

Risk Perceptions for Wearable Devices

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ABSTRACT

We performed an online survey to examine risk perceptions surrounding wearable computing devices. We examine different data types that might be captured, and the effect of who the data is shared with. We surveyed 1,784 participants about 88 data types and 4 data recipients to quantify risk perceptions across a wide range of scenarios, and evaluate of which factors contribute to the severity of these risks. Following previous work, we also asked participants to perform a risk/benefit analysis of 20 new technologies along with other well-understood technologies. The results of this study can be used to guide future research in wearable device security, especially research that helps protect sensitive data and design effective privacy notifications or indicators.

Categories and Subject Descriptors

K.6.5. [Management of Computing and Information Systems]: Security and protection—*Unauthorized access*

Keywords

Privacy, Security, User Studies, Risk Perception, Ubiquitous Computing, Wearable Devices

1. INTRODUCTION

With their ability to constantly capture data and help users, wearable devices, or “wearables,” are the new frontier of ubiquitous computing. Wearable technology has many potential benefits, ranging from a more natural, human-centered interface for computing, to healthier living through fitness tracking. Forbes has named 2014 the “Year of Wearable Technology” [26], and a top 25 market research company estimates that 52% of technology consumers are aware of wearables and 33% said they were likely to buy one [5].

The market for wearable devices is currently in infancy. It is hard to predict what device and applications will be most popular, but we use the current interest as a baseline. A survey of 3,956 respondents with high interest in wearables

found that, currently, the most popular devices are fitness bands (61%), followed by smart watches (45%) and mobile health devices (17%) [22]. It is estimated that 20% of the general population owns at least one wearable and 10% use at least one in their daily lives [9]. Most wearables consumers are young (48% are between 18 and 34), but this \$700 million industry will reach other demographics soon [2].

Wearable devices bring with them new potential security and privacy concerns. Many concerns exposure of users’ activities without their awareness or consent. For instance, Fitbit’s fitness profiles were public by default and also allowed sex to be tracked as exercise [14], resulting in the inadvertent disclosure of sensitive information. Additionally, public discomfort prevented companies from enabling capabilities; Google Glass apps are prohibited from using facial recognition to mitigate potential privacy concerns [21].

To avoid scandalous breaches of privacy and public opposition to new capabilities, it is critical we understand user concerns surrounding wearable devices before wearables become increasingly powerful and ubiquitous [20]. A better understanding of users’ risk perceptions will enable researchers and companies to focus on users’ concerns. The goal of this paper is to gain a better sense of what those concerns are.

We surveyed 1,784 Internet users for their perceptions of wearable devices. In this work, we contribute the following:

- We compare users’ perceptions of a range of privacy and security risks of wearables. Users care much more about the type of data, than the recipient of the data.
- We observed that users make little distinction between sharing data with friends, co-workers, or the general public, but are relatively comfortable with an application’s servers receiving their data.
- Our participants viewed data-collection capabilities of wearable devices as benign compared to more familiar technologies. However, we suspect that this may be due to a lack of exposure to these newer technologies.

2. METHODOLOGY

Our survey contained two main sections. In one section, we presented participants with several scenarios—something undesirable that might happen with their wearable device—and asked them to rate their level of concern if each scenario were to happen. This was intended to elicit their perception of the severity and impact of the risk. In the other section, we asked participants to compare the risks and benefits of

wearable technologies to better understood technologies, following the same methodology as a seminal study in risk perception by Fischhoff *et al.* [13]. Our survey design is based on two prior perception studies, as we describe next.

2.1 Methodology Motivation

2.1.1 Smartphone Risk Scenarios

Felt *et al.* previously studied the security concerns of smartphone users by conducting a large-scale online survey [11]. Their survey asked 3,115 smartphone users about 99 risk scenarios. Participants were asked how upset they would be if a certain action had occurred without permission. Participants rated each situation on a Likert scale ranging from “indifferent (1)” to “very upset (5).” Our methodology closely follows that study, but with different scenarios chosen to shed light on security and privacy risks of wearable devices.

