly Caine, and Ginger White. 2014. From checking on to checking in: designing for low socio-economic status older adults. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1933–1936.

[8] Brooke Auxier, Lee Rainie, Monica Anderson, Andrew Perrin, Madhu Kumar, and Erica Turner. 2019. Americans and privacy: concerned, confused and feeling lack of control over their personal information.

[9] Liat Ayalon, Alison Chasteen, Manfred Diehl, Becca Levy, Shevaun D Neupert, Klaus Rothermund, Clemens Tesch-Römer, and Hans-Werner Wahl. 2020. Aging in times of the covid-19 pandemic: avoiding ageism and fostering intergenerational solidarity. *The Journals of Gerontology: Series B*.

[10] Natã Miccael Barbosa, Joon S Park, Yaxing Yao, and Yang Wang. 2019. " what if?" predicting individual users' smart home privacy preferences and their changes. *Proc. Priv. Enhancing Technol.*, 2019, 4, 211–231.

[11] J Graham Beaumont and Pamela M Kenealy. 2004. Quality of life perceptions and social comparisons in healthy old age. *Ageing & Society*, 24, 5, 755–769.

[12] Jesse Bennett, Richard Fry, and Rakesh Kochhar. 2020. Are you in the american middle class? find out with our income calculator.

[13] Jeremy Birnholtz and McKenzie Jones-Rounds. 2010. Independence and interaction: understanding seniors' privacy and awareness needs for aging in place. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 143–152.

[14] Virginia Braun and Victoria Clarke. 2012. Thematic analysis.

[15] Robin N Brewer. 2022. "if alexa knew the state i was in, it would cry": older adults' perspectives of voice assistants for health. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts*, 1–8.

[16] Kelly E Caine, Celine Y Zimmerman, Zachary Schall-Zimmerman, William R Hazlewood, L Jean Camp, Katherine H Connelly, Lesa L Huber, and Kalpana Shankar. 2011. Digiswitch: a device to allow older adults to monitor and direct the collection and transmission of health information collected at home. *Journal of medical systems*, 35, 5, 1181–1195.

[17] Gabriela Cajamarca, Valeria Herskovic, and Pedro O Rossel. 2020. Enabling older adults' health self-management through self-report and visualization—a systematic literature review. *Sensors*, 20, 15, 4348.

[18] Clara Caldeira, Matthew Bietz, Marisol Vidauri, and Yunan Chen. 2017. Senior care for aging in place: balancing assistance and independence. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1605–1617.

[19] Clara Caldeira, Novia Nurain, and Kay Connelly. 2022. "i hope i never need one": unpacking stigma in aging in place technology. In *CHI Conference on Human Factors in Computing Systems*, 1–12.

[20] Ann Cavoukian. 2009. Privacy by design.

[21] Pamara F Chang, Natalya N Bazarova, and Elaine Wethington. 2020. How older adults with chronic pain manage social support interactions with mobile media. *Health Communication*, 1–13.

[22] Yu Chen, Yunan Chen, Mirana Michelle Randriambelonoro, Antoine Geissbuhler, and Pearl Pu. 2017. Design considerations for social fitness applications: comparing chronically ill patients and healthy adults. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1753–1762.

[23] Eun Kyoung Choe, Bongshin Lee, Haining Zhu, Nathalie Henry Riche, and Dominikus Baur. 2017. Understanding self-reflection: how people reflect on personal data through visual data exploration. In *Proceedings of the 11th EAI International Conference on Pervasive Computing Technologies for Healthcare*, 173–182.

[24] Sunny Consolvo, Peter Roessler, and Brett E Shelton. 2004. The carenet display: lessons learned from an in home evaluation of an ambient display. In *International conference on ubiquitous computing*. Springer, 1–17.

[25] Denise A Copelton. 2010. Output that counts: pedometers, sociability and the contested terrain of older adult fitness walking. *Sociology of health & illness*, 32, 2, 304–318.

