Exploring Defaults and Framing effects on Privacy Decision Making in Smarthomes

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ABSTRACT

Research has shown that privacy decisions are affected by heuristic influences such as default settings and framing, and such effects are likely also present in smarthome privacy decisions. In this paper we pose the challenge question: How exactly do defaults and framing influence smarthome users' privacy decisions? We conduct a large-scale scenario-based study with a mixed fractional factorial design, and use statistical analysis and machine learning to investigate these effects. We discuss the implications of our findings for the designers of smarthome privacy-setting interfaces.

1. INTRODUCTION

The term 'smarthome technology' describes a multitude of devices that communicate with one another to support the automation of various day to day activities. This comes at the cost of collecting large amounts of information from the user, which can be perceived as intrusion of the user's privacy. And while most smarthome devices provide privacy settings, privacy management in a smarthome environment involves making decisions regarding a dazzling number of interrelated contextual factors [1]. Evidence suggests that users are ill-equipped at making such decisions. For example, a number of authors demonstrate that users' privacy decisions are influenced by default settings and the framing of the decision [3, 9, 8, 7]: Such heuristic influences are likely also present in smarthome privacy decisions.

A largely unanswered question is *how* defaults and framing influence users' decisions. There are several psychological explanations for these effects. For defaults, researchers have argued for a *direct* behavioral effect on decisions: people go with the default to avoids the effort of making an active decision [2, 5, 12, 4]. Some have argued that both defaults and framing *moderate* the effect of users' attitudes: people tend to cognitively regard the default or framing as a reference point to which alternatives are compared [5, 6, 11]. Finally, some have argued that attitudes *mediate* the effects of default and framing: according to them, defaults and framing act as an implied endorsement by the system [10, 13]. In all cases, the effects of defaults and framing are presumed to *reduce the quality* of users' decisions, although few researchers have demonstrated this effect (a notable exception is [8]).

In this paper we present the results of a study where we manipulated the framing of decisions and the default choices, and demonstrate how these manipulations impacted participants' decisions towards different smarthome scenarios. We uncover through statistical analyses the *process* by which defaults and framing affected participants' decisions. Then we use machine learning to show that especially defaults reduce the quality of the *outcome* of users' decision process.

2. EXPERIMENTAL DESIGN

We conducted a survey study with 1133 U.S.-based adult participants (53.53% Female, 45.75% Male, 8 participants did not disclose) recruited through Amazon Mechanical Turk. Each participant was presented with 13 information-sharing scenarios based on a mixed fractional factorial design, which manipulated five different Parameters: Who, What, Purpose, Storage and Action. A total of $8(who) * 12(what) * 4(purpose) * 4(storage) * 3(action) = 4608$ scenarios were tested this way. An example scenarios is: *"Your smart TV (Who) uses a camera (What) to give you timely alerts (Purpose), the data is stored locally ('Storage') and used to optimize the service ('Action')."* At the end of each scenario, participants were asked whether they would enable/disable the scenario (decision) and to rate their attitudes towards the scenario in terms of risk, comfort, appropriateness, usefulness, and expectedness, each on a 7-point scale.

For the Decision question, the framing and default were manipulated between subjects at three levels each: positive framing ("Would you enable this feature?", options: Yes/No), negative framing ("Would you disable this feature?", options: Yes/No) or neutral framing ("What would you do with this feature?", options: Enable/Disable); combined with a positive default (enabled by default), negative default (disabled by default), or no default (forced choice).

3. STATISTICAL ANALYSES

Here we evaluate the direct effects of default and framing on on users' decisions, followed by their moderation of the effect of users' attitudes on their decision.

3.1 Direct Effects

While the contextual parameters of the scenario have a strong effect on users' decisions (chi^2-values between 1488 for storage and 77 for action), our focus here is on the effect of defaults and framing. Table 1 shows the results of a *general-*

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Table 1: Effect of defaults and framing on decision

Model	χ^2	*df*	*p*-value
decision $\sim (1\|sid)$			
+Default	82.87	2	$< .0001$
+Framing	7.82	2	.0199
Interactions			
+Default:Framing	2.62	4	.6225

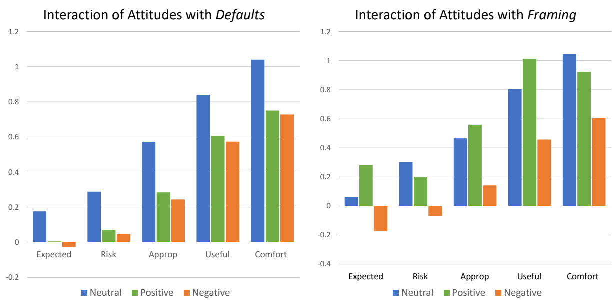


Figure 1: Effect of attitudes on decision in each default/framing condition

ized linear mixed effects regression with a logit link function (to account for the binary outcome variable) and a random intercept (to account for multiple scenarios per participant).

