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Comfortability with the passive collection of smartphone data for monitoring of mental health: An online survey

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ABSTRACT

Background: For successful integration of mobile sensing solutions in existing mental health services, patients' comfortability with mobile sensing is crucial.
Objective: We thus aimed to investigate people's comfortability with mobile sensing and explore personal, mobile sensing app and data privacy related variables' impact on comfortability.
Methods: We conducted an online survey including 491 participants aged >18 and ran three models of linear regression with comfortability with mobile sensing as primary outcome and personal variables as predictors in the 1st model; mobile sensing app related variables as predictors in the 2nd model; and general data privacy related variables as predictors in the 3rd model. Then, we ran an aggregated model of the previous three including all significant predictors.
Results: Like of features, perceived control and trust in mobile marketers had the highest impact on comfortability with data sensing and they also predicted intentions to accept app permissions.
Conclusions: People are more comfortable with sharing their data and more willing to take the risks of using mobile sensing apps if they find that the features provide them with valuable feedback related to their health. It is highly important for users that they can trust the people they provide access to their data and feel in control of the data they share.

1. Introduction

Electronic health solutions will undoubtedly play an important role in transforming mental healthcare (Torous & Baker, 2016). Through the acquisition of data from the smartphone's built-in sensors, mobile sensing apps offer novel opportunities to clinically monitor people's behaviors, psychological states, and environmental conditions. For example, changes in mobility and social behavior, measured using global positioning system (GPS) and communication log data, were found to predict clinical relapse in schizophrenia and mood disorders (Barnett et al., 2018; Faurholt-Jepsen, Bauer, & Kessing, 2018). This high potential of mobile sensed data to support mental health care brings the question of users' comfortability with their data being collected via mobile sensing apps. The patients' ethical acceptance (Favaretto, De Clercq, Briel, & Elger, 2020; Schneble, Elger, & Martin Shaw, 2020; Schneble, Elger, & Martin Shaw, 2020) and practical and psychological comfortability (Chivilgina, Wangmo, Elger, Heinrich, & Jotterand, 2020) with mobile sensing is absolutely crucial to the successful integration of mobile sensing apps into existing mental health services.

As the sensitivity of mobile sensing data is so high, perceived confidentiality and data privacy are extremely important to patients

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who might consider the use of apps to support their mental health care (Proudfoot et al., 2010). The types of mobile sensing data collected by apps for mental health monitoring can range from sleep and physical activity to location, communication logs and social activity. The varying degree of perceived sensitivity of the types of data being collected can influence users' willingness to use mobile sensing apps. Previous reports found that people are more comfortable sharing sleep, mood and physical activity information than communication logs, location and social activity data (Nicholas et al., 2019). The majority of patients also like to be informed of signs of their health status worsening and encourage daily reports of mental state. Additionally, comfort levels with sharing data were found to depend on the recipient of these data. In general, individuals feel more comfortable sharing their sensed data with their doctor than with their electronic health record system or family members (Nicholas et al., 2019).

Moreover, individual characteristics of users may influence attitudes towards mobile sensing apps as well. Age might have a significant impact on users' willingness to share data. Younger people were found to have less concerns about the collection and sharing of sensed data than older people (Lin, Liu, Sadeh, & Hong, 2014), although research findings are not consistent in terms of age (Beierle et al., 2020). Study results indicate that gender might also play a role and female users are less willing to share their data compared to male users (Beierle et al., 2020; Rieger et al., 2019). Race has also been associated with willingness to share data, with Caucasians being the most willing to share their data (Rieger et al., 2019).

Most patients consider electronic health solutions to be important and enriching for medicine in general. The more importance they attribute to eHealth solutions, the more functionalities of an app they support. This shows that patients initiate use of functionalities if they perceive them as aligned to their individual needs (Hendrikoff et al., 2019). The number of data types people supported collecting was further found to correlate with their technology experience, which suggests that increased usage or expertise with technology could also determine the acceptance of different types of data being collected via mobile sensing apps (Hendrikoff et al., 2019). Thus, with the growing experience and expertise of users with mobile sensing apps, the acceptability of these apps could increase and open up new avenues for advancing mental health care.

Currently health apps are primarily used for self-monitoring, which includes using data for awareness and understanding, tracking progress and patterns over time, and long-term records (Chen, Bauman, & Allman-Farinelli, 2016). The majority of people do not share their health-tracking data. Those who do typically share their data with family or friends (Chen et al., 2016). However, in one study, three out of four mental health patients who were receiving therapy indicated that they would be willing to share their data with their therapists (Rieger et al., 2019). Thus, mental health apps have the potential to be used as part of existing mental health services to improve mental health care.

