Public Opinion Quarterly, Vol. 85, Special Issue, 2021, pp. 423–462

SHARING DATA COLLECTED WITH SMARTPHONE SENSORS
WILLINGNESS, PARTICIPATION, AND NONPARTICIPATION BIAS

BELLA STRUMINSKAYA*
PETER LUGTIG
VERA TOEPOEL
BARRY SCHOUTEN
DEIRDRE GIESEN
RALPH DOLMANS

Abstract Smartphone sensors allow measurement of phenomena that are difficult or impossible to capture via self-report (e.g., geographical movement, physical activity). Sensors can reduce respondent burden by eliminating survey questions and improve measurement accuracy by replacing/augmenting self-reports. However, if respondents who are not willing to collect sensor data differ on critical attributes from those who are, the results can be biased. Research on the mechanisms of willingness to collect sensor data mostly comes from (nonprobability) online panels and is hypothetical (i.e., asks participants about the likelihood of participation in a sensor-based study). In a cross-sectional general population randomized experiment, we investigate how

Bella Struminskaya is an assistant professor in the Department of Methodology and Statistics at Utrecht University, Utrecht, The Netherlands. Peter Lugtig is an associate professor in the Department of Methodology and Statistics at Utrecht University, Utrecht, The Netherlands. Vera Toepoel is an assistant professor in the Department of Methodology and Statistics at Utrecht University, Utrecht, The Netherlands. Barry Schouten is a senior methodologist at Statistics Netherlands, The Hague, The Netherlands, and a professor in the Department of Methodology and Statistics at Utrecht University, Utrecht, The Netherlands. Deirdre Giesen is a senior methodologist at Statistics Netherlands, The Hague, The Netherlands. Ralph Dolmans is an information and communication technology developer at the Blaise team at Statistics Netherlands, Heerlen, The Netherlands. The authors thank Ole Mussmann for assistance in preparing the sensor plug-ins; Jelmer de Groot, Annemieke Luiten, and Vivian Meertens for assistance with data collection; three anonymous reviewers for feedback on an earlier draft of the manuscript; and Frederick Conrad for his invaluable feedback during the finalization of the paper. Data collection was funded by an internal grant from Statistics Netherlands. *Address correspondence to Bella Struminskaya, Utrecht University, Padualaan 14, 3584CH, Utrecht, The Netherlands; email: b.struminskaya@uu.nl.

doi:10.1093/poq/nfab025 Advance Access publication September 3, 2021

features of the request and respondent characteristics influence willingness to share (WTS) and actually sharing smartphone-sensor data. We manipulate the request to either mention or not mention (1) how participation will benefit the participant, (2) participants' autonomy over data collection, and (3) that data will be kept confidential. We assess nonparticipation bias using the administrative records. WTS and actually sharing varies by sensor task, participants' autonomy over data sharing, their smartphone skills, level of privacy concerns, and attitudes toward surveys. Fewer people agree to share photos and a video than geolocation, but all who agreed to share photos or a video actually did. Some nonresponse and nonparticipation biases are substantial and make each other worse, but others jointly reduce the overall bias. Our findings suggest that sensor-data-sharing decisions depend on sample members' situation when asked to share and the nature of the sensor task rather than the sensor type.

Introduction

In recent years, social and behavioral scientists have increasingly used sensing technology to gain insights into human behavior. Native smartphone sensors allow much more frequent and detailed measurement of phenomena that are difficult or impossible to capture via self-report. For example, GPS sensors and accelerometers can measure geographic mobility (e.g., Geurs et al. 2015) and physical activity (e.g., Rosli et al. 2013; Kapteyn et al. 2018); logging smartphone use can provide knowledge about social interactions (Stopczynski et al. 2014); and the combined use of light and ambient noise sensors allows measurement of sleep (e.g., Wang et al. 2014).

Smartphone sensing technology is also attractive for social research because it can reduce social desirability and recall biases inherent in self-reports. Furthermore, sensor data can be linked to auxiliary data and in-situ self-reports collected via Ecological Momentary Assessment (e.g., Larson and Csikszentmihalyi 1983), enabling research on topics such as how green spaces influence a person's mood and well-being (e.g., MacKerron and Mourato 2013), and how physical activity is related to happiness (e.g., Lathia et al. 2017).

However, it remains unclear whether smartphone sensing is well suited to studying the general population. Most studies have relied on specific populations such as students (e.g., Wang et al. 2014), recently paroled inmates (Sugie 2018), elderly people (Fritz et al. 2017; York Cornwell and Cagney 2017), and opt-in participants. Researchers have often provided devices to study participants. Only a few recent feasibility studies using smartphone sensors have collected data from general populations (Scherpenzeel 2017; Jäckle et al. 2019; Kreuter et al. 2020; McCool, Schouten, Mussmann, and Lugtig 2021). More typically, these studies are conducted with volunteer panels rather than randomly sampled members of the population. The pre-existing relationship that such participants have with the organization requesting data-sharing likely increases their trust in the organization and the "survivorship bias" (Lynn and Lugtig 2017) in which only loyal members remain in a panel; both might increase willingness and sharing rates.

The general population members have to be willing and able to share smartphone-sensor data. If the willing and unwilling sample members differ systematically on an attribute measured by the sensor, the results will be biased. Several studies have investigated willingness to collect sensor data (Pinter 2015; Scherpenzeel 2017; Keusch et al. 2019; Revilla, Couper, and Ochoa 2019; Wenz, Jäckle, and Couper 2019; Kreuter et al. 2020). However, they too used data from panel studies, possibly inflating participants' motivation and trust in the research (Hillygus, Jackson, and Young 2014; Matthijsse, De Leeuw, and Hox 2015). Moreover, previous studies have focused on hypothetical willingness to share sensor data (Keusch et al. 2019; Wenz et al. 2019). How hypothetical willingness relates to actual participation/sharing is unclear. Whatever the relationship, nonparticipation bias in studies using smartphone sensing has not received much attention.

In the current study, we quantify participants' willingness to share and the extent to which they *actually* share different sensor measurements as well as nonparticipation bias (difference between those who do and do not share) in a representative sample of the Netherlands' general population. We explore the mechanisms underlying participation in sensor-based studies by asking relevant survey questions and nonparticipation bias by comparing register data for the survey respondents who do and do not share.

Background and Research Questions

Previous research has shown large variability in willingness to participate and actual participation in a range of sensor measurements and tasks (e.g., sharing geolocation, allowing smartphone use tracking, using a smartphone camera to take a picture or a video[1]), study populations, and countries. The reasons for this could be variation in sample sources (e.g., probability vs.

1. We refer to smartphone cameras as sensors, although technically cameras are equipped with image sensors. Several smartphone measurement studies include camera-related tasks: scanning bar codes; taking pictures of receipts (Jäckle et al. 2019); taking pictures of food for food diaries (e.g., Yan 2019); or combining sensor measurements (e.g., geolocation and pictures of neighborhoods, Fritz et al. 2017), making smartphone cameras important measurement tools in surveys. Note that our definition of smartphone sensor measurement refers to any nontextual information collected using smartphones, whether it requires active involvement of the participant for each

nonprobability), respondents' trust in the survey organization and its corresponding influence on their confidentiality concerns, or the perception of particular sensors as more or less intrusive. Revilla et al. (2016) found a willingness of 25 – 52 percent for taking pictures using one's smartphone cameras, and a willingness of 19 – 37 percent for sharing geolocation across six countries. In the Dutch LISS Panel, the willingness varied from 18 percent for taking a photo of oneself to 30 percent for sharing geolocation and 60 percent for wearing a fitness bracelet (Struminskaya et al. 2020). In another study, 37 percent of the LISS Panel respondents were willing to share their geolocation and accelerometry data, 81 percent of whom actually shared these data; and 57 percent were willing to wear a fitness bracelet, 90 percent of whom actually did (Scherpenzeel 2017). In the UK Understanding Society Innovation Panel, 17 percent downloaded a budget app to photograph purchase receipts (Jäckle et al. 2019). In the German PASS Panel, 16 percent downloaded a research app that tracked location and social interactions of the participants (Kreuter et al. 2020).

To account for this variability in willingness, several studies have focused on the mechanisms underlying willingness to participate in smartphone-sensor data collection (e.g., Keusch et al. 2019; Wenz et al. 2019; Struminskaya et al. 2020). Generally, they point to study, task, and respondent characteristics that might influence stated willingness to share sensor data.

Among study/task characteristics that have been shown to affect willingness to share (WTS) are: (1) autonomy, with WTS higher for tasks where participants have perceived or actual autonomy over data collection (Keusch et al. 2019; Revilla et al. 2019; Struminskaya et al. 2020); (2) study sponsor, with WTS higher for university vs. market research and government statistical office (Keusch et al. 2019; Struminskaya et al. 2020); (3) framing, with emphasizing benefit for the respondents (e.g., time savings) or for researchers (e.g., scientific value) showing a slight but nonsignificant increase in WTS compared to the neutral framing (Silber et al. 2018), and a lower odds of WTS if the benefit framing emphasized time savings (Struminskaya et al. 2020); (4) incentives, with a positive effect on WTS (e.g., Pinter 2015; Keusch et al. 2019); and (5) providing/promising feedback, associated with greater likelihood of WTS (Struminskaya et al. 2020).

Among respondent characteristics that have been shown to influence WTS are: (6) privacy concerns, with high concerns about data privacy and/or security associated with lower WTS (Jäckle et al. 2019; Keusch et al. 2019; Revilla et al. 2019; Wenz et al. 2019; Struminskaya et al. 2020); (7) smartphone skills, with the more frequently activities such as using GPS, taking pictures, and online banking are performed on smartphones the higher

individual task (e.g., photographs) or a one-time active involvement and follow-up passive data collection (e.g., geolocation).

the WTS (Keusch et al. 2019; Wenz et al. 2019; Struminskaya et al. 2020); (8) experience with smartphone apps or sharing sensor data, with previously downloading a research app being associated with a higher likelihood of WTS (Keusch et al. 2019; Struminskaya et al. 2020); and (9) perceived value of surveys with respondents rating the survey as important for scientific research being associated with greater willingness to share sensor data (Struminskaya et al. 2020).[2]

Thus, our first goal is to understand the WTS mechanisms among the general population. A second goal is to investigate how patterns of nonparticipation bias could affect substantive results. To our knowledge, only Elevelt, Lugtig, and Toepoel (2019) have investigated nonparticipation bias in a sensor study and found large biases on the dependent variable *time use* between those who shared geolocation and those who did not. It is important to assess how nonparticipation bias can compromise the accuracy of sensor data. However, benchmark data that contain the information on both respondents and nonrespondents as well as participants and nonparticipants of sensor studies is not widely available. We improve upon earlier studies by using survey data that were collected from a cross-sectional sample so that consent rates would not be inflated by participants' existing relationship with the research organization and administrative data linked to the survey data, making available information on nonrespondents and nonparticipants in the smartphone-sensor measurements.

