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Privacy Concerns in Assisted Living Technologies

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Abstract The challenges of an aging population require the adoption of in-home and medical technologies to complement the traditional caregiver model. Adoption of such technologies is, however, impinged by privacy concerns. This study investigates a four dimensional framework that explains the tradeoffs between functionality and privacy as constructed by older adults. The four dimensions constitute perceived utility, data granularity, data recipient, and activity sensitivity. We conducted a survey based study to empirically examine the applicability and robustness of this framework. Our results have implications for the adoption of a wide range of privacy enhancing technologies. By focusing on the intersection of an under-studied group (non-technical older adults) and sensitive data (medical and at home), this work has the potential to enable Privacy Enhancing Technologies (PETs) that might be widely adopted.

Keywords Older Adults · Privacy · Assisted Living

1 Introduction

As the baby boomers approach the age of retirement, older adults have become the fastest growing demographic in United States and across the world [23].

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Currently adults over 65 form 13% of United States' population. This is expected to increase to 20.7% by 2050[1]. 80% of older adults in the United States have been diagnosed with a chronic health condition, and 50% of those have two or more chronic conditions[2]. This increasingly aging population creates several challenges for the traditional healthcare model [27]. There has been a drive to investigate technological solutions to such challenges, including developing technologies for assisted living that encourage living in place. However, older adults have not been targeted by designers of security and privacy technologies, in part because of the lack of simple design heuristics.

Increasingly older adults are being presented with a dichotomous choice; either a move to institutionalized care with corresponding loss of autonomy or installing invasive assistive monitoring technologies[3], which allow aging in place, and loss of privacy. There is often a hidden third choice, i.e. adopting assistive technologies that are privacy preserving and where the data flow is transparent to the older adult. Given the absence of this third choice in the market, studies often observe that older adults are unconcerned about privacy [7]. However, older adults have not previously been given the option of privacy-preserving technologies.

In this paper we report our survey older adults regarding their willingness to adopt four prototype technologies (described in detail in this paper). These technologies have been designed to be minimally invasive, privacy preserving, and to provide a transparent data flow to the older adult. The one exception is the video camera, which while being privacy infringing can be customized to be less invasive and still provides a transparent flow of data such that the stakeholders are aware how the data is being used. Would older adults be willing to adopt these technologies, thereby indicating that they do care about privacy? If so, what are the underlying determinants of their privacy valuation or tradeoffs? Is it the perceived usefulness of the technology? Is it the sensitivity of the activity about which the information is being collected? Is it the granularity of the data being collected? Or is it the recipient of the data which has the most influence?

Assisted living and medical technologies require monitoring older adults to provide caregiving services. The quality of data collected is critical to the quality of care provided. Thus, technologies that enable older adults to age in place have privacy and health implications [21]. Privacy concerns can hinder adoption as security risks disproportionally expose this vulnerable population to information leakage [11]. While several studies have examined contextual construction of privacy [26] and its impact on adoption, the demographics of sampling make it hard to generalize the findings to older adults [5, 18, 16]. Risk perception can vary significantly with age and this may be true for privacy risks as well.

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[1] `http://www.census.gov/population/www/projections/usinterimproj/`, accessed June 15th, 2012

[2] `http://www.cdc.gov/brfss`, accessed October 15th, 2011

[3] Assistive monitoring technologies refer to solutions that can be used by individuals with chronic conditions and their health care providers to monitor their health behaviors.

Based on initial qualitative studies evaluating current common operationalizations for privacy in home-based and related technologies [?,?], this paper reports on a survey of 101 older adults, grounded in specific aging in place prototypes developed as a result of those earlier studies. Our results suggest that across all of our prototypes, older adults wish to be selective in how they share personal data and information gathered by assistive living technologies. The respondents shared among them a significant disinclination to allow such information to be used by vendors and commercial entities, but would be willing to share with caregivers, medical professionals, and researchers. Similarly, they perceive certain activities monitored by such technologies as "sensitive" (financial information or bathroom/bedroom activities), "generic" (such as eating), or "moderately sensitive" (sleeping, sending/reading email) and wish to filter based on such perceptions. While these findings seem somewhat self-evident, there has been little prior research specifically focused on and grounding perceptions of privacy among older adults and home-based activities. In this paper, we discuss in greater detail the background literature and resultant privacy framework developed in the earlier studies, explain the specific prototypes, and discuss the survey and its results in greater depth. We conclude with limitations of the current study and suggest hypotheses/themes for further exploration and design.

2 Related Work

2.1 Aging in Place

As populations around the world grow older, current models of care may not be sustainable. The costs of institutionalized care, which include assisted living and skilled long term care, will challenge current old age benefit programs. One solution is to develop innovative programs to help older adults to age in place. In the US, 95% of adults over the age of 75 want to stay in their homes as they age [1] and for good reason: aging in place improves perceived quality of life, and supports dignity and independence [13]. Aging in place is also cost effective: health care costs of staying at home are a fraction of the costs of institutionalization [25,30]. With a 3.8% rise in U.S. nursing home costs in 2012, [3], the Administration on Aging has urged all U.S. communities to transform themselves into 'supportive communities' for older adults. Supportive communities modernize systems of care, provide consumers with more control over their lives, and improve the overall quality of life of older adults to ensure that they 'remain at home as long as possible' [2]. Technological solutions can facilitate aging in place for elders and their caregivers. But there are obvious challenges in both adoption of assistive technologies and considerations of personal privacy.

2.2 Adoption of Assistive Technology

The motivators for the adoption of new technology are many, both intrinsic and extrinsic [33]. Perceived usefulness, ease of use, and subjective norms are some of the factors that are often taken into account when assessing how and why a particular technology will be accepted and used [32]. Previous studies exploring older adults‘ acceptance and use of technology has found perceived usefulness to be the most critical determinant for adoption [7,31,24,14]. Demographic predictors such as age, gender, education, and prior experience with technology also influence adoption and use. These studies have focused on relatively impersonal technologies such as computer, internet, and cell phone use by older adults. There is little research using models of technology acceptance of home-based technologies by older adults.