In sum, mobile sensing apps hold great promise for mental health services in the future, but peoples' comfort with sharing mobile sensed data is highly important to realize this potential. We thus aimed to assess the comfortability of users with data being collected via mobile sensing apps in a large-scale survey. We investigated comfortability with data being collected via mobile sensing apps and explored personal, mobile sensing app and general data privacy related variables' impact on people's comfortability ratings. Extending previous work, we involved participants from the general population with and without past mental health treatment. We assessed their comfortability with a diverse set of sensors, and explored in unprecedented detail personal, mobile sensing app related and general data privacy related potential predictors of comfortability with mobile sensing apps. Similarly, we assessed intentions to use mobile sensing apps. It was hypothesized that personal, mobile sensing app, and data privacy related variables are significantly associated with people's comfortability with sharing individual sensor data as well as with their intention to use mobile sensing apps for health. We hypothesized that comfortability with different types of data being collected via mobile sensing apps is higher among participants with mental health treatment given the higher perceived relevance and comfortability ratings depend on the format of data collection.

2. Methods

2.1. Procedure

To this purpose, we conducted an online survey from 23 May 2020 to 7 June 2020 recruiting participants via Amazon's Mechanical Turk. Importantly, AMT has become an increasingly accepted way of collecting responses from diverse participants (Buhrmester, Kwang, & Gosling, 2011; Casler, Bickel, & Hackett, 2013; Hirsh, Kang, & Bodenhausen, 2012; Thomas & Clifford, 2017). The procedures of the online survey abided by the Declaration of Helsinki and were approved by the research ethics board at Dalhousie University. Informed consent was obtained from the participants.

2.2. Participants

To take part in the online survey, we invited all AMT users aged 18 or older from varying backgrounds. Adults culturally associated with 23 different countries all over the world, 56% from North and South America and 40% from Asia, participated in the survey, which was administered in English. Participants received 0.5 USD financial compensation for answering the survey's questions which required 20 min of their time in average. From all the participants, those who provided incorrect responses to 5 attention check questions were excluded and incomplete responses were also discarded. No other inclusion or exclusion criteria were applied. The attention check questions were included in different parts of the survey; for example: "If you are paying attention pick option 3″ or "If you read this, select Strongly disagree". Participants who provided incorrect answer to any of the attention check questions or did not respond to all questions were excluded. The survey was entered by 1151 participants; 491 (43%) participants completed the questionnaire after filtering out 109 (9%) incomplete and 551 (48%) incorrect responses to attention-determining questions.

2.3. Measure

We created an ad-hoc online questionnaire based on below literature which evaluates the following variables:

2.3.1. Outcomes of interest

Our primary outcome of interest was comfortability with data being collected via mobile sensing apps. Specifically, participants were asked to rate how comfortable they would feel when different types of data were collected from their mobile phone such as call, SMS, Bluetooth, location, weather and device information, walking/running distance and movement, light and noise level, battery status, music, screen time, notifications and pickups. Participants rated their comfortability on a 5-point Likert scale from 1 (Not at all) to 5 (Extremely) for those different types of data to be collected. Comfortability with data sharing was rated at two sampling frequencies differing in their level of detail (exact/continuously and aggregated). As secondary outcomes of interest we assessed intentions to accept app permissions (Degirmenci, 2020; Malhotra, Kim, & Agarwal, 2004) and to use mobile apps for health in the future (Xu, Gupta, Rosson, & Carroll, 2012; Xu & Teo, 2004).

