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Would You Preserve Your Privacy or Enhance it? How to Best Frame Privacy Interventions for Older and Younger Users

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Abstract

In this paper, we examine the role of personalized communication in promoting the effective use of privacy measures for different age groups. Research has shown that due to differences in cognitive processing, older and younger adults respond differently to rationally identical presentations of the same message (i.e., the framing effect). Therefore, messages that are designed to nudge users towards more privacy protective behaviors should be tailored according to the age of the user groups. We conducted a controlled experiment where we presented a privacy and security technology with a gain framing of "Privacy Enhancing Technology" vs. a loss framing of "Privacy Preserving Technology." Our results show that older adults are more motivated to protect themselves by a loss-framed message than a gain-framed message, while younger adults' responsiveness to either a gain- or loss-framed message depends on their level of privacy concern. The findings highlight the importance of personalized communication in promoting privacy and security measures among different age groups.

Keywords: privacy, older adults, framing.

1. Introduction

Older adults (individuals at or above 65 years old (U. S. Census Bureau, 2016)) are disproportionately vulnerable to security and privacy threats compared to younger adults. Studies have consistently demonstrated that older adults face greater challenges in safeguarding their privacy and security while interacting with technology. Notably, older adults require more time to acquaint themselves with new technologies (Rogers et al., 1998) and experience heightened anxiety when confronting security and privacy threats (Frik et al., 2019). This demographic shows a pronounced concern regarding online information sharing. Nonetheless, they are sometimes less inclined to adopt technical measures to mitigate these risks (Munteanu et al., 2019). These insights underscore the necessity for designing security and privacy systems with the specific needs and challenges of older adults in mind.

Motivating individuals with encouraging messages (nudging) to protect their privacy and security is one way to promote such behaviors among them. For instance, giving users feedback about the strength of their passwords can lead to having stronger passwords (Egelman et al., 2013). However, most of the prior work on privacy nudging focuses on the general population. In this work, we raise a case for tailoring privacy nudges to the older adult population and study whether and how this approach can result in optimum privacy and security behaviors.

The necessity of customizing privacy nudging messages for older adults stems from their distinctive decision-making processes on risk-taking/aversing. Research in psychology has shown the substantial differences between how older and younger adults approach risky decisions. Notably, while younger adults are more geared to take risks for acquiring gains, older adults tend to exhibit more cautious behavior towards taking risks (Byrne and Ghaiumy Anaraky, 2020; Ghaiumy Anaraky et al., 2021; Worthy et al., 2014) and prioritize security and stability over potential gains, demonstrating their preference for avoiding loss rather than seeking rewards (Byrne and Ghaiumy Anaraky, 2020. Given this background, enhancing the effectiveness of privacy nudging messages for older adults necessitates a tailored approach that aligns with their risk-taking attitude and decision-making preferences. However, to the best of our knowledge, no

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work has incorporated older adults' risk-taking attitudes into the design of privacy nudges. There exists a gap in developing effective privacy protection strategies by acknowledging and leveraging the decision-making characteristics unique to older adults.

To address this gap, we draw on the findings from behavioral psychology suggesting that loss-framed messages are more motivating for older adults to spend effort on a task, whereas gain-framed messages are more motivating for younger adults (Byrne and Ghaiumy Anaraky, 2020). We pose the following research question:

RQ: *How can we personalize privacy nudging messages to users of different age groups (i.e., older vs. younger adults)?*

To answer this research question, we design a between-subject experiment where we present a fictitious privacy protection technology, 'SensorData,' in a gain context of *Privacy* ***Enhancing*** *Technology (PET)* or a loss context of *Privacy* ***Preserving*** *Technology (PPT)*. Our findings show that we can optimize the behavioral intention of adopting the SensorData by using different types of framing (PET vs. PPT) depending on the user's age and their level of privacy concerns. Our findings have important implications for policy design and in encouraging individuals to adopt privacy protection technologies.

2. Related Work and Hypothesis Development

In this section, we review related work on the differences between older and younger adults in technology use, the framing effect and the theoretical support behind why we hypothesize that privacy nudging messages should be customized between different age groups.