2.1.2 Technology Risk Perception

Fischhoff *et al.* performed a seminal study of perceived risks with 30 widely used technologies [13]. In their study, participants were asked to separately rate the risks and benefits for those technologies. They were told to think about all people affected by the technology, and to think about long-term vs. short-term risks and benefits. Then, the participants rated these technologies with respect to each other on a numerical scale, being instructed to rate the least risky or least beneficial technology a 10 and scaling the ratings linearly (e.g., a technology with risk rating 20 is considered twice as risky compared to a technology with a risk rating of 10). We apply their methodology to evaluate perceived risks and benefits of several technologies related to wearable computing.

2.2 Survey Questions

In our survey, each participant answered 27 questions, across five different sections:

- 2 comprehension questions
- 6 questions about wearable computing scenarios
- 2 questions about smartphone scenarios
- 2 risk/benefit questions
- 15 demographic questions

We randomized the order participants saw sections of the survey (with the exception of the comprehension and demographic questions, which were always first and last, respectively), as well as the order of questions in each section.

2.2.1 Comprehension Questions

Because participants might be biased to specific companies (e.g., visceral reactions to Google Glass based on popular media stories), we based our questions on a fictitious wearable. Thus, the beginning of the survey introduced participants to the “Cubetastic3000,” which was the basis for all questions on wearables risks. We highlighted the capabilities of this device and described use cases. To ensure that participants had read and understood this device’s capabilities, we ask them two multiple-choice comprehension questions.

2.2.2 Wearables Scenarios

We presented scenarios involving data capture using the Cubetastic3000 and asked them to rate how upset they would be if a particular data type (e.g., video, audio, gestures, etc.)

Every once in a while, an app might do something on your Cubetastic3000 without asking you first. Depending on what the app does, your feelings could range from indifference (you don't care) to being very upset.

5. How would you feel if an app on your Cubetastic3000 learned what medical conditions you have and shared that with your friends, without asking you first?

Indifferent
-
-
-
Very Upset

☐
☐
☐
☐
☐

Figure 1: An example of a wearable scenario question participants saw while taking the survey.

were shared with a particular data recipient without asking first (see Figure 1). Responses were collected on a 5-point Likert scale (from “indifferent” to “very upset”), which was modeled after Felt *et al.*’s study of smartphone users’ risk perceptions [11]. Our questions were of the format:

“How would you feel if an app on your Cubetastic3000 learned <data> and shared it with <recipient>, without asking you first?”

We created an initial pool of 288 questions by combining 72 data types (<data>) with 4 data recipients (<recipient>). The 4 possible data recipients were:

- Your work contacts
- Your friends
- The public
- The app’s server (but didn’t share it with anyone else)

The purpose of these questions was to determine the extent data types and data recipients play a role in upsetting participants when data is inappropriately shared. Additionally, we added 16 questions about other misbehaviors that did not follow this format, lacking either <data> or a <recipient>, but we found relevant nonetheless. An example of one of these questions was, “How would you feel if an app on your Cubetastic3000 turned your device off, without asking you first?” There were a total of 304 questions in this set, from which we randomly 6 questions for each participant.

2.2.3 Smartphone Scenarios

We presented participants with a second set of scenarios to control for the type of device being used. These questions followed the format of the previous question set, but substituted “smartphone” for “Cubetastic3000.” Rather than using the previous pool of 288 <data> and <recipient> combinations, we selected 5 of the scenarios that Felt *et al.* found least and most concerning to their participants [11]. We randomly presented each participant with 2 of these 5 questions:

1. How would you feel if an app on your smartphone vibrated your phone without asking you first?
2. How would you feel if an app on your smartphone connected to a Bluetooth device (like a headset) without asking you first?
3. How would you feel if an app on your smartphone unmuted a phone call without asking you first?
4. How would you feel if an app on your smartphone took screenshots when you were using other apps, without asking you first?

5. *How would you feel if an app on your smartphone sent premium (they cost money) calls or text messages, without asking you first?*

2.2.4 Risk and Benefit Assessment

In addition to investigating reactions to particular scenarios, we examined broad perceptions of new technologies and how those compared to perceptions of other understood technologies. We modeled this section after a seminal risk perception study by Fischhoff *et al.* [13], in which participants ranked technologies by their relative risk and benefit to society. We asked participants to perform this exercise for 4 technologies previously examined by Fischhoff *et al.*: handguns, motorcycles, lawnmowers, and electricity, which were chosen to span varying levels of risks and benefits.