2.3.2. Potential predictors

In line with mobile users' information privacy concern (MUPIC) construct (Degirmenci, 2020), we asked participants to provide information about personal, mobile sensing app and general data privacy related predictors of comfortability. As personal predictors, we considered basic demographic data, previous usage of apps for physical and mental health, knowledge about technology and mobile sensing apps as well as participants' opinion about the utility of mobile sensing to assess health status rated on a 5-point Likert scale. As mobile sensing app related predictors, we assessed like of features, preference of notification, app permission concerns (Degirmenci, 2020; Smith, Milberg, & Burke, 1996), perceived surveillance (Degirmenci, 2020; Xu, Gupta, et al., 2012), intrusion (Degirmenci, 2020; Xu, Dinev, Smith, & Hart, 2008) and concerns about secondary use of personal information (Degirmenci, 2020; Smith et al., 1996) related to the mobile sensing app. Like of features was assessed by asking participants to rate on a 5-point Likert scale to what extent they would like various hypothetical features. The concept of these features was described to participants as potential functionalities that an exemplary mobile sensing app could have. All the hypothetical features provided users with feedback related to their health based on the data collected. For example, the app tracks the user's health and sleep patterns and sends notification when they are unusual. Finally, we collected general data privacy related predictors of comfortability such as ratings of computer anxiety (Degirmenci, 2020; Stewart & Segars, 2002), previous privacy experience (Degirmenci, 2020; Xu, Gupta, et al., 2012), privacy concerns (Kang & Shin, 2016), privacy protection behavior (Kang & Shin, 2016), perceived control (Degirmenci, 2020; Xu, Teo, & Tan, 2012), trust in mobile marketers (Kang & Shin, 2016) and perceived benefit (Sun, Fang, & Hwang, 2019; Xu, Luo, Carroll, & Rosson, 2011) of using mobile sensing apps.

2.4. Statistical analysis

First, we calculated descriptive statistics and compared the likability of features and the comfortability with different types of data being collected via mobile sensing apps among participants with and without past mental health treatment using independent samples t-tests. Next, we ran three models of linear regression with comfortability with data being collected via mobile sensing apps as our primary outcome, intentions to accept app permissions and intentions to use mobile apps for health as secondary outcomes. We divided the predictors into 3 groups: 1) personal predictors, which included demographics and knowledge about technology and mobile sensing apps, 2) mobile sensing app related predictors, which included the likeability of the app's features, concerns and perceived intrusion when accepting the app's permissions, 3) general data privacy related predictors, which were related to the broad concepts of privacy, benefit and trust in apps. We included demographic information (age, gender, and education), previous usage of apps for physical and mental health, technology and mobile sensing app knowledge as well as opinion about the utility of mobile sensing to assess health status as predictors in the 1st model; like of app features, app permission concerns, perceived surveillance, intrusion and concerns about secondary use of personal information as predictors in the 2nd model; and computer anxiety, previous privacy experience, privacy concern, privacy protection behavior, perceived control, trust in people behind the mobile app and perceived benefit when using mobile sensing apps as predictors in the 3rd model. Finally, we ran an aggregated model of the previous three including all the significant variables of model 1, 2 and 3 as predictors and comfortability with data being collected via mobile sensing apps as the outcome to estimate the relative impact of all significant predictors. We supplemented our results regarding perceived comfortability with analyses including intention to accept app permissions and intention to use mobile sensing apps for health monitoring in the future as dependent variables repeating the above outlined analytic procedure. To ensure our regression models were representative for both participants with and without past mental health treatment, we ran sensitivity analyses including treatment status as covariate. Finally, we explored if comfortability ratings depend on the format of data collection, for example, whether the mobile sensing app records start and end time of every single call or just an average duration of calls a day. For an overview of the analysis flow see Fig. 1.

3. Results

3.1. Participants' characteristics

Eighty-four percent of participants had already used a mobile sensing app to track their fitness (N = 411) and 50% had used an app to track or manage their mental health (N = 247). Fifty-seven percent rated themselves as very much or extremely knowledgeable about mobile sensing apps (N = 280) and 69% agreed that mobile sensing apps can be used to determine mental health and wellbeing (N = 338). Thirty-one percent (N = 151) of participants received treatment for mental health illness in the past/present. We observed no significant differences in demographic variables, technology and mobile sensing app knowledge as well as opinion about the utility of mobile sensing to assess health status between those who received and who didn't receive treatment. However, participants who have received mental health treatment were more likely to have used a mobile sensing app to track their fitness ($t(365) = 2.47$, $P = 0.014$) or an app to track or manage their mental health ($t(334) = 8.51$, $P < 0.001$. Specifically, 76% of those, who received mental health treatment (N = 115), had already used a mobile sensing app to track or manage their mental health. Further details of the sample are shown in Table 1.

3.2. Sensor data type

Overall, participants indicated that they were comfortable with data being collected via mobile sensing app. The percentage of those who were not at all comfortable with data varied between 3 and 19% (N = 14–95) depending on the type of data being collected, while the proportion of those who were very much or extremely comfortable with sharing data ranged between 33% (N = 163) and 66% (N = 324). Of the different types of data being collectable via mobile sensing apps,

Model1

Age	Gender	Education	Knowledge Technology	Knowledge Mobile sensing	Utility of mobile sensing to assess health status	Mental Health App use	Fitness & health App use

Model2

Like of features	App permission concerns	Perceived surveillance	Perceived intrusion	Concerns about secondary use of personal information

Model3

Computer anxiety	Previous privacy experience	Privacy concern	Privacy protection behaviour	Perceived control	Trust in mobile marketers	Perceived benefit

Fig. 1. Analysis flow and variables included in varying regression models
SPSS, version 25 was used for all data analyses and the criterion P value was set at $P < 0.05$.