To address our twin goals, we ask the following research questions: (1) What are the rates for WTS sensor data and actually participating in particular sensor measurement tasks? (2) What study and task characteristics influence WTS and actual sharing of smartphone-sensor data? (3) What respondent characteristics influence WTS and actually sharing sensor data? (4) What is the extent of nonparticipation bias in relation to nonresponse bias?

We tested mechanisms for WTS proposed in the literature that are concerned with consent to perform smartphone sensor measurements. Here we manipulate the wording of the consent request, in particular whether the request emphasizes benefits of participation as time saved, whether participants are promised autonomy over data collection, and how they are assured their data will be confidential. Empirical tests of these mechanisms have been conducted on hypothetical WTS (e.g., Keusch et al. 2019; Struminskaya et al. 2020), which was affected by (1) framing (i.e., positive or negative presentation), (2) the degree to which autonomy over data collection is emphasized, and (3) the degree to which privacy is emphasized. For mechanisms of actual data sharing, there are no studies on smartphone sensors; however, positive ("allow") framing increased the rates of disclosure of sensitive information compared to negative ("prohibit") framing (Samat and Acquisti 2017).

2. Note that Keusch et al. (2019) did not find a significant relationship between WTS attitudes toward surveys.

Regarding autonomy, Brandimarte, Acquisti, and Loewenstein (2013) found that individuals who believe they have control over who can access and use the data shared more personal information. However, Peer and Acquisti (2016) found that emphasizing either the reversibility (i.e., ability to change the permission granted to the researcher) or merely pointing out the irreversibility of data-sharing decreased disclosure of sensitive information. Emphasizing privacy practices caused participants to reflect on privacy (Tan et al. 2014; Shih, Liccardi, and Weitzner 2015), which led to changes in data-sharing behavior. We test how these mechanisms apply to willingness to share and actually sharing sensor data.

Hypotheses

Studies have shown that willingness to use smartphone cameras is higher than allowing one's location to be tracked (Revilla et al. 2019; Wenz et al. 2019; Keusch, Struminskaya, et al. 2020). However, different tasks performed with cameras might differ in their perceived privacy, potentially reversing this pattern. For example, respondents in a nonprobability panel were more willing to allow geolocation tracking than to take a video of their face (Revilla et al. 2019). Although no theoretical justification for this has been proposed, geolocation coordinates might be more abstract than pictures and reveal information that participants find less sensitive. In our study, sponsored by a national statistical office, respondents at home might have recognized that their addresses were already known to the researchers, but pictures and videos of their environment or themselves would reveal information they preferred to keep private. We expect:

H1. WTS and actual sharing will be lower for pictures and videos of personal content than sharing of geolocation.

In addition, features of the request affect participants' sharing decisions. Studies on the consent to link survey data to administrative data find positive effects of benefit framing in terms of time savings (e.g., Sakshaug, Stegmaier, et al. 2019), but this has failed to replicate in sensing studies (Silber et al. 2018; Struminskaya et al. 2020). Panel members, the participants in these studies, might see less benefit in being asked fewer questions—their membership in the panel suggests they are not particularly burdened by answering survey questions—than members of a cross-sectional sample for whom the reduced burden of fewer questions may appear more beneficial. We hypothesize:

H2. Framing the request in terms of benefits, in particular time savings, will increase the WTS and actual sharing of sensor-collected data compared to neutral framing.

Several studies have found that WTS is higher for tasks in which participants have autonomy over data collection. WTS is higher when participants can turn off data collection (Keusch et al. 2019) or when they can anticipate and control what content they ultimately share with researchers. Compare being asked to take photos or scan bar codes (more autonomy) with agreeing to have one's geolocation tracked or their social media posts analyzed (less autonomy). Revilla et al. (2019) report a significant relationship between autonomy ("Respondent Control") and WTS. Autonomy is closely related to how actively or passively participants engage in the measurement process. Generally, WTS is higher for sensor tasks requiring active participation, like taking photos or scanning bar codes, than if data are collected passively, for example, tracking travel or posts (Wenz et al. 2019). Thus, we expect that emphasizing autonomy will increase perceived control over data collection and increase WTS:

> *H3. Emphasizing autonomy over the data-sharing process will be associated with higher willingness to share and actual sharing of sensor data compared to a request with no such emphasis.*

When asked to share data collected on smartphones that goes beyond completing questionnaires (e.g., taking pictures, scanning bar codes, sharing accelerometry measures or geolocation, downloading an app to track smartphone use), some participants express concerns about privacy (Keusch, Struminskaya, et al. 2020). Accordingly, willingness to share sensor data is lower for respondents with high privacy concerns (Keusch et al. 2019; Revilla et al. 2019; Struminskaya et al. 2020). We expect that addressing these concerns in the sharing request will lead to higher WTS and increased rates of actual sharing because it might increase trust:

> *H4. Emphasizing privacy protection will be associated with increased willingness to share and actual sharing of sensor data.*[3]

The final block of hypotheses is about the influence of respondent characteristics. Participants may find some sensor data to be private (e.g., pictures or videos of the respondent or their surroundings) or their potential use to be abstract (e.g., geolocation). Both perceptions might raise concerns about sharing data. Survey respondents' concerns that the collection of paradata might violate their privacy have been shown to negatively affect their willingness to participate in surveys (Couper et al. 2008, 2010; Couper and Singer 2013). Similarly, high levels of concern about data privacy and/or data security are associated with lower stated WTS (Keusch et al. 2019;

3. The competing hypothesis would be that emphasizing privacy increases respondents' awareness about data sensitivity and could lower the willingness, as has been shown for survey response (Singer, Hippler, and Schwartz 1992) and actually sharing sensitive data (Peer and Acquisti 2016).

Revilla et al 2019; Wenz et al. 2019; Struminskaya et al. 2020). Thus, we expect:

H5. Respondents with high privacy concerns and high concerns about data sharing will be less willing to share and less likely to actually share sensor-collected data.

However, privacy concerns may be mitigated by increased smartphone skill (Keusch, Struminskaya, et al. 2020), which is associated with higher stated willingness (e.g., Pinter 2015; Keusch et al. 2019). Thus, we hypothesize:

H6.1. The more activities participants perform on their smartphones, the higher the WTS and actual sharing rates.

H6.2. The more frequently participants use certain sensors for specific tasks on their smartphone, the more likely they will be willing to share and will actually share data collected with that sensor.

Consistent with the positive association between experience downloading research apps and higher stated willingness (Keusch et al. 2019; Struminskaya et al. 2020), we expect:

H7.1. Previously downloading a research app will be associated with higher likelihood of WTS and actual sharing.

H7.2. Previously sharing sensor-collected data will be associated with higher likelihood of WTS and actual sharing.

Methods

SURVEY DATA

The current experiment is embedded in a survey. The sample consists of respondents from one of the cross-sectional general population surveys that Statistics Netherlands periodically conducts. The sample members had previously participated in at least one Statistics Netherlands survey using either a smartphone or tablet in the preceding six months and had indicated they were willing to be contacted again to participate in another survey. The preceding survey(s) were conducted in the web mode and followed by the telephone and/or face-to-face interviews; the sampling was done from the population register, which is centrally available in the Netherlands. Overall, 3,618 persons were invited to participate in the online survey[4] by postal mail and received up to two reminders. Of those, 1,965 persons

4. The questionnaire was browser based and implemented in an experimental version of Blaise 5.3 that enables sensor-data collection.

participated (AAPOR COOP2[5] = 54.3 percent). The fieldwork took place in July–August 2018. The median questionnaire completion time was 16.2 minutes. A total of 15 (0.76 percent) respondents indicated that they were not users of smartphones or tablets, and for those whose device could not automatically be detected, 82 (4.17 percent) reported that they completed the questionnaire on a PC or laptop or "other device." These respondents were not asked about WTS and were excluded, yielding an analytical sample of 1,868.

ADMINISTRATIVE DATA

For all survey respondents and nonrespondents, we use data from several administrative data sources that are maintained by various Dutch authorities. This information can be legally accessed and linked for all sample members by Statistics Netherlands for the purposes of research by Statistics Netherlands without respondents' consent. We use these data to investigate nonresponse bias by comparing respondents to the gross sample (i.e., respondents and nonrespondents), and to study nonparticipation bias by comparing those respondents who also participate in smartphone sensor measurement to all respondents. Nonresponse and nonparticipation bias was calculated for *age, gender, marital status*, and *ethnic background* from the general population register maintained by municipalities; *level of education* from the education register maintained by the Dutch Ministry of Education, Culture and Science and in which all persons entering the education system are registered (however, immigrants and persons whose education began prior to mid-1990s are missing); *number of household members* (derived from information about marital status and income from the households register[6] maintained by Statistics Netherlands); *car ownership* and *possession of a driver's license* from the register maintained by the Ministry of Infrastructure and Water Management and in which all motorized vehicles are registered; *home ownership* from the dwelling register maintained by the Ministry of the Interior and Kingdom Relations and in which addresses are classified as self-owned or rented; *employment status* from the employment register maintained by the Ministry of Social Affairs; *income information* (the percentile of the respondent's income) from the tax register maintained by the Ministry of Finance; and urbanization (*urbanicity, size of township*) derived by aggregating the addresses from the general population register over postal codes.

5. Since our study sampled not from the population register directly but from those persons who participated in at least one of the general population surveys and for whom it was known that they owned a device, a cooperation rate rather than a response rate is reported.

6. Because the register does not contain household composition data for about 10 percent of the households, this information is inferred.

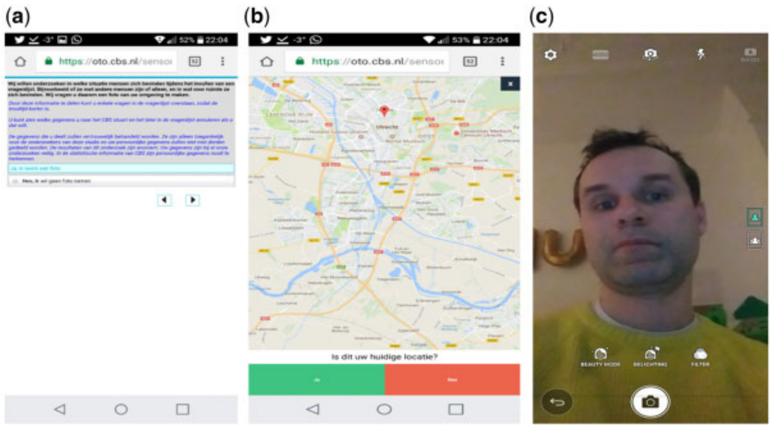

Figure 1. Screenshots of the in-browser survey and sensor measurements. Panel a: Screenshot for a question to share a picture of the house *(We would like to know in what kind of house you live. To receive this information, we would like to ask you to take a photo of your house.)* with benefit framing *(By sharing this information, you can skip some questions so that the completion time will be shorter.)*, autonomy over data collection *(You can see what information you are sending to Statistics Netherlands and undo the measurements later if you like.)*, and emphasis on privacy *(The data you provide will be treated confidentially. It will only be available to researchers conducting this study and your personal information will not be shared with third parties. The results of the survey will only be made available in the anonymized form. Your data is safe in all of our surveys. Personal information can never be inferred from the statistical information collected by Statistics Netherlands.)*. Panel b: Screen on which GPS location was shown to respondent, with a question *(Is this your current location?)*. Panel c: Author Peter Lugtig demonstrating the camera mode that was used for taking pictures and video.