[26] Karen L Courtney. 2008. Privacy and senior willingness to adopt smart home information technology in residential care facilities. *Methods of information in medicine*, 47, 01, 76–81.

[27] Ine D'haeseleer, Kathrin Gerling, Dominique Schreurs, Bart Vanrumste, and Vero Vanden Abeele. 2019. Ageing is not a disease: pitfalls for the acceptance of self-management health systems supporting healthy ageing. In *The 21st International ACM SIGACCESS Conference on Computers and Accessibility*, 286–298.

[28] Cathrine Degnen. 2007. Minding the gap: the construction of old age and oldness amongst peers. *Journal of Aging Studies*, 21, 1, 69–80.

[29] George Demiris, Brian K Hensel, Marjorie Skubic, and Marilyn Rantz. 2008. Senior residents' perceived need of and preferences for "smart home" sensor technologies. *International journal of technology assessment in health care*, 24, 1, 120–124.

[30] George Demiris, Debra Parker Oliver, Geraldine Dickey, Marjorie Skubic, and Marilyn Rantz. 2008. Findings from a participatory evaluation of a smart home application for older adults. *Technology and health care*, 16, 2, 111–118.

[31] Audrey Desjardins, Heidi R Biggs, Cayla Key, and Jeremy E Viny. 2020. Iot data in the home: observing entanglements and drawing new encounters. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–13.

[32] Robert F Dickerson, Eugenia I Gorlin, and John A Stankovic. 2011. Empath: a continuous remote emotional health monitoring system for depressive illness. In *Proceedings of the 2nd Conference on Wireless Health*, 1–10.

[33] Julie Doyle, Niamh Caprani, and Rodd Bond. 2015. Older adults' attitudes to self-management of health and wellness through smart home data. In *2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*. IEEE, 129–136.

[34] Julie Doyle, Lorcan Walsh, Antonella Sassu, and Teresa McDonagh. 2014. Designing a wellness self-management tool for older adults: results from a field trial of yourwellness. In *Proceedings of the 8th international conference on pervasive computing technologies for healthcare*, 134–141.

[35] John Duncan, L Jean Camp, and William R Hazelwood. 2009. The portal monitor: a privacy-enhanced event-driven system for elder care. In *Proceedings of the 4th international conference on persuasive technology*, 1–9.

[36] Marılia Duque. 2021. Performing healthy ageing through images: from broadcasting to silence. *Global Media and China*, 6, 3, 303–324.

[37] Daniel Epstein, Felicia Cordeiro, Elizabeth Bales, James Fogarty, and Sean Munson. 2014. Taming data complexity in lifelogs: exploring visual cuts of personal informatics data. In *Proceedings of the 2014 conference on Designing interactive systems*, 667–676.

[38] Daniel A Epstein, Mira Dontcheva, James Fogarty, and Sean A Munson. 2020. Yarn: adding meaning to shared personal data through structured storytelling. In *Graphics Interface*.

[39] Daniel A Epstein et al. 2020. Mapping and taking stock of the personal informatics literature. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 4, 4, 1–38.

[40] Marcelo Fernández, Iyubanit Rodrıguez, Pedro O Rossel, Carolina Fuentes, and Valeria Herskovic. 2017. Inmyday: a digital diary to promote self-care among elders. In *International Conference on Ubiquitous Computing and Ambient Intelligence*. Springer, 486–497.

[41] Clayton Feustel, Shyamak Aggarwal, Bongshin Lee, and Lauren Wilcox. 2018. People like me: designing for reflection on aggregate cohort data in personal informatics systems. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2, 3, 1–21.

[42] Joel E Fischer, Andy Crabtree, Tom Rodden, James A Colley, Enrico Costanza, Michael O Jewell, and Sarvapali D Ramchurn. 2016. " just whack it on until it gets hot" working with iot data in the home. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 5933–5944.

[43] Susannah Fox and Maeve Duggan. 2013. *Tracking for health*. Pew Research Center's Internet & American Life Project.