Table 1
Participants' characteristics.

(%, n)	Mental Health treatment						Total		
	No			Yes					
	67.0%	/	329	30.8%	/	151	100.0%	/	491
Gender									
Female	32.8%	/	108	42.4%	/	64	36.5%	/	179
Male	66.9%	/	220	57.0%	/	86	63.1%	/	310
Other	0.3%	/	1	0.7%	/	1	0.4%	/	2
Age									
18 to 24	17.6%	/	58	22.5%	/	34	19.1%	/	94
25 to 34	51.4%	/	169	45.7%	/	69	49.7%	/	244
35 to 44	15.2%	/	50	15.9%	/	24	15.5%	/	76
45 and above	15.8%	/	52	15.9%	/	24	15.7%	/	77
Education									
Less than High school	0.9%	/	3	0.0%	/	0	0.6%	/	3
High school or equivalent	7.9%	/	26	16.6%	/	25	10.6%	/	52
College diploma	6.4%	/	21	4.0%	/	6	5.5%	/	27
Bachelor's degree	65.3%	/	215	62.9%	/	95	64.8%	/	318
Master's degree	17.6%	/	58	15.9%	/	24	17.1%	/	84
Doctorate degree	1.2%	/	4	0.0%	/	0	0.8%	/	4
Other	0.6%	/	2	0.7%	/	1	0.6%	/	3
Mobile sensing app use									
Mental Health*	39.2%	/	129	76.2%	/	115	50.3%	/	247
Fitness*	81.5%	/	268	89.4%	/	135	83.7%	/	411
Technology knowledge									
Not really	1.2%	/	4	1.3%	/	2	1.2%	/	6
Somewhat	15.5%	/	51	17.2%	/	26	15.9%	/	78
Moderate	52.9%	/	174	55.6%	/	84	54.0%	/	265
Very much	30.4%	/	100	25.8%	/	39	28.9%	/	142
Knowledge Mobile sensing									
Not at all	1.2%	/	4	1.3%	/	2	1.2%	/	6
Slightly	9.4%	/	31	8.6%	/	13	9.2%	/	45
Moderately	34.0%	/	112	29.8%	/	45	32.6%	/	160
Very much	45.3%	/	149	48.3%	/	73	46.4%	/	228
Extremely	10.0%	/	33	11.9%	/	18	10.6%	/	52
Utility of mobile sensing to assess health status									
Strongly disagree	1.5%	/	5	0.0%	/	0	1.0%	/	5
Disagree	2.7%	/	9	1.3%	/	2	2.2%	/	11
Neither agree not disagree	29.2%	/	96	25.2%	/	38	27.9%	/	137
Agree	52.6%	/	173	60.3%	/	91	55.2%	/	271
Strongly agree	14.0%	/	46	13.2%	/	20	13.6%	/	67

*significant difference between groups ($p < 0.05$).

participants were the least comfortable with sharing SMS data and most comfortable with sharing physical activity data (such as walking or running). Comfort levels were significantly higher than average for sharing physical activity ($t(489/486) = 12.39/11.09$, $P < 0.001$), weather ($t(490) = 8.70/8.00$, $P < 0.001$), battery ($t(490) = 5.33$, $P < 0.001$) and screen time data ($t(490) = 3.63$, $P < 0.001$, aggregated) and significantly less than average for tracking SMS ($t(490) = 8.68/6.08$, $P < 0.001$), call ($t(490) = 3.23$, $P = 0.001$, exact/continuously), Bluetooth