SMARTPHONE SENSOR-DATA-SHARING REQUESTS

Respondents were asked to share their *current geolocation*, and photos and videos taken on their smartphone (or tablet) (*H1*). Willing respondents were shown a map with their current location (measured through GPS), which they then had to confirm (figure 1). Respondents were asked if they would be willing to use their smartphone or tablet camera to take *a video of their surroundings; a photo of the exterior of their house; a photo of a receipt of a recent purchase; a photo of themselves ("selfie").* After agreeing, respondents were transferred to the camera app that is used on their device for taking photos or videos. After taking a photo or video, respondents could review it before sharing it with the researchers or retake the photo. We collected latitude and longitude coordinates for geolocation and time stamps, file sizes, and other metadata for the photos and video, but no actual photos or videos were captured, to which participants were alerted at the end of the questionnaire.

THE EXPERIMENTAL DESIGN

Survey respondents were randomly assigned to one of six sensor-data-sharing requests, corresponding to a fully crossed 2 (framing) x 2 (autonomy) x 2 (privacy) design.

Benefit framing (H2): When survey respondents were asked to share their sensor data, they were either told this would save them time (experimental condition) by reducing the number of questions they would be asked, or the request made no mention of time (control). For each sensor measurement, respondents who were not willing to share data from a particular sensor received additional questions, for example, concerning their whereabouts if they were not willing to share geolocation, whether there were other people present if they were not willing to share a video of their surroundings, whether the dwelling had a balcony or terrace if they were not willing to share a photo of the house, a question about the type of purchase, store, and total amount if they were not willing to share a photo of a receipt, and their happiness if they were not willing to take a selfie.[7]

Autonomy over data collection (H3): The experimental condition specified that respondents would be able to view what information they were sending to Statistics Netherlands and could undo the measurements later. The control condition did not include such text.

Assurance of confidentiality (H4): The experimental condition included the following statement:

The data you provide will be treated confidentially. It will only be available to researchers conducting this study and your personal information will not be shared with third parties. The results of the survey will only be made available in anonymized form. Your data is safe in all of our surveys. Personal information can never be inferred from the statistical information collected by Statistics Netherlands. The control condition did not include such text.

Willingness to share sensor data was measured using a binary choice (yes/no). The individual data requests were asked in one fixed order

7. The question about happiness was asked since the request to take a selfie was prefaced with *"Using new technologies, it is possible to estimate your age and recognize your emotions from a photo. To try it out, we would like to ask you to make a photo of your face."* This phrasing was used to provide the rationale for the request; the recognition of the emotions was not actually performed. Respondents were debriefed at the end of the questionnaire that the images they took were not stored.

(geolocation, a video, and photos of the house, receipt, and self) to maximize statistical power within the individual cells.[8] Respondents were randomized in the same conditions for all five data-sharing requests.

Respondents who were not willing to share smartphone sensor data were asked why they were not willing. Furthermore, respondents received questions about their smartphone skills, device use (*H6.1, H6.2*), previous data sharing and app download experience (*H7.1, H7.2*), attitudes toward privacy and data sharing (*H5*), attitudes toward surveys, and socio-demographic characteristics. See appendix for the question wording.

Analysis Plan

To answer our first research question about the rates of willingness to share and actually sharing smartphone-sensor data, we calculated proportions of respondents who (1) answered *yes* to the request to share and (2) actually shared data by the sensor tasks. To answer our second research question about the influence of study characteristics and task features, we used five logistic regressions predicting (1) WTS and (2) sharing conditional on WTS. We account for the dependency of observations by using clustered standard errors.[9] For our third research question, which concerned the influence of respondent characteristics, we add respondent characteristics to the logistic regressions predicting WTS and sharing. For the survey attitude scale, we conducted a factor analysis following De Leeuw et al. (2019), assigning items to the factors of enjoyment, value, and burden (see Question 8 in Appendix B), and calculating mean scores for each dimension.

To answer our fourth research question, which concerned the prevalence of nonresponse and nonparticipation bias, we calculated the biases using the following formulae for the variables from the registry:[10]

8. Studies that randomized the order of the hypothetical data-sharing requests have found that the first request evoked higher WTS (Silber et al. 2018; Struminskaya et al. 2020). We look for any evidence that the order of sharing requests might have affected the outcome in tables A2 and A3.
9. In these models, we tested the interactions of the main experimental conditions as well as concerns about privacy and data sharing because perceived risk has been shown to moderate the effects of framing (Samat and Acquisti 2017), autonomy over data collection (Peer and Acquisti 2016), and consequences for privacy (Gates et al. 2014) on data sharing. We also included the interactions of main effects with the number of smartphone activities since concerns about sensor-data sharing are negatively associated with smartphone skills (Keusch, Struminskaya, et al. 2020). The results appear in the Supplementary Material, tables S1 and S2.
10. For ease of interpretation, continuous variables were recoded into categories (age: 16–24, 25–34, 35–44, 45–54, 55–64, 65+; number of household members: 1, 2, 3, 4+; income percentiles: 1–24, 25–49, 50–74, 75–100) with the modal category chosen as reference. Other variables are dichotomized.

$$Non - Response\ Bias\ (\bar{y}_{ADMIN}) = \bar{y}_{ADMIN,\ respondents} - \bar{y}_{ADMIN,\ gross\ sample}$$

$$Non - Participation\ Bias\ (\bar{y}_{ADMIN}) = \bar{y}_{ADMIN,\ participants} - \bar{y}_{ADMIN,\ respondents}$$

To calculate the standard errors of the differences, we adapted Lee's (2006) calculation of noncoverage bias to our context.

Nonresponse bias:

$$se(p_{respondents} - p_{gross\ sample}) = \frac{n_{gross\ sample} - n_{respondents}}{n_{gross\ sample}} \sqrt{var(p_{respondents}) + var(p_{nonrespondents})}$$

Nonparticipation bias:

$$se(p_{participants} - p_{respondents}) = \frac{n_{respondents} - n_{participants}}{n_{respondents}} \sqrt{var(p_{participants}) + var(p_{nonparticipants})},$$

where p is the proportion for each variable in the reference category. To compare nonresponse and nonparticipation biases, we used one-sample t-tests treating the sample data as benchmark data.[11] We calculated the Average Absolute Bias across the variables from the registry by summing the absolute value of individual biases and dividing the result by the number of variables included in the calculation. The analyses are based on unweighted data.

Results

WTS RATES AND SHARING OF SENSOR DATA

Table 1 shows the willingness to share and actual sharing rates, with the latter being a percent of all those who indicated they were willing to share. For example, for the first question, 67 percent of respondents are willing to share their geolocation, but 69 percent of those (that is, 46 percent of all respondents) actually share it. Each treatment's effect on the two measures is compared to the no-text (control) condition and its significance is tested with one-sided z-tests.

11. This method is common for studies on bias (e.g., Yeager et al. 2011 used t-tests; Antoun 2015; Sakshaug, Cernat, and Raghunathan 2019; and Keusch, Bähr, et al. 2020 all used z-tests). With our large sample, t-tests and z-tests produce comparable results.

Table 1. Willingness to share and actual sharing conditional on willingness by sensor tasks (percentages)

	GPS location	Video of surroundings	Photo of house	Photo of receipt	Photo of self
Overall ($N = 1{,}868$)					
Willingness to share	66.6	15.7	12.4	18.7	14.5
Actual sharing	68.6	100.0	100.0	100.0	100.0
No additional text ($N = 235$)					
Willingness to share	63.4	17.0	12.8	17.0	13.2
Actual sharing	74.5	100.0	100.0	100.0	100.0
Benefit framing ($N = 237$)					
Willingness to share	59.9	12.7	9.3	14.4	12.2
	0.782	*0.909*	*0.886*	*0.788*	*0.622*
Actual sharing	69.7	100.0	100.0	100.0	100.0
	0.818				
Autonomy over data collection ($N = 237$)					
Willingness to share	**71.7**	17.3	13.1	**23.6**	16.9
	0.027	*0.468*	*0.460*	*0.037*	*0.131*
Actual sharing	66.5	100.0	100.0	100.0	100.0
	0.942				
Assurance of privacy ($N = 265$)					
Willingness to share	62.3	15.1	12.1	17.4	16.6
	0.604	*0.720*	*0.592*	*0.460*	*0.142*
Actual sharing	71.5	100.0	100.0	100.0	100.0
	0.724				
Benefit & autonomy ($N = 224$)					
Willingness to share	**75.9**	17.9	15.2	20.1	16.5
	0.002	*0.407*	*0.229*	*0.200*	*0.159*
Actual sharing	71.2	100.0	100.0	100.0	100.0
	0.747				
Benefit & privacy ($N = 227$)					
Willingness to share	59.5	13.2	12.3	17.6	13.7
	0.807	*0.873*	*0.556*	*0.433*	*0.442*
Actual sharing	70.4	100.0	100.0	100.0	100.0
	0.781				
Autonomy & privacy ($N = 233$)					
Willingness to share	67.8	18.0	12.9	15.0	11.1
	0.158	*0.388*	*0.486*	*0.722*	*0.749*
Actual sharing	60.8	100.0	100.0	100.0	100.0
	0.995				

(*continued*)

Table 1. (*continued*)

	GPS location	Video of surroundings	Photo of house	Photo of receipt	Photo of self
Benefit & autonomy & privacy ($N = 210$)					
Willingness to share	**72.9**	14.8	11.9	**25.2**	15.2
	0.016	*0.742*	*0.609*	*0.017*	*0.269*
Actual sharing	64.7	100.0	100.0	100.0	100.0
	0.968				

NOTE.—N overall = 1,868; actually sharing conditional on willingness to share. Treatment effects are compared to *no additional text* (control) condition (Row 1). Significance based on one sided z-tests (significant effects in bold; p-values in italics). Less than 1% of respondents changed their initial willingness to *will not share* after providing the sensor-collected data; they are treated as nonwilling.

