Privacy Framework for Older Adults

Vaibhav Garg
School of Informatics and Computing
Indiana Univeristy
Bloomington, USA
gargv@indiana.edu

L. Jean Camp
School of Informatics and Computing
Indiana University
Bloomington, USA
ljcamp@indiana.edu

Katherine Connelly
School of Informatics and Computing
Indiana University
Bloomington, USA
connelly@indiana.edu

Kalpana Shankar
School of Informatics and Computing
Indiana University
Bloomington, USA
shankark@indiana.edu

Lesa Mae Lorenzen-Huber
School of Health, Physical Education, and Recreation
Indiana University
Bloomington, USA
lehuber@indiana.edu

***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 technology is, however, mediated 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 large scale survey to empirically examine the applicability and robustness of this framework, *n=101*. 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 PETS that might be widely adopted.**

[1]

I. 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 [1]. Currently adults over 65 form 13% of the population. This is expected to increase to 20.7% by 2050[2]. 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[3]. This increasingly aging population creates several challenges for the traditional healthcare model [2]. There has been a drive to investigate technological solutions to such challenges, including developing technologies for assisted living that encourage living in place. Simultaneously, older adults have not been targeted by designers of security and privacy technologies, in part because of the lack of simple design heuristics.

Assisted living and medical technologies require monitoring older adults to provide services. The quality of data collected is critical to the quality of care provided. Thus technology adoption has privacy implications. Privacy concerns can hider adoption [3] and security risks disproportionally expose this vulnerable population. While several studies have examined contextual construction of privacy and its impact on adoption, the demographics of sampling make it hard to generalize the findings to older adults [4]. Risk perception can vary significantly with age and this may be true for privacy risks as well.

Huber et al. [5] introduced a four dimensional framework that examines older adults' perceptions of privacy risks. 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. This study empirically tests the theoretical grounding of this framework by conducting a large scale survey, n=101. The goal is to develop heuristics for design and documentation of Privacy Enhancing Technologies (PETs), medical technology, and assisted living technology to align with elder expectation and improve diffusion.

Section II introduces related work. Section III discusses methodology. In section IV we present our results. In section V we discuss the implications of our findings and their limitations. Section VI concludes.

II. Related Work

Technology adoption is motivated by several factors. Over time several models have emerged to capture the underlying determinants of this decision process [6]. Theory of reasoned action constitutes attitude towards behavior and subjective norm [7]. Technology adoption model includes perceived usefulness, perceived ease of use, and subjective norm [8]. Motivational models examine both extrinsic and intrinsic motivation [9]. Theory of planned behavior extends theory

[1]Draft intended for discussion at Security and Human Behavior, June 17- 18, 2011, Carnegie Mellon University Pittsburgh, PA (USA).

[2]http://www.census.gov/population/www/projections/usinterimproj/

[3]http://www.cdc.gov/brfss

of reasoned action by including perceived behavioral control [10]. A further model combined technology acceptance model with theory of planned behavior. Models of PC utilization includes job-fit, complexity, long-term consequences, affects towards use, social factors, and facilitating conditions. Innovation diffusion theory combines relative advantage, ease of use, image, visibility, compatibility, results demonstrability, and voluntariness of use. A key limitation of these models is that they do not consider the context in which a specific technology may be used. They also do not consider the opportunity cost of adoption.

For example, adoption of ubiquitous technologies, such as those provided by assisted living, may also be mediated by privacy concerns [11]. Models that effectively describe the 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 [12]. It is reasoned that when threatened with the loss of their independence, most elders will choose the lesser evil: the loss of privacy that comes with monitoring technologies. Yet even after having moved into assisted care, elders will seek to avoid technology that violates privacy.

For example, in a previous study it was seen that older adults were more comfortable sharing information with their doctor or caregiver as compared to family members of friends [13]. Another study found that older adults were even less comfortable sharing information with insurance companies or government agencies [14].

Privacy vs. ubicomp is a Hobson's choice. The ubicomp projects in this area claim that technology will help family members decide when an elder must be moved to an assisted living facility. So by definition, the technology is being introduced before the elder is faced with the either or choice presented above. In addition, the technology is presented in its entirety, with potentially privacy influencing design choices embedded and without the possibility of the participant's examination. Finally, the collected data can threaten the autonomy of the elder. For example, if a caregiver knows a certain number of falls have occurred, no matter how minor, they might insist on a move to assisted living. As such, it is essential that research in this area addresses the issues of privacy surrounding sensing and monitoring technologies in the home.