2.1. Older vs. Younger Adults Technology Use

The literature on older adults' technology use tends to focus on the difficulties that older adults face regarding technology adoption, use, and security and privacy behaviors (Zeissig et al., 2017). For example, Roger et al. (Rogers et al., 1998) report that it may take more time for older adults to learn new technology. However, older and younger adults are two different populations. For example, they have different thinking mechanisms (Worthy et al., 2011) where older adults are more loss-averse and younger adults are more gain seekers (Byrne and Ghaiumy Anaraky, 2020). Therefore, some researchers have argued that these problems are due to the design of technology, which is often tailored to a younger adult audience and is not addressing the needs and preferences of the older adult population (Ghaiumy Anaraky et al., 2021; Knowles and Hanson, 2018). For example, older adults' low rate of technology adoption may be due to their legitimate, unaddressed concerns rather than an inability to learn how to use the technology (Knowles and Hanson, 2018).

To design older adult-friendly technologies, it is essential to understand and acknowledge the differences between older and younger adults. In this paper, we limit our scope to the communication of privacy notices (i.e., the framing of the message) that are designed to encourage an audience to take protective action and adopt a privacy protection technology. Therefore, we study the literature on how older and younger adults respond differently to various messages.

2.2. Framing Effect

The way we present (i.e., frame) some information to the audience can determine how the information is received, resulting in various behavioral outcomes (Levin and Gaeth, 1988). This is called the framing effect. Levin and Gaeth's (Levin and Gaeth, 1988) framing study is one of the first studies showing the framing effect. They presented a pack of ground beef as "75% lean" or "25% fat". While the two options are rationally identical, participants favored the "75% lean" product over the "25% fat" product.

In the privacy literature, scholars studied the framing effect in different scenarios (Anaraky et al., 2018, 2020, 2023; Ghaiumy Anaraky et al., 2024; Johnson et al., 2002). For example, Samat and Aquisti (Samat and Acquisti, 2017) measured participants' disclosure tendencies in a survey using a "*prohibit* my responses to be shared with a marketing company" vs. "*allow* my responses to be shared with a marketing company" framing. They showed that participants who saw the 'allow' framing expressed a higher willingness to share their data. This finding could be due to the different thinking processes that "prohibit" and "allow" keywords can trigger. The "prohibit" keyword would nudge participants to think about the reasons to prohibit and not share their data. This thinking process would make the participants less likely to share information. In contrast, the "allow" keyword nudges the participants to think about reasons to allow data sharing, making them more likely to share. As another example, Johnson et al.(Johnson et al., 2002) conducted a survey about personal health. At the end of the survey, they asked participants about their willingness to subscribe to future surveys with their email addresses. They presented the subscription question with different framings, and showed that the message framing of 'Notify me about

Construct	Items	Factor loadings
Privacy Concerns AVE: .872	All things considered, the Internet causes serious privacy problems	
	Compared to others, I am more sensitive about the way online companies handle my personal information	0.742
	To me, it is the most important thing to keep my privacy intact from online companies	0.757
	I believe other people are too concerned with online privacy issues	
	I am concerned about threats to my personal privacy today	0.611
	Compared with other subjects on my mind, personal privacy is very important.	0.937
Behavioral Intention AVE: .984	In the future I intend to manage my privacy using SensorData technology.	0.967
	I will frequently use SensorData technology in the future.	0.999
	I will strongly recommend others to use SensorData technology.	0.940

Table 1. Confirmatory Factor Analysis

more health surveys' would result in more email subscriptions than the framing of 'Do not notify me about more health surveys.' Similarly, Ma and Birrell (2022) found that users presented with a cookie banner framed negatively (i.e., 'degrade your experience') were less likely to accept cookies compared to those presented with positive framing (e.g., 'improve your experience').

Overall, the findings suggest that various logically equivalent forms of presentations of a choice option could lead to different privacy behaviors. However, little work has explored whether the privacy nudging messages should be tailored to different user populations, e.g., older vs. younger adults. As suggested by psychology literature, older and younger adults have different attitudes and behaviors in risky decision-making (Byrne and Ghaiumy Anaraky, 2020; Worthy et al., 2014). Thus, the effect of privacy nudging messages might vary between the two age groups. In the following, we explain how message framing influences different age groups of older and younger adults differently.