[44] Colleen Galambos, Marjorie Skubic, Shaung Wang, and Marilyn Rantz. 2013. Management of dementia and depression utilizing in-home passive sensor data. *Gerontechnology: international journal on the fundamental aspects of technology to serve the ageing society*, 11, 3, 457.

[45] Shelagh K Genuis and Jenny Bronstein. 2017. Looking for "normal": sense making in the context of health disruption. *Journal of the Association for Information Science and Technology*, 68, 3, 750–761.

[46] Kathrin Gerling, Mo Ray, Vero Vanden Abeele, and Adam B Evans. 2020. Critical reflections on technology to support physical activity among older adults: an exploration of leading hci venues. *ACM Transactions on Accessible Computing (TACCESS)*, 13, 1, 1–23.

[47] Erving Goffman. 2016. The presentation of self in everyday life. In *Social Theory Re-Wired*. Routledge, 482–493.

[48] Richard Harper et al. 2011. *The connected home: The future of domestic life*. Springer.

[49] Christina N Harrington, Ben Jelen, Amanda Lazar, Aqueasha Martin-Hammond, Alisha Pradhan, Blaine Reeder, and Katie Siek. 2021. Taking stock of the present and future of smart technologies for older adults and caregivers. *arXiv preprint arXiv:2104.00096*.

[50] Christina N Harrington, Lauren Wilcox, Kay Connelly, Wendy Rogers, and Jon Sanford. 2018. Designing health and fitness apps with older adults: examining the value of experience-based co-design. In *Proceedings of the 12th EAI international conference on pervasive computing technologies for healthcare*, 15–24.

[51] Tad Hirsch, Jodi Forlizzi, Elaine Hyder, Jennifer Goetz, Chris Kurtz, and Jacey Stroback. 2000. The elder project: social, emotional, and environmental factors in the design of eldercare technologies. In *Proceedings on the 2000 conference on Universal Usability*, 72–79.

[52] Martha B Holstein and Meredith Minkler. 2003. Self, society, and the "new gerontology". *The Gerontologist*, 43, 6, 787–796.

[53] Lesa Lorenzen Huber, Kalpana Shankar, Kelly Caine, Kay Connelly, L Jean Camp, Beth Ann Walker, and Lisa Borrero. 2013. How in-home technologies mediate caregiving relationships in later life. *International Journal of Human-Computer Interaction*, 29, 7, 441–455.

[54] Laura C Hurd. 1999. "we're not old!": older women's negotiation of aging and oldness. *Journal of aging studies*, 13, 4, 419–439.

[55] Cynthia S Jacelon and Allen Hanson. 2013. Older adults' participation in the development of smart environments: an integrated review of the literature. *Geriatric Nursing*, 34, 2, 116–121.

[56] Ian Rees Jones and Paul F Higgs. 2010. The natural, the normal and the normative: contested terrains in ageing and old age. *Social science & medicine*, 71, 8, 1513–1519.

[57] Dmitri S Katz, Blaine A Price, Simon Holland, and Nicholas Sheep Dalton. 2018. Data, data everywhere, and still too hard to link: insights from user interactions with diabetes apps. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–12.

[58] Stephen Katz and Barbara L Marshall. 2018. Tracked and fit: fitbits, brain games, and the quantified aging body. *Journal of aging studies*, 45, 63–68.

[59] Gary Kenyon. 2015. Physical activity and dementia: tai chi as narrative care. In *Physical Activity and Sport in Later Life*. Springer, 92–100.

[60] Bran Knowles et al. 2020. The harm in conflating aging with accessibility. *Communications of the ACM*.

[61] John Kretzmann and John P McKnight. 1996. Assets-based community development. *National civic review*, 85, 4, 23–30.

[62] Albrecht Kurze, Andreas Bischof, Sören Totzauer, Michael Storz, Maximilian Eibl, Margot Brereton, and Arne Berger. 2020. Guess the data: data work to understand how people make sense of and use simple sensor data from homes. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–12.

[63] Sarah Lamb. 2014. Permanent personhood or meaningful decline? toward a critical anthropology of successful aging. *Journal of aging studies*, 29, 41–52.

