Effect of Priming on Smart Home Privacy Preferences

Reza Ghaiumy Anaraky
Clemson University

Paritosh Bahirat
Clemson University

Moloud Nasiri
Clemson University

Xinru Page
Brigham Young University

Bart P. Knijnenburg
Clemson University

Andrew T. Duchowski
Clemson University

Abstract

As people are increasingly surrounded by IoT devices in their homes, the amount of personal data collected by these devices can become overwhelmingly large. Consequently, it can be difficult for users to manage their privacy, especially if they must make individual decisions about every type of information. A proposed solution to this problem is to offer users a set of privacy profiles that each represent a set of default options. However, it has been shown in past privacy research that how such settings are presented can greatly influence the user's subsequent choices. In this study, we tested the effect of framing on users' choice of privacy profile for a home IoT system. We contrast a framing that emphasizes the benefits of data collection (positive priming) with a framing that focuses on the privacy drawbacks of data collection (negative priming). While priming did not lead to significant differences in participants' choice of privacy settings, we use eye tracking technology to show how such priming does affect the extent to which users consider certain options. This work has implications for understanding how framing may affect users' attention to certain privacy options.

1 Introduction

Users of smart home devices face an inherent privacy trade-off, as these devices must collect some data to provide their services. Indeed, privacy and security concerns are among the biggest reasons for low levels of household IoT adoption [4]. Privacy researchers have long suggested that users make this trade-off between the risks and benefits of using a service using a process referred to as the "Privacy Calculus" [5, 10]. However, more recent research has found that contrary to a rational choice, user privacy decisions tend to be mostly heuristic in nature, which makes it vulnerable to spurious influences [3, 8, 15].

For example, Nosko et al. [12] tested the "priming effect" by showing half of the participants in their study a text about a stalking incident and the other half a neutral text, before asking them to modify their Facebook privacy settings. Participants who had read the stalking story, ended up applying more restrictive settings and consequently disclosed less information than participants who had read the neutral story. Arguably, the stalking story had *primed* these participants: this negative example made them more conservative in their privacy decisions. We intend to take this idea further and apply it to IoT privacy decision making scenarios. To the best of our knowledge, we are the first who investigate the following research question: Does priming also influence users' decisions concerning their IoT privacy settings?

How does priming work? Economic literature suggests that people are more concerned about avoiding losses than about obtaining gains. Kahneman and Tversky [14] were the first to codify this loss aversion in their *prospect theory*. In the realm of privacy, loss aversion has been demonstrated by Acquisti et al. [2], who showed that users demanded a much higher price to sell their information (a loss of privacy) than they would be willing to spend for protecting their information (a gain of privacy). Likewise, we argue that priming participants with a negative text can potentially trigger a loss aversion state in which participants would put more effort into investigating their available options to avoid a potential loss of privacy, while those primed with a positive text would put comparatively less effort into the decision task.

To measure the occurrence of this difference in decision effort, we leveraged eye tracking technology. Eye tracking is being used to e.g., understand user behavior [6], to evaluate the usability of systems [13], and trace user decision processes [11]. Tracking the user's gaze enables us to measure what they are looking at; this can be an indication of visual attention and

Copyright is held by the author/owner. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee.
USENIX Symposium on Usable Privacy and Security (SOUPS) 2020.
August 9–11, 2020, Boston, MA, USA.

thought processing. This will help us to further investigate if priming changes users' decision-making practices, e.g., by making them more likely to consider options in line with the message they had been primed with.

2 Methodology

2.1 Stimulus

To operationalize our research questions, we used the privacy profile selection interface developed by He et al. [7] shown in Figure 1. He et al. ran a study in which 1133 participants expressed their sharing preferences regarding 4608 contextual scenarios and developed an algorithm that clustered these participants based on their sharing decisions into five clusters. They subsequently developed a set of five privacy profiles that best matched the preferences of the participants in each cluster. As an example, the 'Enable All' profile was developed for the cluster of participants who allowed the collection and sharing of data for almost every scenario presented during the study, while the 'No Sharing' profile was developed for the cluster of participants who generally allowed scenarios involving the collection of data, but rejected scenarios in which collected data was shared with third parties. He et al. then created an interface displaying the profiles ordered from liberal (Enable All) to conservative (Disable All). They argued that this interface could serve as a first step in users' privacy-setting experience: When a person selects one of the five profiles, the default settings described in that profile are pre-configured in the subsequent privacy settings interface (See He et al. [7] for a detailed explanation). He et al. argued that the purpose of this profile selection interface is to reduce the cognitive effort associated with making numerous privacy settings. We use these profiles to study how priming influences users' evaluation and profile selection.