2.3. Framing an Encouraging Message for Older Adults

The selection, optimization, and compensation theory suggests that older and younger adults have different strategies for allocating their cognitive and physical resources (Baltes, 1997). With a decline in cognitive and physical resources, older adults are more selective in effort allocation. They adjust their goals from a growth focus to a maintenance or a loss-prevention focus (Baltes, 1997; Carpentieri et al., 2017).

Building on the selection, optimization, and compensation theory, Byrne et al. (2020) conducted an experiment where they presented older and younger adults with gain or loss-framed tasks. For each task, participants could select between spending a high effort (pressing the left arrow key 50 times, followed by the right arrow key 50 times) vs. a low effort (pressing the spacebar 30 times). In the gain-framed experimental condition, participants could increase their potential monetary reward by choosing the high-effort task. In the loss-framed condition, participants could reduce the amount of monetary loss by taking on the high-effort task. Overall and in line with the selection, optimization, and compensation theory, the study showed that loss-framing encourages a higher effort expenditure for older adults. In contrast, gain-framing encourages higher effort expenditures for younger adults. This study highlights the importance of personalizing message framing to the age of the audience for optimal results.

Based on this literature, we hypothesize that a loss frame is more motivating for older adults than a gain frame message, such that a loss frame will increase older adults' motivations (i.e., privacy concerns) and lead to higher behavioral intentions to adopt privacy-preserving technologies. For the younger adults, however, we argue that a gain-framed message is more effective, leading to increased privacy concerns and behavioral intention than the loss-framed message.

H1: *For older adults, a loss-framed message ("privacy preserving technology") leads to higher privacy concerns than a gain-framed message ("privacy enhancing technology").*

H2: *For older adults, a loss-framed message ("privacy preserving technology") leads to higher behavioral intentions to adopt privacy protective technologies than a gain-framed message ("privacy enhancing technology").*

H3: *For younger adults, a gain-framed message ("privacy enhancing technology") leads to higher privacy concerns than a loss-framed message ("privacy* *preserving technology").*

H4: *For younger adults, a gain-framed message ("privacy enhancing technology") leads to higher behavioral intentions to adopt privacy protective technologies than a loss-framed message ("privacy preserving technology").*

Prior privacy research has extensively shown that privacy concerns act as a catalyst for users to adopt a more cautious approach in information disclosure (Smith et al., 1996) and a critical determinant in a variety of privacy decisions (Min and Kim, 2015). For instance, higher privacy concerns leads to a reluctance to disclose personal information (Stewart and Segars, 2002), and more adoption of privacy protective technologies (Malhotra et al., 2004). However, no work has explored whether the effect of framing differs for people with different levels of privacy concerns. Thus, we hypothesize that the effect of framing on behavioral intention to adopt privacy protective technologies might be mediated by privacy concerns, and such mediation might differ between older and younger adults. Additionally, some previous studies also show that the effect of external stimuli on privacy decisions is sometimes moderated by privacy concerns. For instance, the effect of contextual factors, such as the relationship with recipients on disclosure decisions is different for users with various levels of privacy concerns (Li and Kobsa, 2020). Furthermore, the effect of the trustworthiness of the sellers on online purchasing behaviors is moderated by consumers' privacy concerns, such that trustworthiness is a stronger predictor of purchase decisions for consumers with higher privacy concerns (McCole et al., 2010). Therefore, we will explore the mediating and moderating effects of privacy concerns among older and younger adults.