Across the main experimental conditions, WTS and actual sharing rates do not differ much from the rates in the control condition. Emphasizing autonomy over data collection for geolocation increased WTS by 8.3 p.p. (p=.027) and 6.6 for sharing a photo of a receipt (p=.037). Emphasizing autonomy over data collection together with benefit framing increased the WTS for sharing geolocation by 12.5 p.p. (p=.002). Emphasizing autonomy, assuring privacy, and mentioning the benefits of sharing increases WTS by 9.5 p.p. (p=.017) for geolocation and by 8.2 p.p. (p=.016) for a photo of a receipt. Given that autonomy over data collection is the only significant main effect, it is possible that it might drive significant interaction effects.

The overall WTS rates for camera-related tasks (sharing a video of one's surroundings and three photos) vary between about 12 percent (photo of the house) and 19 percent (photo of a receipt), and are much lower than the geolocation rates. This provides partial support for *H1*. The proportion of respondents who report willingness to share their data from camera-related tasks who actually share their data is 100 percent.

One explanation for the lower willingness rates for camera-related tasks might be that respondents learn from the (earlier) geolocation question that the survey not only asks about willingness to share, but actually requests sharing data.

A related explanation is that the results are an artifact of question order. In studies that randomized the order of multiple data-sharing requests, the first request achieved higher willingness than later requests (Silber et al. 2018; Walzenbach et al. 2019; Struminskaya et al. 2020). Our experimental design precludes directly testing whether more sharing of geolocation data is because the request is the first of many or whether respondents are simply less open to sharing the data from camera-related tasks. To check whether sharing one piece of data influences the subsequent data sharing for other tasks, we analyzed the sharing patterns (tables A2 and A3). The largest group, 51.3 percent, declined all requests and did not share any data; 25 percent shared only geolocation; 18 percent shared 2.6 pieces of data on average across all subsequent requests, and only 5.7 percent declined all subsequent requests after sharing two or more pieces of data. These findings argue against the order of the requests determining the consent patterns, suggesting that it is the nature of the task, that is, sharing geolocation versus camera-related tasks, that is responsible. But we can't conclude this definitively.

MECHANISMS OF WTS AND SHARING OF SENSOR DATA

In addition to the effects of how the data-sharing request was worded and the nature of the task, we are interested in the effects of respondent characteristics on WTS and actual sharing. For this, we turn to multivariate analyses shown in table 2. We differentiate between willingness to share and actual sharing for geolocation, but for the camera tasks, we report only WTS since all who were willing to share did in fact share (see table 1).

Model 1 (baseline) tests the effects of the experimental conditions for the four sensor tasks. The only significant effect is for autonomy over data collection, which leads to 1.62 times higher odds of willingness to share geolocation, and 1.33 higher odds of willingness to share a photo of a receipt. The highest average marginal effect (AME) is estimated at 0.11 for geolocation data (table 1). Thus, *H3* (autonomy) is partially supported while *H2* (benefit framing) and *H4* (privacy) are not.

Model 2 adds respondent characteristics as predictors. In addition to effects of autonomy observed in model 1, some respondent characteristics affect WTS in model 2. First, respondents who perform more activities on their smartphones are more likely to be willing to share data from camera-related tasks (supporting *H6.1*), although for each additional smartphone activity, respondents are only about 1 p.p. (= AME $\times$ 100) more willing to share data. Frequency of using smartphone camera functions does not affect WTS; however, frequency of using GPS is significantly related to some tasks (partially supporting *H6.2*). Also, self-assessed smartphone skills do not predict WTS or sharing sensor data, consistent with Keusch et al. (2019) and Struminskaya et al. (2020).

Second, previously having downloaded an app increases the odds of sharing a photo of a receipt (+12.6 p.p.); paradoxically, having been asked to download but not downloading an app increases the odds of sharing a video of surroundings (+13.5 p.p.) and taking a photo of the house (+9.7 p.p.); taken together, these results provide partial support for *H7.1*. Sample sizes are small, though, with only a handful of respondents being asked to

Table 2. Logistic regressions predicting sensor data sharing: odds ratios, robust standard errors in parentheses, and average marginal effects; for the camera tasks, all who were willing to share did in fact share; therefore, actual sharing is not modeled, since it is identical with willingness to share

	Willingness GPS	AME	Shared GPS	AME	Video of surroundings	AME	Photo of house	AME	Photo of receipt	AME	Photo of self	AME
Model 1: *Experimental conditions only*												
Benefit framing	1.027		1.041		0.844		0.951		1.062		0.985	
	(0.101)		(0.128)		(0.108)		(0.134)		(0.127)		(0.130)	
	0.787		*0.746*		*0.185*		*0.721*		*0.614*		*0.911*	
Autonomy	**1.621**	0.106	**0.762**	−0.058	1.207		1.164		**1.328**	0.043	1.077	
	(0.161)		(0.094)		(0.154)		(0.163)		(0.158)		(0.142)	
	0.000		*0.028*		*0.140*		*0.280*		*0.017*		*0.572*	
Privacy assurance	0.911		0.840		0.934		0.980		0.998		0.965	
	(0.090)		(0.103)		(0.119)		(0.138)		(0.119)		(0.127)	
	0.345		*0.155*		*0.594*		*0.885*		*0.984*		*0.784*	
Intercept	**1.641**		**2.705**		**0.190**		**0.136**		**0.194**		**0.167**	
	(0.158)		(0.340)		(0.024)		(0.019)		(0.024)		(0.022)	
	0.000		*0.000*		*0.000*		*0.000*		*0.000*		*0.000*	
Model fit statistics:												
Log Likelihood	−1178.76		−769.46		−811.05		−700.22		−896.64		−771.50	
Pseudo R-squared	0.0105		0.0044		0.0026		0.0009		0.0033		0.0003	
N	1,868		1,242		1,868		1,868		1,868		1,868	

(*continued*)

Table 2. (*continued*)

	Willingness GPS	AME	Shared GPS	AME	Video of surroundings	AME	Photo of house	AME	Photo of receipt	AME	Photo of self	AME
Model 2: *Experimental conditions and respondent characteristics*												
Benefit framing	1.027		1.045		0.816		0.945		1.070		0.978	
	(0.110)		(0.133)		(0.109)		(0.140)		(0.133)		(0.137)	
	0.807		*0.729*		*0.128*		*0.700*		*0.585*		*0.875*	
Autonomy	**1.646**	0.096	0.788		1.207		1.174		**1.328**	0.040	1.075	
	(0.177)		(0.100)		(0.160)		(0.173)		(0.165)		(0.150)	
	0.000		*0.061*		*0.155*		*0.278*		*0.022*		*0.606*	
Privacy assurance	0.830		0.853		0.873		0.949		0.952		0.945	
	(0.089)		(0.108)		(0.116)		(0.140)		(0.118)		(0.130)	
	0.084		*0.211*		*0.306*		*0.723*		*0.693*		*0.684*	
# Smartphone activities	1.035		1.018		**1.079**	0.009	**1.107**	0.010	**1.069**	0.010	**1.116**	0.012
	(0.026)		(0.030)		(0.037)		(0.044)		(0.032)		(0.042)	
	0.170		*0.547*		*0.025*		*0.010*		*0.026*		*0.004*	
Smartphone skill	1.107		1.144		1.022		0.922		0.974		1.060	
	(0.072)		(0.089)		(0.082)		(0.082)		(0.072)		(0.090)	
	0.120		*0.084*		*0.785*		*0.363*		*0.718*		*0.490*	
Frequency GPS	**1.190**	0.033	**1.100**	0.019	1.029		1.059		1.063		**1.089**	0.010
	(0.036)		(0.036)		(0.034)		(0.040)		(0.033)		(0.039)	
	0.000		*0.003*		*0.391*		*0.132*		*0.051*		*0.016*	
Frequency photos	0.930		1.115		1.048		1.133		1.053		1.031	
	(0.046)		(0.069)		(0.066)		(0.077)		(0.059)		(0.063)	
	0.145		*0.081*		*0.455*		*0.065*		*0.358*		*0.616*	

(*continued*)

Table 2. (*continued*)

	Willingness GPS	AME	Shared GPS	AME	Video of surroundings	AME	Photo of house	AME	Photo of receipt	AME	Photo of self	AME
Frequency videos	0.928		0.919		0.975		0.951		0.930		0.924	
	(0.057)		(0.077)		(0.079)		(0.084)		(0.068)		(0.077)	
	0.229		*0.315*		*0.760*		*0.573*		*0.318*		*0.347*	
Privacy concern	**0.850**	−0.031	1.051		0.942		0.933		0.978		0.897	
	(0.047)		(0.069)		(0.065)		(0.070)		(0.063)		(0.061)	
	0.004		*0.449*		*0.384*		*0.358*		*0.730*		*0.113*	
Concern data sharing	0.898		0.910		0.911		0.907		0.989		0.897	
	(0.054)		(0.062)		(0.066)		(0.076)		(0.068)		(0.153)	
	0.072		*0.170*		*0.200*		*0.242*		*0.869*		*0.153*	
Survey enjoyment	**1.225**	0.039	0.898		**1.417**	0.043	**1.376**	0.032	**1.244**	0.031	**1.380**	0.036
	(0.065)		(0.056)		(0.090)		(0.097)		(0.074)		(0.090)	
	0.000		*0.085*		*0.000*		*0.000*		*0.000*		*0.000*	
Survey value	**0.120**	0.035	0.998		1.074		1.134		**1.220**	0.028	**1.183**	0.019
	(0.074)		(0.073)		(0.082)		(0.094)		(0.088)		(0.096)	
	0.003		*0.979*		*0.351*		*0.129*		*0.006*		*0.039*	
Survey burden	0.925		0.949		0.992		0.923		0.944		1.047	
	(0.050)		(0.064)		(0.064)		(0.067)		(0.058)		(0.068)	
	0.150		*0.440*		*0.900*		*0.270*		*0.344*		*0.483*	
Part. online surveys	0.990		1.324		0.864		1.056		1.188		0.630	
	(0.207)		(0.317)		(0.242)		(0.310)		(0.294)		(0.200)	
	0.961		*0.241*		*0.602*		*0.853*		*0.486*		*0.147*	

(*continued*)

Table 2. (*continued*)