Technology acceptance models do not generally consider context of use [26]. The context of information sharing between an older adult and their formal and informal caregivers can be critical to understanding the dichotomy between expressed attitudes and observed behaviors [19]. Adoption of home-based ubiquitous technologies, e.g. video and sensor monitoring [15], may be impinged by privacy concerns [4]. Models that effectively describe adoption must account for the tradeoffs made by consumers between exposing their personal information and improving their quality of life. Ubiquitous computing has the potential to help older adults live independently, but current trends in ubicomp design have yet to substantively address the inherent privacy challenges. This apathy towards privacy concerns is exacerbated when the only available alternative for the consumer is to move into a nursing/group home or hire a round the clock caregiver. These alternatives are perceived as more privacy infringing than the ubicomp alternatives that attempt to replace them [28].

2.3 Privacy Considerations

Few studies have considered older adults perceptions of privacy related to home-based ubicomp technologies. The research methods used in this work comprises one-time surveys and focus group research [7,34,20]. Findings from these studies suggest that older adults, when faced with the specter of institutionalization, would prefer to trade privacy for the independence and dignity of living in their own homes.

This apparent observed laissez faire attitude toward privacy could result from two misconceptions. First, older adults have a relatively naive understanding of technology which could lead them to perceive an unnecessary trade-off of privacy for independent living. They may, for example, not understand that technologies could be designed to be privacy-friendly and enable the user to control the flow of data. Second, older adults' perceived risk of sharing personal data may be dangerously less than their actual risk. This is particularly problematic given the vulnerability of this population to fraud[4]. Technologies designed to provide transparent data compilation could address elders' underestimation of their privacy risks. The recognition of a need for a better understanding of older adults' perceptions of privacy, particularly in regard to home-based technologies, motivated this work.

Shankar et al. conducted an initial study of the expressions of privacy concerns in assisted living technologies to determine if they fit under the major policy rubrics [29]: seclusion, autonomy, property, or location based [17]. *Seclusion* is the right to be let alone. *Autonomy* refers to agency and an individual's ability to make privacy tradeoffs. The concept of *privacy as property* is grounded in the idea of data is being exchanged; it is transactional. *Location is spatial*; physical location has been long recognized as a critical variable in willingness to share information. Shankar et al.'s initial assumptions were that specific privacy concerns could be determined with qualitative interactions grounded in specific technologies. They conducted a dozen focus groups with 65 participants, which led to the rejection of the formalizations of this legal and economic privacy framework in the case of assistive technologies in the home [29].

Thus, Huber et al. introduced a four dimensional framework that examines older adults' perceptions of privacy risks [22]. The four dimensions consist of perceived usefulness, activity sensitivity, data granularity and data recipient. The framework aims to explain the variance in privacy trade-offs made by older adults in order to address the following questions: Is there a market for assisted living technologies targeted towards older adults that are simultaneously privacy preserving? If so what is the valuation of personal information by older adults, i.e. what price are older adults willing to pay for their privacy? Are the underlying determinants of privacy valuation determined by the perceived usefulness of the technology, the granularity of data being collected, the sensitivity of the activity, and/or the recipient of that data?

This study empirically tests the theoretical grounding of this framework by conducting a survey based study, n=101. The goal is to develop heuristics for design and documentation of Privacy Enhancing Technologies (PETs), medical technology, and technologies to support aging in place so these align with elder expectation and improve diffusion.

3 Methodology

Huber et al. introduced a four dimensional model that captures the privacy vs. technology tradeoffs older adults and associated stakeholders may consider [22]. These dimensions are modeled as perceived usefulness, activity sensitivity, data granularity, and data recipient. Perceived usefulness refers to how

[4] Financial assets owned by older adults are increasing. One-tenth of all publicly held bonds are held by people over 65 years of age [8]. By 2020 older adults will own one-third of all publicly held stocks in America. Older adults are, however, highly susceptible to scams and financial fraud. According to Federal Trade Commission over 20% of the victims of financial fraud are older adults [6]

useful a technology is seen by the consumer. A technology that is not privacy infringing is unlikely to be adopted if it is not perceived to serve a purpose. Activity sensitivity refers to the sensitivity of the activity being recorded by the assisted living technology. For example, reading may not be perceived as highly sensitive, while intimate moments with a partner would.

The complexity of the data collected might also be critical. While less granular data may be desirable in most cases, certain contexts may reverse this preference. For example, the older adult may desire highly granular data on falls. It may be desirable that not only the number of falls is recorded, but also the seriousness of the falls as well as recovery time. This desire for more granular data in this context may be driven by older adults disinclination to be asked to move into a nursing facility, thereby losing their independence. Finally data recipient refers to the entity to which this data is disclosed. Preference here may be driven by perceived trust.

Each of these dimensions may, both individually and in combination, influence the evaluation of the tradeoff between privacy and technology adoption. For example, older adults may be more comfortable sharing data regarding intimacy with their doctor, but not with family members. In this study, we evaluate to what extent these dimensions individually impact technology adoption. Tradeoffs driven by a combination of these dimensions are acknowledged but not evaluated in this study. Thus, we evaluate tradeoffs across dimensions but not between dimensions.

The framework is evaluated by conducting a survey, whose design is detailed later in section 3.2. The survey is used to collect data on older adults' expressed preferences regarding their privacy. Since privacy concerns are contextually situated, we used distinct prototypes of technologies that allow older adults to age in place; these are described below in section 3.1. The data is analyzed to explore whether the mean comfort level of sharing information is driven by its usefulness, granularity of the data collected, the sensitivity of the activity, or whom the data is shared with. Thus, we will compare the difference in average comfort of information sharing, for example, based on whether the information shared is highly granular or not. Intuitively, based on prior work [22] we posit that when information sharing is perceived to be more useful, the data collected is less granular, the sensitivity of the activity is low, and the recipient is more trusted, individuals would be more comfortable with sharing. Finally, we are also interested in how these four dimensions inform the individual's willingness to pay for technology. Thus, we also build logistic regression models to investigate whether a combination of the four dimensions can determine whether or not an individual will pay for the technology.

3.1 Prototypes

In previous research we developed several prototypes to enable older adults' to age in place. One goal with these prototypes has been to make the flow of data visible to the consumer. These designs address a diversity of contexts and thus a diversity of data types. Our previous work examines the usability of these technologies [10]. Here we examined the privacy implications of that these technologies. We considered a subset of technologies consisting of four prototypes to test the applicability of the privacy framework. The four prototypes were chosen to provide a diversity of contexts and eliminate any observations that may arise due to specific situational biases.