Although defaults and framing were manipulated between-subjects, they still had a significant effect on participants' decisions. Compared to no default, participants in the negative default condition were 1.37 times less likely to enable the functionality described in the scenario ($p = .006$), while participants in the positive default condition were 2.57 times more likely to enable the scenario ($p < .001$). Compared to positive framing, participants in the negative framing condition were 1.31 times more likely to enable the functionality described in the scenario ($p = .0205$). Defaults and framing did not have an interaction effect on decision ($p = .623$).

3.2 Moderating and Mediating Effects

We subsequently tested the moderating effect of defaults and framing on the effect of participants' attitudes on their behavior. Table 2 shows significant interaction effects between defaults/framing and all five attitudes. Figure 1 shows the size of the effect of each attitude (in logits) on participants' decision in each default and framing condition.

All attitudes have a stronger effect on decision in the 'no default' condition than in the positive and negative default conditions (Figure 1, left). Response curves for attitudes by default condition are shown in Figure 4 in the appendix.

In the various framing conditions, the attitudes have a substantially different relative effect. All attitudes have a weaker effect in the negative framing condition than in the positive and neutral framing conditions. On the other hand, expectedness, usefulness, and to some extent appropriateness have a relatively *stronger* effect on participants' decision in the positive framing condition than in the neutral framing condition (Figure 1, right). Response curves for attitudes by framing condition are shown in Figure 5 in the appendix.

Note that we do not find any direct effects of defaults and

Table 2: Interaction effects between defaults/framing and attitudes

Model	χ^2	*df*	*p*-value
decision $\sim (1\|sid) + Attitudes$			
+Default	209.28	2	$< .0001$
+Framing	5.44	2	.0658
Interactions-Defaults			
Default:Appropriateness	26.50	2	$< .0001$
Default:Risk	16.47	2	.0002
Default:Comfort	26.43	2	$< .0001$
Default:Expected	11.32	2	0.003
Default:Usefulness	19.88	2	$< .0001$
Interactions-Framing			
Framing:Appropriateness	45.79	2	$< .0001$
Framing:Risk	37.39	2	$< .0001$
Framing:Comfort	50.78	2	$< .0001$
Framing:Expected	51.51	2	$< .0001$
Framing:Usefulness	83.23	2	$< .0001$

framing on attitudes (all *p*s $> .25$), thereby ruling out the possibility that participants' attitudes mediate the effects of defaults and framing on their decision.

4. MACHINE LEARNING

The previous section shows how defaults and framing can influence users' decision-making *process*. In this section we will analyze the effect this has on the quality of their decision *outcome* by modeling the effect using a J48 decision tree.

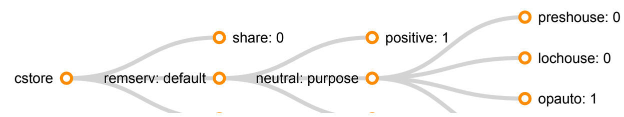
4.1 A Separate Model for Each Default

In our preliminary experiment, we divide our dataset across default conditions, and model the *enable/disable* decision in each group with the five scenario parameters as predictors. We manipulate the degree of model pruning for each condition using J48's *Confidence Factor* (CF): Lowering the CF will incur more pruning. Since users make less cognitively-motivated decisions in the default conditions, our expectation is that the positive and negative default conditions can be modeled with simple trees, while the 'no default' condition is best modeled with a more complex tree.

Table 3 in the appendix shows an overview of the results. Compared to the neutral default group, the positive default and negative default groups both have less complexity but similar accuracy at each CF level. This effect is most prominent for the positive default condition, which has a tree with only 4 nodes, regardless of the amount of trimming that is applied. For framing we do not find such substantial differences in model complexity between conditions.