Alongside the 4 studied technologies, we asked participants to evaluate one of 20 technologies relevant to wearables: internet, email, laptops, smartphones, smart watches, fitness trackers, Google Glass, Cubetastic3000, discrete camera, discrete microphone, facial recognition, facial detection, voice recognition, voice-based emotion detection, location tracking, speech-to-text, language detection, heart rate detection, age detection, and gender detection. We asked about familiar technologies such as the internet, general and specific wearable artifacts, and a range of new capabilities.

To parallel Fischhoff *et al.*'s risk perception study, we gave our participants a similar prompt to numerically express the perceived gross risk/gross benefit over a long period of time for all parties involved. We randomized whether they performed the ranking for risks or benefits first. The prompt is listed in Appendix A. The question format was as follows:

Fill in your <risk/benefit> numbers for the following:

Handguns: _____

Motorcycles: _____

Lawnmowers: _____

<Wearable Technology>: _____

Electricity: _____

2.2.5 Additional Questions

The exit portion of the survey firstly consisted of questions asking for age, gender, and education. Then, we asked participants if they owned a wearable device so we could control for prior exposure, and included an open-ended question on what would be the most likely risks associated with wearable devices. We end with the 10-question Internet Users' Information Privacy Concerns (IUIPC) index [19], so we could control for participants' general privacy attitudes.

2.3 Focus Group

We conducted a one-hour focus group to validate our design, gauge comprehension, and measure fatigue. The focus group began with participants taking the survey. Afterward, we asked participants to give feedback on the format and the content, noting any instructions or questions that were unclear. The focus group concluded with a discussion of possible benefits and risks of wearable devices, in order to brainstorm any additional scenarios to include. Finally, we compensated participants with \$30 in cash. We recruited all of our focus group participants from Craigslist. Of the 13

participants, 54% were female, and ages ranged from 18 to 64 ($\mu = 36.1$, $\sigma = 15.3$). Education backgrounds ranged from high school to doctorate degrees, and professions included student, artist, marketer, and court psychologist.

2.4 Recruitment and Analysis Method

We recruited 2,250 participants August 7th-13th 2014 via Amazon's Mechanical Turk. We restricted participants to those over 18, living in the United States, and having a successful HIT completion rate of 95% or above. Based on incorrect responses to either of the two comprehension questions, we filtered out 366 (16% of 2,250) participants. We filtered out an additional 99 participants (4% of 2,250) due to incomplete responses, and one participant who was under 18, leaving us with a total sample size of 1,784. Of these, 55.10% were male, with a median age of 29 ($\sigma = 10.37$).

In performing our analysis in the next section, we chose to focus on the very upset rate (VUR) of each scenario. The VUR is defined as the percentage of participants who reported a '5' on the Likert scales. We use the VURs rather than the average of all Likert scores for the same reasons as Felt *et al.*: the VUR does not presume that the ratings, ranging from "indifferent" to "very upset," are linearly spaced. Additionally, most were be upset, at least a little, in all scenarios when a device takes action without permission (rating distribution: "1" = 455, "2" = 523, "3" = 902, "4" = 1,746, "5" = 6,654). Thus, the main distinguishing factor of a participant reacting to a given scenario is whether they were maximally upset or not, rather than how upset they were.

In this section, we followed Fischhoff *et al.*'s methodology and did not normalize the numerical responses. Rather, we report medians and quartiles, which are not impacted by outliers. For the open-ended question at the end (i.e., additional privacy concerns), two researchers independently coded 1,784 responses, with an initial agreement rate of 89.7%. The researchers discussed and resolved any disagreements so that the final codings reflect unanimous agreement.

3. RESULTS

In this section, we present our survey results. We first discuss participants' responses to the various data-sharing scenarios, and how data type, data recipient, and device contributed to how threatening a situation was perceived. Next, we discuss participants' risk/benefit assessment of various new technologies relative to well-established technologies. We conclude the section with participants' self-reported concerns about the biggest risks in owning wearable devices.

