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Active and passive measurement in mobile surveys

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Abstract

In this paper we discuss the implications of using mobile devices for online survey completion. With more and more people accessing online surveys on mobile devices, online surveys need to be redesigned in order to be able to meet the characteristics of mobile device usage, such as small screens and short messaging. We discuss mobile friendly design by focussing on survey layout, the length of the survey, special features, and the decision of making the survey app or browser based. Further, we discuss the different sensors that can be used to augment or replace survey questions, and respondents' willingness to share sensor data. We end with three examples of surveys conducted by Statistics Netherlands, where sensors are used for active and passive measurement in mobile surveys.

Keywords: sensor data, mobile surveys, passive measurement, data collection, data sharing

Introduction

The increasing abundance and commodification of data has caused a shift in survey research in the past two decades, reflecting how societies understand and make use of data. Some people are suggesting the eventual demise of social surveys in favor of new and innovative methods for social or human data collection (Savage & Burrows, 2007). However, most survey methodologists seem to believe in a future that harnesses a plurality of data sources, combining survey data with organic data such as web data, administrative data, or data collected through sensors and the Internet of Things. (Couper, 2013). Given the fact that traditional surveys require more and more effort and suffer from increasing costs (de Leeuw, Hox, & Luiten, 2018), new and supplemental data collection methods are very welcome to potentially improve data collection methods. In an era with an abundance of organic data, survey research has begun to explore the opportunities and challenges of augmenting survey data with organic data sources.

One area of new developments in survey research is the use of sensors in mobile devices to capture new types of data. Mobile devises have become an important part of people's lives, and it makes sense to use them for research purposes. Mobile devices have functions such as sensors that can be used to collect data in addition to asking questions. Wenz, Jackle and Couper (2019) divide these sensors into passive and active sensors. Passive sensors include device usage tracking apps, an accelerometer, GPS and the Bluetooth linkage to external devices; active sensors include camera use, text messages and the use of apps to answer questions. Mobile devices give researchers the opportunity to ask new types of questions, because most individuals are acquainted with the smartphone and its functions. Also, since the use of sensors in mobile devices have become normal and easy for many people (e.g. the use of camera, GPS), it might prove beneficial to use sensors for respondents who struggle to answer survey questions such as people with low cognitive ability (Sauer, Auspurg, Hinz, & Liebig, 2011). While many more organic data sources are available, one key advantage of mobile devices is that they can potentially be used by respondents to answer survey questions as well as provide other big data, such as sensor data at the level of the individual. Link et al. (2014) reported in their study on the possible implications of smartphone sensors as research tools that in addition to using sensors to augment or replace survey questions, the use of sensors can add context to survey data.

In this paper we discuss the implications of using mobile devices for online survey completion. We first focus on the design of mobile surveys. Online surveys have traditionally been designed for desktop PC completion. With more and more people accessing online surveys on mobile devices, online surveys need to be redesigned in order to be able to meet the characteristics of mobile device usage, such as small screens and short messaging. In addition, surveys designed for mobile devices can make use of sensors in order to augment or replace survey questions. We discuss mobile friendly design by focussing on survey layout, the length of the survey, special features, and the decision of making the survey app or browser based. Further, we discuss the different sensors that can be used to augment or replace survey questions, and respondents' willingness to share sensor data. We end with three examples of surveys conducted by Statistics Netherlands, where sensors are used for active and passive measurement in mobile surveys.

