Ministry of Infrastructure and the Environment

Exploratory study of alternative trip data collection methods

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Contents

Summary

The use of smartphone technology is the most promising alternative trip data collection method for the Netherlands National Travel Survey (OViN). Compared to the OViN's current collection method, the use of smartphones seemingly enhances the quality of trip data; however, at present, using smartphone technology in large-scale research projects, such as the OViN, remains a bridge too far. Practical considerations play a key role here. The application is for instance restricted to respondents who have their own smartphones. Moreover, respondents themselves will likely continue to play an active role by subsequently supplementing and possibly correcting information. Should smartphone technology continue to develop, and comprehensive testing prove successful, opportunities will emerge for using this method in the large-scale collection of trip data.

Deriving insights into people's travel behaviour is essential for mobility analysis, as such insights allow researchers to monitor trends, explain changes in travel behaviour, and sustain traffic and transport models. The Netherlands National Travel Survey (OViN) provides for such information. This type of national travel survey primarily collects trip information via questionnaires and travel diaries that are completed online, on paper, via telephone or during personal interviews. Alternative methods for collecting trip data have been developed in recent decades.

This report aims to gain insights into whether the OViN can switch to a collection method other than one currently used, and, if so, to what extent. To this end, alternative collection methods are examined and their suitability assessed. Although this report's primarily purpose is to explore innovations within the OViN, comparable national travel surveys could also benefit from its findings. The primary reasons for considering alternative methods include the increasing unwillingness of people to participate in surveys, and the high burden that traditional approaches place on respondents. The general assumption is that alternative types of data collection can potentially enhance the quality of the resulting trip data and/or lower the costs of data collection.

The following collection methods were examined:
- Smartcards (such as the public transport chipcards);
- Data- and call-traffic (the use of smartphone signals; the 'respondent' plays no role in this);
- Social media (such as Twitter);
- GPS-loggers (small measurement devices that the respondents carry);
- Smartphone technology (use of an app with supporting technology).

A collection method's suitability is primarily determined by the extent to which the method covers the OViN's information need and the corresponding quality and cost aspects, which are impacted by response rates and response burden.

Using smart cards, data- and call-traffic, and social media only covers a certain part of the information need; for example, public transport chipcards only provide insights into the trips made via public transportation. Moreover, those three methods provide little or no information about the research participants themselves, and no possibilities exist for acquiring additional information about the trips. The people to whom the trip data pertains are not personally involved. However, such information is crucial to the OViN's stated aims, which, for example, includes explaining the observed trends. Given the lack of personal involvement on the part of 'respondents', one advantage of this method is that there is no response burden.

In principle, using GPS-loggers and smartphones can provide for a national travel survey's information need. Various aspects impact the quality and associated costs of using these methods, and this pertains to both theoretical aspects and data quality, as well as to the more practical matters that play roles in large-scale applications. One such practical issue is that GPS-loggers must be distributed to the

respondents, which involves high costs. In one large-scale case study the distribution of GPS-loggers had an obstructive effect on conducting the research: it proved impossible to provide all potential respondents with GPS-loggers and thus allow them to participate in the research. Moreover, some GPS-loggers were lost or returned slower than anticipated.

The use of GPS-loggers or smartphones both positively and negatively impacts the quality of trip data. The first positive aspect playing a role here is the likelihood that more trips will be recorded, and that these trip records will be more accurate in terms of time and location. The method can also provide additional information, regarding route choice, for example. However, how beneficial this would be depends on the national travel survey's information need. One possible disadvantage of using GPS-loggers or smartphones is that certain modalities (such as busses, trams and metros) and trip purposes are often incorrectly recorded, although this can be overcome by giving respondents the opportunity to correct their imputed trip data. Nevertheless, this is no guarantee that the resulting trip data will be completely correct, but that also applies to the current OViN. GPS-loggers have a few specific disadvantages that indirectly impact data quality, including the fact that respondents are unfamiliar with using GPS-loggers and are burdened by having to carry the GPS-loggers with them during trips. Ultimately, using smartphones seemingly enhances the quality of the trip data, while, for GPS-loggers, this remains uncertain, given the various aspects that positively and negatively impact the data quality.

It is difficult to determine if using GPS-loggers or smartphones will reduce costs, as compared to the OViN's current data collection method, because various other initiatives are presently running that also aim to reduce the OViN's costs. What is clear however is that the GPS-loggers' relatively high costs primarily pertain to the need to distribute the GPS-loggers, which can be delivered to a respondent's home, possibly in combination with a personal interview. Both methods are relatively expensive.

Of all the data collection methods considered, smartphone technology is the most promising alternative to the more traditional collection methods. The information need can be covered, which is not – or not entirely – the case when using smartcards, data- and call-traffic, and social media. Compared to GPS-loggers, smartphone technology delivers higher quality at lower costs. However, smartphone use is limited to the respondents who have smartphones. Moreover, the respondents, by subsequently supplementing and possibly correcting information, are likely to continue playing active roles. An additional focal point in potentially using smartphone technology is the wide range of available smartphone models, and the corresponding software versions that allow the technology to function properly. Various parties are engaged in further developing and comprehensively testing smartphone technology, including transitioning from test environments to large-scale applications, with all the practical problems that entails. Should this development and large-scale testing prove successful, opportunities will emerge for using this method to collect trip data.

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1 Introduction

1.1 Purpose and objective

The government needs information that serves to monitor and explain how mobility is developing among the Dutch population, and which can be used for developing traffic and transport models. The Netherlands National Travel Survey (OViN) is the most important source of data for this purpose (Moons & Hoogendoorn, 2015). The OViN is a large-scale annual travel survey in which large numbers of respondents (37,350 in 2015) record all the trips they take on one particular day.

Mobility studies, like the OViN, are usually conducted by means of questionnaires and travel journals that can completed online, by telephone or via personal interviews. Printed questionnaires can also be sent to the respondents. However, in recent decades, other methods have been developed to collect trip data. The primary reasons for considering alternative methods include the increasing unwillingness of people to participate in surveys, the high burden that traditional approaches place on respondents, and the high costs associated with labour-intensive approaches. The general assumption is that alternative types of data collection can potentially enhance the quality of the resulting trip data and/or lower the associated costs of data collection.

Rijkswaterstaat, the KiM Netherlands Institute for Transport Policy Analysis, and Statistics Netherlands (CBS) jointly launched the OViN innovation program as a means of improving the OViN's quality and/or lowering its costs. This innovation program consists of numerous projects, including this exploratory study of alternative trip data collection methods, which aims to gain insights into whether the OViN can switch to a different collection method than one currently used, and, if so, to what extent. Although this study's primary purpose is to explore innovations within the OViN, its findings are also important for comparable national travel surveys.

1.2 Research approach

The suitability of alternative collection methods is considered from both the theoretical and practical perspectives. From the theoretical perspective, national and international developments in mobility research data collection are outlined, thereby providing an overview of the currently available collection methods and the extent to which they have key characteristics specific to the OViN. This involved determining which alternative collections methods are available, which of the method's characteristics are important for the OViN, and the extent to which the alternative collection methods are suitable for use in the OViN.

The researched collection methods include:
- Smartcards (such as the public transport chipcard);
- Data- and call-traffic (the use of smartphone signals; the 'respondent' plays no role in this);
- Social media (such as Twitter);
- GPS-loggers (small measurement devices that the respondents carry);
- Smartphone technology (use of an app with supporting technology).

This was followed by consideration from the practical perspective: what lessons can be learned from using alternative collection methods? Only GPS-loggers and smartphone applications were examined, because, from the theoretical perspective, these methods seemed most suitable. The respondents' response rates and response burden, as well as other practical matters associated with the method's large-scale application, were examined.

This exploratory study strives to provide the most up-to-date overview of collection methods that could possibly be used in national travel surveys. However, this is rapidly developing field; consequently, the amount of available insights is also rapidly increasing, and hence this report cannot be exhaustive in the sense that it includes all available insights and studies.

1.3 Structure

Chapter 2 describes the OViN's current design, what information need it largely provides for, and which characteristics were identified for testing the collection methods' suitability. Chapter 3 provides an overview of the (active and passive) collection methods. Technological advancements have created great diversity. The accompanying schematic diagrams help position the various collection methods relative to one another, while indicating their similarities and differences. Chapter 4 addresses the passive collection methods, namely, smartcards, data- and call-traffic, and social media. Various applications are discussed, and tests done to determine the extent to which they have the characteristics identified in Chapter 2. Chapter 5 is similar to Chapter 4 but focuses on the active collection methods – GPS-loggers and smartphone technology. Chapter 6 compares the suitability of data collection methods from a theoretical perspective. Chapter 7 examines the practical experiences of using GPS-loggers and smartphones, and the lessons that can be learned. And finally, in Chapter 8, conclusions are drawn as to whether the OViN can switch to a different collection method than its current one, and, if so, to what extent.

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2
The current OViN

This chapter describes the current design of the Netherlands National Travel Survey (OViN) and the information need it generally provides for. Moreover, the respondents' response rates and response burden in the OViN are also examined as a reason for searching for alternative collection methods.

2.1 The research design of the OViN

The Mobility Behaviour Research Study (OVG - *Onderzoek Verplaatsingsgedrag*), the Netherlands Mobility Research Study (MON - *Mobiliteitsonderzoek Nederland*) and the OViN have been measuring the mobility behaviour of the Dutch population since 1978. Statistic Netherlands (CBS - *Centraal Bureau voor de Statistiek*) is responsible for implementing the OViN, in which people from all regions of the Netherlands are randomly selected from municipality registers throughout the year, regardless of age. Residents of institutions, facilities and nursing homes are excluded, however. The OViN takes an annual cross-sectional approach. The people selected for the sample – the research participants – receive letters at home requesting that they record all their trips (chronologically) in a trip logbook on a specific date. For each trip they are asked to record various details, including destination, purpose of trip, transport mode, distance, and arrival and departure times. In addition to trip details, the OViN also asks questions about various personal and household characteristics (including car ownership).

The OViN's observational method is mixed-mode, meaning that multiple data collection methods are used and the findings subsequently combined. The research participants are initially asked to complete trip logbooks via a website (CAWI - Computer Assisted Web Interviewing). If a person will not or cannot respond via internet, they are subsequently contacted by telephone (CATI - Computer Assisted Telephone Interviewing). If the CBS does not have a telephone number, the research participant is personally interviewed at home (CAPI - Computer Assisted Personal Interviewing). One advantage of CAWI is that it is relatively inexpensive compared to CATI and CAPI, as the data is directly entered into the database, without requiring a surveyor's involvement. CAPI, conversely, is extremely labour-intensive and hence expensive.

The OViN, and an appendix to this report, distinguishes research participants and respondents. A research participant is a person who was approached for the research study. A respondent is a research participant who actually participated in the research.

2.2 The information need the OViN provides for

The OViN's aim is provide satisfactory information about the population of the Netherlands' daily mobility. The primary users of this information are the policy directorates of the Ministry of Infrastructure and Environment, the KiM Netherlands Institute for Transport Policy Analysis (KiM), Statistics Netherlands (CBS), and Rijkswaterstaat. Additionally, regional governments, consultancy agencies and universities use this data.

The data is primarily used for three purposes (Moons & Hoogendoorn, 2015):
- Monitoring;
- Explaining;
- Modelling.

That the data are used for such a range of purposes has consequences for the requirements set for the OViN in terms of the information to be collected.

Multiple institutions **monitor** the trend developments in mobility behaviour. The CBS publishes these key figures in Statline; they can pertain to both national and regional trends, and are categorised according to modality, age and gender, for example. The availability of a stable series is crucial for analysis, and with only small margins of uncertainty, as the smaller the margin of uncertainty the more useful the derived conclusions are for policymakers.

Trend developments are subsequently reported to the Dutch House of Representatives in policy documents such as KiM's Mobility Report, which is published annually. As an example: OViN data revealed that Dutch people undertake nearly 40 percent of all trips, and more than half of all their kilometres travelled, as car drivers, and cars are the most important travel mode. Mobility as a car driver increased by 7 percent since 2005, with one-third of this growth occurring during the first two years – from 2005 to 2007. After 2007, the numbers of kilometres travelled as a car driver decreased by half a percent each year (KiM, 2016).

Explaining trend developments is divided into two categories:
1. Explaining trends that are routinely monitored, as in KiM's Mobility Report, for example;
2. Explaining trends that are more closely related to social developments in which policy-related questions arise, or answering complex questions that derive from the routine monitoring. This category is approached more on an ad hoc basis, and a particular subject matter could only be researched once.

In most cases the explanation requires a combination of time-series analysis and socio-economic personal or household characteristics. It is particularly difficult to determine what the (future) information need is for the second category, as this frequently pertains to the sample's specific subpopulations. The increasing use of bicycles is an example of a trend that OViN data provided greater insights into: since 2004, the number of bicycle kilometres has increased by 6.5 percent, with as a large share of this increase attributed to e-bikes, which are primarily used by senior citizens (KiM, 2014).

Finally, the OViN is useful for calibrating and validating traffic and transport **models**, of which the two most important are Rijkswaterstaat's National Model System (LMS) and the Dutch Regional Model (NRM). These models are used to compile forecasts of mobility developments, and to forecast congestion points on the (main) road network. These forecasts are used to assess the impact that policy measures will have on mobility and accessibility, and to assess the environmental impact.

LMS and NRM are disaggregated choice models, meaning the choices are modelled on the level at which they are made, such as on a personal or household level. It is crucial that the OViN's data collection pertains to those levels and that each segment has a sufficient number of observations, including for gender, age category, transport modes and trip purposes.