3.1 Concern Factors

In this section, we discuss factors impacting participants' concern levels for each scenario: the data recipient, the data type, and whether or not the scenario occurred on a wearable or a smartphone. We analyze each factor individually, as well as present a statistical model of participants' concerns as a function of all of factors, including demographic traits.

3.1.1 Data Type

Based on our data, we observed that the largest effect stemmed from the data type being shared in a scenario. We present

Rank	Data	VUR
1	a video of you unclothed	95.97%
2	bank account information	95.91%
3	social security number	94.84%
4	video of you entering in your PIN	92.67%
5	a photo of you unclothed	92.59%
6	an incriminating/embarrassing photo of you	91.39%
7	username and password for websites	89.55%
8	credit card information	88.98%
9	an incriminating/embarrassing video of you	88.41%
10	a random (inward-facing) photo you at home	87.50%
	⋮	
64	eye movement patterns (for eye tracking)	40.51%
65	when and how much you exercise	38.66%
66	when you are happy or having fun	34.75%
67	which television shows you watch	30.20%
68	when you are busy or interruptible	29.50%
69	music from your device	28.06%
70	your heart rate	27.50%
71	your age	24.29%
72	the language you speak	15.86%
73	your gender	15.00%

Table 1: The 10 most and least upsetting data types, across all recipients.

various statistical models in section 3.1.5 to support this conclusion. Due to space limitations, we are unable to show results of the statistical analyses respect to the significance of the VUR rankings of the 88 data types. The 10 most and 10 least concerning data types can be seen in Table 1.

Regardless of the data recipient or the device, participants were most concerned about photos and videos, especially if they contained embarrassing content, nudity, or financial information. As seen in Table 1, photos and videos accounted for 5 of the top 10 concerns. Information that could be used to impersonate someone (e.g., usernames/passwords for websites) or invade privacy (photos of someone at home) were also among the most concerning data types.

Also regardless of the data recipient, the least concerning data types mostly consisted of information that could be observed through observations of public behavior, such as demographic information (e.g., age, gender, language spoken). It is possible that people rated these as un concerning because they think many entities already track this data (e.g., shows watched, music listened to, exercise patterns).

3.1.2 Data Recipient

Across all scenarios, 42.3% of participants stated that they would be “very upset” if their data was shared with only the app’s servers, whereas the VURs for friends (69.5%), work contacts (75.2%), and the public (72.4%) were much higher. A chi-square test indicated that these differences were statistically significant (Table 2). However, these effect sizes were small: the largest effect was between work contacts and an app’s server ($\phi = 0.11$); while the VUR for sharing with work contacts was significantly higher than sharing with friends, the effect size was negligible ($\phi = 0.004$).

We note that this chi-square test violates the assumption of independent observations, since participants responded

Recipients	χ^2	p-value	n	ϕ
Work-App	565.910	<0.0001	5,083	0.111
Public-App	481.776	<0.0001	5,1988	0.093
Friends-App	381.653	<0.0001	5,096	0.075
Friends-Work	20.39	<0.0001	5,037	0.004
Friends-Public	5.41	<0.0200	5,142	0.001
Work-Public	5.00	<0.0253	5,129	0.001

Table 2: Results of a chi-square test to examine VUR based on data recipient, across all data points.

to multiple scenarios. But based on the randomization of treatments and large sample size, we do not believe that this significantly impacted our results. Nonetheless, we repeated the analysis using only one randomly-selected data point per participant to find that the test was robust to this violation. Participants were significantly more concerned about having their data seen by humans (*vis-à-vis* app servers), though differences between specific human groups (between the public, friends, and work contacts) were not significant.