[64] Amanda Lazar, Mark Diaz, Robin Brewer, Chelsea Kim, and Anne Marie Piper. 2017. Going gray, failure to hire, and the ick factor: analyzing how older bloggers talk about ageism. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 655–668.

[65] Amanda Lazar, Norman Makoto Su, Jeffrey Bardzell, and Shaowen Bardzell. 2019. Parting the red sea: sociotechnical systems and lived experiences of menopause. In *Proceedings of the 2019 CHI conference on human factors in computing systems*, 1–16.
[66] Matthew L Lee and Anind K Dey. 2011. Reflecting on pills and phone use: supporting awareness of functional abilities for older adults. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2095–2104.
[67] Matthew L Lee and Anind K Dey. 2015. Sensor-based observations of daily living for aging in place. *Personal and Ubiquitous Computing*, 19, 1, 27–43.
[68] Sukwon Lee, Sung-Hee Kim, Ya-Hsin Hung, Heidi Lam, Youn-ah Kang, and Ji Soo Yi. 2015. How do people make sense of unfamiliar visualizations?: a grounded model of novice's information visualization sensemaking. *IEEE transactions on visualization and computer graphics*, 22, 1, 499–508.
[69] Becca R Levy, Martin D Slade, Suzanne R Kunkel, and Stanislav V Kasl. 2002. Longevity increased by positive self-perceptions of aging. *Journal of personality and social psychology*, 83, 2, 261.
[70] Ian Li, Anind Dey, and Jodi Forlizzi. 2010. A stage-based model of personal informatics systems. In *Proceedings of the SIGCHI conference on human factors in computing systems*, 557–566.
[71] Ann Light, Tuck W Leong, and Toni Robertson. 2015. Ageing well with cscw. In *ECSCW 2015: Proceedings of the 14th European Conference on Computer Supported Cooperative Work, 19-23 September 2015, Oslo, Norway*. Springer, 295–304.
[72] James J Lin, Lena Mamykina, Silvia Lindtner, Gregory Delajoux, and Henry B Strub. 2006. Fish'n'steps: encouraging physical activity with an interactive computer game. In *International conference on ubiquitous computing*. Springer, 261–278.
[73] Siân E Lindley, Richard Harper, and Abigail Sellen. 2008. Designing for elders: exploring the complexity of relationships in later life. *People and Computers XXII Culture, Creativity, Interaction 22*, 77–86.
[74] Stine Lomborg, Henriette Langstrup, and Tariq Osman Andersen. 2020. Interpretation as luxury: heart patients living with data doubt, hope, and anxiety. *Big Data & Society*, 7, 1, 2053951720924436.
[75] Lesa Lorenzen-Huber, Mary Boutain, L Jean Camp, Kalpana Shankar, and Kay H Connelly. 2011. Privacy, technology, and aging: a proposed framework. *Ageing International*, 36, 2, 232–252.
[76] Deborah Lupton. 2018. 'i just want it to be done, done, done!'food tracking apps, affects, and agential capacities. *Multimodal Technologies and Interaction*, 2, 2, 29.
[77] Lucas M. Silva and Daniel A. Epstein. 2021. Investigating preferred food description practices in digital food journaling. In *Designing Interactive Systems Conference 2021*, 589–605.
[78] Lena Mamykina et al. 2017. Personal discovery in diabetes self-management: discovering cause and effect using self-monitoring data. *Journal of biomedical informatics*, 76, 1–8.
[79] Shrirang Mare, Franziska Roesner, and Tadayoshi Kohno. 2020. Smart devices in airbnbs: considering privacy and security for both guests and hosts. *Proc. Priv. Enhancing Technol.*, 2020, 2, 436–458.
[80] Karola Marky, Alexandra Voit, Alina Stöver, Kai Kunze, Svenja Schröder, and Max Mühlhäuser. 2020. " i don't know how to protect myself": understanding privacy perceptions resulting from the presence of bystanders in smart environments. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*, 1–11.
[81] Barbara L Marshall and Stephen Katz. 2016. How old am i.
[82] Barbara L Marshall and Stephen Katz. 2012. The embodied life course: post-ageism or the renaturalization of gender? *Societies*, 2, 4, 222–234.
[83] Andrew McNeill, Pam Briggs, Jake Pywell, and Lynne Coventry. 2017. Functional privacy concerns of older adults about pervasive health-monitoring systems. In *Proceedings of the 10th international conference on pervasive technologies related to assistive environments*, 96–102.
[84] Helena M Mentis, Galina Madjaroff, and Aaron K Massey. 2019. Upside and downside risk in online security for older adults with mild cognitive impairment. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–13.
[85] Tom Merritt. 2007. Cnet top 5: worst products in a decade. (2007).
[86] Alex Mihailidis, Brent Carmichael, and Jennifer Boger. 2004. The use of computer vision in an intelligent environment to support aging-in-place, safety, and independence in the home. *IEEE Transactions on information technology in biomedicine*, 8, 3, 238–247.
[87] Mareike Münch et al. 2019. Mobility assessment with modern technology in older patients' real-life by the general practitioner: the mobitec-gp study protocol. *BMC Public Health*, 19, 1, 1–10.
[88] Erik S Musiek, Meghana Bhimasani, Margaret A Zangrilli, John C Morris, David M Holtzman, and Yo-El S Ju. 2018. Circadian rest-activity pattern changes in aging and preclinical alzheimer disease. *JAMA neurology*, 75, 5, 582–590.