4.2 Integrating Defaults into the Model

We subsequently run the algorithm on the entire dataset, adding the default manipulation as an additional parameters. The decision tree for CF values 0.01-0.16 is shown in Figure 2. The 'storage' parameter has the most significant effect on users' decision: it predicts *disable* for scenarios where data is stored on a remote server and shared with third party, and *enable* for scenarios where data is stored locally. For scenarios where data is stored remotely without sharing, the setting depends on the default condition: for users in the positive and negative default conditions the model predicts *enable* and *disable*, respectively. For the neu-



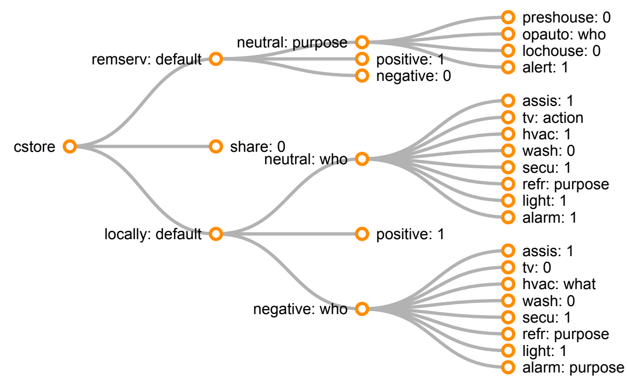


Figure 3: Model with defaults and 5 scenario parameter as model input (CF: 0.18-0.19, Acc: 63.62%)

tral default condition, though, the decision depends on the 'purpose', with users *enabling* smarthome functionality for automation and alerts, but *disabling* functionality for the purpose of detecting one's presence or location in the house. Again, the decisions in the positive and negative default conditions are simpler than those in the 'no default' condition.

The tree for CF values 0.18-0.19 is shown in Figure 3. Again, storage is the root node, followed by defaults. The model predicts *disable* for scenarios where data is stored on a remote server and shared with third parties. For scenarios where data is stored remotely without sharing, the setting depends on which default condition the user is in: for the positive and negative default conditions the model predicts *enable* and *disable*, while the decision for neutral default will depend on the 'purpose' and further the 'who' parameter. For scenarios where data is stored locally, the model predicts *enable* for the positive default condition, while the decisions for the negative and 'no default' conditions further depend on other parameters. The complexity of the 'no default' branch and the negative default branch are comparable. This again suggests that the decisions of users in the positive default condition (and to some extent those the negative default condition as well) are simpler than of those in the 'no default' condition.

Similar observations hold for CF values 0.20 and up. We ran these models for framing too, but we did not find substantial differences in complexity between framing conditions and framing appears at a deep level of the decision trees.

5. DISCUSSION

Our results are in line with previous work when it comes to default effects. We find evidence of a *direct* effect of defaults on participants' decisions (Section 3.1), suggesting a *behavioral* explanation of the default effect. We also find *moderating* effects on the effects of attitudes on participants' decision (Section 3.2). Defaults consistently reduce the effect of attitudes on users' decision, suggesting that defaults entice users to avoid expending *cognitive* effort.

This strong behavioral effect and a reduction of cognitive effort when users are given a default setting is in line with previous findings by Knijnenburg et al. [8]. Our novel contribution is that our machine learning results demonstrate the consequence of this effect: users indeed seem to make less "sophisticated" decisions in the positive and negative default conditions than in the 'no default' condition.

Our results seem to contradict earlier findings regarding framing effects: Both Johnson et al. [3] and Lai and Hui [9] find that negative framing *reduces* acceptance compared to positive framing, while we find that negative framing *increases* acceptance. A reason might be that in previous work frames were presented as statements, while in our work they were formulated as questions, which may have caused users to assume the antagonistic perspective as a reference point. Note also that the main effect of framing is relatively small compared to the main effect of defaults (see Table 1).

In fact, framing has much stronger interaction effects, and these effects show an interesting pattern (see Figure 1, left). Similar to the default conditions, the negative framing condition seems to reduce users' expenditure of cognitive effort. Arguably, the unconventional wording of negatively framed questions ("Do you want to disable this functionality?") throws users off their game, and puts them in a loss-averse reference frame. The positive framing condition, on the other hand, subtly changes the relative relevance of certain attitudes. Particularly, when explicitly asked to *enable* the functionality presented in a scenario, users are more likely to focus on the expectedness, appropriateness, and usefulness (or the lack thereof) of the scenario, and less likely to focus on whether they are comfortable with the scenario and/or find it risky. In sum, while framing does not influence users' attitudes directly, it moderates the importance of existing attitudes in users' decision process.

6. CONCLUSION

In this paper we used statistical analyses and machine learning to demonstrate how users' smarthome privacy decisions were affected by defaults and framing. Our results show that these factors not only have a behavioral effect: framing influences users' cognitive decision processes, while defaults generally reduce these cognitive processes and thereby also quality of users' decisions.