As the previous description indicates, the information need and users' needs are closely related. In order to monitor trends according to one target variable, a large sample, in which few characteristics are required, can suffice, in a manner of speaking; for monitoring trends, small margins of uncertainty are crucial. Conversely, many characteristics are needed to explain trends, yet a small but focused sample can suffice.

Finally, because the OViN involves cross-sectional data collection, it does not provide for the information need of monitoring and explaining individual behaviour. For this reason, KiM initiated the Netherlands Mobility Panel (MPN) (Hoogendoorn-Lanser et al., 2015), which strives to determine changes in travel behaviour on the level of households and individuals. Research focuses on how developments in travel behaviour relate to (changes in) personal and household characteristics, as well as to external factors, including economic growth, taxation and the increasing use of ICT.

2.3 Respondents' response rates and response burdens

As Chapter 1 indicated, the primary reasons for considering alternative methods include people's increasing unwillingness to participate in surveys and the high burden that traditional approaches put on respondents. This section describes the response rates and response burdens in the OViN.

In 2015, the **response** rate via CAWI was 12,537, via CATI 14,317, and via CAPI 10,496. Table 2.1 presents the OViN's response rates per observational method. The CAWI method had a response rate of approximately 20 percent, while for CATI and CAPI that figure was around 50 percent. This is a notably low response rate for CAWI, given high degree of internet access in the Netherlands. According to Eurostat (2015), 96 percent of Dutch households have internet access, which ranks the Netherlands at the top in Europe. Additionally, CAWI response rates reveal a declining trend, which is also observable internationally (Bonnel et al., 2014; SCP, 2013, p.10).

Table 2.1 Response percentages in the OViN. Source: CBS (2016), CBS (2015a), CBS (2014a), CBS (2013), CBS (2012), CBS (2011).

		2010	2011	2012	2013	2014	2015
Response percentages per method	CAWI	23.0%	21.6%	20.4%	19.1%	17.9%	18.7%
	CATI	54.2%	52.1%	52.5%	52.5%	49.1%	47.4%
	CAPI	47.9%	45.7%	45.0%	48.3%	49.4%	47.8%
Total number of respondents in the database		44,165	42,327	43,307	42,350	42,600	37,350

The current OViN has a high **response burden for respondents**, as they must rely on their memories to record their trips at the end of the day. The reliability of the research therefore depends on people's ability to accurately recall the number of trips, arrival and departure locations, time of the trip and trip duration. The accuracy can be improved by giving the respondents a help diary – or memory jogger. Comparisons made between GPS-data and self-reported data reveal that respondents underestimated their number of trips and the distance travelled, while overestimating the trip duration (Stopher et al., 2007; Stopher et al., 2014). A similar comparison of smartcard data and self-reported data revealed that people overreport routine trips and underreport non-routine trips (Spurr et al., 2014). Additionally, respondents may consciously decide not to mention certain trips in a survey, because they want them to remain private.

3

Various types of collection methods

This chapter provides an overview of the various categories of collection methods. Technological developments have created great diversity: a (schematic) diagram helps position the available collection methods relative to one another, while indicating their similarities and differences. The various collection methods' characteristics are successively categorised, and also used in Chapters 4 through 6 to evaluate the collection methods that are most suitable for use in the OViN.

3.1 Self-reporting versus observed data collection

According to Bricka et al. (2014), self-reporting occurs when, to the best of their abilities, respondents report the various aspects of their trips. The reliability of the research depends on a person's ability to accurately recall their number of trips, arrival and departure locations, time of the trip and the trip's duration; however, according to Stopher et al. (2007), people are not proficient at recalling such information. CAPI, CATI and CAWI – the methods used in the OViN – are types of self-reporting.

In addition to self-reported data collection, there is observed (or automated) data collection, which, according to Bricka et al. (2014), occurs when a respondent's actual travel behaviour is passively or actively observed. The reviewed literature contains multiple uses of the terms 'active' and 'passive'. Asakura and Hato (2009) use this distinction between active and passive when describing the relationship between respondents and researchers. For active collection methods, researchers ask respondents to describe their travel behaviour, while, conversely, for passive collection methods, the respondents are not asked to describe their travel behaviour, because the researchers observe the respondents travel behaviour, which closely resembles the distinction Bricka et al. (2014) made between self-reported and observed data-collection.

In a study of possible uses of location determination via cell phones, Eurostat (2014) distinguishes between active and passive location determination. In active location determination, the telecomm service provider or research agency tracks the owner's telephone in real time, which requires the owner's consent. In passive location determination, the anonymous, historical data of all cell phone subscribers are collected. Eurostat primarily examined the individual users, comparing this to the anonymous mass of users.

Saluveer and Ahas (2014), whose focus was on applying GSM-data in mobility research, found that active data collection uses a selected sample of respondents (GSM-users), often in combination with questionnaires. Their definition included the respondent's consent. Moreover, they found that passive data collection occurs as part of a telecom provider's daily operations, which involves automatically generating logfiles of network use, and that this completely bypasses the GSM-users.

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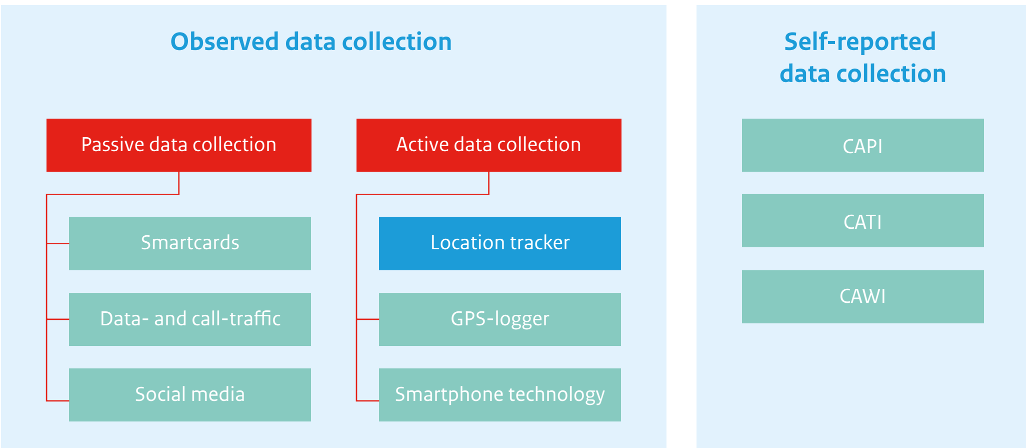
The definitions of active and passive data collection are seemingly ambiguous, owing to the various forms in which they are applied. However, the common denominator is the personal involvement of the research participants. Active data collection occurs when the research participants are aware of the fact that they are participating in a research study and that information about their trips is being stored in databases; in such cases, it is also possible to ask these research participants questions about their trip purposes and social-demographic characteristics, for example. For passive data collection, the research participants are unaware that their information is being used in research studies, and, moreover, it is impossible to give feedback or request additional information from them.

3.2 Overview of the various types of collection methods

As a follow up to Bricka et al. (2014), this study distinguishes between the self-reported and observed data collection categories. A distinction is then made between active and passive data collection in the observed, or automated, data collection method. Active and passive data collection are distinguished by the personal involvement of the research participants. Figure 3.1 provides an overview of the chosen categorisation and specific collection methods discussed in this report. CAPI, CATI and CAWI were previously discussed in Chapter 2. The remaining methods are briefly discussed here, and then comprehensively detailed in Chapters 4 and 5.

Figure 3.1 Schematic overview of the various types of collection methods.



Briefly, **passive data collection** pertains to:

- Smartcards: these are transport passes containing a chip (such as the public transport chipcard) that records the check-in location and transport mode.
- Data- and call-traffic: a person's location can be determined anonymously via internet- and call-activity, and distances derived from this information.
- Social media: messages can be automatically scanned, and, for example, trip information obtained via word recognition.

Passive data-collection can be used for various objectives. Riegel and Attanucci (2014) validated survey data based on the actual number of trips recorded with smartcards. Bonnel et al. (2014) used call-traffic data to devise a trip origin and destination matrix. Yang et al. (2014) construed this based on the so-called social media 'check-ins'. The various benefits of passive data collection include the availability of large amounts of data and the 'respondents' anonymity. Adding social-demographic factors to those data is however a major challenge, which the CBS is engaged in: Daas et al. (2015) for example derived a Twitter-user's gender from the name, short biography, content of the tweets and profile picture.

An overview of types of passive data collection remains incomplete. Bluetooth and automatic license plate recordings (and other possibilities) are also compiled below; however, they are largely unsuitable for use in the OViN and therefore are not considered in this report. Recording license plates for example often occurs on certain routes or at specific locations.

Briefly, **active data collection** pertains to the following collection methods:
- GPS-logger: this is a small device that records a person's location at certain time intervals. It is therefore possible to discern the trips of the person wearing the device.
- Smartphone technology: smartphones contain various sensors that can be used to determine locations and hence also detect trips.

The term location trackers refers to both GPS-loggers and smartphone technology, and both are used to determine a person's location[1]; thereafter, algorithms can derive the transport mode the respondents used during a trip and the purpose of the trip. Active data collection's various advantages include the ability to reduce the response burden, increase the accuracy of observations, and render the respondents' route choices more transparent. Conversely, various challenges include potential technological glitches, the organisation of the research becoming more complex (for example, logistically, or from supporting the respondents), and the need to develop accurate algorithms (Ortúzar & Olszewski, 2009). The ability to provide research participants with immediate feedback via smartphones is a key difference between smartphone technology and GPS-loggers, as GPS-loggers have limited user interfaces. Chapter 6 comprehensively examines the similarities and differences between using smartphones and GPS-loggers, and the pros and cons thereof.

3.3 Key characteristics of the collection methods

In an appendix to this report, the selected collection methods are assessed according to their suitability for collecting trip data for the OViN. From a theoretical perspective, this is done by selecting the characteristics deemed important for a collection method.

As based on the reviewed literature (including Eurostat, 2014), seven key characteristics of collection methods were identified. They are:
1. The information need that is covered;
2. The quality of the collected data;
3. The future sustainability of the collection method;
4. The collection method's costs;
5. The quantity of the collected data;
6. The impact on the respondent's privacy;
7. The impact on the respondent's response burden.

These characteristics appear to be positioned independently of each other, but in reality they are not; for example, (perceived) impacts on privacy and response burdens also impact the response rates, and hence the costs and quality of the research. For the purpose of structure and overview, it was decided to examine each of the seven characteristics separately. They are explained below.

In assessing the collection methods, a qualitative estimation is made as to whether each of the collection method's key characteristics are expected to be better (+), worse (-) or comparable (0), as compared to the current situation. A deliberate choice was made to work within this framework, and to not make more specific estimations. Moreover, within the scope of this research, it is in fact impossible to provide such certainty about the current situation and the alternative collection methods.

[1] In addtion to GPS, both smartphones and GPS-loggers are equipped with various sensors that can be used for location determination, including GSM and WiFi. More about this in section 5.1.

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For a collection method, the most important characteristic is the **information need** to be covered. The primary reason for conducting research is to ultimately obtain information that is useful, because it provides for a need. The OViN is used for three objectives: monitoring, explaining and modelling. For monitoring, as previously established, a distinction is made between national and regional data, and modality, age and gender, for which small margins of uncertainty pertaining to the target variable are important. In addition to this, a time series analysis, combined with socio-economic personal or household characteristics, including gender, age category, transport mode and trip purpose, are needed to explain the mobility trends. Finally, OViN data is used as the foundation for evaluating origin-destination matrices (OD matrices) in traffic and transport models; it is crucial that the data collected in the OViN provides sufficient observations of the transport mode and trip purpose segmentations used in these matrices. In the disaggregated models, such as LMS and NRM, evaluating the choice models also plays a role on the individual level. The relevant associated information is extremely similar to that in the explanation. When assessing collection methods in terms of the information need for modelling, the focus is on using the data for OD matrices. Finally, it is conceivable that the best way of covering the total information need is through a combination of new collection methods and the existing questionnaire-based approach, possibly supplemented by data from external sources.

Quality is a container concept in which many concepts are amassed. As based on the literature study (including Eurostat, 2014; CBS, 2014b), the following quality aspects were identified:
- Representativeness;
- Effectiveness;
- Accuracy;
- Comparability;
- Timeliness;
- Reproducibility.

For the purpose of assessment, these aspects are also (broadly) compared to the current situation.

The OViN's representativeness is currently ensured by the fact that the CBS has access to municipal administrative data, from which it derives representative samples of the Dutch population. And because this sample data is representative, it can be extrapolated to cover society as a whole. The data are weighed to correct for the underrepresentation or overrepresentation of groups. If for example self-selection causes bias in the data, it becomes more complicated to weigh and enhance, because the factor by which this should occur is unknown. In addition to the representativeness of the population, a representativeness of behaviour can also be examined: does one measure what one wants to measure? This is the effectiveness of the sample.

In this study, accuracy means the margins of uncertainty around the statistical parameters. Small margins ensure that the observed mobility trends become more meaningful. Comparisons between years is also important for both monitoring and explaining trends. In order to avoid trend breaks, the OViN is conducted in the same way each year. Timeliness pertains to the time period when the CBS delivers the data, which is currently in mid-May of the year after the research year. OViN data analyses serve as input for policy decisions, hence the overviews of current mobility behaviour must be as up-to-date as possible. Finally, reproducibility is important for validating the research. The outside world must be able to determine precisely how the research was conducted, what exactly was studied, and what the raw data means.