[89] Pardis Emami Naeini, Sruti Bhagavatula, Hana Habib, Martin Degeling, Lujo Bauer, Lorrie Faith Cranor, and Norman Sadeh. 2017. Privacy expectations and preferences in an iot world. In *Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017)*. USENIX Association Santa Clara, 399–412.

[90] Soud Nassir, Tuck Wah Leong, and Toni Robertson. 2015. Positive ageing: elements and factors for design. In *Proceedings of the Annual Meeting of the Australian Special Interest Group for Computer Human Interaction*, 264–268.

[91] Louis Neven. 2015. By any means? questioning the link between gerontechnological innovation and older people's wish to live at home. *Technological forecasting and social change*, 93, 32–43.

[92] Qin Ni, Ana Belen Garcia Hernando, De la Cruz, and Iván Pau. 2015. The elderly's independent living in smart homes: a characterization of activities and sensing infrastructure survey to facilitate services development. *Sensors*, 15, 5, 11312–11362.

[93] Leysan Nurgalieva, Alisa Frik, Francesco Ceschel, Serge Egelman, and Maurizio Marchese. 2019. Information design in an aged care context: views of older adults on information sharing in a care triad. In *Proceedings of the 13th EAI international conference on pervasive computing technologies for healthcare*, 101–110.

[94] Shigeru Ohta, Hiroshi Nakamoto, Yoshimitsu Shinagawa, and Tomohiro Tanikawa. 2002. A health monitoring system for elderly people living alone. *Journal of telemedicine and telecare*, 8, 3, 151–156.

[95] Sebastiaan Theodorus Michaël Peek, Eveline JM Wouters, Katrien G Luijkx, and Hubertus JM Vrijhoef. 2016. What it takes to successfully implement technology for aging in place: focus groups with stakeholders. *Journal of medical Internet research*, 18, 5, e5253.

[96] Sebastiaan TM Peek, Eveline JM Wouters, Joost Van Hoof, Katrien G Luijkx, Hennie R Boeije, and Hubertus JM Vrijhoef. 2014. Factors influencing acceptance of technology for aging in place: a systematic review. *International journal of medical informatics*, 83, 4, 235–248.

[97] Kirsten KB Peetoom, Monique AS Lexis, Manuela Joore, Carmen D Dirksen, and Luc P De Witte. 2015. Literature review on monitoring technologies and their outcomes in independently living elderly people. *Disability and Rehabilitation: Assistive Technology*, 10, 4, 271–294.