Beacon Strip: A beacon strip is an assisted living technology that uses pressure pads to help older adults navigate in the dark. It can detect when an older adult wakes up and light up a pathway from their bed to the restroom. It can also detect falls. It records information such as weight, body temperature, movement patterns, and sleep duration etc.

Video Camera: A video camera is a video recording device in the home of the older adult. Remote caregivers can use the video camera to monitor the activities of the older adult.

Presence Clock: The presence clock is an assisted living technology that allows caregivers to be aware of the older adults movements while being minimally invasive. The presence clock is placed in the home of the older adult and paired with a clock in a caregivers home. The presence clock detects proximity and transmits this data to its sister clocks. Thus every time the older adult is near their presence clock the respective sister clocks would light up. The presence clock can be configured to transmit complementary information such as the number of people present or who those people are.

Ambient Cube: The ambient cube is a USB plugin device. It collects information about the users incoming and outgoing Internet activity. Data collected may include websites visited and information provided on those websites. It identifies spam, scam, phishing websites etc. and warns the user. Thus it allows the user, in this case the older adult, to browse the Internet more safely.

The descriptions provided above were used verbatim in the survey instrument. These descriptions are not always true to what the device is currently capable of achieving. While the video camera is not minimally privacy infringing, it can be customized to be less invasive. Similar to the other prototypes the data flow is transparent to the stakeholders so that they are aware how the data is being used. The presence clock would require additional sensors if used to detect the identity of who is present. Currently, it does provide a 12 hour history of detected movement. The beacon strip does not measure body temperature, instead it evaluates sleep quality. The not quite accurate descriptions of the devices were provided to the participants, so as to facilitate the design of the survey instrument, i.e. questions that would be more helpful in evaluating the four privacy constructs being considered in this study.

3.2 Survey Design

The survey was divided into six sections. The first section contained demographic questions. The format of these questions was adopted from the Consumer Privacy Survey 2005. Sections two, three, four and five referred to each of the respective prototypes. For each prototype the survey provided a description of its function. The respondents were then asked to rate the usefulness of the respective prototype.

Subsequent questions targeted the dimensions of activity sensitivity, data granularity and data recipient. We considered five data recipients: primary caregiver, doctor, family, researchers, and commercial vendors. Respondents were asked to rate their comfort in data sharing with the five recipients on a scale of 1 to 5; 1= Very Uncomfortable (VU), 5= Very Comfortable (VC). Due to the difference in functionality, respective items for activity sensitivity and data granularity were not consistent across prototypes. Similar to data recipient, however, respondents rated their comfort of sharing data regarding the specific activity or data type.

The sixth section consisted of questions regarding willingness to pay for each prototype. In addition the respondents were asked how much they would pay for a cellphone. This was done in order to provide anchoring for evaluation of results.

Privacy is arguably a luxury a good [9]. Thus, the sample was targeted towards older adults with higher education as well as income levels. This homogenous sample would have a higher ability to pay. This ensures that their expressed willingness to pay is a function of the variables of the technology not income. Simultaneously, these individuals should have more experience with technology.

3.3 Data Analysis

Survey participants rated their comfort of sharing data for different activities, varying levels of data granularity as well data recipients. In addition we asked the participants for the perceived usefulness of the device. These measures were made on a five dimensional semantic scale. We compared the means across the different measures for each of the four dimensions of the privacy framework and for each prototype. Since all the participants responded for all the measures, we could not perform a direct T-test based comparison. Instead we first conducted an ANOVA taking the inter-correlations of the dimensions into account. Subsequently if the difference in means was significant we conducted a paired T-test with a conservative p-value of 0.001 corrected from 0.05 based on Bonferroni Correction[5].

We are also interested in how participants willingness to adopt distinct prototypes is influenced by the perceived usefulness of the technology, the granularity of data collected, sensitivity of the activity about which information is being collected, and the recipient of that information. To access this

[5] Bonferroni Correction states that if p the appropriate p-value to avoid Type-1 errors, and n is the number of comparisons being made, then the appropriate p-value should be p/n. In general the number of comparisons being made in this study are 3, the traditionally accepted p-value is 0.05, therefore the p-value in this study should be less than 0.05/3 or 0.01667. We consider an even more conservative estimate of 0.001.

we build logistic regression models with willingness to adopt as the dependent variables and perceived usefulness, activity sensitivity, data granularity, and data recipient as independent variables.

4 Results

4.1 Descriptive Statistics

The study was taken by a total of 101 respondents. The participants were recruited using volunteer sampling from proximal retirement communities and senior care centers. There were 34 males and 67 females. 23 people lived alone and 78 lived with other people. Tables 2–5 provide a distribution of the respondents by education, employment, age, income, online access, and cellphone usage. A summary of the responses for beacon strip, presence clock, and ambient cube is provided by Tables 1–3. We do not present the results for video camera here. The construction of questions for this prototype was not adequately rigorous. In particular, we made the mistake of asking compound questions. Thus, the results for video camera have been left out of the analysis. Tables 1–3 provides a summary of results for the remaining prototypes, i.e. beacon strip, presence clock, and ambient cube; we report the mean values; the standard deviation is reported in parenthesis.