Mobile friendly design

Online surveys are mixed-device surveys in the sense that they are being completed on a range of different devices, such as desktop PCs, tablets, and smartphones. There are several ways to structure the survey with the goal to create an optimal experience for any device. In a device-agnostic approach, the survey will be the same on all devices. In a device-adaptive approach, one can distribute longer surveys on devices with large screens, and shorter surveys or the use of sensors on smaller devices. There are several ways to design a device-agnostic survey. Traditionally, surveys have been designed with a traditional desktop PC in mind. However, more and more surveys use a mobile-first survey design, where the survey is optimized for mobile phones. The rationale behind this is that if it looks good on a small mobile phone screen, it looks good on all devices. Most software for online surveys uses a responsive design, where the questionnaire layout is adapted to the device being used. User agent strings (UAS) can be used to detect the operating system and device. This can be enhanced with JavaScript to capture additional information such as screen size and browser. Some software uses real-time coding, while others use post-survey analyses (e.g. Rossman, Gummer & Kaczmirek, 2020).

Layout

With a mobile-first design perspective in mind, Antoun et al. (2017) have summarized the literature on mobile and mixed-device research and suggest the following guidelines on how to optimize for mobile:

- Use large fonts
- Content should fit to the width of the screen (no horizontal scrolling)
- Response options should be displayed as wide buttons or tiles
- Pictograms can be used for visual relief
- Avoid grid or matrix layout
- Use an auto-advance option

- Eliminate unnecessary elements such as images, progress bars, etcetera, to reduce visual distractions and reduce page-load delays.

Grid questions – were several items are place in the same grid or matrix- are difficult to design for small screen sizes. There are several ways to design grid questions. Some survey software uses a one-item-per-screen format for mobile surveys and a grid or matrix for desktop computer surveys. Some software changes the orientation of the scale to vertically aligned answer categories for mobile devices while retaining horizontally aligned answer categories for grid questions on desktop computers. This is problematic since research has shown response effects due to scale orientation as well as higher inter-item correlations when items are presented on a single screen (e.g. see Toepoel, Das & van Soest, 2009). It is therefore important to make sure that the layout of the survey is similar across devices when respondents use different devices to complete a survey. Alternatives to a grid design are a carousel format (where items fly by with an auto-advance function) and an accordion format (unfolding design, where questions are collapsible and a new question automatically unfolds when a question has been answered). By using an auto-advance function, the efficiency gain for grid questions can be mimicked.

Although dropdown menus are often used in mobile or mixed-device surveys since they save space on a screen, their use is not recommended. They look different on iOS and Android devices. In addition, long response options are sometimes truncated, and some browsers turn dropdown menus into scrolling wheels, whereby the first response option follows the last one on the wheel, affecting context effects.

Survey length

Kelly et al. (2013) show that a 20-minute survey is acceptable for 66% of PC users, while only 27% of smartphone users is willing to spend 20 minutes on a survey. In addition, only 73% of smartphone users is willing to spend 5 minutes on a survey, compared to 98% of computer users. Roberts and Bakker (2018) demonstrate that break off rate is on average 32% on mobile compared to 12% on tablet and 10% on PC for Statistics Netherlands. Reducing survey length seems important in an era where more and more surveys are being completed on mobile devices. The easiest way to accomplish this is to cut questions, but many researchers find it difficult to cut questions. An alternative is a split survey design, where a survey is chunked into smaller parts. Each portion can be fielded separately, and after the data collection, parts can be combined into one holistic data set again (stitching). This can be done across or within respondents. In within-respondent modularization, each respondent is offered all parts, but in several different chunks. Toepoel and Lugtig (2018) have demonstrated that this can increase response rates by about 10 percentage points, and although not all respondents may respond to all individual parts (wave nonresponse), the proportion of missing information can still be lower in the split survey design. Across-respondent modularization is more complex. One module typically contains all important (background) questions and goes to all respondents. Each respondent receives only a particular subset of the remaining modules. Whether modularization is a general solution for survey length is still very much a question, as there are also unsuccessful examples (Lips & Pollien, 2019; Andreadis & Karsounidou, 2020).

As mentioned in the previous section, another way to cut down on participant time to complete a survey is by using an auto-advance option. With this option, the respondent is immediately navigated to the next question without having to press a “next” button.

