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The Persuasive Effect of Privacy Recommendations for Location Sharing Services

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ABSTRACT

Several researchers have recently suggested that in order to avoid privacy problems, location-sharing services should provide finer-grained methods of location-sharing. This may however turn each "check-in" into a rather complex decision that puts an unnecessary burden on the user. We present two studies that explore ways to help users with such location-sharing decisions. Study 1 shows that users' evaluation of their activity is a good predictor of the sharing action they choose. Study 2 develops several "privacy recommenders" that tailor the list of sharing actions to this activity evaluation. We find that these recommenders have a strong persuasive effect, and that users find short lists of recommended actions helpful. We also find, however, that users ultimately find it more satisfying if we do not ask them to evaluate the activity.

Keywords

Privacy, information disclosure, decision-making, personalization, recommender systems, user experience.

INTRODUCTION

Location-sharing services (LSS) enable users to share their location with their friends, and many have some additional benefit such as discounts or recommendations. The adoption of "geosocial services" is however low (Zickuhr, 2012), and research suggest that users are plagued by privacy concerns that cause them to limit their location-sharing (Page, Kobsa, and Knijnenburg, 2012). Recent research has suggested that giving users fine-grained control over their disclosure should reduce their privacy concerns (Consolvo, Smith, Matthews, LaMarca, Tabert, and Powledge, 2005). But this turns location-sharing into a rather complex decision that puts extra burden on the user (Compañó and Lusoli, 2010).

Arguably, then, we should help users in this decision (Knijnenburg and Kobsa, 2013). One way to do this is to frame the decision in a way that matches their *evaluation* of the activity. The question "What do you think about this activity?" is arguably easier to answer than the question "How do you want to share this location?" Moreover, if this evaluation is strongly related to users' sharing behavior, we can use it to *recommend* a (restricted set of) sharing action(s).

This paper presents two studies that explore such privacy recommendations. The first study develops a set of recommenders that can infer the preferred sharing action from users' evaluation of their activity. The second study tests the impact of these recommenders on users' behavior and satisfaction. We present the results and implications of the two studies here; we refer the reader to our manuscript for a complete account of the study procedures and an overview of related work (Knijnenburg and Jin, 2013).

STUDY 1: POTENTIAL FOR ADAPTATION

Our first study is an online user experiment to test the hypothesis that users' evaluation of the activity is a good predictor of users' sharing behavior. We recruited 100 participants (44 females, median age group: 26-30) using Amazon Mechanical Turk. We restricted participation to US workers with a high "worker reputation" and used a number of quality checks to assure careful participation.

Procedure

Participants were asked to imagine using an LSS called "HotSpots", which recommends locations to visit based on previously visited locations and also allows users to share their location on Facebook. We then showed participants 10 scenarios (see Knijnenburg and Jin, 2013) and asked them to choose one of the following 8 disclosure actions (based on Duckham and Kulik, 2005; Li and Chen, 2010; Tang, Hong, and Siewiorek, 2012):

A1. Fully use the system
A2. Restrict Facebook posts to friends that are nearby
A3. Restrict Facebook posts to certain friends only
A4. Restrict Facebook posts to only share city
A5. Restrict Facebook posts to only share city block
A6. Use the system for recommendations only
A7. Turn the system to "private mode" (anonymous)
A8. Turn the system off

Finally, participants chose one of the following 10 evaluations of the activity (based on Kairam, Brzozowski, Huffaker, and Chi, 2012; Sleeper, Balebako, Das, McConahy, Wiese, and Cranor, 2013):

E1. is exciting
E2. is interesting for others
E3. makes me proud
E4. makes me look interesting
E5. needed a good recommendation
E6. is private
E7. embarrasses me

E8. isn't useful for everyone
E9. doesn't really represent me
E10. may have unintended consequences when shared