This report includes two concepts pertaining to **future sustainability**, namely, maintaining and improving the collection method. Maintaining denotes a chosen method that can be consistently used for numerous years. Additionally, potential areas for improving a collection method were examined. A collection method's present possibilities may perhaps be too limited for use in the OViN, yet market parties are working hard to further develop them. Eurostat (2014) identifies changing human behaviour and technological advances as factors impacting the maintenance and improvement of a collection method. One current problem associated with using CATI is the declining use of landline telephones, which is a consequence of technological advancement and behavioural change: namely, cell phone development and making telephone calls via internet.

The **costs** of the current OViN are a key argument for considering alternative collection methods. There is good reason why the OViN's innovation program is broader than merely exploring alternative collection methods (see section 1.1); this also complicates the comparisons between current and future situations. For the OViN, a distinction is made between the fixed costs and variable costs per respondent. Fixed costs also include the start-up costs, such as purchasing hardware and software. Variable costs for instance are the costs to mail surveys. Eurostat (2014) also identifies the cost allocations. If for example the administrator of public transport chipcard data is legally required to sum up the data into aggregated statistical indicators, the result will be a different cost allocation than if it only had to deliver the raw data. In addition to cost allocations, the (un)certainty of costs is important when selecting a collection method. Moreover, it is also important to remember that the types of expenses incurred may change; for example, new expenditures can arise when using new collection methods.

The **quantity** of the collected data depends on the availability of sufficient observations, which is important because accuracy increases with the sample size[2], and this factor is becoming more important due to the increasing unwillingness of Dutch people to participate in surveys. A collection method must also be scalable for use throughout the entire Netherlands.

The impact on the respondents' **privacy** is a key characteristic of a collection method. Aspects pertaining to legislation and regulations, as well as the perceived impact on personal privacy, are important in this regard (Eurostat, 2014). The legal foundation for the CBS is the Central Bureau of Statistics Act (CBS-Act), which states that the government commissions the CBS to conduct statistical research for the purpose of practical applications, policy and science, and to make public the statistics derived from the information compiled in that research. It is beyond the scope of this literature study to test the collection methods according to that legal framework.

Privacy moreover is a recurring topic of societal debate, particularly as it pertains to online security, for example. The perceived impact of mobility research on a respondent's privacy is potentially very high; for example, depending on the research design, one could possibly derive where a respondent brings his children to school, or that no one is home at a respondent's house on Monday nights. If respondents have any doubts about safeguarding their anonymity, this can negatively affect their willingness to participate in the research. This study therefore examines the (perceived) impact that collection methods have on the respondents' privacy.

A collection method's seventh and final key characteristic is the impact on the respondent's **response burden**. As was previously determined, the OViN's current methods place a relatively high burden on a respondent's memory. Moreover, the amount of time that people must spend on the research is important, especially relating to response rates. Finally, the response burden also includes the difficultly of the research process, which may not only pertain to the manner in which respondents are questioned, but also to the extent that respondents must contend with computers or other devices.

[2] Provided that the estimator is consistent, the margins of uncertainty decrease as the sample increases.

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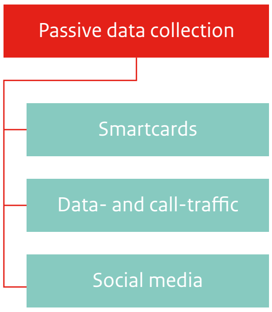
4

Passive collection methods

This chapter explains the passive collection methods in greater detail (see Figure 4.1), including their various applications. The collection methods' key characteristics for the OViN are also assessed, as based on the expectation that they will score better, worse or comparably, as compared to the current collection method.

Figure 4.1 Passive collection methods



4.1 Smartcards

4.1a Location determination via smartcards

A smartcard is a plastic card containing a chip, such as a bank card or the public transport chipcard. Personal information can be stored on these chips, including, in the case of public transport chipcards: birthdate, card ID number, the chipcard balance, the chipcard public transport product code, and the last ten transactions (CBP, 2010). This applies to all personal chipcards, as well as to anonymous public transport chipcards (except for date of birth).

The following information is processed when traveling with Dutch Railways (NS): card ID number, type of subscription, product and entry date, type of transaction (check-in/out), date and time, the balance before and after the transaction, and the transaction's value. Detailed information about an individual person's trip can be derived from this data (CBP, 2010). The fee transaction system, Translink Systems (TLS), records 2.3 billion transactions per year. Dutch Railways, and other Dutch transport operators (GVB, RET and HTM) are TLS's shareholders (Translink, 2016).

At present, these transport carriers do not share passenger-related public transport chipcard data with other organisations; the carriers are the owners of the data. Possible reasons for this include the fear of disseminating business-sensitive information and potential violations of passenger privacy laws (Maartens, 2017). The privacy argument comes into play as soon as individual travel behaviour becomes discernible or reconstructible. Foreign examples of public transportation smartcards include the Oyster Card in London and the Myki Card in Australia.

4.1b The use of smartcards in mobility research

One argument for exploring new collection methods for the OViN is that the quality of a trip logbook is dependent on the respondent's memory. Spurr et al. (2014) used smartcard data to estimate the accuracy of mobility research conducted in Montreal (comparable to the OViN in its use of a trip logbook). Because respondents were not asked for their smartcard numbers, Spurr et al. (2014) compared the respondents' recorded trip routes (n=803, of which n=324 public transport users) with the smartcard transactions (n=579,485 traceable smartcards) recorded on the same day that the surveys were taken. The researchers converted the respondents' travel routes into a transaction series; they successfully managed to find a smartcard that followed the same travel pattern for approximately half of respondents, and, based on their findings, discerned three character types. Firstly, the frequent traveller who correctly recorded his trips in the trip logbook. Secondly, the non-frequent traveller who (especially outside of peak hours) undertook fewer trips. And thirdly, the traveller who recorded a 'typical' travel day instead of the actual trips taken that day, resulting in an (unknown) bias in the data.

Riegel and Attanucci (2014) compared smartcard data with individual data from the London Travel Demand Survey (LTDS). In their case study, some 4,000 respondents voluntarily provided their Oyster card numbers, which served to simplify the process of matching survey data to the actual trips taken. The researchers concluded that approximately half of the reported trips corresponded to the recorded trips[3]. Moreover, they found a greater reported use of public transport than could be validated based on the smartcard data. According to Riegel and Attanucci, the upscaling of annual public transportation use, as based on LTDS data, resulted in an overestimation in their research.

Finally, Chu (2014) used smartcard data as an alternative to panel data. Many costs are associated with maintaining a panel; moreover, participants can experience panel fatigue. According to Chu, smartcard data is continuous rather than periodic, multi-day rather than single-day, and suitable for longitudinal rather than cross-sectional analyses. In this regard, a smartcard's two key characteristics are the time when it is used and the unique card number. For Chu, it was seemingly impossible to match a lost/stolen card to its replacement, which also applies to the situation in the Netherlands. Like Spurr et al. (2014), Chu studied the smartcard system in Montreal for a period of two years. When compiling his sample (n=238,145), he tested the internal consistency (including new card bias: increased use of new cards) and the representativeness of the population (including spatial bias near educational institutions). Finally, to demonstrate the possible uses of smartcards in the longitudinal analysis of travel behaviour, Chu studied the changes in day-to-day travel patterns, between seasons and from year to year.

4.1c The suitability of smartcards as collection method for the OViN

The research examples reveal that smartcards are primarily used for public transportation. According to the 2015 Mobility Report (KiM, 2015), a Dutch person on average takes 4 percent of all trips via train, bus, tram or metro. Combined, these modalities account for 12 percent of the total number of kilometres travelled.

Analysis of smartcard data provides no information about the purpose of the trip; moreover, in many cases, no personal characteristics are available. To assess the background characteristics of the trips and the travellers, secondary analyses of the exhibited travel behaviour are required. Data collection via smartcards alone does not cover the part of the **information need** the OViN provides for – namely,

[3] At issue here are the exact starting and finishing points. The start times, which are also included in LTDS, often deviate greatly.

explaining and modelling (both the estimation of origin-destination patterns (OD-patterns) and choice models). This requires additional questionnaires. However, from the described applications, smartcards do appear to be useful for validating the self-reported data (Spurr et al., 2014; Riegel & Attanucci, 2014). Moreover, smartcards can also be used to help estimate trends in public transportation on an aggregated level, with a small margin of uncertainty.

Other applications are also conceivable. Firstly, the possibility that a respondent in a national travel survey, such as the OViN, could directly add the trip information on his smartcard to the trip logbook by downloading that information from the transaction fee system administrator's server. Respondent could also possibly supplement this with information about the public transport trips they took by purchasing separate tickets. A second application option is for OViN respondents to consent to their trip information being used; the respondent enters his public transport chipcard number(s) and the researcher subsequently asks the TLS for the corresponding trip information. Key points to consider with these possible applications include the fact that a person could possess multiple public transport chipcards, and a person may use someone else's chipcard when travelling.

These latter two possible uses enhance the completeness and accuracy of the data, and hence the **quality** of the data. However, this is not the holy grail: regarding data quality, questions remain about how to process tickets that are purchased separately, the use of anonymous public transport chipcards, and free-riders (i.e. people who travel via public transport without buying tickets).

When using smartcards, there is in principle no **response burden**, because the research participants are not personally involved. Compared to the current OViN, if smartcards are used as supplements, as in the two above-mentioned possible uses, the response burden decreases. Completion of the trip logbook is facilitated if respondents are able to conveniently download travel information, because no burden is placed on their memories. Moreover, the respondents' tasks are simplified if they give their consent for researchers to use their trip information and the researchers subsequently discern their trips from TLS data. However, this does increase the research burden.

In addition to response burden, the perceived impact on their **privacy** is a key factor in the respondents' decisions to respond. The Dutch Data Protection Authority (*College Bescherming Persoonsgegevens*) identified public transport chipcard data as privacy-sensitive (Maartens, 2017). Any possible applications largely depend on the willingness of transport carriers and respondents to share travel information. Because of this heightened perceived impact on privacy, research participants may drop out, despite the fact that the data processing procedure can be anonymised. However, assuming that the respondents in the current OViN have truthfully reported their trips, the use of public transport chipcards does not provide any additional information about the respondents and (thus) scores comparably to the current OViN.

The public transport chipcard has become the most widely used public transport payment method in the Netherlands. However, not all public transport trips are paid for with chipcards. So-called 'non-chipped' card types are also used; for example, in 2014 some 10 percent of all public transport bus trips in Groningen and Drenthe were paid for with paper tickets (OV Bureau Groningen Drenthe, 2015). Moreover, Dutch Railways sells online tickets with a QR code, which are unrecorded in the TLS database. All told, the potential available **quantity** of research participants is no obstacle. For example, the previously cited studies by Spurr et al. (2014), and Riegel and Attanucci (2014), are based on large sample sizes. However, in order to use public transport chipcard data, the carriers must cooperate. At present, the CBS and the various carriers are in discussion about making public transport chipcard data available. In order to share private and/or business-sensitive information with the CBS, the TLS can aggregate the data, but this comes at the expense of its usability in research studies, such as the OViN, because individual rides cannot be combined with door-to-door trips. Public transport chipcard data is of course useful for determining small-margined trends in public transport.

Spurr et al. (2014) state that the **costs** per observation are very low compared to self-reported data collection; for example, no additional hardware is required when using smartcard data, although, conversely, large data storage capacity is required. Perhaps of more importance is the uncertainty about whether Translink Systems and the carriers will make the data set available and at what price. This collection method therefore requires a cost-risk analysis. Further, research surveys must continue to be used, because smartcards only record some of the travel behaviour, and hence the cost-savings are not apparent.

Finally, the **future sustainability** of data collection via smartcards depends on whether the (policy)choice is made to use smartcards as a public transport payment method. However, paying with bank cards or smartphones are possibilities as well, and over time could be used in addition to public transport chipcards (Mortier, 2014).

4.1d Overview evaluation table for smartcards

As based on section 4.1c, the collection method's key characteristics for the OViN were assessed. A +, - or 0 are used to indicate if this method is expected to score better, worse or comparably, as compared to the current collection method.

Smartcards		
Characteristic		**Evaluation**
Information need	Monitoring	0
	Explaining	-
	Modelling (OD-patterns)	-
	Modelling (choice models)	-
Quality		+
Future sustainability		0
Costs		-
Quantity		+
Privacy		0
Response burden		+

Generally, smartcards/the public transport chipcards seemingly cover only a limited part of the information need – smartcards are solely used for public transport –, yet they offer high quality data and low response burden. Further, when potentially opting to use smartcards, it is important to keep in mind the willingness of carriers to cooperate, as well as the price tag that comes with their cooperation. In the short term, public transport chipcard data is seemingly of particular interest for obtaining a relevant enhancement framework. Other possible uses are conceivable within the OViN's framework, but they face privacy issues and technological challenges.

4.2 Data- and call-traffic

4.2a Location determination via GSM

GSM is a global system for mobile telephony, in which cell phones remain in constant contact with the nearest base station, thereby facilitating incoming and outgoing telephone traffic. Because cell phones receive signals from multiple base stations, and the signal strength decreases proportional to the distance from a base station, a cell phone's location can be determined by triangulation. This method is called 'Cell ID'. The location determination is accurate up to around 50 to 100 meters, depending on the density of the network's base stations (Asakura et al., 2014; Van der Mede, 2014). This method is less accurate in open fields than location determination via GPS; however, the increased use of small cells in certain areas, such as stations and shopping centres, is improving the accuracy of location determination (Van der Mede, 2014).