While it was possible in our study to present decisions with no default and a 'neutral' framing, this is rarely possible in privacy-setting interfaces. One solution is to adapt the default setting to the user, but even the data used to determine this adaptive setting may be influenced by the defaults and framing present in the interface. A better solution may be to employ "data-driven design" [1] on framing- and default-free survey data (i.e., a subset of the data presented in this paper) to generate a series of "smart profiles" that reflect a wide range of user preferences. Another solution is to apply "propensity scoring" to users' decisions, thereby amplifying any decisions that counter the default. At the very least, though, we encourage the designers of smarthome privacy-setting interfaces to face the difficult challenge of minimizing the impact of defaults and framing on users' decisions.

7. REFERENCES

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APPENDIX

Table 3: Complexity (Cop) and accuracy (Acc) of models in different default conditions

Conf. Factor	Neutral		Positive		Negative	
	Cop	Acc	Cop	Acc	Cop	Acc
0.01-0.07	8	64.15%	4	64.73%	4	63.24%
0.08-0.16	8	64.15%	4	64.73%	20	64.92%
0.17	16	64.62%	4	64.73%	40	65.54%
0.18-0.19	32	65.74%	4	64.73%	40	65.54%
0.20	48	66.38%	4	64.73%	40	65.54%
0.21	60	66.64%	4	64.73%	40	65.54%
0.22	64	66.73%	4	64.73%	40	65.54%
0.23	68	66.82%	4	64.73%	44	65.74%
0.24	76	66.98%	4	64.73%	68	66.31%
0.25	100	67.68%	4	64.73%	68	66.31%

Table 4: Parameters used in the experiment

Parameter	Levels
Who (Info-sharing): *Your Smart...*	1. Home Security System 2. Refrigerator 3. HVAC System 4. Washing Machine 5. Lighting System 6. Assistant 7. TV 8. Alarm Clock
What (Info-sharing): *...uses information collected by your...*	1. Home Security System 2. Refrigerator 3. HVAC System 4. Washing Machine 5. Lighting System 6. Assistant 7. TV 8. Alarm 9. uses a location sensor 10. uses a camera 11. uses a microphone 12. connects to your smart phone/watch
Purpose (Info-sharing): *...to...*	1. detect whether you are home 2. detect your location in house 3. automate its operations 4. give you timely alerts
Who (Control): *"You can use your Smart...*	1. Assistant 2. TV 3. Alarm Clock 4. Phone/Watch
What (Control): *...to control your...*	1. Home Security System 2. Refrigerator 3. HVAC System 4. Washing Machine 5. Lighting System 6. Assistant 7. TV 8. Alarm Clock
Storage: *The data is stored...*	1. locally 2. on remote server 3. on a remote server and shared with third parties
Action: *...and used to...*	1. optimize the service 2. give insight into your behavior 3. recommend you other services 4. [None]