H5: *Privacy concerns moderate the effect of message framing on behavioral intentions to adopt privacy protective technologies differently between older and younger adults.*

H6: *Privacy concerns mediate the effect of message framing on behavioral intentions to adopt privacy protective technologies differently between older and younger adults.*

3. Methods

3.1. Study Overview

We designed a between-subject experiment with two experimental conditions where we present a fictitious privacy protective technology—SensorData—either in a gain frame as a "Privacy Enhancing Technology (PET)" or in a loss frame as a "Privacy Preserving Technology (PPT)." The framing condition was randomly assigned to participants. After giving consent and accepting to participate in the study, participants read a short piece of information about the SensorData technology and answered some questions about their behavioral intentions of using the SensorData, their privacy concerns, and demographics. Then, they were notified that SensorData is not a real technology and learned about the main purpose of our experiment. Figure 1 shows the study overview. This study was reviewed and approved by an Institutional Review Board (IRB).

3.2. Manipulation Design

In order to design the manipulation text (i.e., the introductory text on SensorData), the authors had several meetings where they discussed the text. The overall goal was to use the relevant gain/loss terminology in each condition while keeping the text concise. One important criterion was that the framing manipulation should not have any semantic implications in the sense that the two PET and PPT versions should communicate the same information. This is especially important because if the two versions communicate different information, we would be unable to know whether any potential findings are due to using different gain vs. loss terminologies or due to the different information presented to the users.

Below, we copy the manipulation. There are several '/' symbols in the text. Participants in the PPT condition read the text before the '/', and participants in the PET condition read the text after the '/'.

Preserve / Enhance Your Privacy

It is essential for one to preserve / enhance their privacy. Privacy-Preserving Technologies (PPT) / Privacy-Enhancing Technologies (PET) can help you defend yourself / increase your protection in the online world. PPTs / PETs are technologies that embody fundamental privacy-preserving / privacy-enhancing principles by minimizing the disclosure / maximizing the confidentiality of personal data, decreasing data breaches / increasing data security, and empowering individuals. PPTs / PETs allow online users to protect / increase the privacy of their personally identifiable information (PII) provided to and handled by services or applications.

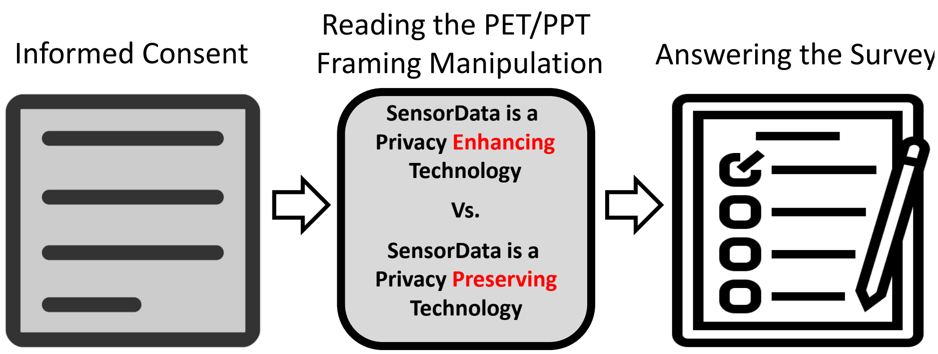

Figure 1. An overview of the study.

Preserve / Enhance Your Privacy The SensorData is a novel privacy preserving / enhancing technology. Many of the services you receive on your phone require you to disclose some personal information. For example, you can use the navigation service in your Maps app by disclosing your location data. However, some apps may ask for data they do not really need or may use your data later for other purposes. SensorData technology helps you manage your data disclosure and helps you preserve / enhance your privacy. This privacy preserving / enhancing technology analyzes and reviews the information disclosure requests made by the apps on your phone and rejects / accepts disclosure requests that are unsafe / safe, therefore, limiting / increasing your mobile device's vulnerability / security.

3.3. Measurement Instruments

Privacy concern is one of the most common variables in privacy studies, and it helps to understand the dynamics behind privacy decisions. To measure privacy concerns, we used Malhotra et al.'s Global Information Privacy Concerns (Malhotra et al., 2004.

In the context of technology adoption, the theory of planned behavior has been widely used to predict and understand one's intention to use technology (Ajzen, 1991. To measure behavioral intention, we adopted an existing scale from the literature (Lallmahamood, 1970 and tailored it to our context.

In addition, we measured the frequency of technology use with a question, 'How frequently do you use technology (e.g., smartphone, computer, internet)?' We recorded the responses on a 7-point Likert scale from 'less often' to 'almost constantly.' Furthermore, participants answered questions about their age and gender.