	Willingness GPS	AME	Shared GPS	AME	Video of surroundings	AME	Photo of house	AME	Photo of receipt	AME	Photo of self	AME
Part. smartphone survey	1.149		1.102		1.474		0.988		0.999		1.355	
	(0.255)		(0.282)		(0.428)		(0.301)		(0.254)		(0.442)	
	0.532		*0.703*		*0.181*		*0.967*		*0.998*		*0.352*	
Shared data (ref=never invited)												
not shared	**0.386**	−0.183	1.176		0.314		0.672		**0.272**	−0.185	0.615	
	(0.123)		(0.635)		(0.199)		(0.356)		(0.156)		(0.335)	
	0.003		*0.764*		*0.068*		*0.453*		*0.024*		*0.373*	
shared	1.452		0.949		1.191		0.988		0.585		1.231	
	(0.957)		(0.518)		(0.611)		(0.616)		(0.328)		(0.702)	
	0.572		*0.924*		*0.733*		*0.985*		*0.339*		*0.715*	
Download app (ref=never invited)												
not downloaded	1.409		1.454		**2.973**	0.135	**2.630**	0.097	2.267		1.580	
	(0.630)		(0.806)		(1.281)		(1.212)		(1.001)		(0.767)	
	0.443		*0.500*		*0.011*		*0.036*		*0.064*		*0.346*	
downloaded	1.987		1.035		1.728		1.203		**2.428**	0.126	1.250	
	(0.938)		(0.442)		(0.750)		(0.572)		(0.938)		(0.589)	
	0.146		*0.936*		*0.208*		*0.698*		*0.022*		*0.636*	
Age	**1.011**	0.002	1.004		**1.010**	0.001	**1.022**	0.002	1.008		**1.016**	0.002
	(0.004)		(0.004)		(0.005)		(0.005)		(0.004)		(0.005)	
	0.004		*0.329*		*0.033*		*0.000*		*0.056*		*0.001*	

(*continued*)

Table 2. (*continued*)

	Willingness GPS	AME	Shared GPS	AME	Video of surroundings	AME	Photo of house	AME	Photo of receipt	AME	Photo of self	AME
Gender (ref=female)	1.097		0.914		0.968		1.191		**0.757**	−0.040	1.053	
	(0.122)		(0.119)		(0.133)		(0.182)		(0.096)		(0.152)	
	0.408		*0.493*		*0.814*		*0.251*		*0.028*		*0.719*	
Education (ref <HS)												
HS & vocational	0.943		1.124		0.977		0.839		1.107		1.123	
	(0.150)		(0.211)		(0.194)		(0.179)		(0.207)		(0.230)	
	0.713		*0.533*		*0.907*		*0.411*		*0.585*		*0.571*	
Applied uni. & Uni.	0.928		0.841		0.951		0.741		0.986		0.782	
	(0.146)		(0.154)		(0.191)		(0.161)		(0.186)		(0.165)	
	0.635		*0.342*		*0.801*		*0.168*		*0.939*		*0.243*	
Intercept	**0.275**		1.447		**0.012**		**0.005**		**0.011**		**0.003**	
	(0.151)		(0.993)		(0.009)		(0.004)		(0.007)		(0.003)	
	0.018		*0.590*		*0.000*		*0.000*		*0.000*		*0.000*	
Model fit statistics:												
Log Likelihood	−1051.10		−737.74		−747.81		−631.67		−836.54		−693.45	
Pseudo R-squared	0.1095		0.0407		0.0736		0.0885		0.0623		0.0902	
N	1,853		1,234		1,853		1,853		1,853		1,853	

NOTE.—Marginal effects are shown only for significant predictors. Significant effects in bold; *p*-values in italics.

participate in app studies. Previously refusing to share sensor data leads to lower willingness to share geolocation (−18.3 p.p.) and lower odds of photographing a receipt (−18.5 p.p.), partially supporting *H7.2*.

Third, being concerned about privacy reduced the odds of being willing to share geolocation (−3 p.p.) but did not affect sharing decisions for the other sensor tasks. Concerns about data sharing are not statistically significant.[12] This provides partial support for *H5*.

Fourth, respondents who enjoy surveys are more likely to share all five types of sensor data and those who value surveys are more likely to share photos, but frequency of survey participation does not significantly affect sharing decisions.

Finally, we find a small effect of age. A 10-year increase in age leads to an AME of 0.02, implying a 2 p.p. increase in willingness to share geolocation or a video/photo.

NONRESPONSE AND NONPARTICIPATION BIAS

It is possible that survey respondents who are willing to share sensor data, in addition to survey responses, differ from respondents who are not willing to share on characteristics that may be relevant to the sensed behavior. For example, respondents willing to share geolocation may differ in their patterns of mobility from respondents who are not willing to share. Thus, we assessed bias due to respondents' nonparticipation in sensor tasks as well as the cumulative effects of nonparticipation and survey nonresponse; that is, if the survey respondents differ from nonrespondents on behavior, such as mobility, this could amplify bias due to nonparticipation. Nonresponse and nonparticipation bias were calculated using register data. Table 3 shows the population percentages from the register variables for the sampled individuals, the bias in these statistics when based only on survey respondents' answers, and when based only on the answers from participants in each sensor task.

The nonparticipation bias is about the same magnitude as the nonresponse bias. Because the characteristics that would ideally be used to measure nonparticipation bias, such as a current location that can affect sharing of geolocation, are probably not in the register, we need to use proxies. For example, to estimate nonparticipation bias for geolocation, register variables such as car ownership, possession of a driver's license, and urbanicity may be reasonable proxies, as they are related to mobility. In fact, nonparticipation

12. But it is possible that under certain circumstances they are significant. Since some respondent characteristics might interact with the experimental conditions, we included these interaction terms in a set of models presented in Supplementary Material tables S1 and S2. The benefit framing decreased the odds of sharing geolocation with higher data-sharing concerns. However, the main effect of benefit framing on sharing geolocation was not significant.

Table 3. Nonresponse and nonparticipation bias by sensor-tasks: percentages, standard errors in parentheses

			Nonparticipation bias (%)					
Administrative data variables	Sample value (%)	Nonresponse bias (%)	GPS shared	Video of surround.	Photo of house	Photo of receipt	Photo of self
Age (25–34)	21.90	**-1.65**	-1.34	**2.81**	-2.37	-0.47	**-2.03**
		(0.063)	(0.087)	(0.211)	(0.229)	(0.185)	(0.212)
		0.014	*0.131*	*0.003*	*0.006*	*0.599*	*0.020*
Gender (man)	42.52	0.93	1.10	1.36	**6.34**	**-3.91**	**3.76**
		(0.075)	(0.109)	(0.250)	(0.297)	(0.227)	(0.273)
		0.260	*0.327*	*0.228*	*0.000*	*0.000*	*0.001*
Education (high)	37.13	**3.40**	-2.22	-0.88	**-6.79**	-2.38	**-7.54**
		(0.089)	(0.124)	(0.280)	(0.338)	(0.265)	(0.302)
		0.000	*0.089*	*0.505*	*0.000*	*0.069*	*0.000*
Ethnic background (non-Dutch)	16.26	**-1.79**	**-1.61**	0.78	**2.96**	**2.42**	**-2.59**
		(0.057)	(0.076)	(0.181)	(0.225)	(0.173)	(0.179)
		0.002	*0.034*	*0.339*	*0.001*	*0.004*	*0.000*
Marital status (married)	45.79	**2.66**	0.47	**-2.67**	**3.47**	1.41	0.63
		(0.076)	(0.109)	(0.250)	(0.297)	(0.231)	(0.273)
		0.001	*0.967*	*0.018*	*0.002*	*0.212*	*0.580*
No. of household members (2 people)	35.78	**2.87**	-0.83	-0.67	**3.47**	-0.26	1.49
		(0.073)	(0.106)	(0.243)	(0.293)	(0.225)	(0.268)
		0.000	*0.446*	*0.544*	*0.002*	*0.814*	*.0178*
Owns a car	46.51	**2.50**	-1.44	0.99	**2.48**	-0.86	-0.68
		(0.076)	(0.109)	(0.251)	(0.297)	(0.231)	(0.273)
		0.003	*0.202*	*0.379*	*0.028*	*0.442*	*0.549*

(*continued*)

Table 3. (*continued*)

Administrative data variables	Sample value (%)	Nonresponse bias (%)	Nonparticipation bias (%) GPS shared	Video of surround.	Photo of house	Photo of receipt	Photo of self
Has a driver's license	82.93	**2.79**	-0.34	0.64	**1.51**	-1.19	**1.64**
		(0.058)	(0.079)	(0.174)	(0.200)	(0.168)	(0.184)
		0.000	*0.671*	*0.408*	*0.045*	*0.144*	*0.029*
Homeowner	74.38	**2.15**	0.10	**-2.03**	**-4.60**	**-2.27**	-1.24
		(0.068)	(0.096)	(0.223)	(0.270)	(0.207)	(0.239)
		0.003	*0.918*	*0.043*	*0.000*	*0.024*	*0.211*
Urban (>=1500 addresses/km^2)	51.50	-0.86	0.06	**5.86**	**7.66**	**6.96**	0.66
		(0.076)	(0.109)	(0.249)	(0.293)	(0.229)	(0.273)
		0.302	*0.959*	*0.000*	*0.000*	*0.000*	*0.557*
Size of township (>50,000)	54.24	-1.00	-0.57	**5.20**	**6.34**	**3.78**	0.67
		(0.076)	(0.109)	(0.248)	(0.292)	(0.229)	(0.273)
		0.228	*0.614*	*0.000*	*0.000*	*0.001*	*0.555*
In paid work	60.54	-0.38	0.53	0.75	**-2.47**	-1.26	-1.95
		(0.075)	(0.107)	(0.246)	(0.294)	(0.228)	(0.270)
		0.645	*0.629*	*0.498*	*0.027*	*0.260*	*0.080*
Income percentile (75th–100th)	39.99	**4.18**	-0.16	1.76	1.33	-1.92	-0.56
		(0.074)	(0.108)	(0.250)	(0.297)	(0.229)	(0.273)
		0.000	*0.886*	*0.119*	*0.240*	*0.086*	*0.620*

(*continued*)

Table 3. (*continued*)

Administrative data variables	Sample value (%)	Nonresponse bias (%)	Nonparticipation bias (%) GPS shared	Video of surround.	Photo of house	Photo of receipt	Photo of self
Average abs. bias		2.09	0.83	2.03	3.98	2.24	1.96
N	3,608	1,961	862	308	235	349	269
N (education)	2,631	1,389	616	232	163	249	194
N (homeowner)	3,509	1,900	830	298	228	334	263
N (in paid work)	3,596	1,958	860	307	234	348	268
N (inc. percentile)	3,586	1,954	859	307	233	348	266

NOTE.—Reference category in parentheses for variables that initially had more than two categories. Significant effects in bold; *p*-values in italics.

biases for sharing geolocation in car ownership, possession of a driver's license, and urbanicity are small (under 2 p.p., n.s.). Participation bias for photographing one's home and videorecording surroundings could be affected by the type of community one lives in. A reasonable proxy could be register variables urbanicity and township size. The difference on these variables for those willing to share a video of their surroundings and those who are not is over 5 p.p. each, both statistically significant. In studies that measure home ownership, willingness to share pictures of one's house may be vulnerable to nonparticipation bias, as homeowners might feel their home is more personal than might renters and thus be less willing to share. In fact, there is significant nonparticipation bias for this task in home ownership (4.6 p.p.) and urbanicity (6–7 p.p.). To the extent that taking photos of receipts suffers from nonparticipation bias, this could be due to financial attributes, although the direction of any effects is not clear on intuitive grounds. In fact, nonparticipation bias in photographing receipts for the register variables paid work and income are small (n.s.). For taking pictures of oneself, age and gender could be important, since younger people and women can be more willing to take photos.[13] However, biases in age, gender, and ethnic background are about 2-3 p.p. For this task, we find a large significant bias for education (-8 p.p.). However, we do not have a theoretical explanation for this effect.