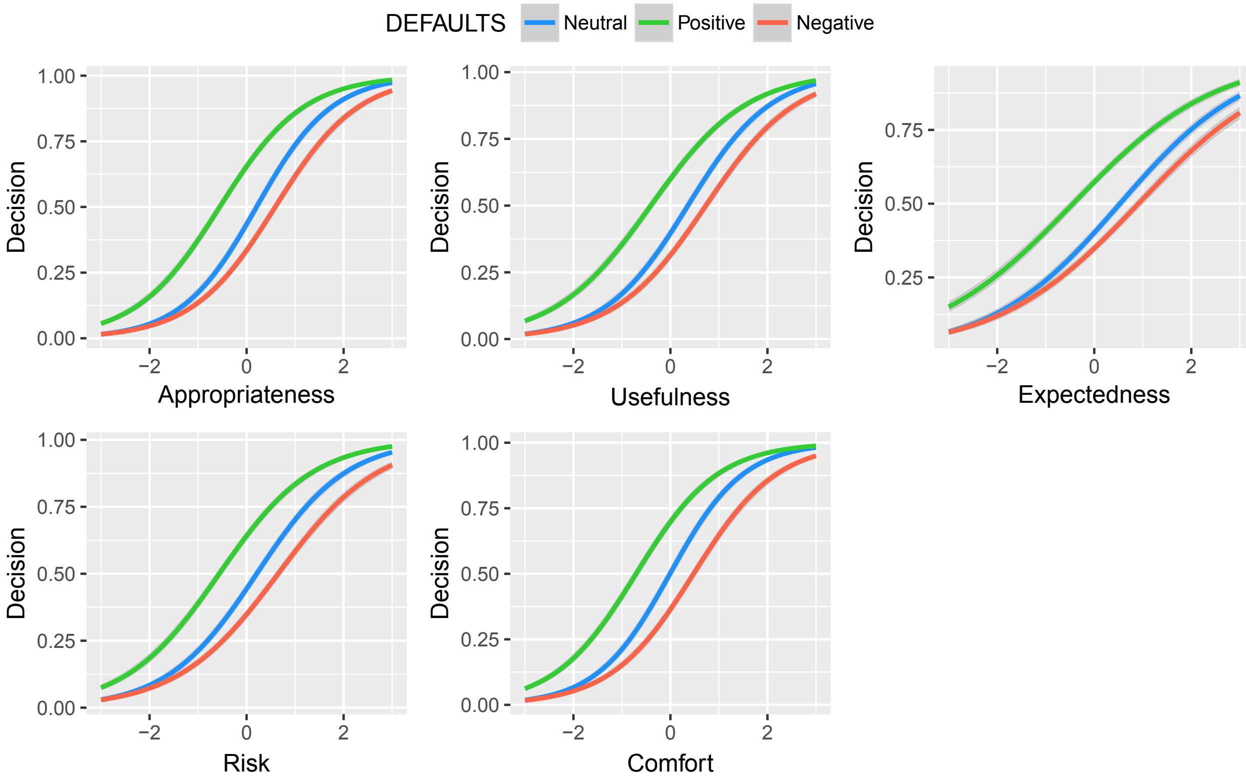

Figure 4: Different attitudes and their interaction with Defaults

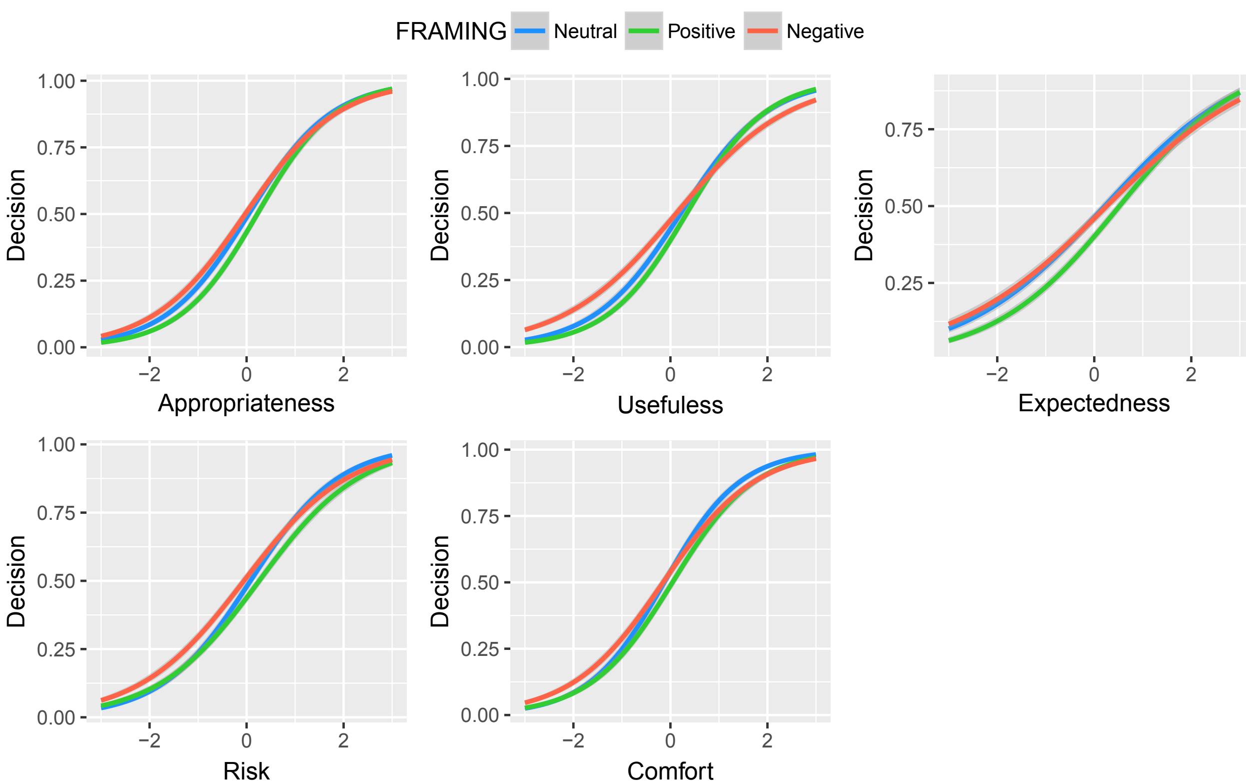

Figure 5: Different attitudes and their interaction with Framing