We compared the 10 most concerning scenarios when sharing with an app servers versus with a humans. We observed that there was a substantial overlap between these groups, in that 6 of the most concerning scenarios were the same:

1. Bank account information
2. A video of you unclothed
3. Social security number
4. Video of you entering your PIN
5. An incriminating/embarrassing photo of you
6. A photo of you unclothed

While the concerning data types do not appreciably change based on the data recipient—even the non-overlapping scenarios all dealt with confidential data (e.g., passcode, credit card information, etc.)—only the level of concern changed. For instance, the 10th most concerning scenario for the non-human audience had a VUR of 66.67%, whereas the 10th most concerning scenario for a human audience has a VUR of 93.88%. This suggests that concern for different data types does not appear to vary relative to other data types based on recipient, but instead the recipient determines the overall magnitude of the concern.

3.1.3 Device

Participants had unique VURs for scenarios only differing in device. Our participants had a 58.79% VUR when asked about wearables and 46.64% VUR when asked about smartphones. The VURs for both devices for all 5 questions are in table 3. However, the effect the device has on the VUR is not considered to be statistically significant (see Table 4). Additionally, there is no statistically significant difference between how people reacted in a given situation; although, participants were statistically significantly upset in Q2. The aforementioned results are only with respect to between subjects analysis, where answers are from participants who received either only the wearables or smartphone version of the 5 questions. Too few instances of participants answering both versions of questions occurred (34 in total for all 5 questions) to perform a sound within-subjects analysis.

Question	Wearable VUR	Smartphone VUR
All	58.79%	46.64%
Q1	14.81%	6.13%
Q2	44.11%	19.85%
Q3	87.09%	58.44%
Q4	52.77%	55.74%
Q5	86.49%	91.82%

Table 3: VURs for the questions described in Section 2.2.3, contrasting smartphones with the Cubetastic3000.

Question	χ^2	p-value	n	ϕ
All	2.202	<0.1378	3,588	0.001
Q1	2.500	<0.1139	714	0.004
Q2	17.333	<0.0001	708	0.024
Q3	0.020	<0.8886	699	0.000
Q4	1.413	<0.2345	730	0.002
Q5	1.604	<0.2054	709	0.002

Table 4: Chi-square test results comparing participants’ VURs between the smartphone and Cubetastic3000 questions.

3.1.4 Demographic Factors

Participants’ responses were correlated with demographic factors. We observed that the biggest predictor of participants’ decisions to rate a scenario as very upsetting was their self-reported level of general privacy concerns, as determined by the IUIPC scale [19]: a Spearman correlation yielded a statistically significant effect between average IUIPC scores with the VUR ($\rho = 0.446$, $p < 0.0005$). Similarly, we observed that age was a significant predictor of VUR ($\rho = 0.121$, $p < 0.0005$). We suspect that the effect of age is due to the significant correlation between age and IUIPC scores ($\rho = 0.188$, $p < 0.0005$); others have observed that older individuals tend to be more protective of their privacy [28].

While we initially observed an effect on VURs based on whether or not participants claimed to already own wearable devices (57.0% vs. 60.8%, respectively; Mann-Whitney $U = 202,896$, $p < 0.032$), this difference did not remain significant upon correcting for multiple testing (Bonferroni corrected $\alpha = 0.01$), nor did the effect of gender. Finally, we observed no correlation between education level and VUR.

3.1.5 Regression Models

In order to examine the relative effect of each factor on participants’ VURs, we constructed several statistical models to predict whether a participant would be “very upset” with a given scenario based on the data type, device, data recipient, and their demographic factors (i.e., age, education, gender, and privacy attitudes). We performed binary logistic regressions using generalized estimating equations, which account for our repeated measures experimental design (i.e., each participant contributed multiple data points).

We created several models using our three dependent variables as factors: device (smartphone vs. wearable), data recipient, and data type. We also used our collected demo-

Parameters	χ^2	df	QIC
(Intercept)	255.0	1	18,477.5
(Intercept)	78.4	1	18,122.9
Device	400.3	1	
(Intercept)	289.1	1	17,667.5
IUIPC (covariate)	368.5	1	
(Intercept)	297.8	1	17,383.6
Data Recipient	913.4	4	
(Intercept)	374.6	1	14,794.5
Data Type	1,866.5	77	
(Intercept)	303.	1	13,942.9
Device	11.1	1	
Data Recipient	624.6	3	
Data Type	1,961.2	76	
(Intercept)	28.4	1	12,752.8
Device	8.8	1	
Data Recipient	577.8	3	
Data Type	1,752.1	76	
IUIPC (covariate)	378.7	1	