Results

Table 1 shows that there is a strong relation between the disclosure action and the evaluation of the activity. Given the evaluation, it is thus possible to *recommend* an action to the user. For instance, if we recommend only the most-selected action for each evaluation, we are recommending the "correct" sharing action to the user 43.2% of the time, which is considerably higher than the 12.5% we would get by recommending a random action. For practical use this is not very accurate, but if we recommend not one but a small set of actions, this set would contain the "correct" option more often than not. For example, if we recommend the dark gray cells in Table 1, we can get 81.5% recall with 2.3 actions on average per evaluation. Increasing the number of recommended actions to just under 4 actions on average per evaluation (dark and light gray cells in Table 1), we can get 95.1% recall.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
A1	34	88	14	25	24	0	0	1	1	1
A2	6	25	1	6	6	3	0	32	0	4
A3	5	16	6	9	6	17	3	41	1	8
A4	1	8	1	11	6	4	2	10	0	2
A5	0	3	4	1	1	2	1	1	1	5
A6	2	5	0	1	23	112	17	58	16	36
A7	0	0	1	0	0	80	18	20	19	40
A8	0	0	0	0	0	34	14	27	4	26

Table 1. The co-occurrence of actions and evaluations. Gray cells show possible action recommendations for each reason.

STUDY 2: TESTING THE RECOMMENDERS

Based on the results of study 1 we can create a system that first asks the user to evaluate the activity and then recommends a subset of the sharing actions that users are likely to choose. Two questions need to be answered when designing such a "privacy recommender":

How many actions should it recommend? Recommender systems researchers have found that list length is an important determinant of user satisfaction (Bollen, Knijnenburg, Willemsen, and Graus, 2010). In our case, a longer list of recommendations would be less restrictive and would have a higher accuracy, but may not help the user enough in terms of simplifying her decision.

How should it present recommendations? The system could hide actions that are not recommended, thereby reducing visual clutter but also increasing the risk that the user cannot find her desired action. Alternatively, the system could *highlight* the recommended actions, keeping all options on the screen, but also increasing the complexity of the interface.

In the second study we explored these parameters by testing five different privacy recommenders against two versions of the default system that just presents the full list of sharing actions. In terms of evaluating these recommenders, we focus on the following aspects:

How accurate is the recommender? Using offline evaluations, previous work has shown relative success in predicting users' binary (yes/no) sharing decisions (cf. Cranshaw, Mugan, and Sadeh, 2011; Toch, Cranshaw, Drielsma, Tsai, Kelley, Springfield, Cranor, Hong, and Sadeh, 2010). Our recommender has to predict among 8 actions though, which is considerably harder. Moreover, offline accuracy evaluations do not always agree with online evaluations (McNee, Albert, Cosley, Gopalkrishnan, Lam, Rashid, Konstan, and Riedl, 2002). We thus purposefully evaluate the accuracy of our recommender in an online evaluation.

Is the recommender persuasive? Merely calling an item a recommendation may increase the chances that users choose it (Cremonesi, Garzotto, and Turrin, 2012; Pathak, Garfinkel, Gopal, Venkatesan, and Yin, 2010). This would result in accuracy levels that are even higher than predicted based on study 1, especially when the recommender hides the other actions.

Does the recommender increase satisfaction? Accurate recommenders are not always more satisfying to the user, and researchers have thus called for a more comprehensive, subjective evaluation of recommender systems (Knijnenburg, Willemsen, Gantner, Soncu, and Newell, 2012). Recommenders may give users a sense that they are helped (Häubl and Trifts, 2000), but they must leave users enough freedom to make their own decisions (Pariser, 2012). Moreover, inaccurate recommendations may be perceived as nefarious (Fitzsimons and Lehmann, 2004), which in our case may manifest itself as privacy threat and reduced trust. We thus evaluate the recommender with a comprehensive post-study questionnaire that measures users' subjective evaluations.