[98] Alexander Peine and Louis Neven. 2019. From intervention to co-constitution: new directions in theorizing about aging and technology. *The Gerontologist*, 59, 1, 15–21.

[99] Tuan Pham, Shannon Mejıa, Ronald A Metoyer, and Karen Hooker. 2012. The effects of visualization feedback on promoting health goal progress in older adults. In *EuroVis (Short Papers)*.

[100] Cassandra Phoenix and Noreen Orr. 2015. The multidimensionality of pleasure in later life physical activity. In *Physical activity and sport in later life*. Springer, 101–112.

[101] Adrienne Pichon, Kayla Schiffer, Emma Horan, Bria Massey, Suzanne Bakken, Lena Mamykina, and Noemie Elhadad. 2021. Divided we stand: the collaborative work of patients and providers in an enigmatic chronic disease. *Proceedings of the ACM on Human-Computer Interaction*, 4, CSCW3, 1–24.

[102] Susan Pickard. 2011. Health, illness and normality: the case of old age. *BioSocieties*, 6, 3, 323–341.

[103] Elizabeth Pike. 2012. Growing old (dis) gracefully?: the gender/ageing/exercise nexus.

[104] Jeannette Pols, Dick Willems, and Margunn Aanestad. 2019. Making sense with numbers. unravelling ethico-psychological subjects in practices of self-quantification. *Sociology of health & illness*, 41, 98–115.

[105] Eduardo Quintana and Jesus Favela. 2013. Augmented reality annotations to assist persons with alzheimers and their caregivers. *Personal and ubiquitous computing*, 17, 6, 1105–1116.

[106] Shriti Raj, Joyce M Lee, Ashley Garrity, and Mark W Newman. 2019. Clinical data in context: towards sensemaking tools for interpreting personal health data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 3, 1, 1–20.

[107] Marilyn J Rantz, Marjorie Skubic, Richelle J Koopman, Lorraine Phillips, Gregory L Alexander, Steven J Miller, and Rainer Dane Guevara. 2011. Using sensor networks to detect urinary tract infections in older adults. In *2011 IEEE 13th International Conference on e-Health Networking, Applications and Services*. IEEE, 142–149.

[108] Blaine Reeder, Jane Chung, Kate Lyden, Joshua Winters, and Catherine M Jankowski. 2020. Older women's perceptions of wearable and smart home activity sensors. *Informatics for Health and Social Care*, 45, 1, 96–109.

[109] Blaine Reeder, Ellen Meyer, Amanda Lazar, Shomir Chaudhuri, Hilaire J Thompson, and George Demiris. 2013. Framing the evidence for health smart homes and home-based consumer health technologies as a public health intervention for independent aging: a systematic review. *International journal of medical informatics*, 82, 7, 565–579.

[110] Yann Riche and Wendy Mackay. 2010. Peercare: supporting awareness of rhythms and routines for better aging in place. *Computer Supported Cooperative Work (CSCW)*, 19, 1, 73–104.

[111] Jennifer Boyd Ritsher, Poorni G Otilingam, and Monica Grajales. 2003. Internalized stigma of mental illness: psychometric properties of a new measure. *Psychiatry research*, 121, 1, 31–49.

[112] Erin L Robinson, Geunhye Park, Kari Lane, Marjorie Skubic, and Marilyn Rantz. 2020. Technology for healthy independent living: creating a tailored in-home sensor system for older adults and family caregivers. *Journal of gerontological nursing*, 46, 7, 35–40.