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4.2b The application of data- and call-traffic in national travel surveys

Van der Mede (2014) presents a number of examples of mobility-related applications of GSM data: depicting crowd scenes, visitor frequencies, foreign visitors, place of origin maps, transport streams and OD-matrices. These applications can be designed both nationally and regionally, as well as locally. To create an OD-matrix, Bonnel et al. (2014) used the anonymous GSM signals (in call detail records, CDRs) of 4 million cell phones in the Paris region, as collected by French telecom provider, Orange, over a 12-day period in 2009.

In their exploratory study, Bonnel et al. (2014) divided Paris into sectors and assumed that an activity was occurring if a telephone remained 'stationary' in the same sector for more than 60 minutes. Trips (therefore) occurred between the sectors. For validation, they compared their results to a seven-sector OD-matrix, as based on the Enquête Globale Transport, the French equivalent of the OViN. The researchers concluded that the total number of trips corresponded well, but significant differences were detected in certain OD-relationships. Moreover, their analysis revealed that the number of trips was highly susceptible to the assumption of remaining 'stationary' for 60 minutes. Bonnel et al. (2014) concluded that their approach had some potential, but was not yet suitable for designing OD-matrices. Additionally, they suggested that a more complete analysis could be achieved by using data traffic (which also occurs via GSM signals).

Telecom providers store anonymous data traffic in data detail records (DDRs) (Eurostat, 2014). A person who uses the internet on his smartphone accumulates on average around 100 DDRs per day (Saluveer & Ahas, 2014), but this can amount to hundreds of location records (Eurostat, 2014; Van der Mede, 2014), thereby making it easier to distinguish between a person's trips and stationary locations, which enhances the quality of the traffic-based OD-matrices. According to Van der Mede (2014), the spatial (in)accuracy of data in the Netherlands is presently limited to the level of the four-digit postal code areas (PC4-level). According to an exploratory study conducted by the CBS (Offermans et al., 2013), small domain estimators can help make estimates more accurate and robust.

Finally, the higher density of observations can serve to identify certain destination, and to attach trip purposes to them (Saluveer & Ahas, 2014). However, one stipulation is that it must be possible to follow people for longer periods of time, and that no ID number that changes daily is linked to a phone. This primarily pertains to locations that many people visit; however, no certainty exists, because locations can have multiple functions, such as, for example, apartments situated above shops.

4.2c The suitability of data- and call-traffic as a collection method for the OViN

Eurostat (2014), Van der Mede (2014), and Saluveer and Ahas (2014) primarily see the use of GPS data as an opportunity to devise good OD-matrices, which can subsequently be used to develop traffic and transport models. The OViN's **information need** is thus partly covered. At present, not enough certainty exists about the characteristics of individual 'respondents', including trip purpose and transport mode. Nevertheless, based on their large numbers, an outline can be derived. However, because no information is provided about the research participants (for example, socio-economic personal or household characteristics), these data are insufficient for assessing choice models and monitoring and explaining trends in mobility development.

According to Saluveer and Ahas (2014), the great advantage of GSM-data is that it delivers a large group of anonymous 'respondents'. The **quantity** of data collected is wide, resulting in small margins of uncertainty. Additionally, the data is collected over longer periods of time, which is advantageous compared to the current OViN. However, according to Saluveer and Ahas (2014), obtaining the data is a major obstacle. Telecom providers must incur **costs** in order to process this data for use by (statistics) agencies. Moreover, they regard this data as a new source of income (Eurostat, 2014). In the Netherlands, Mezuro has partnered with Vodafone, and together they currently have a monopoly in the supply of GSM data, thus allowing them to charge high fees. Perhaps, in future, this monopolistic situation will be broken if other telecom providers dare to offer their GSM data, or if the government intervenes and establishes price regulations, for example. Similarly, survey research must also continue to be used, because data- and call-traffic cover only part of the information need, and hence the cost-savings are not apparent. Consequently, a minus is used here to evaluate the cost aspect.

The use of the word ‘dare’ (in the previous paragraph) primarily pertains to the fear that telecom providers have of damaging their reputations as result of **privacy** violations. Although GSM-data is fully anonymised, the fear can nevertheless remain among telecom company customers that their privacy is being violated. Moreover, they do not have a say in the decision to use ‘their’ data in mobility research. Notwithstanding, national and international regulations protecting privacy are firmly established in law. Additionally, telecom providers do not want to run the risk of revealing business-sensitive information (Eurostat, 2014). The fact that data collection can be anonymised, yet companies remain reluctant to provide data, indicates that privacy is a sensitive aspect of this collection method. This aspect is however extremely difficult to compare with the current OViN, and hence is deemed as neutral in this study.

The representativeness and accuracy of the data are two **quality** aspects cited in multiple studies (Eurostat, 2014; Van der Mede, 2014; Saluveer & Ahas, 2014; Offermans et al., 2013). Statistical errors can occur if people make significantly more or fewer trips without their cell phones. It could also be the case that a person has multiple cell phones with them. For this reason, GPS data is a mobility proxy; it is data generated by devices but representing people.

Given the development of algorithms and use of small cells, which (both) increase accuracy, the quality of the supplied data will likely improve in future. Moreover, compared to what is currently possible with the OViN, the quality of OD-matrices[4] will likely improve due to the large sample size, geographic spread and (potential) dynamic character of the data collection (W. Hendriksen, personal communication, 21 July 2015). Regarding the quality aspect, both the challenges and improvements have been identified; consequently, data- and call-traffic are currently appraised as neutral.

The literature study revealed that the **future sustainability** is not regarded as potentially problematic. Making telephone calls via internet could gradually replace calling via GSM; however, this will not negatively impact the collection method because those calls can also be recorded. Additionally, some improvements are possible, primarily concerning various quality aspects.

There is in principle no **response burden**, because the research participants are not personally involved.

4.2d Overview evaluation table for data- and call-traffic

As based on section 4.2c, the collection method’s key characteristics for the OViN were assessed. A +, - or 0 are used to indicate if this method is expected to score better, worse or comparably, as compared to the current collection method.

Data- and call-traffic		
Characteristic		**Evaluation**
Information need	Monitoring	-
	Explaining	-
	Modelling (OD-patterns)	+
	Modelling (choice models)	-
Quality		0
Future sustainability		+
Costs		-
Quantity		+
Privacy		0
Response burden		+

[4] Estimating OD-matrices is also like a separate branch of sport. The signals that are transmitted by mobile phones are used, without the people carrying the phones being aware of it.

Generally, using data- and call-traffic seemingly only covers a limited part of the information need. This collection method is especially suitable for research in which data aggregation is important, and knowledge about the individual respondent does not matter.

4.3 Social media

4.3a Location determination via social media

Owing to the popularity of smartphones and mobile internet, it is extremely easy (and enjoyable) for users to share status updates and photos with friends: this is called microblogging. Such texts are often short, a maximum of 140 characters in Twitter's case. In 2015, Twitter (2015) reported to have 302 million unique users per month, with an average of 500 million sent tweets per day. A majority of active users send daily messages. Other relevant characteristics of microblogs are that they deal with the here and now, and that most users post about themselves (Zhu et al., 2013). Naaman et al. (2010) classified 3,379 tweets, of which 41 percent were placed in the 'Me Now' category, which was the largest category.

A tweet does not contain location information by default. Users may however opt to add a geo-tag to their messages, which contains the longitude and latitude of their smartphones. Further, another way to add a location to a tweet is via location-based social networks (LBSN), such as Instagram and Foursquare. Twitterers can reveal where they are located by 'checking in' at a 'venue'; the locations of these venues, such as restaurants and sports arenas, are stored in LBSN databases. A person can of course also check-in without sending a tweet.

4.3b The application of social media in mobility research studies

In 2011, Japan was struck by an earthquake, known as the Great East-Japanese earthquake, resulting in a meltdown of the Fukushima nuclear power plant's reactor cores. Hara (2014) studied the trip behaviour of commuters in Tokyo who were unable to travel home by train that day because the service was suspended. Some 5.5 million people were thusly affected. Hara (2014) analysed the Twitter messages of 3,307 users who sent at least two geo tagged tweets on the day of the earthquake. The research aim was to explain the decision to travel home or not to; the non-verbal character (geo-tag) was used as the verbal character (text message) of each tweet. Among Hara's conclusions was that the greater the distance, the less likely people were to walk, yet nevertheless more than 50 percent of people living more than 20 kilometres away did indeed walk home. Moreover, the decision of whether to return home or not was strongly influenced by whether people were aware of the situation at home. A commuter who had received a message that his family was safe more often chose not go home, and instead stayed overnight in a hotel or at his office.

In an exploratory study of the possibilities offered by LBSN data, Yang et al. (2014) evaluated a dynamic (time-dependent) OD-matrix in Chicago, which involved scanning the websites of venues each hour to determine the number of checked-in persons and new check-ins. The researchers did not follow individuals, but rather instead relied on the dynamic of the check-ins and (high) spatial density of the venues, of which there were some 16,000 in Chicago. The check-ins were corrected for the odd chance that someone had checked-in at a venue-category; users for example checked-in relatively frequently at restaurants. By means of a combination of non-parametric cluster- and regression-analyses and a gravity model, the researchers devised dynamic HB-matrices, which, incidentally, did not specify the modality. They compared their findings to the existing HB-matrices, concluding that no major differences existed and that this new approach had potential.

4.3c The suitability of social media as collection method for the OViN

Sections 4.3a and 4.3b describe two collection methods via social media, both of which use different information sources (Twitter data and LBSN data), processing methods and models. Consequently, it is difficult to consider them under one denominator. Nevertheless, they are similar in one respect: a large **quantity** of data is available. The 2016 National Social Media Research Study revealed that some 2.6 million people use Twitter in the Netherlands, of which 0.9 million do so daily. Instagram has

2.1 million users, and 0.9 million people check in at a venue daily (Newcom, 2016). However, the question remains as to whether all of these messages are publicly available; moreover, in many cases, it is impossible to discover information about these trips. Finally, various subgroups exist (for example, elderly people) that rarely post messages on social media, and for whom a relatively small quantity of data is available.

A second concern pertains to the fluctuating popularity of social media. The daily use of Twitter declined by 10 percent from 2015 to 2016, while Instagram's popularity increased by 37 percent. The **future sustainability** of collection methods that are based on social media is therefore highly uncertain. It is extremely difficult to evaluate mobility trends based on data that are, as it were, drawn from different sources each year.

As with data- and call-traffic, OD-matrices can be derived (from LBSN-data), which potentially covers some of the **information need**; namely, the calibration and validation of traffic and transport models. LBSN data is advantageous in that it can generate a high density of locations (particularly) in urban areas, which is a possible advantage compared to the OViN, as the OViN is not always suitable on the local level and requires a supplementary research survey. Given the uncertainties pertaining to the completeness of social media data (for example, the lack of modalities in Yang et al., 2014), this collection method's modelling of HB-matrices is assessed as neutral. These data are not yet suitable for both monitoring and explaining trends in mobility developments, nor for estimating choice models.

Regarding the **quality** of the data, sample bias is a disadvantage. Major differences exist in the usage rates of young people and senior citizens, for example, which can lead to questions about the representativeness and to systematic (statistical) errors. Moreover, the usage rates between young people and senior citizens is an inconstant factor (Newcom, 2016), meaning it is extremely difficult to correct for. When extrapolating to Dutch society, large margins of uncertainty emerge. Additionally, check-ins are unrepresentative of the locations that people visit, and leisure time is a focal point. Finally, transport modes and trip purposes are also uncertain. All told, there is a decrease in quality compared to the current OViN.

Yang et al. (2014) conclude that the use of LBSN-data does not harm **privacy**, because the research is not focused on individuals but rather on the total check-ins. However, Newcom (2016) found that 66 percent of social media users expressed concern about the resale of their personal data, and that 58 percent were unsure of whether social media is trustworthy. At issue here then is a general feeling of distrust that could negatively impact mobility research that also uses social media. For example, in Hara (2014), researchers read some of the tweets, in order to devise a word bundle[5], and this could raise suspicions among users, because many tweets are not public. Compared to the OViN's current collection method, there is seemingly more social resistance to using this data.

Finally, the **costs** of data collection were assessed as neutral. No respondents need be approached, which is a cost-saving. However, the requisite data must be purchased; for example, one day of Twitter data in the Netherlands costs 3,000 euro (Bijsterbosch, 2013). Moreover, in order to use social media in mobility research, special software and models must be developed (through intermediary companies). The size of the data stream can also be quite large, thereby requiring server capacity.

Response burden is not an issue, because the research participants are not personally involved.

4.3d Overview evaluation table for social media

As based on section 4.3c, the collection method's key characteristics for the OViN were assessed. A +, - or 0 are used to indicate if this method is expected to score better, worse or comparably, as compared to the current collection method.

[5] A word bundle is used to mean the words that people use to indicate what they are doing or what they are refering to. For example, the words 'NS', 'train', 'conductor' indicate that the Twitterer is travelling on a train.

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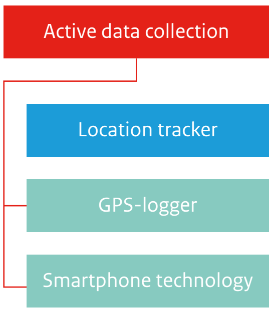
Social media		
Characteristic		**Evaluation**
Information need	Monitoring	-
	Explaining	-
	Modelling (OD-patterns)	0
	Modelling (choice models)	-
Quality		-
Future sustainability		-
Costs		0
Quantity		-
Privacy		-
Response burden		+

Generally, the use of social media seemingly covers a limited part of the information need that the OViN provides for. Doubts also persist about the data quality, and, moreover, the future sustainability (for each media platform) is uncertain. Social media could however be used to answer specific research questions, such as for example the modality choices of festival-goers.