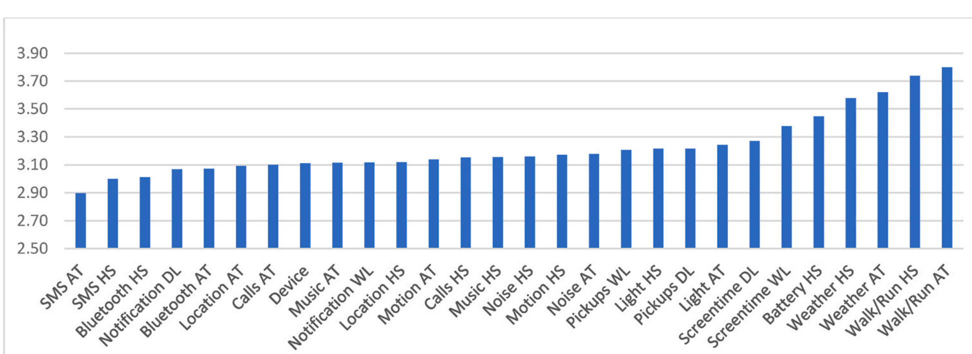

Fig. 2. Participants' average comfort level with sharing different types of data.
AT: all the time, HS: hourly summary, DL: daily, WL: weekly.

(t(490) = 3.68/5.35, P < 0.001), location (t(490) = 3.38/2.75, P = 0.001/0.006), motion (t(490) = 2.46, P = 0.014, exact/continuously), music (t(489) = 2.58, P = 0.010, exact/continuously), notification (t (490) = 4.30/2.92, P < 0.001/ = 0.004) and device information (t(489) = 2.96, P = 0.003). In line with our hypothesis, those participants, who received mental health treatment, were significantly more comfortable with data being collected via mobile sensing apps (t(330) = 3.50, P = 0.001, for details see Supplementary Fig. 3). Comfort levels in sharing the different types of data being collected via mobile sensing apps is displayed in Fig. 2 (for details see Supplementary Fig. 4).

3.3. Like of features, privacy, and behavioral intention

Overall, 43–60% (N = 140–197) of participants liked the features (e.g., tracking health and sleep patterns and sending notification when they are unusual) very much or extremely, while 4–18% (N = 14–58) didn't like the features at all. The likability of health features was the highest, while GPS was the least liked among the features assessed. Forty-six (N = 224) percent of participants had a high preference (4/5 or 5/5) to receive notifications about potential health issues, while 16% (N = 78) did not prefer to receive notifications. Fifty (N = 245) to sixty-two (N = 304) percent rated their willingness, likelihood, probability and possibility to accept the app permissions 4/5 or 5/5, while only 6–9% (N = 27–46) didn't have the intention to accept the permissions.

Those who received mental health treatment liked the health (t(332) = 2.04, P = 0.042) and the communication (t(478) = 2.05, P = 0.041) features more than those who didn't. They were also more willing to share their data with their doctor (t(478) = 2.39, P = 0.017) than those who didn't receive treatment. Finally, they indicated higher intentions to accept app permissions (t(319) = 2.69, P = 0.008) and to use mobile apps for health (t(478) = 2.69, p = 0.007), perceived more benefit (t (478) = 2.74, P = 0.006) and control (t(478) = 2.35, P = 0.019) and had more privacy related experience (t(478) = 2.82, P = 0.005) than the non-treated group. Further details are shown in Table 2.

3.4. Regression analysis

Linear regression models were fit on the continuous outcome of participants' comfortability with data being collected via mobile sensing apps (see Table 3). In the 1st regression model, knowledge about mobile sensing apps had the largest impact among the predictors (ß = 0.284, P < 0.001), while utility of mobile sensing to assess health status had the second highest effect (ß = 0.146, P = 0.001). In the 2nd regression model, like of features was the only significant predictor of comfortability with a strong effect (ß = 0.656, P < 0.001). In the 3rd regression model, trust in people behind the mobile app showed the strongest effect (ß = 0.343, P < 0.001), followed by perceived control (ß = 0.321, P < 0.001) and perceived benefit (ß = 0.105, P = 0.020). In the aggregated model, like of features had the strongest effect (ß = 0.398, P < 0.001), while perceived control was the second (ß = 0.254, P < 0.001) and trust in people behind the mobile app the third largest predictor (ß = 0.196, P < 0.001). Sensitivity analysis revealed no impact of treatment status on prediction models.