App Versus Browser based

Active and passive data collection in mobile surveys is possible via research apps or via the browser (JavaScript or HTML5). A research app is software that can collect data from the phone, which can then be used for data entry. Downloading an app can be an extra obstacle for participation, and may cause respondents to drop out. Apps have more possibilities than browsers, however, such as the use of camera or video's. An app runs in the background and can collect sensor data over a longer period than can a browser. In addition, reminders can easily be sent through an app as well as pop-up questions that need to be answered on the spot. Since programming an app is a lot of effort, apps are particularly suitable for long periods of data collection.

There is a large variety of devices, with (slightly) different operating systems, such as iOS and Android systems, and apps need to be developed for each platform. Different smartphone models include different sensors and displays, with different hardware specifications and software drivers. These specifications can largely influence the quality of the sensor data collected. For example, Read (2019) shows that device variation related to photo quality is very large, particularly due to the operating system and memory.

Technical limitations may constrain how many hours per day an app can gather data. Especially battery-intensive passive data collection like GPS tracking may drain the battery of a respondent's device. Respondents will need to charge their device regularly, which some might forget or perceive as burdensome, inducing nonresponse.

JavaScript may be easier to program than an app, but JavaScript cannot collect data for a long period of time (only for the time that the web-page is open). JavaScript is especially useful for single-time measurement—for example, to collect respondents' current location or when respondents are asked to take a picture. An example of a JavaScript tool is SurveyMotion (Höhne & Schlosser, 2019), that collects respondents acceleration data during an online survey.

Special features

Mobile phones bring new opportunities that are not possible or more difficult on computer devices. For example, push notifications can be sent in the moment. Location-based surveys or highly targeted mobile surveys can be used when people are on a specific premise or leaving a specific premise, such as a festival or business meeting. The notification can even be the question itself. Surveys might also become more conversational or gamified. For example, communicating through apps such as WhatsApp and Snapchat closely resembles natural turn-by-turn conversations between humans. Service chatbots try to mimic that communication style as well, turning a survey into a WhatsApp type of survey. One important feature of mobile surveys is the sensors that come with the mobile device.

Sensors in mobile phones

Smartphones incorporate a large number of sensors which can be logged passively, providing a large and detailed set of measurements about respondents and their environment.

Types of sensors

Based on Toepoel and Elevelt (2020) we discuss the most commonly used sensors for research purposes in social sciences.

Accelerometer: The rate of change of velocity of an object over time. It is measured in meters per second squared (m/s^2). Acceleration can occur on three different axes: the x-axis (i.e., left and right), the y-axis (i.e., up and down), and the z-axis (i.e., back and forth). In addition to the movement level on these three axes, the movement duration and stationary periods can be measured. Accelerometers are typically used to measure respondents' activity or motion level.

GPS Receiver: Respondents' geolocations can be determined both by the GPS receiver incorporated in smartphones or by cellular towers and Wi-Fi networks. All methods result in a GPS location, which is measured in a latitude and longitude. GPS measures can record a location accurately with a precision of about 5 meters (GPS/Wi-Fi), although precision is much lower when cellular networks are used. GPS location can be used to investigate mobility patterns such as respondents' duration of time spent at a specific location, the frequency of visiting locations, distances travelled, and routines in mobility patterns. GPS coverage varies and GPS accuracy depends on satellite geometry, signal blockage, atmospheric conditions, and receiver design features. One has to be cautious, since geographical location may be inaccurate as GPS trackers lose signal indoors or in areas with tall buildings causing positioning errors.

Bluetooth Scanners: Bluetooth is used for short-range communication between devices, including smartphones, hands-free headsets, tablets, and other wearables. A combination of Bluetooth and Wi-Fi can be used to determine whether devices (a.k.a. other respondents) are near. For example, Stopczynski et al. (2014) used Bluetooth sensors to determine whether schoolchildren are close to class mates (<10 meters) to determine their level of interaction.