Table 1 Beacon Strip

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.77 (0.896)
Data Ganularity	(1=Very Uncomfortable, 5= Very Comfortable)
Weight	3.79 (1.254)
Body Temperature	4.03 (1.053)
Fall Information	4.28 (0.948)
Movement Patterns	3.88 (1.112)
Activity Sensitivity	(1=Very Uncomfortable, 5= Very Comfortable)
Reading	3.79 (1.237)
Sleeping	3.70 (1.282)
Intimacy	2.08 (1.227)
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Primary Caregiver	3.88 (1.026)
Doctor	4.02 (0.978)
Family	3.56 (1.117)
Researchers	3.46 (1.282)
Commercial Vendors	1.51 (0.802)

4.2 Beacon Strip

The difference between mean comfort levels for different items measuring data granularity, activity sensitivity and data recipient was statistically significant;

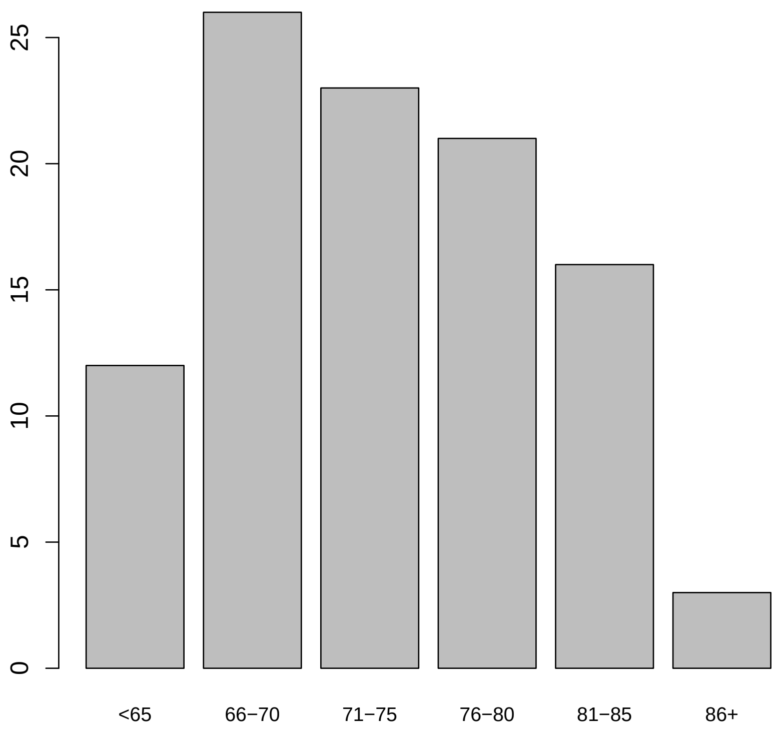

Fig. 1 Distribution of Participants by Age

the respective p-values for ANOVA were all ≈ 0. The different measurement items are ranked in descending order of comfort:
a) Data Granularity: Fall Information > (Weight=Temperature=Movement Patterns)
b) Activity Sensitivity: (Reading = Sleeping) > Intimacy
c) Data Recipient: (Caregiver=Doctor) > (Family=Researchers) > Vendors

For beacon strip data granularity was measured by weight, temperature, fall information, and movement patterns. While weight and temperature are two distinct measurements, the granularity of information is approximately the same. Both weight and temperature are typically constant. Sudden change in either of these quantities may be a cause of concern for the caregivers. Fall information, however, is more granular than either weight or temperature. While changes in weight and temperature are experienced gradually, fall information

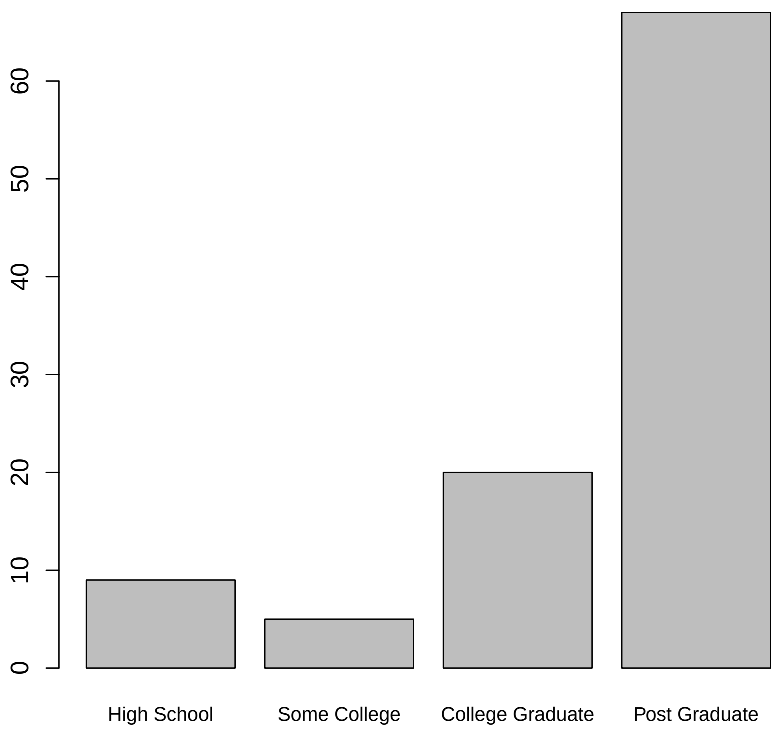

Fig. 2 Distribution of Participants by Education

is of more immediate interest, i.e. fall detection may require immediate intervention. Movement patterns further increase granularity of information; movement patterns would not only include fall information, but also other measures such as length of stride, regularity of footsteps etc. The responses validated some of our assumptions. Participants were least comfortable sharing fall related information. The anti-intuitive finding was that participants perceived weight and temperature similar to movement patterns in terms of information sharing. This may have been because participants did not have an accurate understanding of the term 'movement pattern'. Alternatively, there might not be a direct association between data granularity and comfort of sharing. As noted in section 3, in some cases older adults may wish to share more granular data, e.g. to avoid being moved to a group home.

Activity sensitivity was measured by reading, sleeping, and intimacy. We assumed reading to be the least sensitive activity followed by sleeping. We