5
Active collection methods

This chapter examines the active collection methods (see Figure 5.1). First, the use of GPS-loggers and smartphone technology in mobility research is explained, which serves to clarify exactly what is intended, how the methods work, the differences and similarities, and so forth. The use of prompted recall surveys is also examined; these are surveys in which respondents are asked to recall and record their trips and activities. Finally, the collection method's key characteristics for the OViN are assessed, as based on whether they are expected to score better, worse or comparably, as compared to the current collection methods (see section 2.4).

Figure 5.1 Active collection methods



5.1 The application of location-trackers in mobility research

5.1a The recording of locations

The term location-trackers pertains to the GPS-logger and smartphone technology collection methods, which are both used to determine a person's location. GPS-loggers are small devices that record their locations at certain time intervals (including GPS coordinates). Smartphones can also do this, but the respondents must install a trip application (or app, for short).

Figure 5.2 Examples of GPS-loggers

Which GPS-loggers are available?
In the reviewed literature, little attention was devoted to the various brands and types of GPS-loggers in use. Two such examples are the 747Pro (Feng & Timmermans, 2014) and the MobiTest GSL (Montini et al., 2014a; Kohla et al., 2014); see accompanying photo.

A Global Positioning System (GPS) operates by means of satellite signals. A satellite transmits a signal that contains information about the time and location (in space) of the transmission. If a smartphone or GPS-logger receives a signal from at least three satellites, that device's location can subsequently be determined. A fourth signal improves the accuracy down to just a few meters. However, buildings or clothing can disrupt satellite signals, thereby reducing the accuracy. What are known as urban canyons can exist in highly urbanised areas, because tall buildings disrupt GPS signals and consequently some data is lost (Bricka et al., 2014). In addition to signal disruptions, a cold start is a common reason for incomplete GPS-data (Stopher et al., 2014). A cold start occurs because the smartphone or GPS-logger must first signal that a trip is starting, before the recording will begin.

In terms of the possibilities of equipping with sensors, GPS-loggers and smartphones are not at odds; they both use GPS, as well as GSM (see section 4.2a), a compass (to establish direction), an accelerometer (to measure acceleration), a gyroscope (to detect changes in movement) and WiFi. Detected WiFi signals can be compared to a database of WiFi networks[6] whose locations are known. Combined with the signal strength, the location can be accurately determined down to tens of meters (Lawson, 2012).

5.1b Creating a trip logbook

In order to assess the suitability of each collection method, it is important to have a clear overview of the process involved in creating a trip logbook. This section describes that process, focusing on the (process-orientated) similarities and differences between smartphones and GPS-loggers. The focal points are:

- The various ways of communicating with the researcher's server;
- The similar ways in which imputation algorithms are used.

There are varying ways to communicate with the researcher's server. The first is when uploading the data. A GPS-logger's recorded data can either be uploaded directly to the researcher's server via the GSM network or indirectly via the respondent's USB and PC. For smartphones, the uploading occurs via the smartphone's internet connection, and the respondent need not intervene.

According to Montini et al. (2014a), there are three key steps to creating a trip logbook, which applies to both GPS-loggers and smartphones. These steps are:

1. Cleaning up the raw data. If the location tracker has not been in contact with a sufficient number of satellites, the GPS coordinates will be inaccurate. This can cause one observation to (exorbitantly) leave its designated area and be included with other observations elsewhere.

2. Identifying the trips and activities. A clustering of GPS coordinates indicates an activity, for example. A trip consists of a series of separate GPS coordinates. Imputation algorithms help to identify the trips and activities; imputation means assessing a (missing) piece of data. Imputation algorithms are explained in the accompanying box.

[6] Google compiled such a database when mapping the street networks in Google Street View.

3. Identifying the transport mode and trip purpose, which also involves using imputation algorithms. By matching the GPS coordinates to the GIS, the route travelled can be depicted on a map (including public transport networks); this is called map matching, and, for example, it can indicate that a person has travelled by train. Meanwhile, short, quick accelerations punctuated by numerous stops could indicate that a person travelled by scooter in an urban environment.

Researchers broadly emphasised how import quality is in these steps (for example, Ortúzar & Olszewski, 2009; Asakura et al., 2014; Feng & Timmermans, 2014; Zhao et al., 2014). The first step is a prerequisite for properly executing steps two and three. This chapter primarily focuses on these latter two steps.

BOX 1: What is an imputation algorithm?

Imputation algorithms, or algorithms for short, are series of decision rules. An example of a possible decision rule is: *if the average speed of a ride exceeds 20 km/h, the respondent didn't travel on foot.*

The essential input for algorithms is the geographic distance between two consecutive observed sets of GPS coordinates. The accuracy of an algorithm benefits from the high frequency and accuracy with which the GPS-coordinates are stored. Additionally, algorithms can use contextual information, such as Open Street Map, Google Traffic, and Open OV, as well as ex-ante derived points of interest for the respondent, such as address data.

An algorithm can determine (for example) what mode of transport is most likely. Behind each imputation is a level of security, which increases when more characteristics of a trip are known; in other words, when more information is added (Montini et al., 2014b).

Finally, a learning algorithm occurs when the information a respondent provides during the research is used in subsequent imputations. This information also increases the imputed data's level of security.

Imputation algorithms serve to identify trips and activities, as well as transport modes and trip purposes. How advanced the algorithms are varies per research study, but in principle does not depend on whether GPS-loggers or smartphones are used. However, choices can be made to limit its use to only identifying the trips, for example, so that the previously described step-by-step plan is not fully completed. Additionally, using imputation algorithms increases the research burden, while decreasing the response burden. The researcher assumes the responsibility of developing accurate imputation algorithms. How successful location trackers are as tools in mobility research is therefore partly dependent on the researcher's ability to derive accurate trip characteristics from the data (Srinivasan et al., 2009; Rasouli & Timmermans, 2014).

The final step in this process is to provide the respondents with feedback from the created trip logbook, which is crucial for validating the recordings and imputations (as further explained in the next section, pertaining to prompted recall). Smartphones and GPS-loggers differ greatly on this point. GPS loggers are primarily used to give feedback to respondents afterwards (that is, when the process of recording trips is completed). A smartphone, conversely, offers researchers the opportunity of involving respondents in the recording process at three different stages: before, during and after. Via an app, respondents can be asked to record their transport modes and trip purposes before or during the trip, for example. This approach is beneficial in that there is more certainty about the respondent's (imputed) transport mode. However, an advanced algorithm requires time, which can be obstructive if the feedback to the respondent occurs during the trip. Figure 5.3 provides an example of a process structure, as derived from Zhao et al. (2014).

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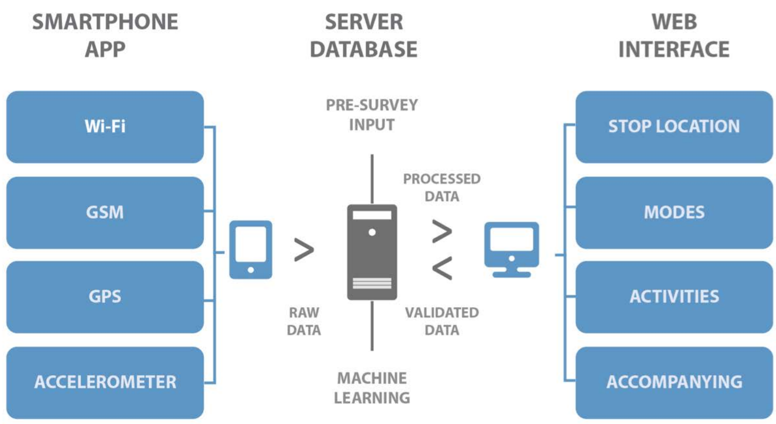
Figure 5.3 The process of creating a trip logbook with the help of smartphone technology. Source: Zhao et al. (2014)



Generally, compared to smartphones, GPS-loggers offer few possibilities. The data can only be uploaded after the fact via USB and PC, or via GSM (if the GPS-logger is equipped with a SIM card), and this is done by the respondents or the research agency once the GPS-logger has been returned. If respondents upload the data, they must wait for feedback from the created trip logbook. The technology allows for feedback to be provided a few minutes after the raw GPS coordinates are uploaded; however, more complex algorithms require more time. Map matching, for example, improves the classification of transport modes. In order to accelerate feedback, Feng and Timmermans (2014) asked the respondents for the addresses of places they regularly frequented before starting to measure with GPS-loggers; this of course is also possible in research studies using smartphones. Location recognition accelerates the workings of the algorithms. An alternative to quick feedback is that respondents are asked to verify the trip logbook at a certain time (for example, one day) after uploading the data; however, a downside is that this process increases the response burden.

Once the research agency subsequently uploads the data, the respondents are no longer responsible for it during the course of the research study. It is only after the research is completed that they must verify their observations, which, generally, is easy do, yet does place some demand on the respondent's memory.

5.1c The *ground truth* and the use of *prompted recall*

The aim of identifying trips and activities, and of identifying transport mode and trip purpose, is to discover the ground truth, which means the respondents' actual travel behaviour. According to Rasouli and Timmermans (2014), nowadays it is relatively easy to determine a trip's time period and the route taken. However, determining the transport mode and purpose of the trip (or the activity) remains a difficult task, and, moreover, the data imputation is not always correct. Imputating the trip purpose is complicated by the multifunctional uses of land and buildings, for example.

For this reason, many research studies use a prompted recall survey, which requires respondents to recall and report their trips and activities. For GPS-loggers, this survey is offered via a browser; for smartphones, it is built into the app. To help prompt the respondents' memories, they receive feedback about their travel behaviour from the location trackers' records (hence the use of the term prompted). A prompted recall survey can collect information that cannot be obtained using location trackers, such as the trip cost or number of travelling companions.

The term success factor denotes the percentage of correctly imputed data – that is to say the imputed data that the respondents have agreed upon in a prompted recall survey. However, when using the term success factor, it is important to note that this is partly influenced by how detailed the transport mode and trip purpose are presented, as well as the homogeneity of the group of respondents in the sample

(Montini et al., 2014b). Additionally, misreporting can impact the success factor (as discussed in the next section). Such concerns render it difficult to compare the success factors of various research studies. Using GPS-loggers, Kohla et al. (2014) developed an algorithm for transport modes that had a success factor of around 80 percent, with the researchers distinguishing between eight transport modes. Montini et al. (2014b), focusing on trip purpose, achieved a success factor of approximately 80 to 85 percent.

Much work is currently being done to improve the algorithmic, including automatically classifying the rides within a trip, distinguishing between trips and activities, and modality recognition. All are challenging issues. Distinguishing between rides within a trip primarily comes into play when people stay in one place for a short period of time, for example. Hence, a respondent who stops cycling in order to give someone directions might record this as two bicycle rides in his trip logbook, which would be deemed a false positive, because a ride was indeed undertaken but was incorrectly split into two separate rides. Conversely, a respondent could depart a train and immediately get into a taxi, but combine both rides as one (a false negative). There is no apparent choice made between having false positives and false negatives, and this is approached in varying ways in the literature (see Zhao et al., 2014; Thomas & Geurs, 2014). At issue is the willingness (effort) and ability (memory) of the respondents to add or subsequently remove rides during the prompted recall survey.

5.1d Challenges associated with using a prompted recall survey

Compared to traditional trip logbooks, using a prompted recall survey reduces the response burden. On a map, the respondents see the route they travelled, as well as their departure and arrival times. The hypothesis here is that this prompts their memories, resulting in more accurate answers about their actual travel behaviour.

However, it is good to remember that, like imputation algorithms, a prompted recall survey is not free from errors. Misrepresentation can occur when respondents are unable to precisely recall their trips and activities, or do not know exactly what they are being asked for (conceptual confusion, for example), or because they are unwilling or unable to alter - add or delete - the data imputed in the survey. The extent of misreporting depends on several factors: of major impact is the time interval between the trip and the moment of receiving feedback in the survey. Feng and Timmermans (2014), in a multi-week survey, encouraged respondents to upload data from the GPS-logger at least twice a week. A smartphone offers the possibility of giving feedback shortly after a trip is completed.

To illustrate the shortcomings of the prompted recall survey, Stopher et al. (2014) described the results of a household survey conducted in Cincinnati, Ohio (USA), in which the researchers discovered that many respondents had altered the starting and finishing times of rides in the survey, despite the fact that the GPS had recorded this extremely accurately and hence no alterations were needed. The researchers also compared some of the algorithm's outcomes with the transport modes and trip purposes indicated by the respondents, discovering that they failed to correspond in 24 and 60 percent of cases, respectively. Respondents for example recorded trips made by foot that had average speeds of 20 km/h, or recorded that they lived in places where they did not actually live.

Stopher et al. (2014) concluded that a prompted recall survey is not a good source for discovering the ground truth. A key concern for this research study (and possible explanation for the erroneous alterations) is the long duration between when the research period is conducted using GPS-loggers and the point in time when feedback is given in a prompted recall survey. Based on the published paper, it could be deduced that this period of time was around three to seven days, which for example is rather long compared to the research of Feng and Timmermans (2014), in which the respondents were responsible for the promptly uploading the data from the GPS-loggers, and already received feedback within a few minutes of uploading.

To discover the ground truth, Stopher et al. (2014) devised an alternative to the prompted recall survey; namely, life-logging cameras, which are small, portable cameras (see Figure 5.4) that can take photos from the point of view of the person wearing the camera at a set frequency, possibly amounting to thousands of photos per day. Such cameras are used in medical science to treat patients with memory loss, for example. Stopher et al. (2014) concluded that using life loggers in trip research could help add rides that the GPS had missed (for example, owing to urban canyons or cold start). Work is currently being done to automatically recognise transport modes and trip purposes. If this is applied to a sub-sample, the quality of data-imputation can be tested.