Microphone: Microphones are high-fidelity sensors that can capture sound waves. FamilyLog (Bi et al., 2017) used the microphone to detect mealtime sounds, thereby determining the timing and frequency of family meals. They extracted clattering sounds, conversations and other sound sources from the recordings to detect family meal behaviour such as specific voices and conversations, speaking rates and turn-taking in conversation. As a more active task in self-administered surveys, researchers can ask respondents to make voice recordings in which respondents answer a question by dictating an answer instead of typing it.

Proximity Sensor: The proximity sensor combines an infrared LED and light detector. Proximity sensors can be used to detect whether a respondent's face is close to the phone.

Camera: The camera can be used for more active tasks in research, such as making photos or movies. For example, Kelly et al. (2015) asked respondents to take one picture every 10 minutes, to reconstruct a record of activities in time use research. Wenz et al. (2019) asked respondents to use the camera to scan receipts, in a budget study. In addition, a front camera can be used to track the respondent's eye movements across the phone's display, for example to investigate screen usage.

Other Logs: Other smartphone data that may be logged passively, although not through sensor data, are calls, app usage, and texts. Incoming and outgoing texts and calls may provide insights into the respondents' social interactions. App usage, or visited websites, can be tracked by having respondents install an app on their smartphone. The logs from this app may provide insight into mobile phone or web behaviour.

Respondents' willingness to provide sensor data

Sensor data are often perceived as intrusive and privacy-sensitive. Participants may not be willing to share sensor data, or willing respondents are specific socio-demographic subgroups, affecting response bias. Empirical studies on willingness to sharing sensor data have shown that hypothetical willingness tends to be higher than observed willingness (Struminskaya et al., 2018). In addition, willingness varies by task; for example, about 61% of the respondents of the Understanding Society Innovation Panel in the United Kingdom hypothetically consented to the collection of acceleration data, while 36.7% consented to sharing a GPS capture and 25.5% to installing a smartphone tracking app (Wenz et al., 2017). In the Netquest opt-in panel, 37.7% of the panel members hypothetically consented to the collection of acceleration data and 17.8% to installing a smartphone tracking app (Revilla et al., 2018). When looking at demographic or behavioural correlates of sharing sensor data, respondents with advanced smartphone skills and who use their smartphone for numerous activities are more likely to share sensor data (Elevelt, Lugtig & Toepoel, 2019; Keusch et al., 2019; Wenz et al., 2019). Willingness is higher for tasks where respondents have control over the reporting of the results (Revilla et al., 2018). Giving participants an option to review, edit, and delete specific data before transmitting may increase respondents' feelings of control and therefore their willingness to share sensor data (Keusch et al., 2019).

Confidentiality and privacy

Two important factors that influence willingness to share sensor data are privacy and confidentiality. High concerns about data privacy and/or security are associated with lower willingness to share sensor data (Jäckle et al. 2019; Sala et al., 2014; Wenz et al. 2019). The decision-making process of respondents to disclose personal information such as sensor data lies in the evaluation of perceived privacy risk and perceived benefits of disclosing that information (Majumdar & Bose, 2016). The decision to share sensor data is dependent on the type of data being shared, with whom and for what purpose. Also, expectations about intended use – depending on who is asking – can differ across tasks.

Struminskaya et al. (in press) conducted an experiment on factors that affect willingness to share information. In one condition they stated that the information that respondents provided would be treated confidentially and anonymously, and personal data could not be inferred from this information. The control condition did not include this text. Emphasizing privacy protection did not influence willingness to share data. Their results also showed that respondents' stated willingness is significantly higher for a university-sponsored study and lower for a market research sponsor compared to a statistical agency sponsor. The influence of the sponsor is more pronounced for sharing geolocation than for other sensors. In addition, respondents who indicated that they have a higher trust that the questionnaire guaranteed anonymity were more likely to be willing to share data. While the most named reason for non-willingness to share sensor data was privacy and anonymity concerns, the absence of an experimental effect of emphasizing privacy protection in question wording suggests that respondents' privacy concerns might be multifaceted.