The nonparticipation bias is conditional on nonresponse bias; that is, in order to participate or not in the sensor task, one must first be a survey respondent. In some cases, both biases are in the same direction, but in others they are in opposite directions. For example, for education, a positive nonresponse bias and a negative nonparticipation bias result in a small total bias for most sensors. Some other biases aggravate each other; for example, non-Dutch are less likely to participate in the survey compared to the gross sample, but those who do respond to the survey are less likely to share a photo of themselves. Across sensor tasks, nonresponse and nonparticipation biases move estimates in different directions, while there are more significant differences for nonresponse than nonparticipation bias. More research is needed to determine whether biases generally aggravate each other or nonparticipation bias is masked by the opposing nonresponse bias.

Discussion

Data collection using smartphone sensors has been investigated by statistical agencies and large-scale panels in numerous studies (e.g., Jäckle et al. 2019, Kreuter et al. 2020, McCool et al. 2021). If participants who share smartphone sensor data differ on key outcomes from those who refuse, research

13. A study by the Pew Research Center shows that women and young adults are among the most likely groups to use Instagram, a photo- and video-sharing platform (Auxier 2020).

conclusions can be biased. To avoid potential biases, it is necessary to understand the mechanisms of participation.

This paper validates and extends the research that focuses on hypothetical willingness to share sensor data. We study the relationship between willingness to share and actually sharing geolocation, photos, and a video. To examine this, we manipulated the wording in the invitation to share in three ways: (1) benefit vs. neutral framing of the request, (2) emphasis on autonomy over data collection, and (3) assurance of privacy, hypothesizing that such emphases would increase both hypothetical willingness to share and actual sharing.

More private camera tasks (e.g., photographing or videotaping one's surrounding or home) evoked lower WTS (under 20 percent), whereas a request to share geolocation, which may not reveal as much personal information as the camera tasks, elicited the highest WTS (about 67 percent).

Emphasizing autonomy increased willingness to share and actually sharing geolocation and increased willingness to share a photo of a receipt. Autonomy also interacted with benefit framing to increase willingness to share geolocation. Overall, effects of request wording are small and the explanatory power of our models that only contain experimental effects is low. Framing effects are also small or nonexistent for disclosure of sensitive information (Gluck et al. 2016; Samat and Acquisti 2017) and hypothetical WTS (Struminskaya et al. 2020).

Consistent with previous studies (e.g., Keusch et al. 2019), the number of tasks performed on one's device, having prior experience with sharing GPS, and being asked to download an app are associated with an increased likelihood of WTS and sharing, even if the prior request to share sensor data had been denied.

Contrary to our expectations, privacy concerns decreased WTS and actual sharing only of geolocation. Privacy preferences and subsequent sharing behavior do not always align: people stating they care about their privacy share more data than they indicated they were willing to share (cf. *privacy paradox*, Norberg, Horne, and Horne 2007). In other contexts, however, individuals make data-sharing decisions consistent with their privacy attitudes (Kokolakis 2017).

Being willing to share data in four camera tasks perfectly predicted actual sharing (i.e., of those participants who indicated willingness to share, 100 percent actually shared). Presumably, the personal nature of the task restricted WTS to the minority of respondents who were unphased and eager to share photos and a video of their circumstances and themselves and so consistently followed through on their "promise" to share. Possibly, the particular uses to which respondents were asked to put the camera rather than using the camera per se are responsible for this pattern. A more mundane use of the camera (e.g., photographing the nearest traffic light) may have produced higher WTS and possibly lower follow-through. In any event, for the camera-related tasks examined here, the respondents were reluctant to share the data irrespective of their privacy concerns or level of autonomy over data collection. The camera tasks might produce information that is not germane to the task (e.g., a messy home) and too private for most participants compared with GPS coordinates. Although geolocation can potentially lead to a greater violation of privacy than a photo, it might not be perceived that way by respondents. If the information to be shared is perceived as very private, varying the request will not affect the underlying—and presumably negative—preferences about sharing.

Why did benefit framing not increase data sharing? We propose this may be due to the request coming from a trustworthy sponsor, creating a ceiling effect above which benefit framing has no impact. This is consistent with the finding of large framing effects only for a less trustworthy sponsor (Samat and Acquisti 2017), and sponsorship effects on hypothetical WTS (Keusch et al. (2019) found that participants from a market research panel were more willing to share if the request came from a market research firm or a university rather than a statistical agency; Struminskaya et al. (2020) found in a university-housed panel that a university sponsor evoked the highest hypothetical WTS, followed by a statistical agency and a market research firm. Our respondents have participated in at least one survey conducted by Statistics Netherlands and agreed to be invited to participate again. They might not perceive question answering as burdensome. Thus, eliminating some questions is not make sharing more attractive. The effect of the study sponsor that is familiar to the respondents might also upwardly bias WTS. Thus, our sharing rates likely fall between those of panel members and a true population cross-section. We hope to see future research with participants who have no experience with the study sponsor.

One implication of the current findings is that the rationale behind the sharing request is key. Explaining the value of the information and the purpose of its collection (cf. Nissenbaum 2009), thus, becomes critical in seeking respondents' consent. In our study, the purpose of the sensor tasks was not clearly communicated mostly because the tasks were administered as part of a methodological experiment, not to gain substantive knowledge.

The nature of the sensor task and the kind of data it captures are also key. Our study concentrated on app-free geolocation and camera measurements to avoid biases associated with selecting sample members who would have downloaded an app. In practice, researchers might wish to use data from other smartphone sensors (e.g., a microphone, a light sensor, or an accelerometer). We believe our results generalize to other sensors. This is because sensors can be classified based on the extent to which participants can directly and intentionally influence what is measured by the sensor (e.g., they can decide what will be in a picture but not their current longitude and latitude). Where a sensor falls on this continuum may affect participants' WTS and help explain why relatively few who "promise" to share actually share for some tasks (inadequate influence over what data are captured), but all of those who indicate they are willing to share follow through for other tasks (sufficient influence over what is captured).

For some sensors (e.g., an accelerometer), it is unlikely that participants will understand what is captured well enough to consider if they can affect what is captured when deciding whether or not to share the data. Thus, researchers may wish to show the participants what kind of data they are being asked to share. We visualized the respondents' location prior to actually sharing, and participants indicated willingness to share these data more often than they actually did. To avoid such "backfire effects," researchers will need to strike a balance between the need to increase sharing and the need to provide detailed information about the data participants are asked to share. Researchers must strike a similar balance when deciding whether to use sensor measurements over which participants have autonomy, such as camera-related tasks. While this kind of control increases participants' WTS, it may increase the very social desirability and reactivity of measurement, for example, only photographing surroundings they believe reflect well on them, that sensor measurement promises to mitigate.

Because the current study concerns the sharing decisions of smartphone and tablet users, one should not generalize the results to other types of data sharing involving the general population, such as financial records that both users and nonusers could be asked to share. Mobile device users are younger than nonusers, more urban, more affluent, and more educated (Antoun et al. 2018; Couper et al. 2018; Keusch, Bähr, et al. 2020), and may think about digital traces differently than nonusers. Instead, our findings indicate that sharing decisions might be quite specific, not just to sensor data but to the nature of the particular sensor task for which data sharing is requested, how the purpose of collecting the sensor data is communicated, and who is asking participants to share these data. It should no longer surprise us that participants' decisions about their involvement in research studies requesting they share sensor data entail considerable nuance.

Appendix A. Descriptive Statistics and Additional Analyses

Table A1. Descriptive statistics of variables used in the analysis ($N = 1{,}868$)

	M	SD	Min	Max	Missing values
Number of smartphone activities	10.588	3.522	0	16	0
Frequency of sharing GPS location	2.746	2.414	0	6	0
Frequency of taking photos	2.400	1.750	0	5	0
Frequency of taking videos	1.247	1.366	0	5	0
Self-assessed smartphone skills	3.894	1.016	1	5	0
Concern about privacy	3.819	1.504	1	7	0
Concern about sharing data with firms	4.056	1.599	1	7	0
Concern about sharing data with governmental agencies	3.378	1.678	1	7	0
Concern about sharing data on social media	4.902	1.823	1	7	0
Mean score concern data sharing	4.112	1.419	1	7	0
Survey attitude: enjoyment	4.043	1.283	1	7	0
Survey attitude: value	5.359	1.087	1	7	0
Survey attitude: burden	3.046	1.199	1	7	0
Participated in online surveys in last 30 days	.3672	.4822	0	1	0
Participated in a smartphone survey in last 30 days*	.2928	.4022	0	1	0
Sharing of GPS, photos, videos					0
Invited not shared	.0246	.1550	0	1	
Never invited	.9668	.1792	0	1	
Shared	.0176	.1318	0	1	
Download of research app					0
Invited not downloaded	.0155	.1237	0	1	
Never invited	.9668	.1792	0	1	
Downloaded	.0177	.1318	0	1	
Age	43.515	18.274	16	98	0
Gender (male)	.4288	.4950	0	1	0
Education:**					15
Less than HS (ref.)	.1743	.3795	0	1	
HS & vocational	.3815	.4859	0	1	
Applied univ. & univ.	.4441	.4970	0	1	

*The question about participating in a smartphone survey was only asked to those who had indicated to participate in an online survey; people who did not participate in an online survey are recoded as 0.

**For 29 respondents who chose the category "other," information on education was replaced by the information from the registry data from 2016, reducing the number of missing values to 15 (0.9%).

Table A2. Percentage of participants by sharing pattern

Pattern	Percent	*N*
Shared data for all five tasks: geolocation, video, photo house, photo receipt, photo self	1.93	36
Shared geolocation, video, photo house, photo receipt; No photo self	1.07	20
Shared geolocation, video, photo house; No photo receipt, no photo self	0.80	15
Shared geolocation, video; No photo house, no photo receipt, no photo self	1.93	36
Shared geolocation only; No video, no photo house, no photo receipt, no photo self	25.00	467
Did not share anything	51.28	958
Other pattern	17.99	336
Total	100.00	1,898

Table A3. Distribution of sharing by other pattern

Shared data for:	Percent	*N*
one of the tasks	12.50	42
two of the tasks	37.50	126
three of the tasks	27.08	91
four of the tasks	22.92	77
Total	100.00	336
Mean, (SD) other pattern	2.60	.97

Appendix B. Question Wordings Used in the Analyses

Prior to starting a questionnaire, a respondent had to provide their name, sex, date of birth, and marital status, which were checked against the frame data of Statistics Netherlands. If respondents' sex or date of birth deviated from the record, they were not allowed to proceed with the questionnaire. The question wordings of those checks are not included.