Table 5: Goodness-of-fit metrics for various binary logistic models of our data using general estimating equations to account for repeated measures. The columns represent the Wald test statistic for each parameter and the overall Quasi-Akaike Information Criterion (QIC) for each model.

graphic factors as covariates: age, gender, education, wearable device ownership (yes/no), and mean IUIPC score. For each model, we performed Wald’s test to examine the model effects attributable to each of these eight parameters and observed that the only covariate that had an observable effect on our models was participants’ IUIPC scores. Thus, we opted to remove the other covariates from our analysis.

Table 5 shows the various models that we examined and the Quasi-Akaike Information Criterion (QIC), which is a goodness-of-fit metric for model selection (lower relative values indicate better fit). As can be seen, while the remaining four predictors all contributed to the predictive power of our model, the data type was the strongest predictor. Conversely, despite being significant, the device was the weakest predictor (i.e., whether participants were answering questions about a smartphone or a wearable device).

3.2 Risk and Benefit Rankings

We asked participants to rate new capabilities related to wearable technologies (e.g., facial recognition) in terms of their risks and benefits. We also asked them to do this for technologies with which they were likely to be more familiar (e.g., smartphones and laptops) in addition to two examples of specific wearable devices, Google Glass and the fictitious Cubetastic3000. To calibrate our results, we also asked about four well-established technologies studied by Fischhoff *et al.* [13]. We found that participants generally rated familiar technologies and those related to wearables as being low-risk. Figure 2 depicts participants’ median ratings. We found that the calibration technologies were all rated as the most risky. At the same time, with the exception of electricity, the calibration technologies were seen as lower benefit than the others.

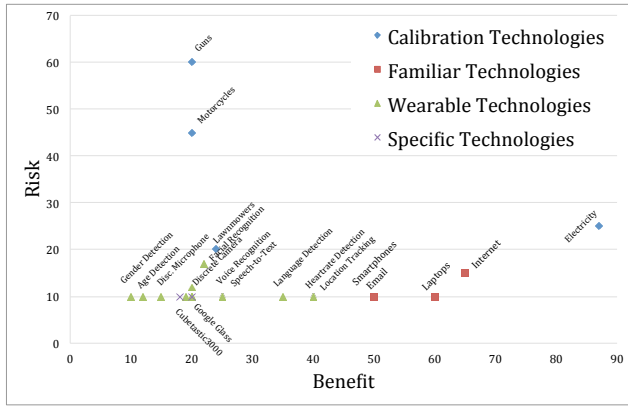


Figure 2: Participants’ median risk-benefit ratings of technologies examined by Fischhoff *et al.* [13], which we used for calibration, alongside familiar technologies (e.g., laptops, the Internet, etc.), wearable technologies, as well as two specific wearable devices (Google Glass and the Cubetastic3000).

As a group, participants rated the familiar technologies as the most beneficial. We believe this is the result of exposure people have to these technologies—most people use these technologies daily. Of the wearable technologies, the most risky were ones perceived to be privacy-invasive; the most risky technologies were facial recognition, the Internet, and discrete cameras, whereas the remainder of the technologies were seen as having minimal—albeit equivalent—risk levels (i.e., a median of “10”). People are becoming increasingly aware of such privacy risks and are comparing these privacy invasion to real physical risks—for instance, the capacity for facial detection on a wearable device is perceived to be almost as risky as interacting with a lawnmower.

These perceptions of the most risky or beneficial technologies may not be reflective of actual risks or benefits. However, they do reflect the general public’s exposure to these technologies and show that people perceive specific risks and benefits. We suspect that the similarity in assessments between the various wearable technologies are because most people are not consciously aware of the possibilities of these technologies or how they could be used. We suspect that performing this experiment longitudinally may yield more interesting results, as these technologies become more and more pervasive (and therefore more familiar to participants).

3.3 Self-Reported Concerns for Wearables

We also wanted to capture the participants’ general reactions to wearable devices as a whole. To do this, we asked the participants the following open-ended question:

What do you think are the most likely risks associated with wearable devices?