2.2 Study procedure

The study was conducted with 18 participants (Male: 11, Female: 7) with an average age of 23.5. The participants were recruited on the Clemson University campus. Participants started the experiment by reading a priming message. The priming message was manipulated between subjects as either a negative (risk oriented) or positive (benefit oriented) narrative, allowing us to study the difference between these two priming conditions. The priming messages are described below. After reading a randomly assigned message, participants were exposed to the main stimulus shown in Figure1, which displayed the privacy profiles. Participants were then asked to choose a profile. To trace users' decision process, we used a Gazepoint GP3 pupil corneal reflection eye tracker. The eye trackers were used mounted below 22 inch Dell P2213 monitor screens with a resolution of 1680×1050.

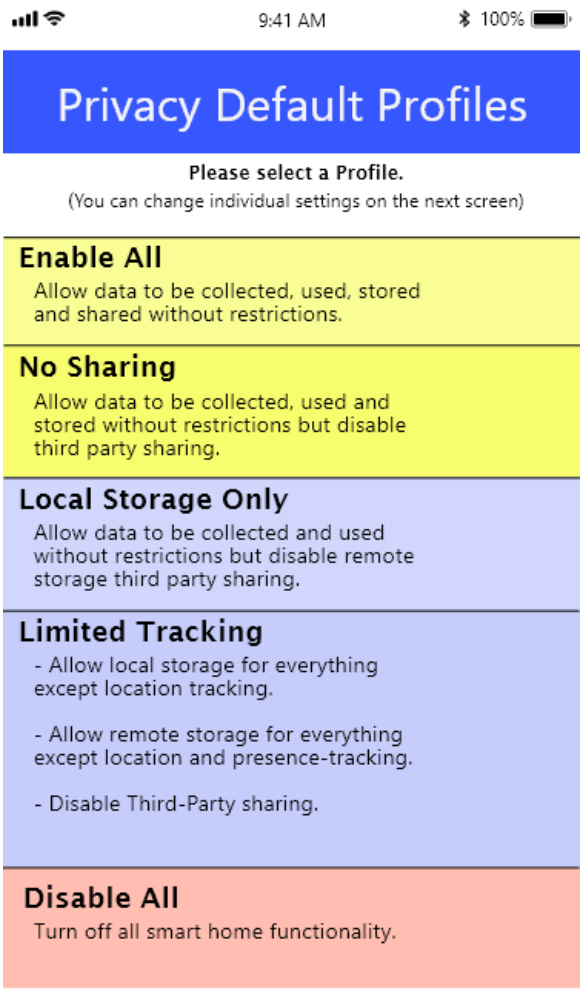
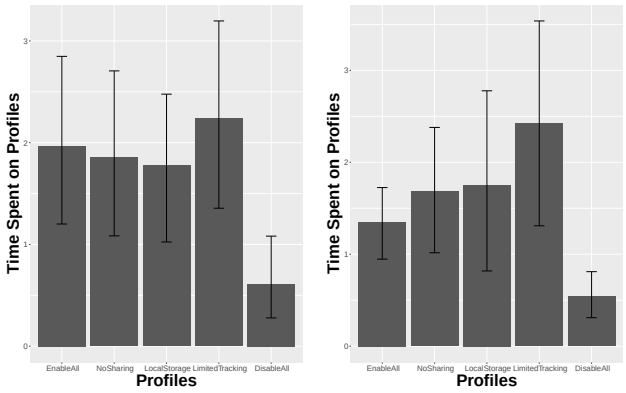


Figure 1: Stimulus interface.

