Understanding the Impact of Information Representation on Willingness to Share Information

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ABSTRACT

Since the release of the first activity tracker, there has been a steady increase in the number of sensors embedded in wearable devices and with it in the amount and diversity of information that can be derived from these sensors. This development leads to novel privacy threats for users. In a web survey with 248 participants, we explored whether users' willingness to share private data is dependent on how the data is requested by an application. Specifically, requests can be formulated as access to sensor data or as access to information derived from the sensor data (e.g., accelerometer vs. sleep quality). We show that non-expert users lack an understanding of how the two representation levels relate to each other. The results suggest that the willingness to share sensor data over derived information is governed by whether the derived information has positive or negative connotations (e.g., training intensity vs. life expectancy). Using the results of the survey, we derive implications for supporting users in protecting their private data collected via wearable sensors.

CCS CONCEPTS

• **Security and privacy** → **Usability in security and privacy**; • **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*;

KEYWORDS

Sensors; Privacy; Sharing Data

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1 INTRODUCTION

The diversity of commercially available mobile and wearable devices is constantly increasing. Often, these devices contain a large number of integrated sensors, each specialized to extract a particular type of information about the user and context. Eventually, this information is used for a variety of applications such as sports trackers or quantified self applications. While most of the wearable devices are wrist-worn, smart textiles are gaining importance and prominence (e.g., Project Jacquard [9]). Given their close proximity to users' bodies, smart textiles allow for a more pervasive assessment of physiological responses, such as breathing rate or pulse [7, 13]. In other words, recent developments allow for more personal data to be extracted, which has an increasing potential to violate user-desired levels of personal privacy.

Wearable technology poses an implicit contradiction that users and designers have to resolve. On the one hand, users are led to believe that it is desirable to track and share their activities, for example in the case of motivational applications that are based on fitness trackers. On the other hand, there are wide-spread concerns regarding privacy and data security, resulting from functions such as GPS tracking via mobile phones or the unobtrusive taking of pictures of public spaces. Most recently, the controversial use of Google Glasses in public spaces initiated a debate over the permissible extent of data collected via wearables and resulted in a blanket ban of Google Glasses from a number of public locations [8]. While this particular discussion was centered around the issue of non-consensual photography of others, a new dimension of privacy threats results from user-based information being extracted from wearable sensors. Additionally, users can be largely unaware that their private information are collected and tracked by devices they have acquired themselves [4]. Allowing users' informed consents on which data is collected and shared and with whom is a central challenge that remains underexplored.

Thus far, related work has mainly focused on a generic and easy to understand situation, in which users' privacy is threatened, namely the extraction of location information from GPS sensors [16, 17]. In contrast, wearable sensors pose novel and multi-faceted challenges. Here, the recognition of possible threats to privacy requires the user to understand the potential violations that can result from the information extracted from the sensor data. Almuhimedi et al. show that raising the awareness of data access of mobile applications could lead participants to reconsider their previous willingness to share information with applications [1]. Even putting the potential privacy threats more into the focus when installing mobile applications affects the user‘s decision on installing applications which potentially share private information [5]. However, it remains unclear how well users understand potential privacy risks by allowing access to specific sensors.

We explore users' understanding regarding which information can be derived from wearable sensor data. For this, we conducted an online survey that assessed users' willingness to share their data when the data was requested either at the sensor level (e.g., accelerometer) or at the level of information that can be derived from the sensor data (e.g., step count). Henceforth, we will refer to these two different levels as the *representation levels* of users' private data. We show that the willingness to share information varies as a function of the representation level – sensor data vs. derived information. In addition, we find that the type of the derived information influences users' willingness to share. Users seem to prefer sharing information with positive connotations (e.g., step count) compared to information with negative connotations (e.g., stress).

2 REPRESENTATION LEVELS

We first performed a literature review on wearable sensors and the information that could be derived from them. We thereby reviewed different devices commonly used in the literature and available in the market that can be placed at different parts of the user‘s body (e.g., wrist-worn fitness trackers, heart-rate sensors at the chest) [14]. Next, we conducted a non-exhaustive literature survey on information that can be extracted from these sensors. We looked into different domains (e.g., sport, physiology, medicine) that utilize sensor data to gain insights into human behavior and cognition. We picked ten types of derived information that provide insights we believed users can understand but not necessarily relate directly to the sensor used in each study. The sensors and the information derived from them will be described in the following.