[113] Wendy A Rogers and Arthur D Fisk. 2010. Toward a psychological science of advanced technology design for older adults. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 65, 6, 645–653.
[114] Yvonne Rogers, Kay Connelly, Lenore Tedesco, William Hazlewood, Andrew Kurtz, Robert E Hall, Josh Hursey, and Tammy Toscos. 2007. Why it's worth the hassle: the value of in-situ studies when designing ubicomp. In *International conference on ubiquitous computing*. Springer, 336–353.
[115] Jim Rowan and Elizabeth D Mynatt. 2005. Digital family portrait field trial: support for aging in place. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, 521–530.
[116] Herman Saksono, Carmen Castaneda-Sceppa, Jessica A Hoffman, Magy Seif El-Nasr, and Andrea Parker. 2021. Storymap: using social modeling and self-modeling to support physical activity among families of low-ses backgrounds. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–14.
[117] Rachel Sanders. 2017. Self-tracking in the digital era: biopower, patriarchy, and the new biometric body projects. *Body & Society*, 23, 1, 36–63.
[118] John S Seberger, Marissel Llavore, Nicholas Nye Wyant, Irina Shklovski, and Sameer Patil. 2021. Empowering resignation: there's an app for that. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–18.
[119] Kalpana Shankar, L Jean Camp, Kay Connelly, and Lesa Huber. 2011. Aging, privacy, and home-based computing: developing a design framework. *IEEE Pervasive Computing*, 11, 4, 46–54.
[120] Yannick Stephan, Aına Chalabaev, Dana Kotter-Grühn, and Alban Jaconelli. 2013. "feeling younger, being stronger": an experimental study of subjective age and physical functioning among older adults. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 68, 1, 1–7.
[121] Damien Stones and Judith Gullifer. 2016. 'at home it's just so much easier to be yourself': older adults' perceptions of ageing in place. *Ageing & Society*, 36, 3, 449–481.
[122] Madiha Tabassum, Tomasz Kosinski, and Heather Richter Lipford. 2019. " i don't own the data": end user perceptions of smart home device data practices and risks. In *Fifteenth Symposium on Usable Privacy and Security (SOUPS 2019)*, 435–450.
[123] Peter Tolmie, Andy Crabtree, Tom Rodden, James Colley, and Ewa Luger. 2016. "this has to be the cats" personal data legibility in networked sensing systems. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, 491–502.
[124] Anne M Turner, Jean O Taylor, Andrea L Hartzler, Katie P Osterhage, Alyssa L Bosold, Ian S Painter, and George Demiris. 2021. Personal health information management among healthy older adults: varying needs and approaches. *Journal of the American Medical Informatics Association*, 28, 2, 322–333.
[125] Kea Turner, Ara Jo, Grace Wei, Amir Alishahi Tabriz, Alecia Clary, and Heather SL Jim. 2021. Sharing patient-generated data with healthcare providers: findings from a 2019 national survey. *Journal of the American Medical Informatics Association*, 28, 2, 371–376.
[126] Jenny Vafeiadou, Asimina Vasalou, and George Roussos. 2021. Self-tracking in parkinson's the lived efforts of self-management. *Proceedings of the ACM on Human-Computer Interaction*, 5, CSCW1, 1–25.
[127] Yasmin van Kasteren, Dana Bradford, Qing Zhang, Mohan Karunanithi, Hang Ding, et al. 2017. Understanding smart home sensor data for ageing in place through everyday household routines: a mixed method case study. *JMIR mHealth and uHealth*, 5, 6, e5773.
[128] Dimitri Vargemidis, Kathrin Gerling, Vero Vanden Abeele, Luc Geurts, and Katta Spiel. 2021. Irrelevant gadgets or a source of worry: exploring wearable activity trackers with older adults. *ACM Transactions on Accessible Computing (TACCESS)*, 14, 3, 1–28.
[129] John Vines, Stephen Lindsay, Gary W Pritchard, Mabel Lie, David Greathead, Patrick Olivier, and Katie Brittain. 2013. Making family care work: dependence, privacy and remote home monitoring telecare systems. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing*, 607–616.
[130] Lisa M Vizer, Jordan Eschler, Bon Mi Koo, James Ralston, Wanda Pratt, and Sean Munson. 2019. "it's not just technology, it's people": constructing a conceptual model of shared health informatics for tracking in chronic illness management. *Journal of medical Internet research*, 21, 4, e10830.
[131] Emily A Vogels. 2020. About one-in-five americans use a smart watch or fitness tracker. (2020).
[132] Alexandra Voit, Dominik Weber, Elizabeth Stowell, and Niels Henze. 2017. Caloo: an ambient pervasive smart calendar to support aging in place. In *Proceedings of the 16th International Conference on Mobile and Ubiquitous Multimedia*, 25–30.
[133] Shuang Wang, Marjorie Skubic, and Yingnan Zhu. 2012. Activity density map visualization and dissimilarity comparison for eldercare monitoring. *IEEE Transactions on Information Technology in Biomedicine*, 16, 4, 607–614.
[134] Jenny Waycott, Frank Vetere, Sonja Pedell, Amee Morgans, Elizabeth Ozanne, and Lars Kulik. 2016. Not for me: older adults choosing not to participate in a social isolation intervention. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 745–757.