Overall results of the regression models including intention to accept app permissions and intention to use mobile apps for health monitoring were very similar to those obtained from models for comfortability (see Table 3). In the 1st regression model, knowledge about mobile sensing apps was still one of the strongest predictors (ß = 0.284, P < 0.001). Interestingly, previous usage of fitness apps had a significant effect on intention to use mobile sensing apps for health monitoring in the future (ß = 0.127, P = 0.003). In the 2nd regression model, like of features was again the most significant predictor (ß = 0.540, P < 0.001). In the 3rd regression model, trust in people behind the mobile app had even higher effect on intentions to accept app permissions (ß = 0.420, P < 0.001) or to use mobile apps for health monitoring (ß = 0.465, P < 0.001) then comfortability. Similarly, to results for comfortability, perceived benefit had a significant effect on intention to accept app permissions (ß = 0.128, P = 0.004) and intention to use mobile apps for health monitoring (ß = 0.200, P < 0.001). Perceived control had significant impact only on intention to accept app permissions (ß = 0.271, P < 0.001). In the aggregated model, like of features (ß = 0.189, P < 0.001) and trust in people behind the mobile app (ß = 0.328, P < 0.001) remained the most significant predictors of intentions, with perceived control (ß = 0.209, P < 0.001) being the second most significant predictor of intention to accept app permissions.

4. Discussion

This study explored the comfortability of participants with and without a history of mental health treatment with personal data being collected via mobile sensing apps in the context of mental health care. We found that the majority of participants were at least moderately

Table 2
Participants' ratings of like of features, Privacy and Behavioral Intention.

Mean/SD	Mental health treatment						Total		
Group	No			Yes					
Like of features	3.31	/	0.90	3.46	/	0.82	3.36	/	0.87
Preference for notification									
Notifications Share with doctor*	3.05	/	1.28	3.35	/	1.22	3.13	/	1.26
Notifications Don't share with doctor	3.74	/	1.17	3.83	/	1.05	3.77	/	1.12
Comfortability with data sharing*	3.14	/	0.84	3.40	/	0.73	3.23	/	0.81
Intention to accept app permissions*	3.38	/	1.01	3.63	/	0.91	3.46	/	0.98
Intention to use apps for health*	3.41	/	0.96	3.65	/	0.86	3.48	/	0.93
App permission concerns	3.38	/	1.03	3.43	/	0.97	3.40	/	1.01
Perceived surveillance	3.64	/	0.80	3.69	/	0.79	3.65	/	0.79
Perceived intrusion	3.64	/	0.83	3.66	/	0.85	3.65	/	0.83
Secondary use of personal information	3.67	/	0.91	3.68	/	0.85	3.67	/	0.89
Computer anxiety	3.29	/	0.87	3.42	/	0.89	3.33	/	0.87
Previous privacy experience*	3.03	/	0.89	3.27	/	0.79	3.11	/	0.86
Privacy concern	3.59	/	0.84	3.57	/	0.84	3.59	/	0.84
Privacy protection behaviour	3.41	/	0.75	3.50	/	0.73	3.44	/	0.74
Perceived control*	3.02	/	1.11	3.27	/	1.03	3.10	/	1.08
Trust in people behind the mobile app	3.20	/	1.05	3.38	/	1.02	3.26	/	1.03
Perceived benefit*	3.18	/	0.86	3.41	/	0.79	3.25	/	0.84

*significant difference between groups (p < 0.05).

Table 3
Model summary of participants' comfortability and intentions.

Lin.Regr.	Significant* predictors	Comfortability with data tracking			Intention to accept app permissions			Intention to use mobile apps for health		
		ß	B	SE	ß	B	SE	ß	B	SE
Model 1	Age	−0.115	−0.100	0.037						
	Education	0.091	0.086	0.040				0.115	0.124	0.045
	Knowledge Mobile sensing	**0.284**	**0.273**	**0.048**	**0.284**	**0.327**	**0.059**	**0.202**	**0.222**	**0.054**
	Utility of mobile sensing to assess health status	0.146	0.161	0.049	0.112	0.148	0.060	0.212	0.267	0.054
	Mental Health App use	0.126	0.209	0.074	0.129	0.257	0.091	0.138	0.260	0.083
	Fitness & Health App use							0.127	0.334	0.112
Model 2	Like of features	**0.656**	**0.615**	**0.033**	**0.540**	**0.606**	**0.044**	**0.541**	**0.578**	**0.042**
	Perceived intrusion				−0.137	−0.161	0.073			
Model 3	Previous privacy experience				0.091	0.102	0.046			
	Privacy concern				−0.183	−0.214	0.054	−0.169	−0.188	0.055
	Privacy protection behaviour				−0.168	−0.221	0.057			
	Perceived control	**0.321**	**0.241**	**0.035**	**0.271**	**0.244**	**0.041**			
	Trust in people behind the mobile app	**0.343**	**0.270**	**0.038**	**0.420**	**0.396**	**0.044**	**0.465**	**0.417**	**0.045**
	Perceived benefit	0.105	0.102	0.044	0.128	0.149	0.051	0.200	0.221	0.052
	Utility of mobile sensing to assess health status							0.117	0.146	0.046
	Fitness & Health App use							0.113	0.297	0.093
Model 1 + 2 + 3	Like of features	**0.398**	**0.373**	**0.041**	**0.189**	**0.212**	**0.049**	**0.196**	**0.209**	**0.049**
	Perceived intrusion				−0.144	−0.169	0.053			
	Previous privacy experience				0.106	0.120	0.047			
	Privacy concern							−0.189	−0.211	0.042
	Privacy protection behaviour				−0.144	−0.188	0.058			
	Perceived control	**0.254**	**0.191**	**0.034**	**0.209**	**0.188**	**0.042**			
	Trust in people behind the mobile app	**0.196**	**0.155**	**0.038**	**0.328**	**0.310**	**0.047**	**0.363**	**0.326**	**0.044**
	Perceived benefit				0.113	0.131	0.051	0.162	0.180	0.049