3.4. Participant Recruitment

Participants were recruited via Prolific, a crowd-sourcing / study participant recruitment platform. We recruited from older adult populations (aged 65 and above) and younger adult populations (between 25 and 35) who live in the U.S. Overall, we recruited 122 older and younger adult participants. After removing three participants who missed our attention check question, we were left with 61 older and 59 younger adults. Older adults were, on average, 69 years old (SD = 3.94), with 40 females and 21 males. In addition, they reported high usage of technologies such as smartphones, computers, and the internet. Thirty-five reported use of technology 'almost constantly,' 25 used technology 'several times a day,' and one of them '3-5 days a week'.

Our younger adult participants were, on average, 26.96 years old (SD = 4.18). Out of 59 younger adult participants, we had 31 females, 26 males, and two participants from the 'other' genders. Similar to our old adult participants, the young adults were also persistent technology users. Forty-four participants reported that they use technologies 'almost constantly,' 14 of them used it 'several times a day,' and one participant '3-5 days a week'. Indeed, our old and young adult samples were not significantly different regarding technology use ($p = 0.124$).

3.5. Data Analysis

We first subject our data to Confirmatory Factor Analysis (CFA). Although we borrowed measurement instruments from the literature, we conducted a CFA to assess the model fit and validity of the measurement model with our sample. We examined model fit indices like Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker–Lewis Index (TLI), as well as the convergent and discriminant validity of the factors, such as factor loadings and Average Variance Extracted (AVE). Convergent validity is confirmed by factor loadings above 0.6 and AVE exceeding 0.5, and discriminant validity is established when factor correlations are below 0.85 and less than the square root of AVEs. Then, we used factor scores for behavioral intention and privacy concern constructs to conduct linear regressions. We operationalized the age group as a categorical variable of ”Older adults” (¿65 years old) vs. ”Younger adults” (25 - 35 years old).

4. Results

4.1. Confirmatory Factor Analysis

We subjected the data to CFA and followed the guidelines in the literature by removing the items with low loadings (Brown and Moore, 2012). Two items in privacy concerns were removed due to low factor loadings. Table 1 reports the results of the CFA. The measurement model demonstrates robust convergent and discriminant validity: all factor loadings are above the 0.6 threshold. The Average Variance Extracted (AVE) for each construct exceeds 0.5. Furthermore, discriminant validity is established as the correlations between latent factors do not exceed 0.8 and are less than the square roots of the AVEs. Based on the measurement model, we calculated the factor scores for each construct and used the factor scores in the subsequent analysis.

4.2. Effect of Framing Between Older vs. Younger Adults (H1-4)

In order to study the main effects of experimental manipulations on older and younger adults, we conducted linear regression models on older and younger adult sub-samples. In the older adults sample, results show that participants in the PPT framing condition have 0.512 standard deviations higher privacy concerns than participants in the PET framing condition ($b = 0.512, p = 0.028$—**H1 supported**[1]) for the older adult sample (see in Figure 3). Similarly, as shown in Figure 4, PPT framing results in greater behavioral intentions for older adults such that the PPT framing increases older adults’ behavioral intentions to adopt SensorData by 0.460 standard deviations ($b = 0.460, p = 0.028$—**H2 supported**). For the younger adult sample, we did not find any effect of framing on privacy concerns ($p = 0.371$—**H3 rejected**) or behavioral intentions ($p = 0.423$—**H4 rejected**).

[1]The p-values reported in Section 4.2 are one-sided since we are testing specific directional hypotheses.