It is difficult to grasp exactly what the intrinsic value of privacy is. Respondents do not only value privacy because they value the integrity and the protection of their own data, but also because they value having control over their data. Privacy, therefore, can be considered as something that not only ensures the protection of the information that is being provided by respondents, but also a concept that ensures that this information is collected, analysed and disseminated properly (Nissenbaum, 2010). Legal frameworks protect the privacy of respondents, such as the European Statistics Code of Practice and the European General Data Protection Regulation (GDPR). By stressing the importance of confidentiality and integrity in the data collection process, the Code of Practice focuses on the security of the respondent data from potential third-party intervention. The GDPR is more focused on how to deal with the collection of personal data. GDPR, therefore, focuses on various implications such as how to anonymize data in order to increase the protection of the respondent against the possible use of third parties, and how to be sure that data are going to be collected only with the consent of the respondent and cannot lead back to the respondent. To make the most of sensor data, confidentiality and privacy are central in the data collection process and harvesting new opportunities.

Active and passive measurement with sensors

New data collection opportunities such as the use of sensors (e.g., geolocation, physical movements, online behaviour, app usage, social media usage, text messages) and experience sampling methods (ESM), as well as wearables connecting with Bluetooth can increase data collection opportunities. These opportunities can replace or augment survey questions. Although surveys face difficulties and organic data is abundantly available, there have been few efforts to integrate surveys with organic data beyond ad-hoc methods.

A major advantage of combining sensor data with survey questions, is that it can simplify the response task for individuals. For example, in many surveys it is important that respondents report exactly what they do at what time. Estimates of time use (Fisher & Gershuny, 2013), consumption (Lagiou, & Trichopoulou, 2001) or travel behaviour (Axhausen et al, 2002) have long relied on diary studies that respondents have to complete for several days. Apart from issues of nonresponse, diary study data are often incomplete. Health surveys suffer from inaccurate statistics of how physically active people are. Respondents find it difficult to remember how much time they are physically active, let alone how intense these periods of activity are. A more general push factor of surveys is that they are hard to conduct due to increasing surveys costs and high nonresponse rates. A major pull factor of using sensors to collect data in addition to survey questions is the availability of sensor data. Furthermore, the costs of using sensors in mobile phones are low. Still, there are costs in terms of time and effort to access, process and store the data. A distinction can be made between active and passive tasks in smartphone research. Active tasks involve taking pictures, whereas passive tasks include sharing GPS locations or having an app that tracks mobile behaviour.

In the following section, we will provide three case studies of experimental surveys conducted by Statistics Netherlands where survey data are being combined with sensors from mobile phones. In each of the studies, the specific nature of the study topic and sensors used has led to different design decisions in how sensor data and surveys were integrated into the data collection instrument.

Examples of the use of active and passive measurement in surveys

Travel and mobility

Travel surveys are routinely conducted by official statistics agencies at the country and regional level to inform public policy makers on travel patterns, including travel modes, trip lengths and durations. Travel surveys typically rely on respondents either keeping a diary with them for a certain number of days and completing this whenever a trip is made, or to recall all trips for the period of the diary. In both situations, the underreporting of short trips in particular is a problem (Richardson, Ampt, and Meyburg 1995).

Figure 1 illustrates the approach taken by Statistics Netherlands, which has been taken by several other researchers as well. Respondents are invited by letter to install an app, allow location measures to be taken, and watch an instruction video of the app (upper panel). After this, a diary of visits and trips is automatically populated in the app, and the respondent is asked to label the visits (name, reason of visit) and trips (mode of transportation), and is asked some questions about the day generally (middle panel). The lower panel shows how the collected location information is fed back to respondents, and how the reason for a visit can be manually amended. For more information on how the app worked, please see McCool et al (2020) or Smeets et al (2019).