Figure 5.4 Life-logging cameras. Left: a woman wearing a camera on her shirt (source: Narratives). Right: photos indicating that the person wearing the camera travelled by train (Stopher et al., 2014).

- Summary: Using a prompted recall survey to verify and validate the imputed data is extremely important for the data quality and completeness. However, it should be noted that such use can also lead to misreporting, with the various associated problems that come with that, including misinterpreting the meaning of ‘rides’ and ‘trips’, omitting transport modes or trip purposes, and recording a transport mode or trip purpose that the actual GPS data proved to be an incorrect answer.

Enhancing the survey’s user-friendliness can solve some of these problems; a large degree of self-reporting is preferable. Additionally, it is important to enhance the accuracy of the algorithms used, as this facilitates validation by respondents. Finally, crucial is the moment in time when the feedback is given: the faster the better.

5.2 GPS-logger

5.2a The suitability of GPS-loggers as collection method for the OViN

The first issue pertaining to the use of GPS-loggers is that respondents must take the devices with them when travelling, which possibly heightens the **response burden**. Additionally, the risk exists that respondents will forget their devices. Using GPS ensures that the respondents’ travel routes and travel times can be closely monitored, and that transport modes and trip purposes can also be imputed. This potentially reduces the response burden when completing a trip logbook. Consequently, one could even say that it is no longer a question of completing but rather of supplementing and correcting, although this is no guarantee of low response burden, as making such corrections can still be difficult, especially when it pertains to altering times and locations. Additionally, the accuracy of the imputations can come at the expense of the speed at which feedback on the imputed travel behaviour is given. Slow feedback can result in long waiting times and irritation on the part of respondents, and thus a higher response burden.

Finally, in order to use this collection method, respondents must have some basic knowledge of computers and the internet. The respondents must for example download software and then upload their own data; this aspect does not apply to GPS-loggers that use GSM or when research agencies extract the data from GPS-loggers. Respondents must also contend with a digital survey. The survey’s degree of difficulty is particularly heightened if data is missing, owing to an empty battery, GPS signal failure, or because the respondent forget to take the GPS-logger, for example. However, this does not seem to be more difficult than in the current OViN.

- Summary: GPS-loggers remove the burden from the respondent's memory and potentially reduce the time it takes to complete the logbook. The potential installation and use of software increases the **response burden**. Because GPS-loggers have aspects that both heighten and lower the response burden, they are assessed as neutral on this point.

If research is conducted using GPS- loggers in combination with imputation algorithms, a validation method must be used to safeguard the **data quality**. For Feng and Timmermans (2014), the prompted recall survey is a crucial method for this purpose, yet they also recognize its disadvantages, namely, the misreporting. Stopher et al. (2014) identified the same disadvantages and therefore experimented with alternatives, such as life-logging cameras.

Misreporting diminishes the accuracy of the data collection, and hence also the data quality. However, arguments exist for why using a prompted recall survey in the OViN would result in a relatively low degree of misreporting compared to other mobility research studies (such as Feng & Timmermans, 2014; Montini et al., 2014b; Stopher et al., 2014). Firstly, in the OViN, respondents must only report during one day, which means they have relatively few trips to check and alter in the prompted recall survey. Secondly, it is easier to encourage respondents to complete the survey if it should appear they are failing to do so. Finally, the most accurate algorithm can be used; even though it is relatively slow, and respondents therefore receive feedback on the (imputed) trip data relatively late, it only needs to be used once in the OViN. The imputed data is therefore extremely accurate, and certainly when compared to the current method.

Finally, the research participants may drop out if the response burden is too high or impact on their privacy too great, and this can adversely affect the sample's representativeness if it occurs selectively. This aspect also pertains to the current OViN.

- Summary: GPS-loggers are accurate and the algorithmic constantly improving. Using GPS-loggers is expected to increase the **data quality**, as compared to the current quality in the OViN.

The data quality increases as more detailed information about the respondents becomes known. However, respondents could feel that this violates their **privacy**. In the reviewed literature, little attention was devoted to the impact that GPS loggers have on the respondents' privacy. For example, Montini et al. (2014a) focused on the user experience, but privacy was not part of it, which could indicate that the researchers did not receive any signs from the respondents that they were concerned about their privacy. Because the focus (in an academic setting) is on voluntary participation, it is conceivable that those who did not participate in the research study had in fact declined for privacy-related reasons. This type of non-response could indeed be greater than is the case in the current OViN, because more personal details are known about the respondents.

Additionally, when using life-logging cameras as an alternative to the prompted recall survey, the risk exists that public opinion will be against them for privacy reasons, as at issue here are both the respondents' privacy (does one turn off the camera when using the bathroom, for example?) and that of those being photographed. Google decided not launch its Google Glass technology on the market, partly owing to fears of lawsuits pertaining to privacy infringement. Conversely, the use of cameras is now commonplace in society.

- Summary: using GPS-loggers means that more personal details are known about the respondents than is the case in the current OViN. Consequently, a greater impact on **privacy** is expected.

For research studies using GPS-loggers, respondents are selected and personally approached; this means it is possible to request additional information from the respondents, such as socio-economic personal or household characteristics. GPS-loggers collect detailed information about the respondent's trip behaviour, and additional information about each ride may be requested in a prompted recall survey, including the number of travel companions, for example. The same **information need** is therefore provided for as in the current OViN.

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One possible additional advantage arises from the fact that the respondents exact routes are known, and this information can be used to analyse their route choices. Knowledge of a traveller's route choices can be helpful for improving the origin-destination matrices (OD-matrices) in traffic and transport models. If the route choice information is missing, a probability distribution function is used to assess a person's route choice. Knowledge about the actual choice behaviour can be used to test the probability distribution function.

- Summary: a survey using GPS-loggers can provide for the same **information need** as the current OViN. Moreover, this offers possible additional advantages, as more details are known about the route of trip.

Because virtually the entire Dutch population can be asked to participate in a national travel survey using GPS-logging, **quantity** is seemingly not an issue. As previously mentioned when discussing the quality aspects, if people decline to participate due response burden or privacy concerns, this could indicate that additional efforts are needed to achieve the required sample size.

It is in principle possible to scale the GPS-logger research study to the national level; however, this would require a major logistical operation, which must correspond to the CBS's current procedures. Great effort is required to distribute and retrieve the GPS-loggers, although this is largely a cost argument.

- Summary: regarding the **quantity** aspect, using GPS-loggers offers no significant advantages or disadvantages (except for the costs, as discussed in the following section). This collection method therefore scores comparably with the current OViN.

Upscaling to the national level entails high **costs**. The associated fixed costs primarily pertain to purchasing or leasing large numbers of GPS-loggers. As for the variable costs, the costs pertain to distributing and retrieving the GPS-loggers among respondents (including shipping costs and working hours), additional (telephone) support for using GPS-loggers, the accompanying software, and, lastly, leasing the server capacity[7] needed to process and store large amounts of data. Box 2 presents a sample calculation in which the shipping costs alone already substantially contribute to the high variable costs.

- Summary: the OViN's **costs** are likely to increase when using GPS-loggers. The primary reason for this is the rapidly increasing variable costs, which are primarily incurred when distributing and retrieving the GPS-loggers among respondents.

BOX 2: Sample calculation of the costs for purchasing and distributing GPS-loggers
This sample calculation provides an estimation of the costs associated with purchasing and distributing GPS-loggers for four years among OViN respondents. Personnel costs are excluded.

Reference information for the calculation:
- A GPS-logger costs 100 euros and can be used for four years.
- Due to replacement and repairs of GPS-loggers, an extra 10 percent is added to the purchase price.
- A respondent is estimated to use a GPS-logger for six weeks on average. This means that one GPS-logger can be used by approximately nine respondents per year.
- The shipping costs per return shipment is 12.50 euros.
- The required sample size is 36,000 respondents.

All research participants are asked if they are willing to participate, and those who are agree are sent a GPS logger. For this calculation, it is assumed that all of these people agreed.

There are 36,000/9 = 4,000 GPS-loggers required for this research. The purchase price is 100 x 4000 = 400,000 euros. Added to this is an extra 10 percent for replacements and repairs: 400,000 x 1.1 = 440,000 euros. That accounts to 440,000 / 4 = 110,000 euros per year.

[7] One respondent per day requires 11 MB of capacity (Strnad, personal communication, 8 September 2015).

The shipping costs are 36,000 x 12.50 = 450,000 euros. It is assumed that no unused GPS-loggers are returned and therefore no other people need be recruited. In practice, however, this could occur, and hence this estimate is an underestimation.

The total cost of purchasing and distributing GPS loggers is 560,000 euros a year, of which 80 percent consists of variable costs. The number of respondents is therefore a key driver of the high costs.

GPS-loggers are seemingly fully developed; no functionalities are expected to be added or removed, and as long as they continue to be produced they can be used in national travel surveys. This collection method is therefore **future sustainable**, but under the condition that the associated software is regularly updated (it must remain compatible with the latest versions of Windows, for example). If this does not occur, the software will not function properly on the PCs/operating systems that respondents use at home. The question is to what extent market parties will continue to maintain a fully developed collection method[8].

A national travel survey using GPS-loggers cannot be considered separately from the prompted recall survey. In the current OViN, it is consistently difficult to find enough respondents. If the prompted recall survey is made shorter and easier, this could serve to bolster the collection method's future sustainability.

Improving the underlying algorithm could potentially make the prompted recall survey shorter and easier, thereby reducing the response burden and enhancing the data quality. The scientific focus is therefore primarily on developing better algorithms. Work is currently being done to develop the algorithm's ability to learn; however, this development would have little impact in a one-day research study, such as the OViN.

- Summary: GPS-loggers are now and in **future** suitable for national travel surveys. One issue is that the software must be kept up-to-date. Improvements will primarily be made to the underlying algorithm.

5.2b Overview evaluation table for GPS-loggers

As based on section 5.2a, the collection method's key characteristics for the OViN were assessed. A +, - or 0 are used to indicate if this method is expected to score better, worse or comparably, as compared to the current collection method.

GPS-loggers		
Characteristic		**Evaluation**
Information need	Monitoring	0
	Explaining	0
	Modelling (OD-patterns)	+
	Modelling (choice models)	0
Quality		+
Future sustainability		0
Costs		-
Quantity		0
Privacy		-
Response burden		0

[8] It rather frequently occurs that certain products are no longer supported, for example Windows XP.

Generally, GPS loggers are suitable for use in the OViN, and this would result in improvements to a number of points. Costs are likely to increase, however. With an eye toward the future, GPS-loggers are deemed to be a stable collection method, as is the current OViN.

5.3 Smartphone technology

5.3a Challenges associated with the use of smartphone technology

The first (known) experiment using smartphones to collect trip data occurred in Florida in 2007 (Bricka et al., 2014). Fourteen respondents participated; the primary purpose of the test was to demonstrate the potential uses of smartphones in national travel surveys. Since that time large amounts of literature have become available and numerous smartphone applications were developed.

At issue here then is a relatively new collection method that contrasts with the GPS-logger, which, apart from the algorithm, is fully developed[9]. Because smartphone technology is still being developed, the focus here is on a closer examination of two specific challenges for smartphones; this primarily pertains to battery use, which numerous articles cite as a challenge (Geurs et al., 2014; Montini et al., 2014a; Zhao et al., 2014). The second focal point is the wide range of available smartphone brands; however, experiences on this point differ (Montini et al., 2014a; Geurs et al., 2014; Safi et al., 2014; Thomas & Geurs, 2014).

There are two main reasons why **battery use** is an extremely relevant characteristic of a smartphone application. First, battery failure leads to underregistration. Thomas and Geurs (2014) found the number of rides recorded via their MoveSmarter app (see Box 3) was approximately 20 percent lower than the number of rides following a prompted recall, and that this percentage was higher for longer rides and for the last ride of the day, indicating that battery failure was the underlying cause. Montini et al. (2014a) found that respondents turned off the app as soon as they noticed their smartphones threatened to run out of battery, which resulted in underregistration.

BOX 3: Examples of trip apps
This box presents various smartphone applications that are used in trip research.

A. Name: MoveSmarter. Developer: University of Twente and Mobidot (Netherlands). Described in: Geurs et al. (2014) and Thomas and Geurs (2014).
MoveSmarter automatically records trips. This also applies to uploading the raw data and the feedback via prompted recall. Imputation algorithms are used for the transport modes and trip purposes. This app was tested for a few weeks on a representative sample (n=600), selected from the Dutch LISS panel. Rather remarkably, this occurred for three consecutive years (2013-2015). Mobidot is moreover involved in Bicycle Tele-week, in which cyclists use this bicycle-app to record their bike rides. This app shares many similarities with the MoveSmarter app.

B. Name: Future Mobility Survey (FMS). Developer: Singapore-MIT Alliance for Research and Technology (Singapore). Described in: Zhao et al. (2014), Dias et al. (2014) and Carrion et al. (2014).
FMS works in a similar way as MoveSmarter, and also uses imputation algorithms and prompted recall. The app was tested both longitudinally (for four months with eight volunteers) and cross sectionally (n=1500). Notably, the cross-sectional research was conducted in parallel with the Singaporean household research survey.

[9] The development of the algorithm is relevant for both GPS-loggers and smartphone technology, see section 5.1c.

C. Name: PEACOX journey planning application. Developer: IVT - Institute for Transport Planning and Systems (Switzerland). Described in: Montini et al. (2014a).
PEACOX is a project to achieve behavioral change, thus reducing CO2 emissions. The app works automatically, using imputation algorithms and prompted recall. Each respondent's trip logbook (n=31) was generated at night. This research is notable for the fact that the respondents recorded their trips with a GPS logger and the PEACOX-app.