2.3 Priming manipulation

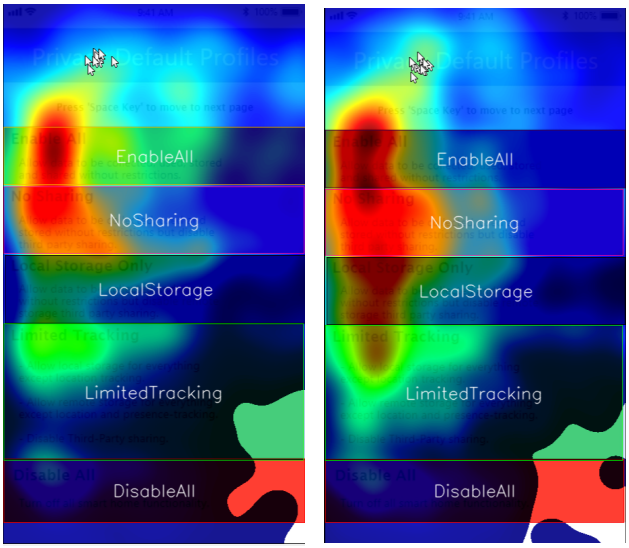
The positive priming message read as follows:

"In today's Smart-home, one can expect to find all the appliances of a regular household. The only difference is that appliances in a Smart-home will be capable of various functionalities without needing human interference. These functionalities improve convenience of routine household activities and tasks. For example, a Smart Thermostat can detect the presence of the person in the house by contacting a Smart-lock in the door. Then it can use this information to automate the temperature controls for the home. Smart-homes are beneficial because they help in automating several day to day tasks without the occupant's intervention. This automation can also be helpful in energy savings and eventually reducing electricity costs. For example, a smart lighting system will automatically dim the lights based on existing natural light and also turn them ON/OFF based on occupants' presence."



(a) (b)

Figure 2: Total time spent per profile for (a) positive and (b) negative priming conditions.



(a) (b)

Figure 3: Averaged heat map for participants in the (a) positive and (b) negative priming conditions.

The negative priming message read as follows:

"Smart-homes are comprised of several routine appliances found in an ordinary household. The key difference though is the additional functionality provided by these appliances. For example, a smart assistant in your home can order you a taxi in case of a bad weather. This convenience however comes at a cost. This cost is not only financial. The several devices in a smart-home environment with built in sensors heavily rely on collection of data from the owner or the people in these environments. The devices passively collect large amounts of data, whether a person is present inside home or not, what are the likes and dislikes of the people living in the smart-homes and so on. The devices not only share the data with different appliances in the home but can also share it with Manufacturers or third parties. This shared data can be used to give targeted advertisements and recommendations to you."

3 Results

We first conducted analyses to see if there are any differences in users' profile selection across the positive and negative priming conditions. We ordered the selected profiles from 0 (disable all) to 4 (enable all). We ran a t-test with priming condition as the independent variable and selected profiles as dependent variable. We did not find a significant difference between the positive and the negative priming condition ($t(13.473) = -0.71$, $p = 0.490$). Similar results were obtained running a non-parametric test (Mann-Whitney U test) and running a test where profiles are considered an unordered categorical variable (Chi-square test).

To test whether priming influenced users' consideration of different options (their gazes), we conducted multilevel regression analysis. The number of fixations per second (Saccades) on a given profile was our dependent variable and profile and priming served as independent variables. within-subjects and between-subjects independent variables. We first created a baseline model which predicted the Time/Saccades by only a random effect (participant ID). Profile and priming were added to this baseline model in a forward stepwise manner. Using model comparison tests we checked whether the addition of these variables improved the model. Neither profiles ($\chi^2(4) = 5.608$, $p = 0.346$) nor priming ($\chi^2(1) = 0.761$, $p = 0.382$) improved the model. We also did not find an interaction effect between profile and priming ($p = 0.138$).

Despite the lack of an overall interaction effect, figure 2 and the heat maps in figure 3 show some notable differences between the positive and negative priming conditions, particularly when comparing the two most extreme conditions: enable all as the most liberal privacy setting and disable all as the most conservative privacy setting. The average time people spent looking at the enable all profile was higher for participants in the positive priming condition (3.93 seconds) compared to the negative priming condition (2.69 seconds). This difference however was not significant ($p = 0.226$).

4 Discussion

We did not find significant effects of priming on participants' profile selections. Furthermore, our overall model suggests that priming does not predict profile considerations. These non-significant overall statistical results can potentially be due to the low number of participants in our study. Indeed, our heat maps suggests that the participants did pay attention to profiles differently across the different priming conditions: participants in the positive priming condition tended to linger

on the enable all profile 1.24 seconds more than those in negative priming condition. Arguably, users in the positive priming condition had more positive information available in their minds (a gain frame), and thereby showed more interest in the liberal profiles (See Figure 3a). In contrast, participants who saw a negative priming message seemed to cover a wider spectrum of profiles (See Figure 3b). Arguably, participants who are primed with a negative message take on a loss frame. In line with prospect theory [14] these participants put more effort into avoiding that loss than those who are put into a gain frame (i.e., those in the positive priming condition) spend on obtaining a gain.