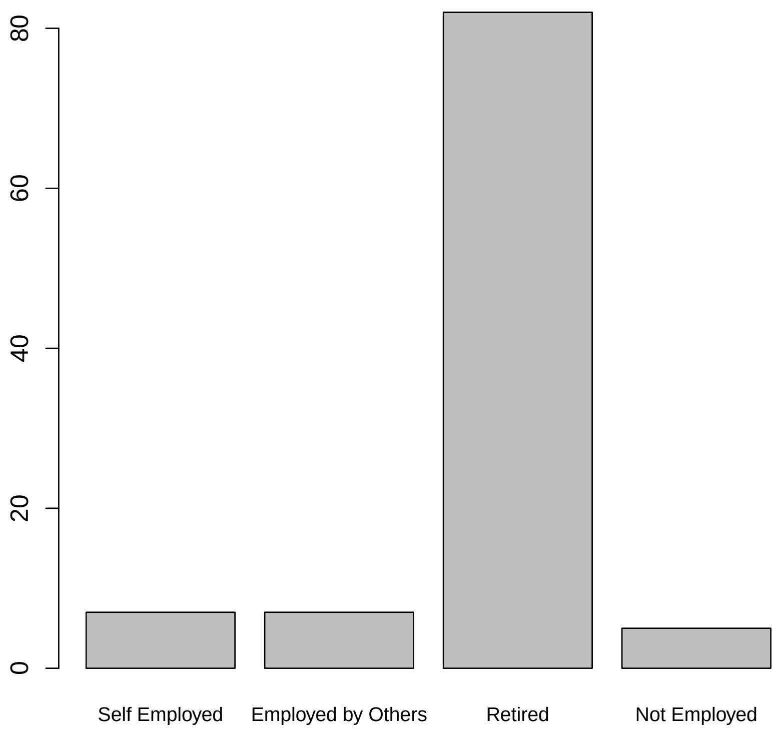

Fig. 3 Distribution of Participants by Employment

assumed intimacy to be most sensitive. Results indicate that participants did consider intimacy to be most sensitive. However, they did not perceive a difference between sleeping and reading in terms of privacy. We had five data recipients in the survey: primary caregiver, doctor, family, researchers, and vendors. We assumed that the primary caregiver and doctor would be self-similar. Participants were assumed to be most comfortable sharing data with primary caregiver and doctors. This was followed by family and then researchers with vendors being the least trusted data recipients. The assumption for data recipient is consistent across all prototypes.

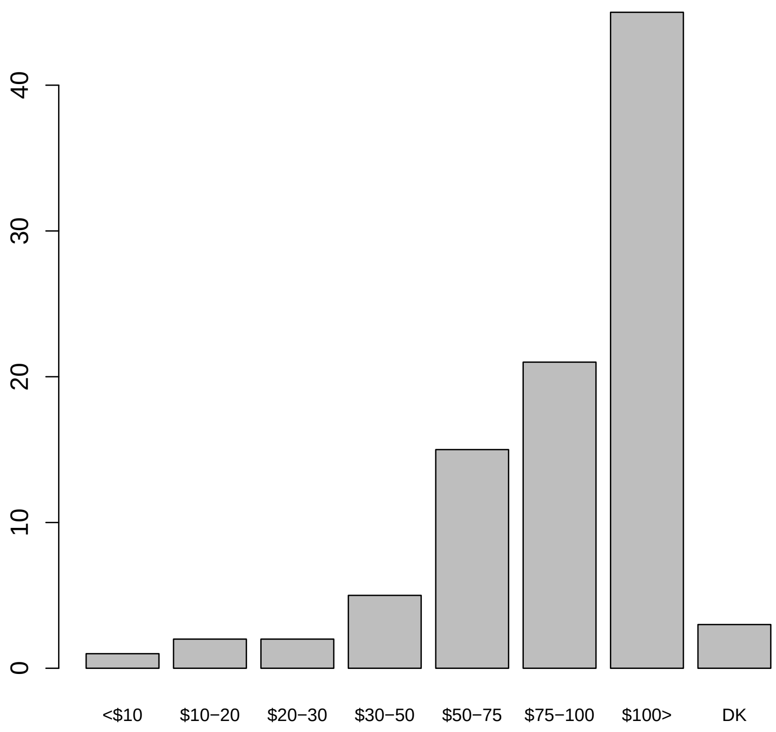

Fig. 4 Distribution of Participants by Income ($1000, DK=Don't Know)

4.3 Presence Clock

The difference between mean comfort for different granularity levels was not statistically significant. However, the difference between items for activity sensitivity and data granularity was significant. The presence clock can detect if a person is in proximity. It can, however, also detect how many people are nearby as well as their identities. We assumed that with increased granularity participants would become less comfortable. This relationship was, however, not reflected in the participants' responses. For this prototype, we used physical space as proxy for activity sensitivity. We assumed that bedroom and bathroom are likely to be considered to be more private spaces as compared to living room or kitchen. This assumption is confirmed by the data. The assumptions for data recipient were the same as those for beacon strip as described in the previous section. While participants were statistically least

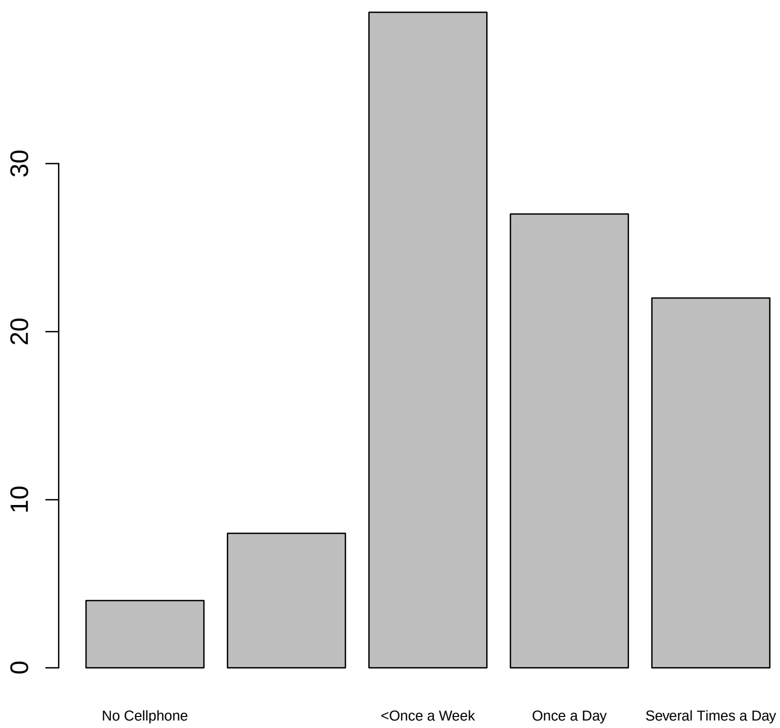

Fig. 5 Distribution of Participants by Cellphone Access

comfortable sharing data with vendors, all other recipients were perceived to be equally trustworthy.