Variable	B	Standard Error	p-value
Intercept	-0.063	0.174	0.716
Framing (PPT vs. PET)	0.312	0.247	0.209
Age Group (YA vs. OA)	-0.050	0.242	0.836
Privacy Concerns	0.322	0.193	0.098
2-way: Framing X Age Group	-0.258	0.345	0.457
2-way: Framing X Privacy Concerns	-0.056	0.270	0.837
2-way: Age Group X Privacy Concerns	-0.549	0.264	0.040
3-way: Framing X Age Group X Privacy Concerns	0.882	0.369	0.019

Table 2. A report on the three-way interaction effect

4.3. The Moderating Effect of Privacy Concerns (H5)

To further explore whether the effect of PPT framing differs for different age groups with varying levels of privacy concerns, we regressed the behavioral intentions to adopt SensorData on a three-way interaction between age groups, privacy concerns, and experimental manipulation. This model accounts for 11.7% of the variance in the data (adjusted R-squared). Our results show a significant three-way interaction ($b = 0.882, p = .018$, see Figure 2). This finding implies that for older adults, the effect of privacy concerns on behavioral intentions to adopt SensorData is similar for both PET and PPT framing, indicating that the effect of PET/PPT framing on older adults’ intention to adopt SensorData is independent of the levels of older adults’ privacy concerns. However, this is not the case for younger adults. Young adults with a high privacy concern show a greater behavioral intention when presented with the PPT framing, whereas young adults with a low privacy concern show greater behavioral intention when presented with a PET framing, indicating that the PET/PPT framing should be customized for younger adults based on their different levels of privacy concerns. Hence, **H5 partially supported**. Table 4.3 reports the full regression results. [2]

4.4. The Moderating Effect of Privacy Concerns (H6)

Next, we conducted a mediation model for older adults to study whether and how privacy concerns

[2]The frequency of technology use and gender did not significantly predict dependent variables and were trimmed out of the model.

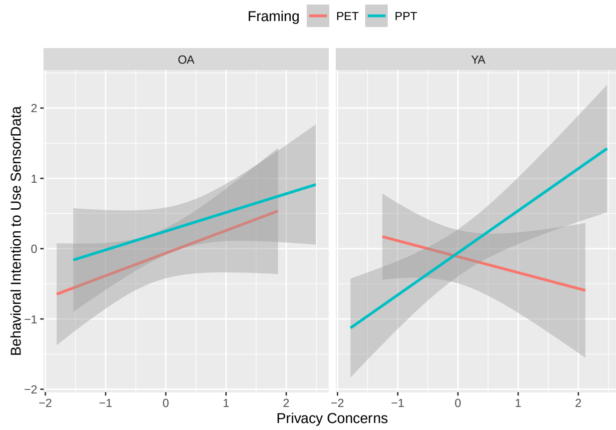

Figure 2. The three-way interaction effect between age group, framing, and privacy concern variables predicting the behavioral intentions to adopt SensorData. The panels show older and younger adult groups, and the line colors show Privacy Enhancing and Privacy Preserving framings.

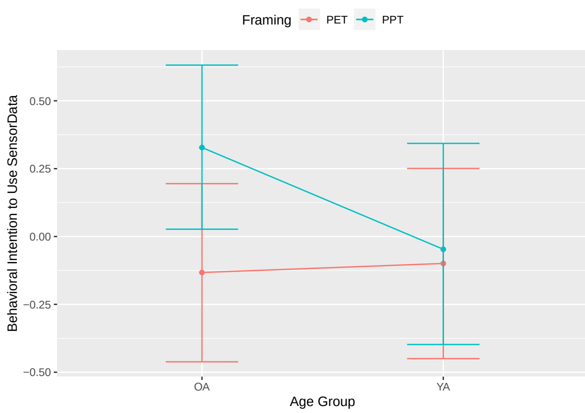

Figure 3. The effects of Framing on Behavioral Intention for younger and older adults.

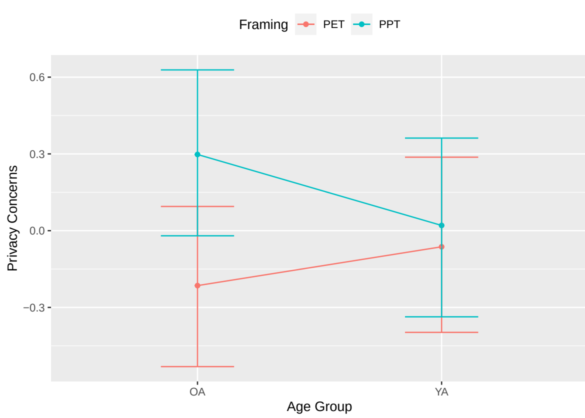

Figure 4. The effects of framing on Privacy Concerns for younger and older adults.