This question was asked along with demographics questions (but before any IUIPC questions to avoid biasing). The participants were presented with a blank box to write in, with no character limit to their open-ended responses.

Concern	Responses	Frequency
Privacy	452	25.32%
Being Unaware	275	15.40%
Health Risk	191	10.70%
Safety	185	10.42%
Social Impact	157	8.80%
Financial Cost	151	8.46%
Security	144	8.07%
Accidental Sharing	69	3.87%
Miscellaneous	57	3.19%
None	51	2.86%
Social Stigma	39	2.18%
False Information	33	1.85%
Don’t know	31	1.74%
Aesthetics	19	1.06%
Don’t care	11	0.62%

Table 6: A table listing the self-reported most common risks associated with owning a wearable device.

Without a doubt, the most common self-reported concern of wearables for the average user is the *possible loss of privacy*. This top concern surpassed all other concerns by about an order of magnitude or more (see Table 6). Other significant secondary concerns included being unaware of what the device is collecting, doing, or which information it is using (Being Unaware), long-term health effects caused from wearing the device such as cancer from emf waves (Health), safety hazards from wearing the device such distractions causing car accidents (Safety), resulting changes in social behaviors, such as dependencies on devices or spending less time with loved ones (Social Impact), the high financial cost of buying, replacing, or caring for the device (Financial), and information compromise (Security).

4. DISCUSSION

Here, we discuss complementary future research directions in fields of privacy, ubiquitous computing, and user studies, along with specific limitations of this survey.

4.1 Future Research Directions

Wearables are still in infancy. Perceptions of situations and capabilities will change rapidly with advancements and increased exposure. However, videos and textual information are considered to be significantly sensitive by our participants, along with past participants of smartphone user perception studies. Various systems which detect and take actions for sensitive objects in photos and videos will be critical as wearables and other devices become more ubiquitous.

While privacy and security concerns were expected, consider these self-reported concerns as inspiration for future research: the high financial costs of wearables, health concerns from constant use, safety issues related to operation, any social impacts of use, and improving device aesthetics.

4.2 Limitations

One of the main limitations of this work is that our participants might not have interest, or an accurate idea of wearables and their capabilities. 83% of our participants reported that they do not own a wearable device, but at this time,

about 15% of the general population own and use wearable devices [22, 9], which makes our study reflective of the status quo. We believed that getting a representative survey base was a useful endeavor, although we could have easily recruited only wearables owners or people specifically interested in wearables. However, that will also have its own biases and limitations, since this does not reflect the general population. We expect user perceptions to change as rapidly as wearable technologies and the rate of adoption change.

5. RELATED WORK

In this section, we discuss related work that has examined users' perceptions surrounding security and privacy risks.

5.1 Ubiquitous Sensing

Many authors have emphasized that we are rapidly moving towards a world of ubiquitous sensing and data capture, with ensuing privacy challenges [1, 23, 6]. Many researchers have worked to study how privacy can be preserved in such a future. Examples of such efforts include frameworks to design for privacy [4, 7, 18] or evaluate privacy [25] in ubiquitous computing applications. Others have suggested various models for understanding privacy in ubiquitous computing systems [15, 17]. However, none of these works attempted to quantify or rank user concern over different privacy risks.

5.2 Smartphones and Wearables Concerns

Many researchers have attempted to study end-user concerns about security or privacy issues associated with their smartphones [8, 24, 12].

Recently Denning et. al studied privacy concerns bystanders have when others around them are wearing a wearable device [10]. Participants in their study expressed concerns due to the nature of wearables (subtle UI and potentially ubiquitous). While their research examined the privacy concerns of bystanders in the presence of wearables, we are aware of no work that has looked at the privacy concerns of owners.

5.3 User Perceptions and Behaviors

In this paper we focus on measuring people's perceptions of security and privacy risks. One limitation of user perceptions is that people don't always have enough information to make privacy-sensitive decisions; even if they do, they often trade off long-term privacy for short-term benefits [3]. Also, actual behavior may deviate from self-reported behaviors [16] and privacy preferences [27].