The difference between mean comfort levels for different items measuring data granularity was not statistically significant (the p-value for the ANOVA was 0.64); the difference for activity sensitivity and data recipient was statistically significant with the respective ANOVA p-values being ≈0. The different measurement items are ranked in descending order of comfort:
a) Activity Sensitivity: (Kitchen=Living Room) > (Bedroom=Bathroom)
b) Data Recipient: (Caregiver=Doctor=Family=Researchers) > Vendors

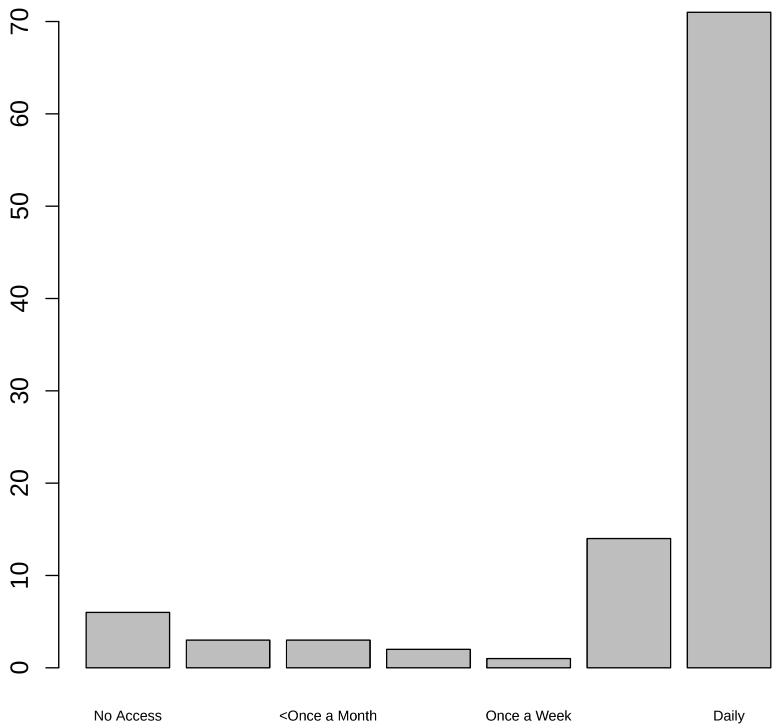

Fig. 6 Distribution of Participants by Online Access

4.4 Ambient Cube

Table 3 provides a summary of results we got for the presence clock prototype. The difference between mean comfort levels for different items measuring data granularity, activity sensitivity and data recipient was statistically significant; the respective p-values for ANOVA were all $\approx$0. The different measurement items are ranked in descending order of comfort:
a) Data Granularity: (Websites=Online Purchases) > Keystrokes > Passwords
b) Activity Sensitivity: (Email Friends=Email Family=Watch Video) > Check Bank Accounts
c) Data Recipient: (Family=Researchers) > Vendors

In addition to the measures listed above, for the cube participants were also asked to report comfort levels for different services provided by the prototype.

Table 2 Presence Clock

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.24 (0.991)
Data Ganularity	(1=Very Uncomfortable, 5= Very Comfortable)
Someone is present	3.34 (1.012)
Number of people present	3.30 (1.064)
Who is present	3.32 (1.016)
Activity Sensitivity	(1=Very Uncomfortable, 5= Very Comfortable)
Bathroom	2.65 (1.235)
Bedroom	2.89 (1.323)
Living Room	3.48 (1.168)
Kitchen	3.50 (1.154)
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Primary Caregiver	3.62 (1.035)
Doctor	3.52 (1.114)
Family	3.40 (1.130)
Researchers	3.09 (1.282)
Commercial Vendors	1.68 (0.848)

Table 3 Ambient Cube

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.15 (1.125)
Comfort	2.96 (1.198)
Detect a fraudulent website	3.82 (1.170)
Detect spam	3.84 (1.157)
Automatically fill out forms	2.80 (1.210)
Takes you to frequently visited websites	3.21 (1.221)
Data Ganularity	(1=Very Uncomfortable, 5= Very Comfortable)
Websites visited	3.02 (1.390)
Online Purchases	2.93 (1.380)
Passwords	1.91 (1.092)
Keystrokes	2.40 (1.288)
Activity Sensitivity	(1=Very Uncomfortable, 5= Very Comfortable)
Email a friend	2.80 (1.258)
Email a family member	3.22 (1.254)
Check your bank account	3.07 (1.040)
Watch a video	2.51 (1.191)
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Family	3.07 (1.336)
Researchers	2.80 (1.336)
Commercial Vendors	1.47 (0.796)

These services were chosen to have different levels of perceived usefulness; respective p-value for ANOVA was ≈ 0. The comfort levels were ranked in descending order as: (Fraud=Spam) > (Frequently visited websites=Automatically fill out forms)

Websites browsed and purchases made online were assumed to be similar. Passwords, in comparison, should be seen as more private. Keystrokes should similarly be seen as even more granular as keystrokes would capture not only the passwords but also any other data that is entered with keyboard as the

Table 4 Beacon Strip: T-test p-values

Data Granularity	Fall Information	Weight	Temperature	Movement Patterns
Weight	0.003	1	0.163	0.613
Temperature	0.09	0.163	1	0.344
Movement Pattern	0.009	0.613	0.344	1

Activity Sensitivity	Reading	Sleeping	Intimacy
Sleeping	0.61	1	≈ 0
Intimacy	≈ 0	≈ 0	1

Data Recipient	Caregiver	Doctor	Family	Researcher	Vendor
Doctor	0.33	1	0.003	0.001	≈ 0
Family	0.05	0.003	1	0.54	≈ 0
Researcher	0.02	0.001	0.54	1	≈ 0
Vendor	≈ 0	≈ 0	≈ 0	≈ 0	1

Table 5 Presence Clock: T-test p-values

Activity Sensitivity	Kitchen	Living Room	Bedroom	Bathroom
Living Room	0.92	1	0.001	$\approx$0
Bedroom	0.001	0.001	1	0.20
Bathroom	$\approx$0	$\approx$0	0.20	1

Data Recipient	Caregiver	Doctor	Family	Researchers	Vendors
Doctor	0.54	1	0.47	0.19	$\approx$0
Family	0.17	0.47	1	0.92	$\approx$0
Researchers	0.003	0.19	0.92	1	$\approx$0
Vendors	$\approx$0	$\approx$0	$\approx$0	$\approx$0	1

input. Some of the assumptions were reflected in the participants' responses. Participants were less comfortable sharing keystrokes and passwords compared to websites and online purchases. However, participants were less comfortable sharing passwords as compared to keystrokes. This result suggests that the participants may not have an accurate understanding of the term keystrokes.