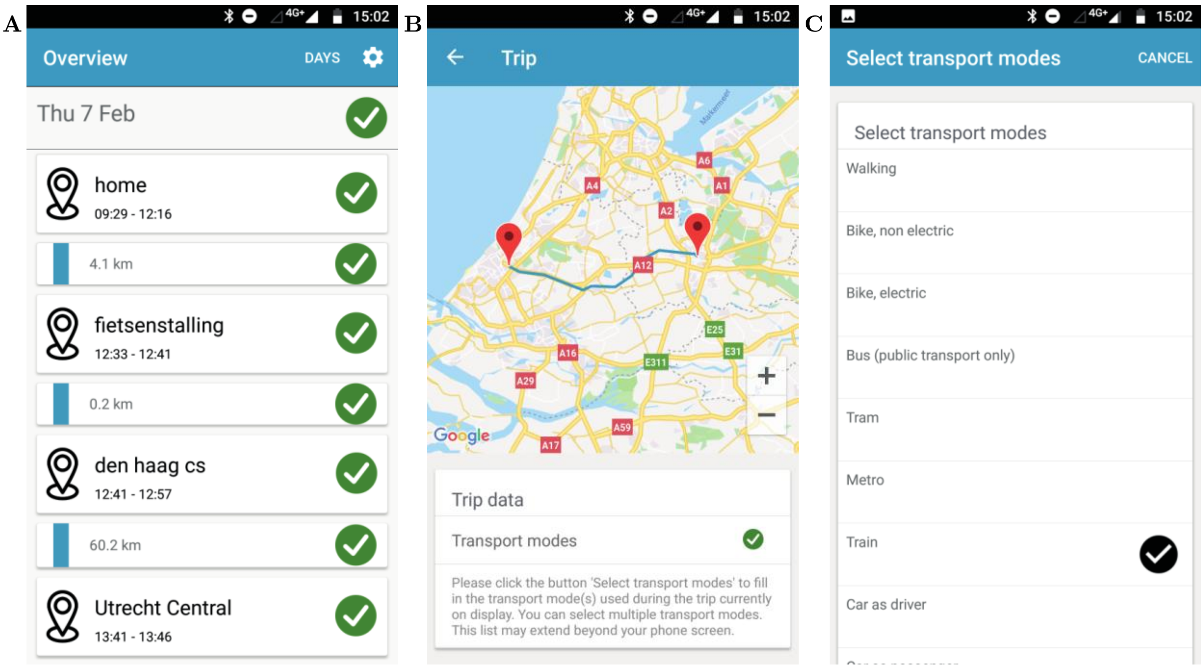

Figure 1: *Automatic trip detection with the CBS travel app and labelling by respondents. The left panel shows the daily diary that was automatically generated for respondents. Respondents could label the stops (locations) with names (left panel) When a respondent would click on a trip, he was presented with the trip trajectory (middle panel) and asked to indicate the transport modes used (right panel).*

Generally, we found the app was much better in detecting short trips than a comparative diary study that was conducted just 2 months prior to the app study, among partially the same respondents. The results in Figure 2 show all the data plotted geographically (left panel) and the amount of kilometres travelled per respondent per day in the travel app study, and comparative diary study (ODiN, short for Onderweg in Nederland). For more details, see McCool (2020) or Smeets (2019).