*$p < 0.05$ The coefficients of predictors with ß>0.19 at least in two of the models are highlighted in bold.

comfortable with data being collected via mobile sensing apps and rated their comfortability as 3 or above on the 5-point Likert-scale. Interestingly, participants who received mental health treatment were more comfortable with data being collected via mobile sensing apps than participants not having received any treatment. Possible explanations for these findings could be that these patients had a stronger and more trusting relationship with their mental health professionals, but also that these patients, due to cognitive and emotional implications of their disease spectrum, had a different, possibly less complete, understanding of involved risks. Mental health professionals must be aware of the vulnerabilities of their patients and devote additional time to ensure full understanding and truly informed consent of their patients. The level of comfort and intentions of usage were further dependent on types of data collected, previous usage and knowledge of mobile sensing apps, like of features, perceived control and benefit as well as trust in people behind the mobile app.

Participants were slightly less comfortable in sharing SMS, call, Bluetooth, location, music, and notification data compared to the mean calculated across all the features. This is in line with the contextual integrity framework (Nissenbaum, 2009), which states that privacy expectations are influenced by contextual factors such as data type. According to this framework SMS, call, Bluetooth, location, music, and notification data might be perceived as more personal resulting in less willingness to share this data. In addition, the way in which different data types fit within existing information norms in the health care context could further explain the observed differences. The data types that participants were the least comfortable with sharing are not commonly discussed with health care professionals. Thus, discussing these data types may go beyond perceived usual practices and therefore be less willingly shared by participants.

In this study, knowledge about mobile sensing apps was found to be a much more significant factor for participants' comfortability and intentions to use the app in the future than education or age. This indicates that by helping people understand mobile sensing apps (what type of data is being recorded, and how they will be used) one can ensure their comfortability with data being collected via mobile sensing apps and simultaneously enhance their willingness to use such apps – acceptance and adoption. Our results also show previous experience with app usage to be a similarly important predictor of participants' comfortability. As the proportion of those who use fitness apps is in general higher than those who use mental health apps, the experience of using fitness apps can strongly influence considerations for using a mobile sensing app for health in the future.

While knowledge and prior usage of mobile sensing apps had a significant impact on comfortability, the likability of features was the strongest predictor of participants' comfortability and also highly important for their intentions to use mobile sensing apps for health in the future. The high relevance of likability shows that if people appreciate the features of mobile sensing apps, they feel not just more comfortable, but are also more willing to take the risks of using mobile sensing apps. In addition, perceived benefit was found to strongly predict intentions of usage, which is in line with the expectation-confirmation model stating that perceived benefits are the strongest indicators of users' continued intentions (Bhattacherjee, 2001). Thus, app designers should strongly integrate users' perspectives into the app development ensuring likability and perceived benefit of features to promote app usage.

Finally, perceived control and trust in people behind the app emerged as strong predictors of participants' comfortability and intentions of usage. It is highly important for users that they feel in control of who has access to their data being collected via mobile sensing apps and that they can trust the people they provide access to their data. Users may attribute more trust to a specific person with whom a relationship discussing health has been established, rather than the health system in general. Indeed, previous research has shown that when a trusting relationship is not established, participants resist sharing sensed data with health providers (Ng, Reddy, Zalta, & Schueller, 2018). Perceived control and trust can further compensate for potential impacts of perceived intrusion and privacy concerns of users as well as the privacy protection behavior and thereby encourage usage of mobile sensing apps. Altogether, widespread worries about data privacy and security need to be addressed thoroughly and app designers should strongly consider the implementation of precautionary measures in their app design.