For activity sensitivity we assumed that there would be no difference between emailing friends and family as well as watching videos. Bank account information is clearly more sensitive. This was confirmed by participants' responses. Vendors were again seen as entities with whom participants were least willing to share information with. The other data recipients were perceived as similar.

4.5 Adoption

In this paper we used willingness to pay as a proxy for adoption. While perceived usefulness, data granularity, activity sensitivity, and data recipient might form the underlying determinants of older adults privacy preferences, we also wanted to investigate the extent to which these determinants impinged their desire to adopt a technology. Since our outcome variable was not continuous we also performed a logistic regression for all the prototypes. The outcome variable was converted to binary. Willingness to pay had three levels: less than

Table 6 Ambient Cube: T-test p-values

Data Granularity	Websites	Online Purchases	Passwords	Keystrokes
Online Purchases	0.666	1	≈ 0	0.008
Passwords	≈ 0	≈ 0	1	0.007
Keystrokes	0.002	0.008	0.007	1

Activity Sensitivity	Email Friend	Email Family	Bank Account	Watch Video
Email Family	0.66	1	≈ 0	0.47
Bank Account	0.0002	≈ 0	1	0.0004
Watch Video	0.78	0.47	0.0004	1

Data Recipient	Family	Researchers	Vendors
Researchers	0.17	1	≈ 0
Vendors	≈ 0	≈ 0	1

Usefulness	Fraud	Spam	Autofill	Websites Visited
Spam	0.94	1	≈ 0	0.0006
Autofill	≈ 0	≈ 0	1	0.022
Websites Visited	0.0007	0.0006	0.022	1

$50, between $50 and $100, and more than $100. Table 7 details the results in terms of number of participants that were willing to the relevant amount of money for each prototype. We considered between $50 and $100 and more than $100 as one category. Then the outcome variable had two levels: unlikely to pay and likely to pay. As some participants did not respond to the question, they were not considered in the analysis. Recall that there are four independent variables: 1) usefulness, 2) data granularity, 3) activity sensitivity, and 4) data recipient. The results of the logistic regressions are given in tables 8-10.

Table 7 Willingness to Pay: Number of Individuals

Money	Beacon Strip	Presence Clock	Ambient Cube
Less than $50	56	67	66
$50-$100	31	22	18
More than $100	7	4	6
Did not respond	7	8	11

For beacon strip, the fit provided by the model consisting of all the measure gave an AIC[6] value of 101.39; Table 8. The only statistically significant measure was movement patterns, with a positive estimate[7]. The best fit was given by perceived usefulness, fall information, movement patterns, sleeping, intimacy, primary caregiver, and vendors, AIC value=96.407.

For presence clock, the fit provided by the model consisting of all the measures gave an AIC of 102.1; Table 9. The statistically significant dimensions

[6] Akaike's Information Criterion (AIC) quantifies how well a model fits the data. AIC cannot provide an absolute measure of the fit. Thus, the goodness of the fit is relative. In general, a smaller AIC value indicates a better fit.

[7] A positive estimate implies that an increase in the independent variable leads to an increase in the dependent variable.

Table 8 Beacon Strip: Logistic Regression

Independent Variable	Estimate	Std. Error	p-value
(Intercept)	-0.39	0.279	0.17
Usefulness	0.14	0.074	0.06
Weight	-0.11	0.108	0.33
Temperature	0.12	0.127	0.33
Fall Information	-0.19	0.110	0.09
Movement Pattern	0.18	0.075	0.02 *
Reading	-0.05	0.109	0.63
Sleeping	0.12	0.098	0.21
Intimacy	0.05	0.056	0.43
Primary Caregiver	0.09	0.106	0.40
Doctor	-0.16	0.123	0.20
Family	0.04	0.073	0.57
Researchers	0.01	0.064	0.91
Commercial Vendors	0.07	0.072	0.36

$0.5 < * < 0.01 < ** < 0.001 < *** < \approx 0$

Dispersion parameter for gaussian family taken to be 0.1926355
Null deviance: 17.973 on 72 degrees of freedom
Residual deviance: 11.365 on 59 degrees of freedom
AIC: 101.39
Number of Fisher Scoring iterations: 2

consisted of primary caregiver and doctor. While the former had a positive estimate the latter had a negative. The best fit was given by primary caregiver, doctor, vendors, and kitchen, AIC value=89.56. Primary caregiver and doctor were statistically significant.

Table 9 Presence Clock: Logistic Regression

Independent Variable	Estimate	Std. Error	p-value
(Intercept)	-0.47	0.232	0.05 *
Usefulness	0.10	0.109	0.36
Someone is present	-0.14	0.157	0.36
Number of people present	0.06	0.150	0.70
Who is present	0.03	0.150	0.87
Bathroom	-0.01	0.089	0.87
Bedroom	0.01	0.094	0.89
Living Room	-0.19	0.217	0.40
Kitchen	0.26	0.199	0.20
Primary Caregiver	0.28	0.127	0.03 *
Doctor	-0.23	0.104	0.03 *
Family	-0.04	0.098	0.68
Researchers	0.06	0.069	0.41
Commercial Vendors	0.09	0.064	0.17

$0.5 < * < 0.01 < ** < 0.001 < *** < \approx 0$

Dispersion parameter for gaussian family taken to be 0.1825362
Null deviance: 16.13 on 76 degrees of freedom
Residual deviance: 11.50 on 63 degrees of freedom
AIC: 102.1
Number of Fisher Scoring iterations: 2

For ambient cube, the fit provided by the model consisting of all the measures gave an AIC of 105.85; Table 10. None of the measures were statistically significant. The best fit was given by perceived usefulness, online purchases, keystrokes, researchers, vendors, and watch video, AIC value=91.35.