The *accelerometer* is one of the most common sensors found in wearable devices. Usually, data from wrist-worn accelerometer are used to derive information on *step count* [11] and the amount of *active minutes* [3]. Besides this, *sleep quality* [2], coarse *location* [20], and the type of *activity* [10] can also be inferred from accelerometer data. The *heart rate sensor* plays an important role with respect to the user's *health status* [15] and *life expectancy* [21]. The level of skin conductance, as measured by the *SCA sensor*, is determined by the activity of a human's sweat glands. Therefore, this sensor provides information about the user's *stress level* [18]. For monitoring *training intensity*, measurements from the *skin temperature sensor* can be used [12]. The *light sensor* provides information about ambient brightness and can, therefore, indicate the amount of *sunlight* that the user is exposed to [6].

3 TARGET AUDIENCE

We identified four different target audiences for information sharing ranging from *everybody* over a *theme-based community* (e.g., a sports group) and a *certain person* (e.g., a close friend) to *no one*. Even though there may be further target audiences, we believe that these groups allow a sufficiently fine grained assessment of the willingness to share information.

4 SURVEY ON SHARING BEHAVIOR

To assess users' willingness to share information from wearables, we conducted an online survey. We were particularly interested in the effect that the representation levels as well as the different target audiences might have on participants' willingness to share sensor information. To this end, we presented participants with 15 different statements, each addressing the participants' willingness to share a certain type of information (i.e., one of the five types of sensor data or the ten types of derived information). The presentation order of these statements was randomized between participants. Each statement was further subdivided into four simultaneously presented variations – one for each target audience (e.g., "I would share the accelerometer data with a theme-based community."). Participants rated their agreement with each of the four variations on a 7-point Likert item (1 = "totally disagree"; 7 = "totally agree"). We provided brief explanations for the sensor type statements to ensure that the participants were able to understand what each sensor measures (e.g., "An accelerometer is a device that measures the acceleration in three axes (top/down, front/back, left/right).") In addition, we collected information about participants' demographic background such as age, gender, and occupation and asked them to rate their self-perceived expertise with regards to wearable devices.

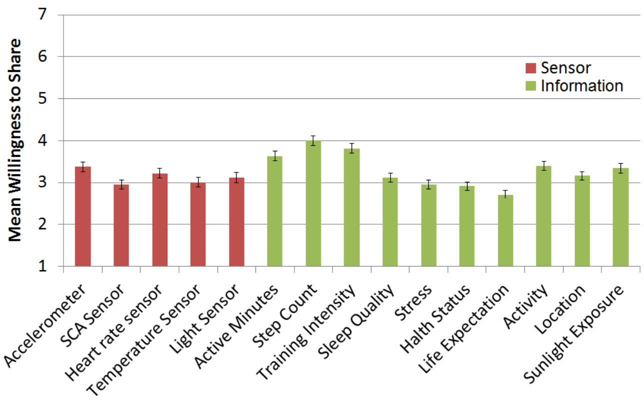

Figure 1: The mean values for each data presentation averaged across the four target audiences. The error bars show the standard error.

Value Proposition

To illustrate why and when users would have to share private data, we provided a hypothetical scenario that involved the acquisition of a new wearable device. Setting up this device involved the installation of an application on users' mobile phones. Subsequently, users were asked to grant the application access to their personal data for the purpose of sharing. We presented this scenario at the beginning of the questionnaire and thus it applied to each of the 15 statements.

Participants

We invited the participants via various channels to attract a diverse set of participants including University‘s mailing lists, social media, fitness groups, and sport clubs. Overall, 249 participants (127 male, 115 female, 7 did not specify) completed the questionnaires. Their mean age was 34.3 years (SD = 12.2). Our participants had diverse backgrounds that included: computer science (20%), natural science (12%), commercial occupations (31%), social science (7%), craft industry (7%) and not specified (23%). Before analyzing the data, we excluded any participants whose survey completion time was more than one standard deviation below the group mean ($M = 10.15$ minutes, SD = 6.39 minutes). This criterion applied to four datasets. One more dataset was excluded since completion took longer than one hour.