Procedure

We recruited 368 participants using Amazon Mechanical Turk (166 females, median age group: 26-30). Each participant was assigned to one of 7 conditions and asked to use a mock-up of HotSpots to choose a sharing action for 10 scenarios (same as in study 1). They then answered a questionnaire to evaluate their subjective experience.

Measurement

The 22 questionnaire items were submitted to a confirmatory factor analysis to measure 5 factors: perceived decision freedom, perceived decision help from the system, perceived threat from the system, trust in the company, and satisfaction with the system (see Knijnenburg and Jin (2013) for measurement properties).

Experimental conditions

We developed 5 versions of the privacy recommender (see Figure 1), to be tested against 2 baseline conditions (resulting in a total of 7 between-subjects conditions):

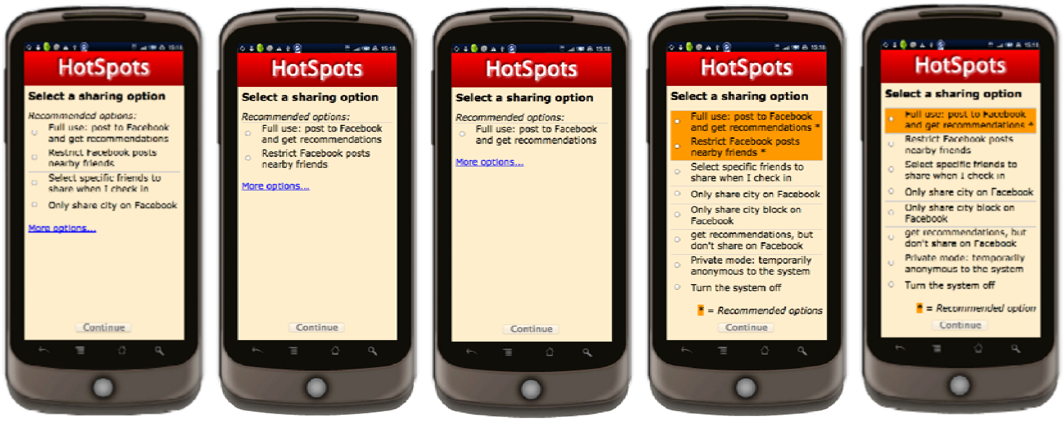

Figure 1. Mockups of the recommenders used to test conditions C2-C6.

		C2: Long list, rest hidden	C3: Short list, rest hidden	C4: One item, rest hidden	C5: Short list, highlighted	C6: One item, highlighted
1	**Recall in study 2**	98.7%	92.2%	75.0%	86.6%	62.5%
2	**Recall in study 1 (ex-post)**	95.1%	81.5%	42.8%	81.5%	42.8%
3	**Recall based on C1, study 2**	87.3%	67.3%	36.0%	67.3%	36.0%
4	**Odds ratio line 1 and 2**	5.03, $p < .001$	2.80, $p < .001$	5.20, $p < .001$	1.46, $p = .107$	2.55, $p < .001$
5	**Odds ratio line 1 and 3**	16.7, $p < .001$	7.51, $p < .001$	7.23, $p < .001$	3.93, $p < .001$	3.55, $p < .001$

Table 2. Recall in the 5 recommender conditions (C2−C6).

C1. **No recommendation**: Regardless of the users' evaluation, all sharing actions are displayed (this is the "comparable baseline" condition).

C2. **Long list, rest hidden**: The dark gray and light gray actions from Table 1 are listed as "recommended options"; the rest is hidden under a "more options" link.

C3. **Short list, rest hidden**: The dark gray actions from Table 1 are recommended; the rest is hidden.

C4. **One item, rest hidden**: Only the most popular action for that evaluation is displayed, the rest is hidden.

C5. **Short list, highlighted**: All actions are displayed, but the dark gray actions from Table 1 are highlighted.

C6. **One item, highlighted**: All actions are displayed, but the most popular for that evaluation is highlighted.