D.Name: SmartMo. Developer: Verkehrplus GmbH (Austria). Described in: Berger and Platzer (2014).
SmartMo is an app that must be activated before the user departs, after which the measuring begins. Users enter the transport mode and trip purpose; no use is made of imputation algorithms. The app was tested (n=100) on a group of smartphone users (self-selection) for three days. A notable finding from the user evaluation was that battery use was deemed to be a very minor issue, which was perhaps owing to the fact that app only measured during trips.

E. Name: ATLAS II. Developer: The University of Queensland (Australia). Described in: Safi et al. (2014).
ATLAS II is a prompted recall app that does not use algorithms, but automatically starts/stops when the respondent travels. Afterwards, respondents are asked to fill in the transport modes and trip purposes. Safi et al. (2014) compared the app's performance with that of CAWI, GPS-logger, and GPS recording by smartphone without using a trip app (n=500). Respondents preselected two collection methods. Battery use was rarely deemed problematic.

The second reason why battery use is important pertains to the response burden. Geurs et al. (2014) found that half of the respondents in their travel survey (n=534) deemed battery usage to be disconcerting aspect, and this figure was even higher among respondents using loaner smartphones. One distinction here however is that this study lasted for four weeks, and that high battery usage for shorter studies may indeed be more acceptable. Dissatisfaction with battery usage could render people less willing to participate in research studies.

Owing to the probability of the smartphone failing (and thus also to respondents possibly dropping out), developers are striving to make their apps energy efficient. A number of possibilities exist for doing this, of which the following three are discussed here.

Firstly, measures can be taken to avoid the battery-intensive GPS; for example, if a person stays in a certain place for a longer period of time, the phone can be switched to Wi-Fi or GSM. However, this comes at the expense of accuracy (see sections 4.2a and 5.2a). The GPS starts as soon as the WiFi signal is lost. A risk is that the first part of the next trip will not be recorded (cold start). Additionally, Zhao et al. (2014) noted jumps in locations during long dwell times, resulting in unmade short rides. The reason was that respondents entered a building and the smartphone switched from the GSM base station. Similar unmade short rides were also found in the research of Montini et al. (2014a).

Secondly, the app can 'pause', which simply means that the app does not record the observations of the sensors. Montini et al. (2014a) took a rigorous approach to this by programming the app so that it stopped measuring between 22:00 and 06:00. Rides taken at night were therefore unrecorded. Thomas and Geurs (2014) attempted to make the app 'smarter' by inserting historical data; the sensors stopped measuring as soon as it seemed likely that the respondent had reached his destination, or that the respondent was engaged in a long (routine) ride whose destination was known. However, this approach only works in longer term research studies.

Thirdly, the possibility of using immediate feedback more intensively. This approach could also be used to remind respondents to take a phone charger with them and to charge their smartphones more often. This would not lessen the use of the app, but rather counteract the unwanted effects of battery failure

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(non-recording of rides). However, this approach does break the app's 'silence'. Berger and Platzer (2014) sent numerous respondents in their research study an SMS message three times a day to remind them to recharge their smartphones. The subsequent user evaluation revealed that this approach was ineffective and extremely disruptive. In terms of response burden, it is important to find a good balance in this respect.

- Summary, a balance appears to exist between battery use on the one hand, and data accuracy, data completeness and response burden on the other. These are issues that must be seriously considered in the research design and objective.

There are indications that high battery use is acceptable in short-term research, but that for longer term studies the respondents become annoyed and do not want to record their trips; that period of time was seemingly from 10 to 14 days (Montini et al., 2014a; Thomas and Geurs, 2014). Apart from battery usage, Berger and Platzer (2014) arrived at a compelling conclusion: the respondents in their research forgot to record the fewest number of rides on the third day (of a three-day study). This could possibly be due to either a learning effect or familiarity effect. However, it could also mean that in terms of data accuracy, data completion and response burden, the optimum duration for national travel surveys using smartphones is between three and ten days.

In addition to battery usage, the **wide range of available smartphones** is a focal point. Different operating systems, brands, and types of smartphones exist, and this means, firstly, that the software used in the research must remain up-to-date for all the various types. And this updating must occur quickly, because otherwise a trip app may cease to function. Secondly, and crucially for a national travel survey, the researchers must understand the relationships between the various smartphone types and the quality of recordings. Montini et al. (2014a) discovered a discrepancy between the various smartphone models in terms of number of valid GPS observations per minute. In research conducted by Safi et al. (2014), glaring differences were found in the percentage of deleted rides between the two operating systems - Android and IOS - used in the research. Geurs et al. (2014) found that the operating systems differed in terms of percentages of properly imputed transport modes; however, notably, this difference was not found in a follow-up study, for which no explanation was given (Thomas & Geurs, 2014). Ultimately, there is seemingly no clear answer to the question of what practical effect a wide variety of smartphones has on the quality of trip recordings.

5.3b The suitability of smartphone technology as collection method for the OViN

Samsung's slogan for the Galaxy S4 is Life companion, and for good reason: people virtually always have their smartphones with them. The phones are a type of life logger, and hence potentially a very useful tool in mobility research. The sensors in smartphones can be used to increase the accuracy and completeness of the recorded rides in a trip log, as compared to a trip logbook that is solely based on a person's memory and assessment skills. Consequently, the smartphone **data quality** is higher.

Some concerns do however remain about the data collection, and they (could) negatively impact the data quality. First, the GPS observations are incomplete; this can occur because the phone a) is located inside, b) has an empty battery, or c) takes time to start the GPS. In such cases it is necessary for the respondents to be asked, via prompted recall, to fill in the missing information.

Secondly, there is a risk of coverage error (Berger & Platzer, 2014), because not everyone in the Netherlands has a smartphone or wants to use their smartphones for research. Coverage error occurs when a particular population group cannot be included in the sample, resulting in a bias in the findings that detracts from the representativeness and diminishes the data quality. Providing people with loaner smartphones reduces this risk; however, respondents relatively often forget to take loaner smartphones with them (Thomas & Geurs, 2014). As further discussed later in this section, the differences in smartphone ownership rates among the various age groups is diminishing, and this is beneficial in terms of the representativeness of travel surveys using smartphones.

Thirdly, there is a risk of behavioural change in respondents. The reviewed literature reveals that respondents largely enjoyed participating in research studies (Berger & Platzer, 2014; Montini et al., 2014a), which, in and of itself, is positive, but the risk does remain that the respondents will want to test the app by taking extra trips. Some trip apps even purposely aim to influence behaviour, by reducing CO2 emissions or encouraging people to be more physically active, for example (Montini et al., 2014a). The sole aim of the OViN is to observe, and not to bring about change. The risk is that the study's accuracy will decrease, as it is no longer the 'routine' behaviour that is measured. However, this concern is far less applicable when only one day is being observed in the survey.

A fourth risk is that the type of smartphone, and hence the quality of the recorded rides, correlates with a person's income and trip behaviour (see paragraph 5.3a). Based on the reviewed literature, this cannot be ruled out. However, this issue should be addressed when conducting travel surveys based on smartphone technology.

In addition to data collection, it is also important to consider data imputation. A variety of apps exist (see Box 2), some of which predominantly use imputation algorithms, while others rely on input from respondents. Incidentally, there is not a single app that does not rely on the respondents' input; the apps do not work completely autonomously.

The previous section referenced the serious work being done to algorithmically improve the automatic recognition of rides within a trip, the distinction between trips and activities, and modality recognition. The discussion here pertains to false positives and false negatives, in which the findings adhere to the willingness of respondents to alter the imputed trip logbook. These findings are not apparent and demand further research by app developers, as they must determine the optimum value of certain parameters in their algorithms, such as those pertaining to dwell times.

Finally, the reviewed literature revealed that little attention has been devoted to the automatic recognition of trip purposes. Montini et al. (2014a) found that the imputed trip purposes were less often corrected than the imputed transport modes, but could not conclude that the algorithm used was more accurate.

- Summary: smartphones are more proficient than people at completely and accurately recording trips. Combined with imputation algorithms and prompted recall, trip logbooks can achieve a higher **data quality** than in current OViN. However, a number of risks are involved that must be taken into account.

In smartphone research, respondents are selected and personally approached, thereby making it possible to request additional information from them, including about socio-economic personal or household characteristics. Smartphones collect more detailed information about the respondent's trip behaviour, and, in a prompted recall app, additional information about each trip can be requested, such as number of travel companions. Consequently, this can provide for the same **information need** as the current OViN.

One possible additional advantage arises from the fact that the respondent's exact route is known, and this information can be used to analyse the travellers' route choices. Knowledge of the traveller's route choices can be helpful in improving the origin-destination matrices (OD-matrices) in traffic and transport models. A person's route choice is therefore currently estimated using a probability distribution function. Knowledge of the actual choice behaviour could test this probability distribution function.

- Summary: Smartphone research can potentially provide the same **information need** as the current OViN. Presently, it is important for the algorithmic to continue developing and for the integration of prompted recall to occur. Moreover, there are additional benefits, because more details about the trip route are known.

Privacy considerations are key in the respondent's decision to participate in a research study (Berger & Platzer, 2014; Eurostat, 2014). Because many details are available about the exact departure and arrival location and route travelled, it could transpire that a research participant refuses to participate in the study.

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What the research participants take into consideration can vary widely, hence it is possible that they may not trust the team of researchers. However, it is also conceivable that a research participant may want to conceal from his partner an illicit visit to a lover or to a pub, for example. Additionally, respondents initially use their own personal smartphones, which can have an even greater emotional impact on privacy. If this proves to be a reason for research participants deciding to drop out, a subsequent reaction could be to offer them loaner smartphones, although this increase the costs.

Privacy considerations can also impact how the recorded data is handled, and how it is communicated. Berger and Platzer (2014) offered respondents the opportunity to 'cut off' the beginning and end of their rides, therefore allowing them to conceal the exact locations of their homes.

From the reviewed literature, respondents were seemingly untroubled by the fact that their GPS-coordinates were continuously being stored (Berger & Platzer, 2014, Eurostat, 2014). In other studies, the privacy issue was not given much attention, which may indicate that the researchers did not receive any signs from respondents that they were concerned about their privacy. Because many respondents participated via self-selection, it is conceivable that those who did not respond had dropped out precisely because of their privacy concerns. Given the fact that more details are known about the respondents, this type of non-response could indeed be more prevalent than is the case in the current OViN.

- Summary: for respondents, privacy is a key consideration in their decision to participate in national travel surveys. Smartphone technology provides substantial amounts of detailed information about the respondents, and this occurs on the same level as in the current OViN. The risk is that a greater perceived impact on **privacy** arises, owing to the fact that respondents use their own personal smartphones. Additionally, owing to the self-selection of respondents, the impact on privacy in the literature may be underestimated. The impact on privacy is therefore seemingly greater than in the current OViN.

In order to use smartphone technology in mobility research, the respondents are required to download and install the application on their own smartphones. Moreover, they must ensure that the battery is fully charged and that they always have their smartphones with them. In particular, battery use increases the **response burden**, as shown by the experiences found in the literature (including Geurs et al., 2014; Montini et al., 2014a; Zhao et al., 2014).

The next step in the process is entering the rides and activities in the app. In some apps, the respondents must do this themselves (Berger & Platzer, 2014; Safi et al., 2014), while in other apps the imputation algorithms already fill in some of the information (Montini et al., 2014a; Thomas & Geurs, 2014; Zhao et al., 2014). Whether this requires a lot or a little effort depends on the quality of recorded rides and of the algorithmic. In both cases the response burden of completing a trip logbook is lowered because the respondents' memories and assessment skills are supported. One might even state that it is no longer a question of completing a trip logbook, but rather of only supplementing and correcting the logbook. However, this no guarantee of a lower response burden; it can also be difficult and burdensome to make corrections, especially when pertaining to shifting time periods and locations.

If the automatic ride recordings and associated algorithm are applied in the OViN, the response burden is consequently lowered, and it may be possible to convert the OViN into a multi-day research study, although it is beyond the scope of this literature study to delve deeper into the possible pros and cons of such action. Regarding the response burden, it was determined that battery usage is an issue that will ultimately irritate the respondents (see section 5.2b). Conversely, benefits can be derived from learning-algorithms, and by the fact that over time the respondents become more proficient in processing their trip data.

Unlike the response burden, the research burden has increased. Researchers in particular are responsible for developing accurate imputation algorithms. The success of location-trackers, including smartphones, as a tool in the mobility research is therefore partly dependent on the ability of researchers to derive accurate trip characteristics from the data (Srinivasan et al., 2009; Rasouli & Timmermans, 2014).

Moreover, it is difficult to compare the success factor of various algorithms, or the percentage of correct imputations (Kohla et al., 2014; Montini et al., 2014b).

Finally, using this collection method requires some basic knowledge of how to use smartphones, which, in practice, particularly applies to people who do not have their own smartphones or use them infrequently. However, even the somewhat more advanced smartphone users will have to learn how to operate the app. The more opportunities that respondents are given to alter their recorded rides, the more they must learn.

- Summary: the **response burden** is likely to decrease due to the fact that the respondents' memories and estimation abilities are supported. Technological developments - both to smartphones and algorithms – have a positive impact on the response burden.