Previous studies exploring older adults acceptance and use of technology found perceived usefulness to be the critical determinant for adoption [15], [16], [17], [18]. Demographic predictors such as age, gender, education, and prior experience with technology also influence adoption and use. Most of these studies have considered technologies such as computer, internet, and cell phone use. Few studies have considered older adults perceptions of privacy related to home-based ubicomp technologies. The research that does exist in this area is primarily one-time survey and focus group research [15], [13], [19]. Findings from these studies suggest that older adults are somewhat unconcerned about protecting their personal information. Faced with the specter of institutionalization, most older adults would easily trade their privacy for the independence and dignity of living in their own homes.

Previous studies' findings that older adults have a somewhat 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 user-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 be transparent about what data is being compiled could address elders underestimation of their privacy risks.

III. Methodology

Huber et al. [5] introduced a four dimensional model that captures the privacy vs. technology tradeoffs older adults and associated stakeholders may consider. These tradeoffs are modeled as perceived usefulness, activity sensitivity, data granularity and data recipient. Perceived usefulness refers to how 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 ubicomp technology. For example, reading may not 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 are 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 adult's disinclination to be

[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 [20]. 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 [21]

asked to move into a nursing facility, thereby losing their independence. Finally data recipient refers to the entity to whom 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. Here we describe the design of the evaluation strategy.

A. Prototypes

We considered 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.

1) 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, sleep duration etc.

2) Video Camera: A video camera is a video recording device in the home of the older adult. It can be used by remote caregivers to monitor the activities of the older adult.

3) 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 caregiver's 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.

4) Ambient Cube: This a USB plugin device. It collects information about the user's 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.

B. Survey Design

The survey was divided into six sections. The first section contained demographic questions. The format of these questions was taken 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[5]. 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[5]. 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.

IV. Results

In this section we present the results of our survey. The study was taken by a total of 101 respondents. There were 34 males and 67 females. 23 people lived alone and 78 lived with other people. Tables I and II provide a distribution of the respondents by education, employment, age, and income. A summary of responses for beacon strip, presence clock, and ambient cube is provided by Tables III, IV, and V. 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. A summary of responses for this prototype is present in Appendix A.

The 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 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 intercorrelations 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 .001 corrected from .05 based on Bonferroni Correction[6].

A. Beacon Strip

Table III provides a summary of results for the beacon strip prototype. The difference between mean comfort levels

[5] 1= Very Uncomfortable, 5= Very Comfortable

[6] Bonferroni correction requires us to divide the estimated p-value by the number of comparisons made to correct for Type 1 error due to repeated measurements. The maximum number of comparisons made for any dimension in this study is 10. Therefore assuming a p-value of .05, under this scheme a p-value of less than .005 would be significant.

Table I
DISTRIBUTION OF RESPONDENTS BY EDUCATION AND EMPLOYMENT

Education Level	No. of Respondents
Less than High School	0
High School	9
Some College	5
College Graduate	20
Post Graduate Training	60

Employment Status	No. of Respondents
Self Employed	7
Employed by someone else	7
Retired	82
Not Employed	5

Table II
DISTRIBUTION OF RESPONDENTS BY AGE AND HOUSEHOLD INCOME

Age	No. of Respondents
$<$ 65	12
66-70	26
71-75	23
76-80	21
81-85	16
86+	3

Income	No. of Respondents
<$10,000	1
$10,000-$20,000	2
$ 20,000-$30,0000	2
$30,000-$50,000	5
$50,000-$75,000	15
$75,000-$100,000	21
$More than 100,000	45
Don't know	10

for different items measuring data granularity, activity sensitivity and data recipient was statistically significant. The different measurement items are ranked in descending order of comfort:

1) Data Granularity: Fall Information $>$ (Weight=Temperature=Movement Patterns)
2) Activity Sensitivity: (Reading = Sleeping) $>$ Intimacy
3) 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 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 confirmed 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 suggests that participants may not have an accurate understanding of the term 'movement pattern'.

Activity sensitivity was measured by reading, sleeping, and intimacy. Reading is clearly the least sensitive activity followed by sleeping. We 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 primary caregiver, doctor, family, researchers, and vendors. We assumed that the primary caregiver and doctor would be self similar. Participants are assumed to be most comfortable sharing data with primary caregiver and doctors. This is followed by family and then researchers with vendors being the least trusted data recipients. The assumption for data recipient is consistent across all prototypes.

B. *Presence Clock*

Table IV provides a summary of results we got for the presence clock prototype. 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 will 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 previously in section IV-A. While participants were statistically least comfortable sharing data with vendors, all other recipients were perceived to be equally trustworthy.