Ethicists have raised concerns that mobile sensing studies challenge traditional research ethics' tenets of informed consent and risk mitigation, because data collection is both unobtrusive (easily forgotten and not easily avoided) and pervasive (recording many aspects of a users' daily life routines over long time periods) (Vitak, Shilton, & Ashktorab, 2016; Zimmer, 2018), and the potential harms of passively collected data are often poorly understood (Beckwith & Mainwaring, 2005). As trusting relationships have merged as a major factor increasing comfortability with data collection, health care professionals play an important role to ensure that patients are truly and comprehensively informed. Trust may indeed be based on purely emotional factors of a doctor appearing trustworthy without any evidence that risk and data management is ethical and safer than with other untrusted actors. Our findings suggest that trust is enhanced by offering individual choices: mobile sensing studies should use contextual factors to guide research design and should revise and adapt participant consent processes to address these ethical concerns. For example, users should be given the opportunity to select specific allowances for data sharing based on factors such as type, purpose, recipient, time period, and sensitivity, rather than providing a blanket consent. However, from an ethical point of view, this should not remain simply a design "trick" to increase participation. Instead, strong criteria should govern data protection and acceptable risks. Research ethics committees are still lagging behind internationally to establish a clear and binding framework that goes beyond minimal data protection laws that varies between countries. Further, researchers should not assume that the acceptability of using sensed data is easily generalized across different research contexts or types of data collected without first considering the comparability of the contextual norms.

To address such concerns, designers could employ User Permission Control mechanism in mobile sensing apps to allow users to control what data get recorded. Beyond the user's explicit consent, which is required before any data will be recorded in line with principle *choice and consent* (Langheinrich, 2001), individuals should have the right to decide how the data recorded should be used; a user could allow a particular data to be recorded but decline its use for a specific purpose – *use limitation* (Langheinrich, 2001). Users should also have the flexibility to revoke the permission at any time, view what data an app has about them, and request edit as they deem necessary – *user control*. Irrespective of the privacy mechanisms that may be implemented in the app, ensuring data protection is essential, such as data deletion, deidentification, and restrictions on sharing. Appropriate data encryption approaches should be used to secure the data and data should be stored in a highly secured server. As the processing power of mobile devices increases, a large volume of sensed data could be processed locally (in users mobile), thereby reducing the need for the data to be transmitted in their entirety to the server, hence reducing security and privacy risk.

4.1. Limitations

A considerable limitation of our survey is that our sample, though well-stratified and diverse, was not random, people who have an interest in mobile sensing technologies might have been more likely to take part in this online survey. The sample also included an elevated proportion of highly educated people, who may be more comfortable with data tracking and more willing to use mobile sensing apps. Most of the participants had already used an app to track their fitness and half of them had used an app to track their mental health. Therefore, the participants might have been more knowledgeable and experienced with mobile sensing app than the general population. Thus, the results can be primarily generalized to a population with higher education and previous usage of mobile sensing apps. The figures might further be slightly biased by social desirability. However, we assume that such effects should only have been minimal given the anonymity of participants in the survey. Nevertheless, our data do represent the views of people who are open to using personal mobile sensing apps. Another potential limitation of the study could be the use of MTurk; however, according to prior research, MTurk has demonstrated validity and reliability as an online survey tool (Bentley, Daskalova, & White, 2017; Buhrmester et al., 2011; Thomas & Clifford, 2017). The researchers also embedded five attention check items within the online survey to exclude potentially invalid data.

The study also assessed comfortability with data tracking and intentions to use mobile sensing apps and did not observe actual behavior such as accepting/rejecting app permissions or using the mobile sensing apps for monitoring mental health. Intentions and real actions may defer and intention to use mobile sensing apps does not always result in actual use, therefore independent variables' impact on usage needs further assessment.

4.2. Future directions

Currently, we know that likability of features, trust in mobile marketers and perceived control have an impact on people's comfortability with data sharing. However, further research is required to better understand which aspects contribute to the likeability of a feature, how people would expect to control their data sharing, and which factors are influencing trust in marketers. In addition, future research should consider the perceived benefits of usage might differ for people who receive mental health treatment and for those who do not. Such information is essential to better understand people's needs and expectations while using mobile sensing apps for health and to ensure full respect to ethical principles such as fully informed consent, absence of coercion, and, ultimately, prevention of harm and maximization of benefit.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2021.100134.

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