5 RESULTS

For all subsequent analyses, the polarity of the Likert item for the target audience *no one* was inverted to correspond to the polarities of the Likert items for the other three target audiences (i.e., stronger agreement equals higher willingness).

To analyze the Likert item data, we applied the Aligned Rank Transform (ART) procedure [19] to our data before performing analyses of variance with the within-subject factors *representation level* (2 levels: sensor data vs. derived information), *target group* (4 levels), and the between-subject factor *self-rated expertise* (7 levels: 1 = low expertise, 7 = high expertise). Significant effects were explored in more detail using post-hoc pair-wise comparisons of least square means with Bonferroni corrections. In the following, we report all significant effects of interest.

Figure 2 (left) shows average ratings for questions regarding *sensor data* and *derived information* as a function of *target group*. Our analysis revealed a main effect for the two factors *representation level* ($F(1, 242) = 39.3$, $p < .001$, $\eta^2 = 0.003$) and *target group* $F(3, 726) = 183.2$, $p < .001$, $\eta^2 = 0.22$). With regard to representation level, participants are less willing to share sensor data as compared to derived information (arithmetic means: $M = 3.13$, $SD = 2.49$ and $M = 3.30$, $SD = 2.54$, respectively; $p < .001$). With regard to target group, we find that willingness to share decreased with increasing size of the target group (all pair-wise comparisons between the four target groups were significant with $p < .001$). We also find an interaction between representation level and target group ($F(3, 726) = 31.2$, $p < .001$, $\eta^2 = 0.003$). Specifically, participants indicated a higher preference to share derived information compared to sensor data for smaller audiences, as is evident from Figure 2 (left). The difference between derived and sensor data is larger for target groups no one, person, and community as compared to all, and also larger for person compared to community (all $p < .001$).

Next, we investigated whether self-rated *expertise* influences the willingness to share. The number of participants falling into each level of expertise was approximately uniform across the seven levels ($M = 35.6$ participants per level, SD = 4.8). Expertise was moderately correlated with the ownership of a wearable (point-biserial correlation, $r = 0.36$, $p < .001$). Figure 2 (right) shows participants' ratings for sensor and derived data as a function of expertise. The analysis revealed a main effect for expertise ($F(6, 242) = 5.7$, $p < .001$, $\eta^2 = 0.08$) as well as a 2-way interaction between expertise and representation level ($F(6, 242) = 4.4$, $p < .001$, $\eta^2 = 0.002$) and a 3-way interaction ($F(18, 726) = 6.4$, $p < .001$, $\eta^2 = 0.004$). Specifically, participants with low and medium expertise (levels 1 to 5) discriminated more between sensor data and derived information and were less willing to share their data. There was no significant interaction between expertise and target group ($F(18, 726) = 1.2$, $p = .22$).

We also conducted a control analysis, where we added the demographic variables gender and age (separated at the mean age into two groups – younger vs. older users) as factors into the multifactorial design. While these two variables do not change the overall conclusions, we find an influence of both variables on *willingness to share*. Women are generally more willing to share than men (arithmetic means: $M = 4.11$, SD = 2.2 vs. $M = 3.82$, SD = 1.98; $F(1, 215.5) = 12.7$,