mediates the effect of framing manipulation on behavioral intentions to adopt SensorData. The results show that privacy concerns fully mediates the effects of framing on behavioral intentions to adopt SensorData for older adults, which further confirms that a loss-framed message (PPT framing) increases older adults' privacy concerns and subsequently reduces their behavioral intention to adopt privacy protective technologies (SensorData). However, such mediation effect does not exist for younger adults, as we have a moderation effect instead of mediation. Hence, for younger adults, the framing needs to be customized for different levels of privacy concerns, instead of one-size-fits-all. **H6 partially supported**. Figure 5 shows the decision models for each age group.

5. Discussion

This experiment addressed our research question; in order to encourage individuals to adopt privacy and security technologies, we should tailor the communications to the audience. A loss framing communicates a stronger message for the older adult population. For the younger adult population, the most encouraging framing is dependent on their levels of privacy concerns, with a loss framing being more motivating for highly concerned young adults and a gain framing being more motivating for young adults with lower concerns.

The selection, optimization, and compensation (SOC) theory of lifespan development (Baltes, 1997) suggests that older adults cope with the decline in their cognitive and physical resources by tuning their goals from being gain-focused to being loss-averse

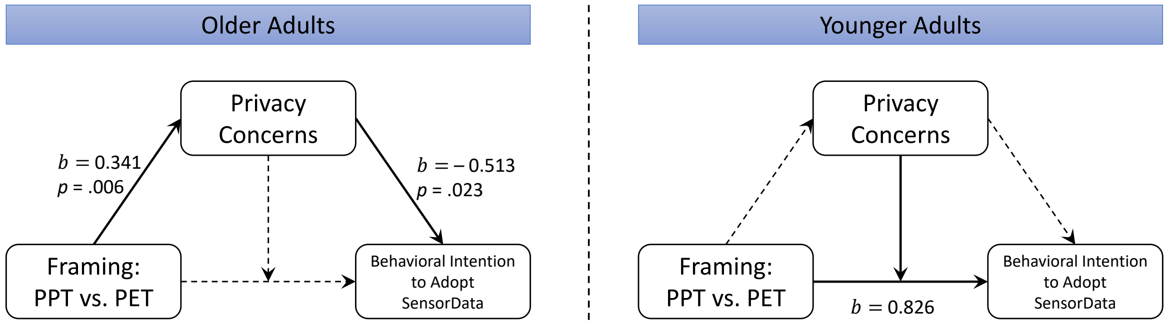

Figure 5. The decision models for older and younger adults show that privacy concerns fully mediates the effect of framing manipulation on behavioral intentions to use SensorData for older adults. For younger adults, privacy concerns moderates the effects of framing manipulation on behavioral intention to use SensorData. Non-significant effects are presented in dashed lines.

(Carpentieri et al., 2017). Therefore, a loss-framed message is a stronger message for older adults than a gain-framed message (Byrne and Ghaiumy Anaraky, 2020). We expanded this finding into the privacy and security decision-making domain. In our context, framing a privacy protective technology as "Privacy Preserving" arguably reminded older adults that their privacy is an asset to them and they should protect it. This loss framing increased older adults' behavioral intentions to adopt privacy and security measures (Figure 3) and increased their privacy concerns (Figure 4) more so than a gain framing of "Privacy Enhancing."

The results also showed a three-way interaction effect (see Figure 2, suggesting that the level of privacy concerns was a determinant parameter for the efficacy of our framing manipulations for the younger adult sample. Prospect theory posits that individuals show loss aversion behaviors in the loss context and perceive losses as more significant than gains (Kahneman and Tversky, 1984). A potential privacy or security breach is arguably perceived as a loss if one expresses privacy concerns. However, for individuals with low levels of privacy concern, the privacy or security breach may not loom as a loss since they have low concerns, to begin with. Therefore, our loss-framed PPT message was more persuasive for individuals with higher privacy concerns who consider privacy as an important issue. Consequently, these individuals show higher behavioral intentions to adopt the SensorData technology. On the contrary, those with a low level of privacy concerns do not consider privacy and security breaches as a loss as much. Therefore, the loss-framed message is not as strong for them, while the gain-framed message shifts them to a gain-seeking mode.