C7. **No evaluation**: Same as C1, but the user does not evaluate the activity (this is the "optimized baseline" condition, because no evaluation is needed if the system is not using it for recommendations).

In every condition (except for C7), the system first asks the user to evaluate the activity using one of 7 options[1]. Each recommender then tailors the display of the 8 sharing actions to the selected evaluation.

Results

Recommendation accuracy

The first line in Table 2 shows the *recall* of each recommender: the proportion of decisions that were in line with the recommended action. As expected, longer lists have a higher recall, but the short lists perform particularly well given the lower number of recommendations. Moreover, the recommenders that hide items have a higher recall than the recommenders that highlight items. The "rest hidden" recommenders are thus more persuasive than the "highlighted" recommenders (more on persuasion below). This is likely due to the additional effort it takes in these systems to select an option that is not initially listed.

User behavior

Line 2 of Table 2 shows the recall when applied ex-post to the study 1 data. Ex-post recall is high "by design", because the recommenders were derived from this data. In comparison, line 3 tests the robustness of the recommenders by testing them on the "new" data of the C1 condition. The fact that the recall based on C1 data is lower than the ex-post recall indicates that we slightly over-fitted the recommenders to the behavior of the study 1 participants.

Interestingly, though, the "actual" recall in the recommender conditions (line 1) is *higher* than the ex-post recall (line 2): the mere fact that certain options were presented as "recommendations" increased their likelihood to be chosen. In other words, the system *persuaded* participants to choose one of the recommended actions.

Subjective evaluations

Participants' behavior was influenced by the recommenders, but what about their subjective evaluations? Figure 2 compares the recommenders (C2–C6) against the two baseline conditions (C1 and C7) in terms of perceived decision freedom, perceived decision help, perceived threat, trust in the company, and system satisfaction.

Temporarily ignoring the optimized baseline (C7), we observe the following: Although the recommenders result in somewhat lower (yet not significantly lower) perceived decision freedom, they do result in somewhat higher perceived decision help, especially the "short list, rest

[1] We combined E2/E4, E6/E10, and E7/E9 because they were similar evaluations and also showed very similar behavior (see Table 1).

hidden" recommender (C3), which is perceived as significantly more helpful than the baseline system without recommendations (C1; $\beta = -.483$, $p = .025$). The recommenders also result in slightly lower perceived threat, and C3 seems to instill some trust in the company (albeit not significantly: $\beta = .305$, $p = .118$). In terms of system satisfaction, the recommenders are on par with C1.

Returning to the optimized baseline, Figure 2 shows that this system has a significantly higher decision freedom ($\beta = .449$, $p = .040$), higher decision help ($\beta = .465$, $p = .021$), lower threat ($\beta = -.429$, $p = .038$), and higher satisfaction ($\beta = .455$, $p = .022$) than baseline C1. The difference between C7 and the other conditions is that participants in C7 are not asked to evaluate the described activity before choosing a sharing action. This poses an interesting dilemma: Although a recommendation (i.e., C3) can increase the perceived decision help, asking for the evaluation that is necessary to give such a recommendation actually ruins the positive effect of the recommendation itself. Asking for an evaluation thus thwarts the positive effect of the recommender system.

CONCLUSION

This paper explored ways to help users of LSS to choose among a several sharing actions. Study 1 showed that users' evaluation of their activity is a good predictor of their sharing behavior. Study 2 explored a number of "privacy recommenders" that tailor the list of sharing actions to the selected evaluation. Our results show that these recommendations are indeed accurate. In fact, we found that the recommenders were persuasive: users were disproportionally more likely to choose a recommended sharing action over an action that was not recommended.

Companies can use this persuasive power to influence users' behavior through recommendations (Cremonesi et al., 2012). Note, however, that recommending items that the user clearly does not like is likely to result in *reactance* (behavior that explicitly counters the recommended action) and lower satisfaction (Fitzsimons and Lehmann, 2004). This argument is in line with Wilson et al. (2013), who also warn that the subset of available sharing options has to be "carefully considered" because it "can influence users to share significantly more without a substantial difference in comfort".