[135] David Weiss and Alexandra M Freund. 2012. Still young at heart: negative age-related information motivates distancing from same-aged people. *Psychology and aging*, 27, 1, 173.
[136] Ginger White, Tanya Singh, Kelly Caine, and Kay Connelly. 2015. Limited but satisfied: low ses older adults experiences of aging in place. In *2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)*. IEEE, 121–128.
[137] Bethany Wilton-Harding and Tim D Windsor. 2021. Awareness of age-related gains and losses and their associations with psychological well-being: a longitudinal examination. *The Journals of Gerontology: Series B*.
[138] Marisol Wong-Villacres, Carl DiSalvo, Neha Kumar, and Betsy DiSalvo. 2020. Culture in action: unpacking capacities to inform assets-based design. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–14.
[139] Wenlong Wu, James M Keller, Marjorie Skubic, Mihail Popescu, and Kari R Lane. 2021. Early detection of health changes in the elderly using in-home multi-sensor data streams. *ACM Transactions on Computing for Healthcare*, 2, 3, 1–23.
[140] Susanne Wurm and Gerben J Westerhof. 2015. Longitudinal research on subjective aging, health, and longevity: current evidence and new directions for research. *Annual review of gerontology and geriatrics*, 35, 1, 145–165.
[141] Yang Yang. 2006. How does functional disability affect depressive symptoms in late life? the role of perceived social support and psychological resources. *Journal of health and social behavior*, 47, 4, 355–372.
[142] Salifu Yusif, Jeffrey Soar, and Abdul Hafeez-Baig. 2016. Older people, assistive technologies, and the barriers to adoption: a systematic review. *International journal of medical informatics*, 94, 112–116.

# A APPENDIX

Table 2. Detailed information about data collected for each participant. Dates are provided in MM/DD/YY format. The median number of sensors is 14 and the median time of participation in the study is 2 years and 5 months. The number of days and interviews vary due to participants dropping out of the study, opting out of certain interviews, or being unavailable. These variations were influenced by the COVID-19 pandemic.

| P | Sensors | Start date | End date | Days of data collected | Interviews |
|---|---|---|---|---|---|
| 1 | 12 | 10/23/18 | 08/08/21 | 342 | 9 |
| 3 | 10 | 12/06/18 | 08/20/19 | 233 | 7 |
| 4 | 16 | 12/10/18 | 06/14/21 | 441 | 9 |
| 6 | 14 | 12/11/18 | 08/20/19 | 189 | 9 |
| 7 | 15 | 12/21/18 | 06/14/21 | 393 | 1 |
| 8 | 19 | 01/17/19 | 09/17/21 | 295 | 9 |
| 9 | 15 | 01/24/19 | 08/20/19 | 158 | 8 |
| 10 | 13 | 02/07/19 | 06/14/21 | 275 | 7 |
| 12 | 13 | 03/06/19 | 08/20/19 | 112 | 1 |
| 13 | 14 | 01/22/19 | 09/06/21 | 233 | 2 |
| 14 | 11 | 03/14/19 | 06/14/21 | 319 | 8 |
| 15 | 16 | 12/05/18 | 06/14/21 | 165 | 8 |

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