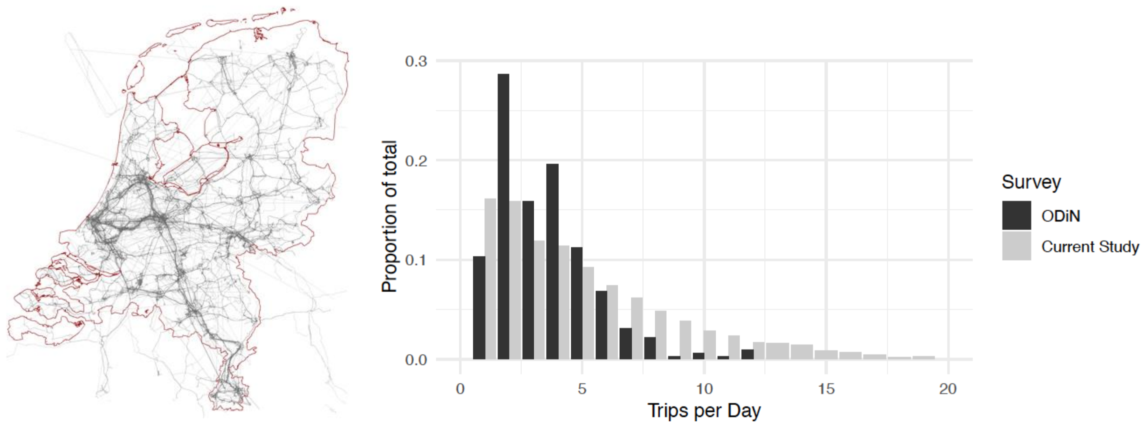

Figure 2: *All tracks collected with CBS Travel-app study among respondents in a 1-week period in November 2018 (left panel), and the number of trips per day in the diary study (ODiN, short for Onderweg in Nederland) and the travel app (current study) (right panel)*

The travel app generated precise location data over time. The app was much better in documenting very short trips made on foot or by bike. We also found however that some of the trips in the app were erroneous. The long right-tail in the number of trips sometimes is a sign of problems with signal loss or missing data more generally.

Household budget

Household consumption is typically measured through diary studies in which part or all purchases in a specified time period need to be reported. Such household budget surveys are known to be time-demanding and burdensome to respondents. To reduce respondent burden and to increase participation rates and quality of reported consumption data, there is a strong incentive to introduce smart features. See for example Jäckle (2019a; 2019b).

Smart features can be introduced in at least four ways: The first way is to assist respondents in searching for products through detailed search lists. Product search may be further enhanced by memorizing what products households have bought in earlier reporting days. The second way is by introducing data entry through scans of receipts. Receipts then go through text recognition and product classification steps either in-app or in-house. The third way is geo-fencing, where respondents consent to measure location and locations within certain geographical areas lead to in-app notifications or messages. The last way is data donation where respondents themselves request access to data about them that is stored by external parties. Examples of such parties are banks or supermarkets through loyalty cards or scanner transaction data. The different options have very different privacy and ethics consequences, and may not all be equally feasible in terms of respondent willingness and data protection legislation.

Figure 3 shows screenshots of the HBS app developed by Statistics Netherlands, partly funded by Eurostat, in which there are three options to include expenditures: through manual entry, through scans of receipts and through bank API's.