In terms of subjective evaluations, the recommenders did not have a very large impact, although the recommender that presents a short list of recommendations and hides the rest (C3) is perceived as more helpful than a system that just presents all 8 sharing actions (C1). The fact that this recommender is both persuasive and regarded as helpful gives credence to the idea that recommendations are *adaptive defaults*: they facilitate the decision process by nudging users towards an option that meets their needs (Smith, Goldstein, and Johnson, 2013).

Recent studies show that users' sharing behavior can be influenced by subtle changes in the decision environment (Acquisti, John, and Loewenstein, 2012; John, Acquisti, and Loewenstein, 2011; Knijnenburg, Kobsa, and Jin, 2013), and our current results corroborate these findings. Highlighting certain options makes them more likely to be chosen, and hiding the other options results in an even stronger persuasive effect. Taking this practice one step further, one could even remove certain sharing options altogether. Knijnenburg et al. (2013) show that in that case users' choices among the remaining options will be subject to well-known decision context effects.

The recommenders did not improve the usability of our LSS over the optimized baseline (C7). This reduces the practical applicability of our results, but it highlights that an adaptive privacy system, no matter how accurate, needs to be accepted by users as well (cf. Knijnenburg et al., 2012). In this specific case, the initial premise that evaluating the activity is easier than choosing a sharing action could be false. Alternatively, by asking users to evaluate the rather "risqué" scenarios, we may have inadvertently alerted them of the dangers of location-sharing. Luckily, day-to-day location sharing rarely involves such extreme scenarios, and this "inadvertent awareness effect" would thus arguably be smaller in reality.

The fact that our recommenders did not increase user satisfaction presents two opportunities for future research. The first is to explore alternative ways to support location sharing that balance privacy and usability. Finding the optimal level of control is of key importance here: increased control can help to reduce users' perceptions of privacy risk, but it can at the same time overwhelm the user (Compañó and Lusoli, 2010). Carefully designing the sharing options is a good initial step in this direction (cf. Knijnenburg et al., 2013). The other opportunity is to find a way to recommend sharing actions without explicitly asking the user to evaluate the activity. For example, it may be possible to "extract" the evaluation of the activity from a status update. Alternatively, users' previous sharing actions at similar locations may be used (cf.

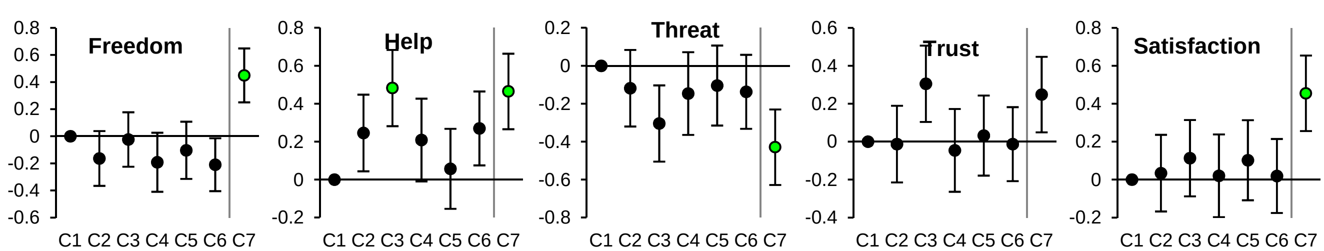

Figure 6. The effect of the recommenders (C2–C6) on subjective measures. Because factor scores have no inherent scale, the measures are fixed to zero at C1, and scaled in sample standard deviations. The error bars are ±1 SE of the comparison with C1.

Cranshaw et al., 2011; Toch et al., 2010). Regardless, the findings presented in this paper show that the idea of recommending sharing actions to reduce the decision burden on the user is worthy of further exploration.

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