The different measurement items are ranked in descending order of comfort:

1) Activity Sensitivity: (Kitchen=Living Room) $>$ (Bedroom=Bathroom)

Table III
BEACON STRIP

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.77
Data Ganularity	(1=Very Uncomfortable, 5= Very Comfortable)
Weight	3.79
Body Temperature	4.03
Fall Information	4.28
Movement Patterns	3.88
Activity Sensitivity	(1=Very Uncomfortable, 5= Very Comfortable)
Reading	3.79
Sleeping	3.70
Intimacy	2.08
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Primary Caregiver	3.88
Doctor	4.02
Family	3.56
Researchers	3.46
Commercial Vendors	1.51
Adoption	(1=Less than \$50, 2=\$50-\$100, 3=More than \$100)
Willingness to pay	1.47

2) Data Recipient: (Caregiver=Doctor=Family=Researchers) > Vendors

C. Ambient Cube

Table V 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 different measurement items are ranked in descending order of comfort:

1) Data Granularity: (Websites=Online Purchases) > Keystrokes > Passwords
2) Activity Sensitivity: (Email Friends=Email Family=Watch Video) > Check Bank Accounts
3) 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. These services were chosen to have different levels of perceived usefulness. 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 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.

D. 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 adult's privacy preferences, we also wanted to investigate the extent to which these determinants mediated their desire to adopt a technology. In order to do so we ran multiple linear regressions with willingness to pay as the dependent variable[7]. Variance in willingness to pay for beacon strip was best accounted by a combination of perceived usefulness, fall information, movement patterns, sleeping, intimacy and vendors[8]. For presence clock the variance was best accounted for by perceived usefulness, living room, doctor, and primary caregiver[9]. For ambient cube the variance was accounted for by perceived usefulness, online purchases, keystrokes, researchers, and watching video[10].

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 \$50, between \$50 and \$100, and more than \$100. We considered between \$50 and \$100 and more than \$100 to be one category. Now the outcome variable had two levels: unlikely to pay and likely to pay.

[7]In order to perform linear regressions, the dependent variable must me continuous and normally distributed. Given the size of the sample, n=101, it was reasonable to assume that the normality requirement was met.

[8]Adjusted R-Square value =.2707, p-value<.001

[9]Adjusted R-Square value=.1544, p-value=.002

[10]Adjusted R-Square value=.1464, p-value=.004

Table IV
PRESENCE CLOCK

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.24
Data Ganularity	(1=Very Uncomfortable, 5= Very Comfortable)
Someone is present	3.34
Number of people present	3.30
Who is present	3.32
Activity Sensitivity	(1=Very Uncomfortable, 5= Very Comfortable)
Bathroom	2.65
Bedroom	2.89
Living Room	3.48
Kitchen	3.50
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Primary Caregiver	3.62
Doctor	3.52
Family	3.40
Researchers	3.09
Commercial Vendors	1.68
Adoption	(1=Less than \$50, 2=\$50-\$100, 3=More than \$100)
Willingness to pay	1.32

Table V
AMBIENT CUBE

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.15
Comfort	2.96
Detect a fraudulent website	3.82
Detect spam	3.84
Automatically fill out forms	2.80
Takes you to frequently visited websites	3.21
Data Ganularity	(1=Very Uncomfortable, 5= Very Comfortable)
Websites visited	3.02
Online Purchases	2.93
Passwords	1.91
Keystrokes	2.40
Activity Sensitivity	(1=Very Uncomfortable, 5= Very Comfortable)
Email a friend	2.80
Email a family member	3.22
Check your bank account	3.07
Watch a video	2.51
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Family	3.07
Researchers	2.80
Commercial Vendors	1.47
Adoption	(1=Less than \$50, 2=\$50-\$100, 3=More than \$100)
Willingness to pay	1.33

For beacon strip, the fit provided by the model consisting of all the measure gave an AIC[11] value of 101.39. The only statistically significant measure was movement patterns, with a positive estimate[12]. A better fit was provided by the model suggested by linear regression, AIC=98.24. The significant measures were perceived usefulness, fall information, and movement patterns. The estimates were positive for perceived usefulness, movement pattern, sleeping, intimacy, and vendors. The estimate was negative for fall information. The best fit was given by perceived usefulness, fall information, movement patterns, sleeping, intimacy, primary caregiver, and vendors, AIC value=96.407. The additional dimension was primary caregiver, which had a negative estimate.