The interaction effect with privacy concerns, however, does not apply to older adults. One reason for this can be that the prospect theory tends to be mitigated for older adults compared to younger adults (Byrne and Ghaiumy Anaraky, 2020). This means that the gap between older adults' decisions in gain vs. loss contexts is less than the gap between younger adults' decisions in gain vs. loss contexts. In line with this argument, Figure 2 shows that older adults' behavioral intention range is narrower than younger adults' range.

In addition to a prospect theory account, our findings can be justified by the way gain and loss keywords change an individual's ways of thinking. Samat and Aquisti (Samat and Acquisti, 2017) argued that the "*prohibit* my responses to be shared with a marketing company" nudges individuals to think about reasons to 'prohibit' data disclosure whereas "*allow* my responses to be shared with a marketing company" nudges individuals to think about reasons to 'allow' the data sharing. In our case, it is possible that the PPT framing nudges individuals to think about the reasons to protect their privacy; research shows that older adults are more subject to privacy and security risks than younger adults. Therefore, the PPT message is more alarming for them as they arguably have more reasons to protect their data. For younger adults, the ones with high privacy concerns may have experienced more privacy and security incidents. Similarly, the PPT framing was more encouraging for them. Future research should measure previous negative privacy and security incidents to see if the PPT framing puts any additional motivates on individuals with more experience of privacy and security breaches or not.

Furthermore, our results suggest that older and younger adults follow different decision-making mechanisms, such that privacy concerns is a mediator for older adults and a moderator for younger adults (see Figure 5). Previous research suggests that young adults follow a model-free decision-making model, where they rely more on heuristics and do not simulate a cognitive mental model of the environment. In contrast, older adults follow a model-based decision-making model(Worthy et al., 2011) where they create a cognitive model of the environment and are concerned with the way different states of the world are connected to each other (Daw et al., 2005). In our case, it appears as older adults created a mental model of the environment by tuning their level of privacy concerns according to the framing manipulation.

Overall, tailoring the messages to the audience can lead to various desired outcomes. For example, we can promote physical activities (Bull et al., 1999), or encourage mask-wearing behaviors during a pandemic (Utych, 2021) with personalized messages. In this paper, we studied how personalized messages can encourage privacy behaviors among older and younger adults. Our results have practical implications for the privacy and security industries, which can leverage message framing to encourage the adoption of their products among different age groups.

In addition, our findings have important implications for policymakers. Ensuring informed consent is a major challenge in policy design (Samat and Acquisti, 2017). Our results show that by using personalized messages, policymakers can potentially promote informed consent. For instance, a loss-framed message such as ”To protect your privacy, please read the policy statement” may be more effective in engaging older adults with policy documents compared to a gain-framed message like ”To improve your privacy, please read the policy statement.” Further research should examine the efficacy of gain vs. loss framing in the policy domain and determine if they are successful in motivating different groups to engage with policies.

6. Limitations and Future Work

The older adults participating in this study reported very high daily use of technology products. We should acknowledge that older adults are not a homogenous population, and their attitudes and behaviors toward technology and privacy vary significantly. Therefore, we cannot expand our findings to the overall population of older adults. Future studies should study older adults who may not be as familiar with digital technologies.

In addition, while the participants did not know that SensorData is not a real technology and only expressed their intention to adopt it, future research can use real-life scenarios and examine the impact of manipulations on concrete behavioral actions, such as signing up for a VPN service or modifying privacy settings. This will provide a more robust understanding of how these framing techniques influence the real-world adoption of security and privacy behaviors.

7. Conclusion

Our study shows that privacy product marketers and policymakers should allocate resources to studying their older adult user base to improve their services to this population. A showcase of this would be tailoring the framing of their messages to the intended audience to improve the chances of adopting privacy and security measures.

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