Note that the wording of questions was adapted for the type of device (smartphone or tablet). For better readability, we only present smartphone wordings here.

Questions marked with * are modeled after Keusch et al. (2019). Questions marked with ** are modeled after Couper et al. (2008; 2010).

Q1.* Do you use your smartphone for the following activities? (yes/no)

Q1a. Sending messages (for example, through SMS, WhatsApp, or Telegram)
Q1b. Browsing websites
Q1c. Reading and/or writing email
Q1d. Taking photos
Q1e. Taking videos
Q1f. Looking at content on social media websites/apps (for example looking at text, images, videos on Facebook, Twitter, Instagram)
Q1g. Posting content to social media websites/apps (for example posting text, images, videos on Facebook, Twitter, Instagram)
Q1h. Making purchases (for example buying books or clothes, booking train tickets, ordering food)
Q1i. Online banking (for example checking account balance, transferring money)
Q1j. Installing new apps (for example from the App Store, Google Play Store)
Q1k. Using GPS/location-aware apps (for example Google Maps, Foursquare, Yelp)
Q1l. Connecting to other electronic devices via Bluetooth (for example smartwatches, fitness bracelets, step counter)
Q1m. Calling (also through Skype or Facetime)
Q1n. Playing games
Q1o. Streaming videos or music
Q1p. Other, please specify ____________________________

If Q1d=yes

Q2. How often do you take photos using your smartphone?

1. Several times a day or more often
2. Every day
3. Several times a week
4. Several times a month
5. Once a month or less often

If Q1e = yes

Q3. How often do you take videos using your smartphone?

1. Several times a day or more often
2. Every day
3. Several times a week
4. Several times a month
5. Once a month or less often

If Q1k = yes

Q4. How often do you use GPS/location-aware apps using your smartphone?

1. GPS is always on
2. Several times a day or more often
3. Every day
4. Several times a week
5. Several times a month
6. Once a month or less often

Q5.* Generally, how would you rate your skills of using your smartphone on a scale from 1 = Beginner to 5 = Advanced?

1. Beginner
2. Somewhat more than a beginner
3. Average skilled
4. Somewhat more than average
5. Advanced

Q6.* How concerned are you about whether or not each of the following organizations will share personal data with other parties? (1 Not at all concerned, 7 Very concerned)

a. Private companies
b. Government agencies (such as municipality, national government)
c. Social media platforms such as Facebook, Twitter, or Instagram

Q7.** In general, how worried are you about your personal privacy? (1 Not worried at all, 7 Very worried)

Q8. *** We would like to ask you some questions about research. Could you please indicate to what extent you agree or disagree with the following statements? (1 = totally disagree, 7 = totally agree)

a. I generally enjoy responding to questionnaires through the mail or Internet. *(E)*
b. I really enjoy being interviewed for a survey. *(E)*
c. Surveys are interesting in themselves. *(E)*
d. Surveys are important for society. *(V)*
e. A lot can be learned from information collected through surveys. *(V)*
f. Completing surveys is a waste of time. *(V, neg.)*
g. I receive far too many requests to participate in surveys. *(B)*
h. Opinion polls are an invasion of privacy. *(B)*
i. It is exhausting to answer so many questions in a survey. *(B)*

(Letters in parentheses indicate constructs of the survey attitude scale by De Leeuw et al. (2019): Enjoyment, Value, Burden). For the survey attitude scale, we conducted a factor analysis that showed a three-factor solution but one survey value item loaded on both the value and the burden factors. We followed De Leeuw et al. (2019) in assigning items to the factors enjoyment, value, and burden.

Q9. In addition to the questions in this survey we would like to collect data on the location where you are completing this survey. This can be done using sensors of a smartphone or a tablet. We are interested whether we can make use of your location data. We will do it once, only for this questionnaire.

[Experimental conditions repeated for all sensor data requests]:
Benefit framing: By sharing this information, you can skip some questions so that the completion time will be shorter

Autonomy: You can see what information you are sending to Statistics Netherlands and undo the measurements later if you like

Assurance of confidentiality: The data you provide will be treated confidentially. It will only be available to researchers conducting this study and your personal information will not be shared with third parties. The results of the survey will only be made available in the anonymized form. Your data is safe in all of our surveys. Personal information can never be inferred from the statistical information collected by Statistics Netherlands.

Do you give permission to share your location?

1. Yes, I give permission to share my location
2. No, I do not give permission to share my location

Q10. We are interested in which situations respondents fill out surveys. For example, whether they are surrounded by other people or alone, and in what kind of space they are. Would you make a short video of your surroundings? Maximal 5 seconds.

1. Yes, I will make a video
2. No, I will not make a video

Q11. We would like to know in what kind of house you live. To receive this information, we would like to ask you to take a photo of your house.

1. Yes, I will take a photo of my house
2. No, I will take a photo of my house

Q12. We would like to know for our research whether it is possible to infer information about purchases from a photo of a receipt. Would you take a photo of a recent receipt? If possible, take a photo of a full receipt.

1. Yes, I will take a photo of a receipt.
2. No, I will not take a photo of a receipt.

Q13. Using new technologies, it is possible to estimate your age and recognize your emotions from a photo. To try it out, we would like to ask you to make a photo of your face.

1. Yes, I will take a photo of myself.
2. No, I will not take a photo of myself.

Q14. How many online questionnaires did you complete in the past 30 days? This can be short questionnaires of one or more questions. Do not include this questionnaire in your count.

1. None
2. 1–5 surveys
3. 6–10 surveys
4. More than 10 surveys

If Q14 > 1

Q15. How many of these online questionnaires did you complete on your smartphone? Do not include this questionnaire in your count.

1. None
2. 1 survey
3. 2 surveys
4. 3 surveys
5. 4 surveys
6. 5 surveys
7. 6-10 surveys (shown if Q14 > 2)
8. More than 10 surveys (shown if Q14 > 3)

Q16.* Have you ever participated in a study, where you were asked to share your geographic location, take photos or videos using your smartphone or tablet?

1. Yes
2. No

IF Q16 = yes

Q17.* Did you then share your geographic location, take photos or videos using your smartphone or tablet?

1. Yes
2. No

Q18.*Have you ever participated in a study, where you were asked to download a research app that automatically collects data such as about your GPS-location, the apps you are using, or the websites you are visiting?

1. Yes
2. No

IF Q18 = yes

Q19.* Did you actually download the research app to your smartphone or tablet?

1. Yes
2. No

Q20. What is the highest level of education that you have completed?

1. Basisonderwijs, lager onderwijs [Basic] (less than HS)
2. LBO, VMBO, VBO, lwoo, vso, vglo, mavo, ulo, mulo [Low] (less than HS)
3. MBO, havo, atheneum, VWO, gymnasium, mms, hbs [Middle] (Vocational)
4. HBO, WO [High] (Uni & Applied Uni.)
5. Een andere opleiding [Other]
6. Geen opleiding voltooid [None] (Less than HS)

Age and gender verified at the beginning of the survey based on the registry data.

Note

For all analyses, we used Stata version 16.0.

Data Availability Statement

REPLICATION DATA AND DOCUMENTATION are not available because of the permission policy of the original data collector. All data used in this study are stored at Statistics Netherlands and require on-site secure access of authorized persons due to the sensitive nature of the sensor data such as the geolocation and administrative data. The editors have waived the journal's replication policy for this manuscript. Please contact the corresponding author for more information. The statistical code for the analysis is available here: https://github.com/peterlugtig/data_archive_POQ21_Shari_data_collected_with_smartphone_sensors.

Supplementary Material

SUPPLEMENTARY MATERIAL may be found in the online version of this article: https://doi.org/10.1093/poq/nfab025.

References

Antoun, Christopher. 2015. “Mobile Web Surveys: A First Look at Measurement, Nonresponse, and Coverage Errors.” Doctoral dissertation, University of Michigan.

Antoun, Christopher, Frederick G. Conrad, Mick P. Couper, and Brady T. West. 2018. “Simultaneous Estimation of Multiple Sources of Error in a Smartphone-Based Survey.” *Journal of Survey Statistics and Methodology* 7:93–117.

Auxier, Brooke. 2020. “8 Facts about Americans and Instagram. Pew Research Center, October 21, 2020.” Available at https://www.pewresearch.org/fact-tank/2020/10/21/8-facts-about-americans-and-instagram/.

Brandimarte, Laura, Alessandro Acquisti, and George Loewenstein. 2013. “Misplaced Confidences: Privacy and the Control Paradox.” *Social Psychological and Personality Science* 4:340–47.

Couper, Mick P., Garret Gremel, William Axinn, Heidi Guyer, James Wagner, and Brady T. West. 2018. “New Options for National Population Surveys: The Implications of Internet and Smartphone Coverage.” *Social Science Research* 73:221–35.

Couper, Mick P., and Eleanor Singer. 2013. “Informed Consent for Web Paradata Use.” *Survey Research Methods* 7:57–67.

Couper, Mick P., Eleanore Singer, Frederick G. Conrad, and Robert M. Groves. 2008. “Risk of Disclosure, Perceptions of Risk, and Concerns about Privacy and Confidentiality as Factors in Survey Participation. *“Journal of Official Statistics* 24:255–75.

———. 2010. “Experimental Studies of Disclosure Risk, Disclosure Harm, Topic Sensitivity, and Survey Participation.” *Journal of Official Statistics* 26:287–300.

De Leeuw, Edith D., Joop J. Hox, Henning Silber, Bella Struminskaya, and Corrie Vis. 2019. “Development of an International Survey Attitude Scale: Measurement Equivalence, Reliability, and Predictive Validity.” *Measurement Instruments for the Social Sciences* 1(9): 1–10.

Elevelt, Anne, Peter Lugtig, and Vera Toepoel. 2019. “Doing a Time Use Survey on Smartphones Only: What Factors Predict Nonresponse at Different Stages of the Survey Process?” *Survey Research Methods* 13:195–213.

Fritz, Heather, Tarraf Wassim, Dan J. Saleh, and Malcolm P. Cutchin. 2017. “Using a Smartphone-Based Ecological Momentary Assessment Protocol with Community Dwelling Older African Americans.” *Journal of Gerontology: Psychological Sciences and Social Sciences* 72:876–87.

Gates, Christopher S., Jing Chen, Ninghui Li, and Robert W. Proctor. 2014. “Effective Risk Communication for Android Apps. 2014.” *IEEE Transactions on Dependable and Secure Computing* 11:252–65.

Geurs, Karst T., Tom Thomas, Marcel Bijlsma, and Salima Douhou. 2015. “Automatic Trip and Mode Detection with MoveSmarter: First Results from the Dutch Mobile Mobility Panel.” *Transportation Research Procedia* 11:247–62.