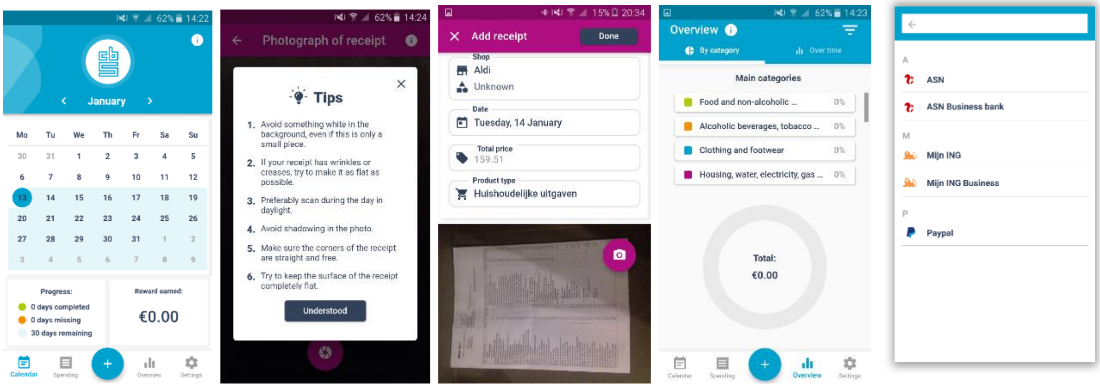

Figure 3: *Screenshots of the Household Budget Survey app developed by Statistics Netherlands. From left to right: Starting screen with calendar, tips to improve quality in scans, example of a scanned receipt, summary statistics, and selection screen of banks that can be consulted through an API after explicit consent*

First test results of the HBS app are promising and respondents are positive about the smart survey. In 2020 and 2021 large-scale field tests will be conducted.

Time Budget Study

A third area where official statistics might be improved is in the production of estimates of time use. As with travel and budget statistics, time surveys have relied on diary studies. Recall problems lead to respondents not reporting activities that were of short duration, or activities that were conducted as a secondary activity (e.g. reading a book while traveling to work). Another problem is the fact that respondents often complete a diary only once a day, implying that the start time, end time and duration of every activity may be off. There are a number of ways that mobile phone apps and sensor data can be used to improve these shortcomings.

First, respondents will carry their mobile phone with them most of the time, allowing them to complete the app more frequently. There is the possibility of sending respondents messages (a text message or push-notification) in case reports from respondents are believed to be missing, or if unclarities exist during the fieldwork period. Data can truly be collected in the moment (see Elevelt et al. 2019a for an example).

A second way to improve time use surveys is by the use of sensors. Chatzitheocari et al. (2017) link time use data to accelerometer data collected using smartwatches. Elevelt et al (2019b) link such data to GPS location data collected within the app. With both these kinds of data, it is possible to potentially understand in much better detail what kind of activity was conducted (accelerometers) and where this was done (GPS). These data may also assist the respondents to the survey in completing their diaries as they can reconstruct a basic day schedule based on detected stops and detected types of activity. Importantly, both types of data may help us to understand and improve our estimates of the start-, end time and duration of activities.

Discussion

Mobile phones may make it harder to conduct surveys due to constraints in how the survey should be displayed and how long it can be. However, mobile phones also offer exciting opportunities for data collection in official statistics and the social and health sciences. This paper has shown some examples of the possibilities that arise when sensor data are combined with surveys on mobile phones, either through browsers or mobile apps. We want to conclude this article with outlining several areas for future research.

1. How to make it work in the real world. Most examples published so far rely on volunteers and use small samples. There are a few examples that have shown that it is possible to achieve reasonably good response rates (>30%) when mobile phone app studies are conducted in the general population, but we need to test and experiment more.
2. Ongoing technical challenges. Mobile phone software, and the way the two main Operating Systems interact with apps changes continuously. App data collection is dependent on what Apple and Google allow for apps. Over time, the Operating Systems are becoming more restrictive in what they allow apps to do and what not to do. Because more and more apps are being developed and installed on mobile phones, there is an increasing need for security measures and battery-life saving settings. Also, users themselves may choose to restrict what data apps can (continuously) collect. It is unclear at this point in what direction the Operating Systems are heading and whether apps truly are the future of data collection.
3. Develop a framework for combining survey and sensor data. In the examples we outlined in this paper, we relied on methods from survey research to draw a random sample, and then for a subset of the sample, we collect additional sensor data. Such a ‘designed big data’ approach allows us to use traditional methods for inference to the general population. In many other examples where, mobile apps are being used, researchers rely on volunteers or ‘citizen science’ to collect data. Such samples will often suffer from selection bias. However, it may be possible to improve inference from such samples when data can be fused or combined with survey data collected from other (or partly overlapping) individuals. The challenge of improving inference for datasets that were not generated by probability sampling is not unique to mobile phone data. It is a general challenge in survey sampling, statistics and science in general.

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