Sensor	M (SD)	Information	M (SD)	Representation Level F	p	η^2	Target Group F	p	η^2	Self-Rated Expertise F	p	η^2
Accelerometer	3.38 (2.52)	Active Minutes	3.63 (2.56)	F(1,242)=13.558	<.001*	.004	F(3,726)=115.794	<.001*	.146	F(6,242)=5.835	<.001*	.067
Accelerometer	3.38 (2.52)	Activity	3.39 (2.56)	F(1,242)= 0.059	.809	<.001	F(3,726)=120.931	<.001*	.145	F(6,242)=7.753	<.001*	.086
Accelerometer	3.38 (2.52)	Location	3.16 (2.46)	F(1,242)= 5.230	.023*	.002	F(3,726)=152.771	<.001*	.174	F(6,242)=4.262	<.001*	.042
Accelerometer	3.38 (2.52)	Sleep Quality	3.12 (2.50)	F(1,242)=10.648	.001*	.004	F(3,726)=126.887	<.001*	.146	F(6,242)=5.957	<.001*	.066
Accelerometer	3.38 (2.52)	Step Count	4.00 (2.59)	F(1,242)=49.617	<.001*	.019	F(3,726)=123.896	<.001*	.153	F(6,242)=8.211	<.001*	.088
Heart Rate Sensor	3.22 (2.53)	Health Status	2.92 (2.45)	F(1,242)=15.535	<.001*	.004	F(3,726)=130.879	<.001*	.158	F(6,242)=3.808	.001*	.042
Heart Rate Sensor	3.22 (2.53)	Life Expectation	2.70 (2.37)	F(1,242)=45.288	<.001*	.016	F(3,726)=128.263	<.001*	.143	F(6,242)=3.515	.002*	.038
Light Sensor	3.11 (2.47)	Sunlight Exposure	3.34 (2.54)	F(1,242)= 6.127	.014*	.002	F(3,726)= 96.479	<.001*	.108	F(6,242)=5.562	<.001*	.065
SCA Sensor	2.95 (2.45)	Stress Sensor	2.95 (2.48)	F(1,242)= 0.280	.597	<.001	F(3,726)=135.241	<.001*	.146	F(6,242)=4.071	<.001*	.048
Temperature Sensor	3.01 (2.47)	Training Intensity	3.81 (2.55)	F(1,242)=73.019	<.001*	.036	F(3,726)=150.792	<.001*	.168	F(6,242)=5.447	<.001*	.056

Table 1: The main effects of the analyses of variance on the aligned and ranked data (ART procedure) with the within-subject factors representation level (2 levels: sensor data vs. derived information), target group (4 levels), and the between-subject factor self-rated expertise (7 levels). Statistically significant comparisons are marked with * (p<.05). Note that η^2 values are affected by the ART and, thus, cannot be interpreted as usual.

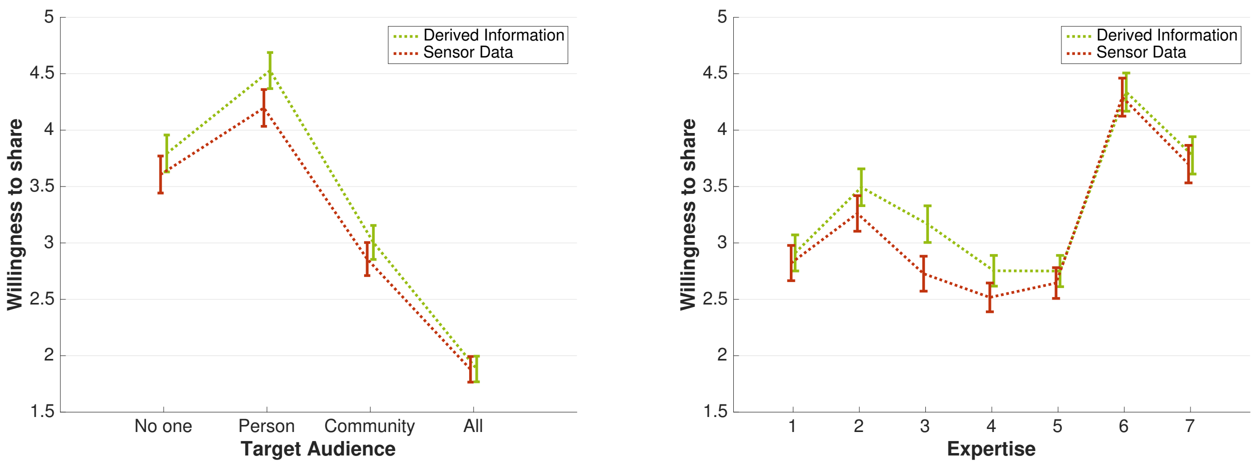

Figure 2: Arithmetic means for sensor data and derived information as a function of target group (left) and as a function of users' self-rated expertise (right). The error bars show the standard error of the mean.

$p < .001$) and older users are more willing to share than younger users ($M = 3.98$, SD $= 2.24$ vs. $M = 3.82$, SD $= 1.98$; $F(1, 214.9) = 4.8, p < .03$). We hypothesized that this may be related to (self-rated) *expertise*. However, we find that women do not rate themselves higher in this regard nor do older participants (one-sided Wilcoxon rank-sum tests; gender: $z = 1.16, p = .12$; age: $z = 0.03, p = 0.51$).