Gluck, Joshua, Florian Schaub, Amy Friedman, Hana Habib, Norman Sadeh, Lorrie Faith Cranor, and Yuvraj Agarwal. 2016. “How Short Is Too Short? Implications of Length and Framing on the Effectiveness of Privacy Notices.” *In Twelfth Symposium on Usable Privacy* *and Security (SOUPS 2016)*, pp. 321–40. Available at https://www.usenix.org/conference/soups2016/technical-sessions/presentation/gluck.

Hillygus, D. Sunshine, Natalie Jackson, and McKenzie Young. 2014. “Professional Respondents in Nonprobability Online Panels.” In *Online Panel Research: A Data Quality Perspective, edited by*. M. Callegaro, P. J. Lavrakas, J. A. Krosnick, R. Baker, J. D. Bethlehem, and A. S. Göritz, pp. 219–37. New York: Wiley.

Jäckle, Annette, Jonathan Burton, Mick P. Couper, and Carli Lessof. 2019. “Participation in a Mobile App Survey to Collect Expenditure Data as Part of a Large-Scale Probability Household Panel: Coverage and Participation Rates and Biases.” *Survey Research Methods* 13:23–44.

Kapteyn, Arie, James Banks, Mark Hamer, James P. Smith, Andrew Steptoe, Arthur Van Soest, Annemarie Koster, and Saw Htay Wah. 2018. “What They Say and What They Do: Comparing Physical Activity across the USA, England, and the Netherlands.” *Journal of Epidemiological Community Health* 72:471–76.

Keusch, Florian, Sebastian Bähr, Georg-Christoph Haas, Frauke Kreuter, and Mark Trappmann. 2020. “Coverage Error in Data Collection Combining Mobile Surveys With Passive Measurement Using Apps: Data from a German National Survey.” *Sociological Methods and Research*. https://doi-org.proxy.library.uu.nl/10.1177/0049124120914924.

Keusch, Florian, Bella Struminskaya, Christopher Antoun, Mick P. Couper, and Frauke Kreuter. 2019. “Willingness to Participate in Passive Mobile Data Collection.” *Public Opinion Quarterly* 83:210–35.

Keusch, Florian, Bella Struminskaya, Kreuter Frauke, and Weichbold. Martin 2020. “Combining Active and Passive Mobile Data Collection: A Survey of Concerns.” In *Big Data Meets Survey Science: A Collection of Innovative Methods*, edited by Craig A. Hill, Paul P. Biemer, Buskirk Trent, Japec Lilli, Kirchner Antje, Kolenikov Stas, and Lars E. Lyberg 657–82. Hoboken, NJ: Wiley.

Kokolakis, Spyros. 2017. “Privacy Attitudes and Privacy Behaviour: A Review of Current Research on the Privacy Paradox Phenomenon.” *Computers and Security* 64:122–34.

Kreuter, Frauke, Georg-Christof Haas, Florian Keusch, Sebastian Bähr, and Mark. Trappman 2020. “Collecting Survey and Smartphone Sensor Data with an App: Opportunities and Challenges Around Privacy and Informed Consent.” *Social Science Computer Review* 38: 533–49.

Larson, Reed, and Mihaly Csikszentmihalyi. 1983. “The Experience Sampling Method.” In *Naturalistic Approaches to Studying Social Interaction. New Directions for Methodology of Social and Behavioral Science*, edited by H. T. Reis, 15:41–56. San Francisco: Jossey-Bass.

Lathia, Neal, Gillian M. Sandstrom, Cecilia Mascolo, and Peter J. Rentfrow. 2017. “Happier people live more active lives: Using smartphones to link happiness and physical activity.” *PloS One*, 12(1):e0160589.

Lee, Sunghee. 2006. “An Evaluation of Nonresponse and Coverage Errors in a Prerecruited Probability Web Panel.” *Social Science Computer Review* 24:460–75.

Lynn, Peter, and Peter Lugtig. 2017. “Total Survey Error for Longitudinal Surveys.” In Total Survey Error in Practice, edited by P. P. Biemer, E. de Leeuw, S. Eckman, B. Edwards, F. Kreuter, L. E. Lyberg, N. C. Tucker, and B. West, pp. 279–98. New York: Wiley.

MacKerron, George, and Susana Mourato. 2013. “Happiness Is Greater in Natural Environments.” *Global Environmental Change* 23:992–1000.

Matthijsse, Suzette M., Edith D. De Leeuw, and Joop J. Hox. 2015. “Internet Panels, Professional Respondents, and Data Quality.” *Methodology* 11(3):81–88.

McCool, Danielle, Schouten Barry, Ole Mussmann, and Peter Lugtig. 2021. “An app-assisted travel survey in official statistics. Possibilities and challenges.” *Journal of Official Statistics* 37:149–70.

Nissenbaum, Helen. 2009. *Privacy in Context*. Stanford, CA: Stanford University Press.

Norberg, Patricia A., Daniel R. Horne, and David A. Horne. 2007. "The Privacy Paradox: Personal Information Disclosure Intentions versus Behaviors." *Journal of Consumer Affairs* 41:100–126.
Peer, Eyal, and Alessandro Acquisti. 2016. "The Impact of Reversibility on the Decision to Disclose Personal Information." *Journal of Consumer Marketing* 33:428–36.
Pinter, Robert. 2015. "Willingness of Online Access Panel Members to Participate in Smartphone Application-Based Research." In *Mobile Research Methods*, edited by D. Toninelli, R. Pinter, and P. de Pedraza, 141–56. London: Ubiquity Press.
Revilla, Melanie, Mick P. Couper, and Ochoa. Carlos 2019. "Willingness of Online Panelists to Perform Additional Tasks." *Methods, data, analyses* 13:223–52.
Revilla, Melanie, Daniele Toninelli, Carlos Ochoa, and Loewe German 2016. "Do Online Access Panels Need to Adapt Surveys for Mobile Devices?" *Internet Research* 26:1209–27.
Rosli, Mohd Hafiz, Mohamad Taufik Hidayat Baharuldin, Muhammad Nazrul Hakim Abdullah, Mohd Sofian Omar Fauzee, Yunus Adam, and Azhar Yaacob. 2013. "Coupling GPS with Accelerometer to Measure Physical Activity." *Procedia—Social and Behavioral Sciences* 91:171–78.
Sakshaug, Joseph, Alexandru Cernat, and Trivellore E. Raghunathan. 2019. "Do Sequential Mixed-Mode Surveys Decrease Nonresponse Bias, Measurement Error Bias, and Total Bias? An Experimental Study." *Journal of Survey Statistics and Methodology* 7:545–71.
Sakshaug, Joseph, Jens Stegmaier, Mark Trappmann, and Frauke Kreuter. 2019. "Does Benefit Framing Improve Record Linkage Consent Rates? A Survey Experiment." *Survey Research Methods* 13:289–304.
Samat, Sonam, and Alessandro Acquisti. 2017. "Format vs. Content: The Impact of Risk and Presentation on Disclosure Decisions." Paper presented at the Thirteenth Symposium on Usable Privacy and Security (SOUPS), 377–84. Available at https://www.usenix.org/conference/soups2017/technical-sessions/presentation/samat-disclosure.
Scherpenzeel, Annette. 2017. "Mixing Online Panel Data Collection with Innovative Methods." In *Methodische Probleme von Mixed-Mode-Ansätzen in der Umfrageforschung [Methodological Problems of Mixed-Mode Approaches in Survey Research], edited by* S. Eifler and F. Faulbaum,27–49. Wiesbaden: Springer.
Shih, Fuming, Ilaria Liccardi, and Daniel Weitzner. 2015. "Privacy Tipping Points in Smartphones Privacy Preferences." *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 807–16.
Silber, Henning, Bernd Weiss, Florian Keusch, Christoph Beuthner, and Jette Schröder. 2018. "Framing Consent Questions in Mobile Surveys: Experiments on Question Wording." Paper presented at the BigSurv18 Conference, Barcelona, Spain.
Singer, Eleanor, Hans-Jürgen Hippler, and Norbert Schwartz. 1992. "Confidentiality Assurances in Surveys: Reassurance or Threat?" *International Journal of Public Opinion Research* 4:256–68.
Stopczynski, Arkadiusz, Vedran Sekara, Piotr Sapiezynski, Andrea Cuttone, Mette My Madsen, Jakob Eg Larsen, and Sune Lehmann. 2014. "Measuring Large Scale Social Networks with High Resolution." *PLOS One* 9(4):e95978.
Struminskaya, Bella, Vera Toepoel, Peter Lugtig, Barry Schouten, Marieke Haan, and Annemieke Luiten. 2020. "Understanding Willingness to Share Smartphone-Sensor Data." *Public Opinion Quarterly* 84(3):725–59.
Sugie, Naomie F. 2018. "Utilizing Smartphones to Study Disadvantaged and Hard-to-Reach Groups." *Sociological Methods and Research* 47:458–91.
Tan, Joshua, Khanh Nguyen, Michael Theodorides, Heidi Negrón-Arroyo, Christopher Thompson, Serge Egelman, and David Wagner. 2014. "The Effect Of Developer-Specified Explanations for Permission Requests on Smartphone User Behavior." *In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 91–100.

Walzenbach, Sandra, Jon Burton, Mick P. Couper, Thomas F. Crossley, and Annette Jäckle. 2019. *"Foot-in-the-Door or Door-in-the-Face? A Survey Experiment on Multiple Requests for Consent to Data Linkage."* Paper presented at the European Survey Research Association (ESRA) Conference, Zagreb, Croatia.

Wang, Rui, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T. Campbell. 2014. "StudentLife: Assessing Mental Health, Academic Performance and Behavioral Trends of College Students Using Smartphones." In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 3–14.

Wenz, Alexander, Annette Jäckle, and Mick P. Couper. 2019. "Willingness to Use Mobile Technologies for Data Collection in a Probability Household Panel." *Survey Research Methods* 13:1–22. doi: 10.18148/srm/2019.v1i1.7298

Yan, T. 2019. "The Feasibility of Using Smartphones to Record Food Acquisitions." Paper presented at the first Mobile Apps and Sensors in Surveys (MASS) Workshop, Mannheim, Germany.

Yeager, David S., Jon A. Krosnick, LinChiat Chang, Harold S. Javitz, Matthew S. Levendusky, Alberto Simpser, and Rui Wang. 2011. "Comparing the Accuracy of RDD Telephone Surveys and Internet Surveys Conducted with Probability and Non-Probability Samples." *Public Opinion Quarterly* 75:709–47.

York Cornwell, Erin, and Kathleen A. Cagney. 2017. "Aging in Activity Space: Results from Smartphone-Based GPS-Tracking of Urban Seniors." *Journals of Gerontology: Series B* 72: 864–75.