Table 10 Ambient Cube: Logistic Regression

Independent Variable	Estimate	Std. Error	p-value
(Intercept)	-0.24	0.203	0.248
Usefulness	0.13	0.085	0.125
Comfort	0.001	0.086	0.991
Detect fraudulent website	-0.27	0.323	0.412
Detect spam	0.20	0.320	0.537
Automatically fill out forms	-0.03	0.059	0.580
Frequently visited websites	0.06	0.063	0.376
Websites visited	-0.01	0.095	0.956
Online purchases	-0.15	0.094	0.122
Passwords	0.08	0.078	0.319
Keystrokes	0.07	0.070	0.311
Email a friend	-0.07	0.112	0.552
Email a family member	0.04	0.106	0.728
Check your bank account	-0.001	0.082	0.991
Watch a video	0.05	0.079	0.534
Family	0.06	0.066	0.362
Researchers	0.06	0.054	0.258
Vendors	-0.02	0.082	0.810

0.5<*<0.01<**<0.001<***< ≈0

Dispersion parameter for gaussian family taken to be 0.1764199
Null deviance: 15.488 on 79 degrees of freedom
Residual deviance: 10.938 on 62 degrees of freedom
AIC: 105.85
Number of Fisher Scoring iterations: 2

5 Discussion

A consistent finding across all prototypes was the older adults disinclination to share information with vendors. This may be driven by a lack of trust for corporations. Older adults may feel that commercial vendors may use that information discriminate in pricing or insurance etc. All other data recipients were mostly perceived as self-similar. While such information is already shared with doctors, caregivers and to a certain extent family members, it is not surprising that participants did not find it disconcerting.

It is, however, surprising that participants were equally willing to share information with researchers. There are at least three possible explanations. First, older adults may perceive a benefit of sharing information with researchers, as it would allow the researchers to improve existing assisted living technologies. Second, an overwhelming number of participants had postgraduate education as such they may trust researchers more than society as large.

Since the participants volunteered to take part in the survey, they clearly trust researchers and perceive benefits in research. Finally, it may simply be a limitation of the survey-based methodology as the participants might be pandering to the researchers, i.e. they might have assumed that the researchers desired a specific repose. Based on the data, however, we can hypothesize that there are two categories of data recipient: commercial and noncommercial.

A similar categorization is seen for activity sensitivity where activities are either seen as highly sensitive or generic. Highly sensitive information was represented by intimacy, bathroom, bedroom and banking. Thus, high sensitivity might pertain to financial information and intimate information, i.e. activities in general are considered non-sensitive unless there is an explicit exposure of financial of intimate information. It could be argued that this categorization emerges due to the specific activities selected as a part of the survey. Reading, watching videos, and kitchen are significantly different from intimacy, bedroom, and banking in terms of severity of information exposure. However, the survey also had moderately risky activities such as sleeping, email, and living room. The participants could have gone either way on these, but the responses indicate that moderately privacy-infringing activities are perceived equally sensitive as those that are mildly intrusive. Future studies should construct a survey items that can be illuminate this hypothesis further.

Similar compartmentalization is also suggested for data granularity. The nature of the compartmentalization changes, however. While the participants were less willing to share information when there was a risk of exposing explicitly personal information (e.g. passwords), they were more willing to share information when there was an explicit utility from information sharing, such as with fall information. Information thus it seems was not impinged by granularity, rather it was a function of sensitivity of the information being collected and the perceived utility thereof. Follow up studies should investigate the difference between data granularity and data sensitivity.

Perceived usefulness was the key determinant across all the prototypes. This finding is not surprising. Several previous studies have identified perceived usefulness as a primary motivator for adoption [7, 31, 24, 14].

Participants indicated a higher willingness to purchase beacon strip than either presence clock or ambient cube. Willingness to share information with vendors was a key predictor of adoption. In general, participants were uncomfortable sharing information with vendors, but those who were willing to pay in terms of information exposure to vendors were also willing to bear the monetary cost of adoption. Older adults who are willing to suffer higher privacy intrusions would also be wiling to pay a higher price for that exposure.

Usefulness was another driving factor for adoption. This has been a consistent determinant for adoption in several previous studies. The impact of this dimension is limited. While it was the most important factor for Ambient Cube, it was less important for beacon strip and even less so for presence clock. However, overall if participants who perceived higher utility also demonstrated higher willingness to adopt.

6 Limitations

The survey was targeted towards a older adult demographic with high incomes and education. Thus, the finding may not be generalizable to a larger population. There were indications for improving the design of the survey instrument. First, we asked compound questions for the video camera. This made it hard to analyze the data as the questions might have been primed. Some anti-intuitive results may have been driven by the use terms that are unfamiliar to older adults. In particular, keystrokes as well as movement information were perceived as less privacy invasive than less granular counterparts. Terms such as keystrokes while familiar to privacy researchers may be less available to older adults. The alternative explanation is that there is no linear relationship between comfort of sharing and data-granularity. Recall that in some cases older adults may wish to share more granular information to avoid being moved to a group home. Finally, the descriptions of the prototypes are not equally value laden. Thus, the findings in this paper are dependent on the descriptions.

7 Conclusion and Future Work

In this study we conducted a survey to empirically test the applicability of a four dimensional model of technology adoption proposed by Huber et al. [22]. These four determinants can influence the tradeoffs between privacy and technology both individually as well in combination with each other. This study exclusively investigates the explanatory power of this model by treating the four dimensions as distinct components. We found that these dimensions can significantly explain older adults' desire to adopt Ubicomp technologies. We hypothesize that a study that examines these components in combination with each other would provide stronger results. Future work needs to investigate this relationship. This would further illuminate the respective importance of different determinants in varying contexts.

The participants in this study were all older adults. However, the decision to adopt Ubicomp may not be made by the older adult in isolation. There are likely to be other stakeholders such as family members and caregivers who may influence this decision. The nature of this influence may differ based on whether the family members live with the older adult or not. This may be particularly important in-group setting where a single older adults privacy preference might impinge the information exposure of several occupants. Thus, these tradeoffs should be investigated under the cultural influence of differing residential structures, for example naturally occurring retirement communities (NORCs) [12] vs. firm/family/friend operated residential choice (FORCs). A holistic approach would survey respective stakeholders, such as providers and peers, to access their perceptions of usefulness, activity sensitivity, data granularity and data recipient. A more complete model would incorporate both individual preferences as well peer-produced privacy tradeoffs.

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