To explore our findings regarding *representation level* in more detail, we conducted ten additional analyses, one for each type of sensor and each type of information derived from that sensor (e.g., accelerometer vs. sleep quality). To retain comparability to the previous analysis, we again used the Aligned Rank Transform procedure with the three factors *representation level*, *target group*, and *self-rated expertise*. The main effects are available in Table 1. However, in the following, we will concentrate on the analysis of representation level results. Eight of the comparisons result in a statistically significant main effect for representation level. In half of these cases, participants indicated a higher willingness to share derived information. Specifically, this is the case for number of active minutes, step count, sun light exposure, and training intensity. In the other half of cases, participants indicated a higher willingness to share sensor data. This was so for location, sleep quality, health status, and life expectation. To paraphrase these results, participants show some lack of awareness that this information can be directly derived from the sensor data. Further, they exhibit differential preferences for or against sharing depending on the particular set of data.

6 DISCUSSION

Sensor Data vs. Derived Information: The results of our online survey demonstrate that users' understanding of the relationship between sensor data and the information derived from these data is still limited. Primarily, users were not consistent in their willingness to share their sensor data and the information derived from this data in a way that could be explained by privacy concerns. This is in line with the work of Tang et al. [16].

If users were purely concerned with data privacy, they should always demonstrate greater willingness to share derived information rather than sensor data since each type of derived information makes use of only a subset of the available sensor data. In other words, since several different types of information can be derived from a single sensor (e.g., active minutes & step count from accelerometer), the overall amount of disclosed data is less with derived information.

Upon closer inspection of the data, we found that this preference is not uniform across different types of information. One possible reason for the increased willingness to share derived information is the connotation linked to the information. On the one hand, participants' willingness to share information with positive connotations was higher than their willingness to share the associated sensor data. This includes mainly information related to sport and fitness (active minutes, step count, and training intensity) and sunlight exposure. These information have connotations such as being athletic, competitive, or disciplined. Even when actual physical performance is not extraordinary, the sharing of such information can communicate a willingness for self-improvement (e.g., increased fitness, weight loss, etc.) and will generally be met with support and approval by the target audience. In short, there are usually no negative repercussions to sharing this information.

On the other hand, their willingness to share information with negative connotations was lower than their willingness to share the associated sensor data. This mainly includes health related information (sleep quality, health status, and life expectation) as well as the user's location. One reason could be that this type of information can have negative consequences, such as disclosing poor health to an employer or one's whereabouts to an unknowing spouse.

User Expertise: The expertise of the user influences their willingness to share. Particularly users with low and medium self-rated expertise were less willing to share. They also showed a larger difference between the willingness to share sensor data and derived information. This indicates that these users were not entirely certain about potential privacy implications when sharing sensor data. Thus, they acted more conservative.

Target Groups: The participants of the online survey showed the highest preference for sharing their data with single persons and lowest preference for sharing with the general public. Thus, our results indicate that users are comfortable with sharing their sensor and information data as long as they retain some control over whom they are sharing this information with. This is also reflected by the fact that users tend to equally dislike sharing sensor data and derived information to the general public (i.e., all).

7 IMPLICATIONS

Request Data Access on Information Level: While current systems often request access at a sensor level, the user may not be aware of the full extent of the information that can be derived from these wearable sensors. Our results suggest that, in the future, data should be requested at the level of derived information instead of at a sensor level. This approach respects the users' desire for information privacy and allows them to gain control over the nature of information being shared.

Allow Fine Grained Selection of Permissions: Our results suggest that users make distinctions regarding how they value the privacy of specific information. For our particular sample of types of derived information, we found information with positive connotations (e.g., training intensity) was more likely to be shared as compared to information with negative connotations (e.g., stress). Regarding potential permission systems for sensors, this implies that users should be presented with a larger number of derived information requests, which users can individually allow or deny.

8 CONCLUSION

In this work, we investigated users' willingness to share sensor data and the information derived from these data. We report two major findings. First, users show differential preferences concerning the sharing of raw sensor data and the information that is derived from these data. The results suggest that this reflects a lack of understanding regarding the relationship between both representation levels. In particular, users do not seem to be fully aware of the type of information that can be derived from different sensors. Second, the willingness to share varies according to potential connotations of the data. Users are more willing to share information with positive compared to negative connotations.

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