For presence clock, the fit provided by the model consisting of all the measures gave an AIC of 102.1. The statistically significant dimensions consisted of primary caregiver and doctor. While the former had a positive estimate the latter had a negative. A better fit was provided by the model suggested by linear regression, AIC=94.76. Doctor was statistically significant with a positive estimate. The best fit was given by primary caregiver, doctor, vendors, and kitchen, AIC value=89.56. Primary caregiver and doctor

[11]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.

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

were statistically significant.

For ambient cube, the fit provided by the model consisting of all the measures gave an AIC of 105.85. None of the measures were statistically significant. A better fit was provided by the model suggested by linear regression, AIC=92.19. Perceived usefulness and online purchases were statistically significant. Usefulness had a positive estimate and online purchases had a negative estimate. The best fit was given by perceived usefulness, online purchases, keystrokes, researchers, vendors, and watch video, AIC value=91.35. Only online purchases had a negative estimate.

V. Discussion

The survey was conducted with a volunteer sample. 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.

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 may be three reasons for this. First, older adults may perceive a benefit of sharing information with researchers as it would allow the researchers to improve existing ubicomp technologies. Second, an overwhelming number of participants had post graduate 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 a specific repose was desired by the researchers. 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. 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.

The analysis based on linear regression suggested that the proposed model can account for significant variance in willingness to pay. Overall variance explained was 14.64% in the worst case for ambient cube and 27.07% in the best case for beacon strip[13]. 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[15], [16], [17], [18].

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. This may be anti-intuitive as better design, including privacy design, should be expected of higher priced technologies. This indicates that older adults do not feel that they can get higher quality care and less privacy invasive ubicomp at the same time. A tradeoff is perceived whether or not it exists.

[13]Too much should not be read into the specific percentages, since the survey design was not conducive to linear regression models

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.

VI. Conclusion and Future Work

In this study we conducted a large scale survey to empirically test the applicability of a four dimensional model of technology adoption proposed by Huber et al. [5]. These four determinants can influence the tradeoffs between privacy and technology both individually as well in combination with each other. This study exclusively investigate the explanatory power of this model by treating the four dimensions as distinct components. We found that these dimensions can significantly explain older adult's 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 hypothesis. 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 settings where a single older adult's 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) [22] vs. firm/family/friend operated residential choice (FORCs)[14]. 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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[14]FORCs refer to residential structures in which older adults reside in their own homes and are monitored by a single entity, such as a pay-for-service company or informal caregiver (e.g. friend or family member).

Appendix

The results for video camera have been summarized in the Table VI.

Tables VII and VIII describe current technology adoption in terms of access to Internet, cellphone usage, and online usage.

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Table VI
VIDEO CAMERA

Usefulness	(1=Strongly Disagree, 5= Strongly Agree)
The device described above is useful	3.65
How comfortable would you be with having photographs taken while you are	(1=Very Uncomfortable, 5= Very Comfortable)
Having breakfast	3.26
Brushing your teeth	3.04
Taking a shower	1.91
Taking a shower only if a fall is detected	3.26
How comfortable would you be with having video taken while you are	(1=Very Uncomfortable, 5= Very Comfortable)
Having breakfast	3.23
Brushing your teeth	2.97
Taking a shower	1.82
Taking a shower only if a fall is detected	3.34
Data Recipient	(1=Very Uncomfortable, 5= Very Comfortable)
Primary Caregiver	3.52
Doctor	3.57
Family	3.30
Researchers	2.91
Commercial Vendors	1.46
Adoption	(1=Less than \$50, 2=\$50-\$100, 3=More than \$100)
Willingness to pay	1.52

Table VII
DISTRIBUTION OF RESPONDENTS BY FREQUENCY OF ONLINE ACCESS AND CELLPHONE USAGE

Online Access	No. of Respondents
No Online Access	6
Have Access but never use	3
Less than once a month	3
Once a month	0
Several times a month	2
Once a week	1
Several times a week	14
Daily	71

Cellphone Usage	No. of Respondents
No Cellphone	4
Have one but never use	8
Less than once a week	39
Once a day	27
Several times a day	22

Table VIII
DISTRIBUTION OF RESPONDENTS BY ONLINE USAGE

Activity	Multiple times a week	Once a week	<Once a week	Never
Purchase goods or services	12	46	5	35
Pay Bills	38	26	18	15
Bank Transactions	36	41	15	5
Research Medical Conditions	20	68	8	2
Research Drugs/Medications	20	70	4	2
Purchase Prescription Drugs	43	44	7	2
General Health/fitness websites	36	48	7	5
Government Health/Disease websites	48	44	4	1
Health plan/HMO websites	57	37	1	0
Doctor/Health care professional website	48	44	3	1

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