6. CONCLUSION

We surveyed 2,250 internet users to determine what contributes to a violation of privacy or security, which technologies are risky, and what users think are the biggest risk for operating wearable devices. Participants how upset they would be if 304 situations occurred, assessed the risk and benefit for 20 new technologies, and gave open-ended responses to express their concerns. We provide insight into how much and why data, recipient, and device contribute to users' perception of a situation, calibrate answers with existing smartphone literature, and provide a regression model. An assessment of a range of new technologies shows that users perceive new technologies to be low-risk

and low-benefit, but we suspect this is due to limited exposure that an average person has with wearables technology. We also state what users perceived as the most significant concerns with respect to wearable devices. We conclude by discussing future research directions in the wearables and user study space.

7. REFERENCES

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APPENDIX

A. FISCHHOFF PROMPTS

We would like to ask you to rate the <risks/benefits> associated with each of the following technologies.

Risks: *Consider all types of risks: the risk of physical harm or death, the risk to others or bystanders, the financial cost of the technology, any distress caused by the technology, what the consequences would be if the technology was misused, any impact on the public, work, or personal life, and other considerations. (e.g. for electricity, consider the risk of electrocution, the pollution caused by coal, the risk that miners need to take to mine the coal, the cost to build the infrastructure to deliver electricity, etc.) Give a global estimate over a long period of time (say, a year) of both intangible and tangible risks.*

Do not consider the costs or risks associated with these items. It is true, for example, that sometimes swimmers can drown. But evaluating such risks is not your present job. Your job is to assess the gross benefits, not the net benefits which remain after the costs and risks are subtracted out.

Please rate the following technologies below with a number. We know that this might be a bit hard to do, but please try to be as accurate as possible, adjusting the numbers until they feel they are right for you. Start with the least risky technology at 10 and assign higher numbers for the more risky technologies. (For instance, a technology rated 14 is half as risky as a technology rated 28.)

Benefits: *Consider all types of benefits: how many jobs are created, how much money is generated directly or indirectly, how much enjoyment is brought to people, how much a contribution is made to the people’s health and welfare, what this technology promotes, and so on. (e.g. for swimming, consider the manufacture and sale of swimsuits, the time spent exercising, the social interactions during swimming, and the sport created around the activity.) Give a global estimate over a long period of time (say, a year) of both intangible and tangible benefits.*

Do not consider the costs or benefits associated with these items. It is true, for example, that electricity also creates a market for home appliances. But evaluating such benefits is not your present job. Your job is to assess the gross risks, not the net risks which remain after the costs and risks are subtracted out.

Please rate the following technologies below with a number. We know that this might be a bit hard to do, but please try to be as accurate as possible, adjusting the numbers until they feel they are right for you. Start with the least beneficial technology at 10 and assign higher numbers for the more beneficial technologies. (For instance, a technology rated 34 is twice as beneficial as a technology rated 17.)

B. CODING LABEL DEFINITIONS

Privacy: “privacy,” revealing personal information, spying.

Security: “security,” compromise, malware, hacking.

GPS tracking: “location,” “GPS,” being monitored.

Unaware use: using data without permission or in a different way than understood by user.

Unaware collection: collecting data without permission.

Unaware access: disclosure of data without permission.

False information: inaccurate or maliciously false data.

Health Risk: radiation, cancer, or long-term effects.

Safety: distractions causing car crashes or injuries, mugging or violence because of the device, injuries from device malfunctions (battery burns).

Discomfort: eye strain, headache, obscured vision, irritation.

Financial cost: getting ripped off by buying the device or device accessories, having to buy another device when broken or stolen, financial compromise caused by device.

Theft: the device getting stolen.

Social Impact: dependency, distance from friends and family, changes in decision making, social changes, etc.

Social Stigma: judgment, hate, or bystander discomfort.

Aesthetics: fashion, the device being ugly, mentions of not looking cool/dorky.

Miscellaneous: odd comments, uncommon concerns.

None: “None,” no threat, perceiving no big concerns

Don’t know: “do not know,” hinting at confusion

Don’t care: “do not care,” nonchalant answers