5 Limitations and Future Work

We acknowledge our small sample size a limitation of our study. Our eye-tracking data and heat maps are sufficient for studying the spread of gaze, but future studies should recruit more participants to attain more robust statistical results. Furthermore, we note that our study tests a mobile interface on a desktop computer screen. Having a different size, angle, and distance may have changed the way people looked at the interface. Finally, in this study the profiles were listed in a fixed listing order, from enable all to disable all. However, the order of the profiles may influence visual attention and decision-making [1, 9]. Hence, in follow-up studies, the order of choice options should be manipulated or randomized.

6 Conclusion

This study showed that priming has the potential to impact users' decision-making process. As our heat maps suggest, users who have a negatively valenced availability heuristic (loss frame), are likely to more widely spread their gaze among available options than those who have a positively valenced availability heuristic (gain frame). Arguably, the latter users are more likely to rely on heuristics when using the system. Insofar as these availability heuristics can be manipulated through priming, system designers should carefully communicate the privacy control features that are designed to align users' preferences to data processing practices. This will be especially crucial for novel technologies, such as IoT: Most users do not have many negative experiences such technologies, so they may take on a gain frame by default, which makes them less likely to carefully consider all the available settings, just like how our participant in the positive primed condition did.

References

[1] Alessandro Acquisti, Leslie K John, and George Loewenstein. The impact of relative standards on the propensity to disclose. *Journal of Marketing Research*, 49(2):160–174, 2012.

[2] Alessandro Acquisti, Leslie K John, and George Loewenstein. What is privacy worth? *The Journal of Legal Studies*, 42(2):249–274, 2013.

[3] Reza Ghaiumy Anaraky, Tahereh Nabizadeh, Bart P Knijnenburg, and Marten Risius. Reducing default and framing effects in privacy decision-making. *Proceedings of the Special Interest Group On Humancomputer Interaction*, 2018.

[4] D Bothun and M Lieberman. Smart home, seamless life: Unlocking a culture of convenience, 2017.

[5] Mary J Culnan. " how did they get my name?": An exploratory investigation of consumer attitudes toward secondary information use. *MIS quarterly*, pages 341–363, 1993.

[6] Laura A Granka, Thorsten Joachims, and Geri Gay. Eye-tracking analysis of user behavior in www search. In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 478–479. ACM, 2004.

[7] Yangyang He, Paritosh Bahirat, Bart Piet Knijnenburg, and Abilash Menon. A data driven approach to designing for privacy in household iot. *ACM TiiS*, 2019.

[8] Eric J Johnson, Steven Bellman, and Gerald L Lohse. Defaults, framing and privacy: Why opting in-opting out. *Marketing Letters*, 13(1):5–15, 2002.

[9] Bart Piet Knijnenburg and Alfred Kobsa. Increasing sharing tendency without reducing satisfaction: finding the best privacy-settings user interface for social networks. 2014.

[10] Robert S Laufer and Maxine Wolfe. Privacy as a concept and a social issue: A multidimensional developmental theory. *Journal of social Issues*, 33(3):22–42, 1977.

[11] Gerald L Lohse and Eric J Johnson. A comparison of two process tracing methods for choice tasks. *Organizational Behavior and Human Decision Processes*, 68(1):28–43, 1996.

[12] Amanda Nosko, Eileen Wood, Miranda Kenney, Karin Archer, Domenica De Pasquale, Seija Molema, and Lucia Zivcakova. Examining priming and gender as a means to reduce risk in a social networking context: Can stories change disclosure and privacy setting use when personal profiles are constructed? *Computers in Human Behavior*, 28(6):2067–2074, 2012.

[13] Michael Schiessl, Sabrina Duda, Andreas Thölke, and Rico Fischer. Eye tracking and its application in usability and media research. *MMI-interaktiv Journal*, 6:41–50, 2003.

[14] Amos Tversky and Daniel Kahneman. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291, 1979.

[15] Amos Tversky and Daniel Kahneman. Loss Aversion in Riskless Choice: A Reference-Dependent Model. *The Quarterly Journal of Economics*, 106(4):1039–1061, 1991.