Smartphones are widespread among the Dutch population. According to GfK, a research agency, around 10.6 million Dutch people over the age of 13 have smartphones, accounting for 80 percent of the total population. Among young people (13-17 years old), smartphone penetration now stands at 93 percent. Further, people aged 65+ are starting to close the gap: as of the end of 2015, 55 percent of people aged 65+ owned smartphones, which is a 10 percentage point increase compared to the end of 2014 (GfK, 2014; GfK, 2015). Although there are still large differences among various age groups, the gaps are becoming smaller.

Given that such large numbers of people now own smartphones, the **quantity** of potential respondents is seemingly not a problem. The fact that people may potentially drop out due to response burden or privacy concerns can mean that extra effort is required to obtain the required sample size. Conversely, the reviewed literature revealed that respondents enjoyed participating in research studies, which benefits the response rate (Berger & Platzer, 2014; Montini et al., 2014).

It is possible in principle to scale up smartphone research to the national level, for which there are three focal points. Firstly, the large-scale collection of GPS and other data requires a large amount of server capacity. If large amounts of data arrive simultaneously, server delays can result. It is however possible to monitor this and add server capacity as needed. Secondly, for the respondents who do not own smartphones or who cannot or do not want to make their smartphones available for research, loaner smartphones must be provided, which increases the research study's logistical operations. Thirdly, a wide range of smartphones are available; consequently, to ensure that trip apps work properly, the software must be updated quickly when new smartphones arrive on the market. It is possible that any new features in a trip app will not be supported on older smartphones. These focal points can be addressed however and primarily impact the associated costs.

- Summary: the popularity of smartphones means that there are enough potential respondents. Compared with the current OViN, it is not necessarily easier nor more difficult to generate a sufficiently large sample. Smartphone technology therefore scores similarly in the **quantitative** aspect.

In this study, **future sustainability** is classified as the sustainability and improvement of the collection method. In terms of sustainability, some uncertainty exists regarding the longer term (+/- ten years); this hypothesis is based on the experiences of the product lifecycles of GSM cell phones. In a 15-year time span (2000-2015), GSM cell phones conquered the market and then lost it again. It is not inconceivable that smartwatches and smartglasses will take over part of the current smartphone market. However, this does not mean that smartphones cannot be used for trip research, as, after all, apps can also be customised and used on new devices. The development of a technology that renders smartphones obsolete is certainly not inconceivable; however, it is virtually impossible estimate this risk.

Battery capacity is one of the characteristics that smartphone manufactures are currently working on. Part of any extra capacity would likely be reserved for new functionalities, but some will be devoted to helping extend battery life. Additionally, trip app developers and university researchers are working to improve the algorithmic, which will reduce response burdens and increase data quality. Work is also being done to give algorithms the ability to learn.

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- Summary: smartphone technology continues to develop and will only improve in **future**. A risk exists that smartphones will eventually be replaced by other devices, but it is exceedingly difficult to estimate that risk level.

Finally, no apparent improvement or worsening occurs on the **cost** level. Because a large share of respondents is expected to use their own personal smartphones, relatively few smartphones need to be purchased. Nevertheless, using smartphone technology means investments in hardware. Investments must also be made to develop and keep up-to-date the app and underlying algorithm.

Conversely, for cleaning up and imputing the data, it is likely that fewer man-hours are needed, because that process is further automated, which could also decrease the number of researchers, because response rates will increase due to lower response burdens.

- Summary: both **cost** increases and decreases occur; however, this is difficult to calculate and requires further study. Because both pluses and minuses exist, the cost effects in terms of convenience are estimated to be unchanged compared to the current situation

5.3c Overview evaluation table for smartphone technology

As based on section 5.3b, the collection method's key characteristics for the OViN were assessed. A +, - or 0 are used to indicate if this method is expected to score better, worse or comparably, as compared to the current collection method.

Smartphone technology		
Characteristic		**Evaluation**
Information need	Monitoring	0
	Explaining	0
	Modelling (OD-patterns)	+
	Modelling (choice models)	0
Quality		+
Future sustainability		+
Costs		0
Quantity		0
Privacy		-
Response burden		+

Overall, smartphones are suitable for use in the OViN, resulting in improvements on a number of points. The impact on privacy could be a reason for the respondents' unwillingness to participate in the research study. This is a key focal point in the communication with the research participants. In long-term studies, high battery use can result in a higher response burden and irritation among respondents.

6 Differences between the collection methods

Thus far national and international developments in the field of national travel survey data collection have been outlined. Additionally, the collection methods were assessed to determine the extent to which they are suitable for various key characteristics of the OViN. This chapter provides an overview of those assessments, before delving deeper into the differences between GPS-loggers and smartphone technology.

6.1 Overview evaluation of collection methods

Various definitions of passive and active data collection are found in the literature, as detailed in Chapter 3. The common denominator here is the personal involvement of the research participants. For five collection methods, Chapters 4 and 5 describe how location determination occurs, and which applications are used in national travel surveys. Moreover, the seven most relevant characteristics for the OViN were evaluated, in which a +, - or 0 are used to indicate if the collection method is expected to score better, worse or comparably, as compared to the current OViN. Table 6.1 provides a summary of these evaluations.

Tabel 6.1 Overview of the evaluation of collection methods. This is an ‘interim score’ derived from the practical experiences with active collection methods (Chapter 7) and definitely denoted in the conclusions (Chapter 8).

		Passive data-collection			Active data-collection	
Characteristic		**Smartcards**	**Data- and call-traffic**	**Social media**	**GPS-loggers**	**Smartphone-technology**
Information need	Monitoring	0	-	-	0	0
	Explaining	-	-	-	0	0
	Modelling (OD-patterns)	-	+	0	+	+
	Modelling (choice models)	-	-	-	0	0
Quality		+	0	-	+	+
Future Sustainably		0	+	-	0	+
Costs		-	-	0	-	0

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	Passive data-collection			Active data-collection	
Characteristic	**Smartcards**	**Data- and call-traffic**	**Social media**	**GPS-loggers**	**Smartphone-technology**
Quantity	+	+	-	0	0
Privacy	0	0	-	-	-
Response burden	+	+	+	0	+

In summary, the use of smartcards seemingly only covers a limited part of the information need, because in the Netherlands this only pertains to public transport trips. However, the data quality is high and the response burden low. It is important to remember when possibly opting to use smartcards for the OViN that Translink Systems must be willing to cooperate, and such cooperation will likely come with a price tag attached.

Data and call-traffic only covers a limited part of the information need, and this collection method is especially suitable for research studies in which data aggregation does not pose a problem, and knowledge about the individual respondent does not matter. Using data- and call-traffic is perhaps an added value for improving origin-destination matrices (OD matrices) in traffic and transport models.

Data analysis of social media also only covers a limited part of the information need. Moreover, doubts remain about the data quality, and the future sustainability (of each separate media platform) is uncertain. Social media could however be used to answer specific research questions for which the OViN is unsuitable, such as the modality choices of festival-goers.

GPS-loggers scored well on multiple fronts. The information need is fully covered and the data quality high. GPS-loggers moreover are a fully developed collection method, which has both advantages and disadvantages regarding future sustainability. Further, using GPS-loggers is likely to increase costs, while the impact on privacy is also heightened.

Finally, smartphone technology was also highly evaluated in terms of the information need, future sustainability and data quality. The impact on privacy could be a reason for respondents to decline to participate in the research study. Communicating with the research participants is a key focal point.
In long-term research studies, high battery usage can result in irritation among respondents and a higher response burden; however, this seemingly would not apply to the short-term OViN.

Overall, active collection measures score better than passive collection methods. The following section therefore delves deeper into the differences between the active collection measures. However, passive collection measures are not excluded; it is conceivable that the best way to achieve the research objective is through a combination of collection measures (Bricka et al., 2014, Eurostat, 2014; Rasouli & Timmermans, 2014). Smartcards for example can be used to validate imputed transport modes. Information about data- and call-traffic can be utilised at specific locations where the OViN has failed to provide sufficient information for satisfactorily modelling transport flows (OD patterns).

6.2 Comparing GPS-loggers and smartphone technology

Both smartphone technology and GPS-loggers are considered as promising elements in a renewed OViN. This section compares both collection methods to each other according to the four steps in the data collection process, in which it is assumed that this pertains to smartphone applications that function as automatically as possible. Hereby, the differences between smartphone technology and GPS-loggers can be explained more clearly in comparison to a detailed description of the differences as based on the (seven) characteristics of collection methods.

The steps in the data collection process are:
1. Participation of the respondents
2. Detection of rides
3. Processing the data into a trip logbook
4. Feedback from the trip logbook

1. Participation of the respondents
The perceived impact on privacy and the response burden are two characteristics of a collection method that are deemed as important in the research participant's decision to participate or not. This study has revealed that both smartphone technology and GPS loggers have a greater impact on privacy than the current OViN. And with smartphones, this impact is perhaps even greater, as the starting point is that the respondents must use their own personal smartphones in the research. However, the literature review found that this seemingly did not negatively impact the response rates. Self-selection of respondents could obscure this fact, however.

The response burden in this stage of the research is approximately equal. In one scenario, a respondent must ensure that he installs an app and always has his smartphone with him, while in another he has an extra device. The distribution of GPS-loggers is expected to increase costs more than the (much smaller scale) distribution of possible loaner smartphones. However, there is an estimated higher risk of losing the (more expensive) smartphones.

Finally, a possible response benefit is that people have indicated that they enjoy participating in smartphone research[10] (Berger & Platzer, 2014; Montini et al., 2014a); although this could entail a selectivity and capacity effect, it nevertheless means a higher response rate. Unlike GPS-loggers, respondents can also use the smartphones apps for private purposes. Apps like Strava (cycling) and RunKeeper (running) are popular, as they let users know where and how fast they have gone.

Finally, it is important to monitor those who are unable or unwilling to respond via GPS-loggers or smartphones. In order to include these people in the survey, it is necessary to keep a trip logbook of the current type (CAWI / CATI / CAPI).

2. Detection of rides
One possible advantage that a smartphone has over a GPS-logger is that smartphones have a dual function, and therefore respondents are less likely to forget to take them with them. Montini et al. (2014a) tested this hypothesis (n = 31) and rather remarkably concluded that the smartphone recorded rides on fewer days. Respondents indicated that they had turned off the app during an activity, in order to save battery power; however, at the start of the next trip, they forgot to restart the app. A key point to note here is that this research study covered a period of eight weeks. Battery usage mainly resulted in a higher response burden in longer term research studies, because people noticed the app was causing their battery to run down sooner, which they found irritating. Any possible use in the OViN would be for a significantly shorter period of time, hence resulting in less irritation and a higher likelihood that respondents would not turn off the app.

A disadvantage for both GPS-loggers and smartphones is that the technology may fail, which for example can occur due to an empty battery or the blocking of GPS signals. Battery usage on its own is an advantage for the GPS-loggers, but a smartphone user has a stronger incentive to ensure that his smartphone battery is charged. Loss of the GPS signal can occur for both devices to a comparable (but limited) degree, because both are equipped with various sensors (including GSM and WiFi). Additionally, the server storing the data may fail, but this is separate issue from the differences between both collection methods.

[10] Storm et al. (2015) studied factors that impacted the success of mobility applications. They concluded that such applications primarily succeed when there is benefit (the product is useful, the user is engaged), convenience (the application is easy to use, its use is self-evident), and enjoyment (a nice deisgn, opportunities for play and enjoyment, etc).

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The literature reveals that GPS-loggers have better sensors than smartphones and thus provide more accurate recordings. The difference in the sensor quality is primarily related to the required physical space within the devices; there is a relatively small amount of space in smartphones. A smartphone is therefore more likely to experience signal loss. Moreover, in border regions, smartphones can switch between a foreign and Dutch telecom provider, which can come at the expense of the quality of GSM data. Finally, owing to battery usage, recording trips with a smartphone is usually limited to the minimum that is required. Montini et al. (2014a) revealed that the average GPS recordings per minute by GPS-loggers were higher than those of smartphones. All told, a GPS-logger is currently more accurate than a smartphone. However, it is expected that in the coming years smartphones will overcome this technological deficit[11], and this will primarily be due to the further development of battery capacity. One uncertain factor in this process is the extent to which this additional battery capacity will be used for other smartphone applications.

3. Processing the data into a trip logbook

Section 5.1b describes the three steps that can occur when creating a trip logbook. The first step is cleaning up the raw data, followed by identifying the trips and activities, and, finally, identifying the transport mode and trip purpose. In this respect, smartphones and GPS-loggers are similar in their methods. Both use a combination of imputation algorithms and prompted recall (see step 4); however, they differ in how the data is uploaded. With GPS-loggers, data can only be uploaded via USBs and PCs, or via GSM (if the logger is equipped with a SIM card). For smartphone technology, this occurs as standard via an internet connection.

4. Feedback from the trip logbook

Both collection methods are the same in that validating the data imputation occurs via a prompted recall survey in most research studies. To support the respondents' memories, they receive feedback about their travel behaviour, as based on the location trackers' recordings. Prompted recall is not perfect however and does contain misreporting, whether consciously or not. Zhao et al. (2014) for example found that respondents were slow to alter the rides submitted to the trip logbook, and this comes at the expense of data quality. If respondents must make many alterations, this means a higher response burden, which further emphasises the importance of accurate records and imputation.

The main difference between both collection methods is the ability that smartphones have of providing direct feedback. GPS loggers have a limited user interface, which only allows for information to be sent. The feedback from the trip logbook occurs via a browser and is therefore indirect.

The direct feedback offered by smartphones has several benefits. Firstly, a respondent can validate the data soon after completing his rides; consequently, minimal pressure is put on the respondent's memory. Secondly, at the start of the research study, respondents can be informed of the higher battery usage or of possible outstanding validations, for example. Thirdly, a respondent can be asked during a ride about his mode of transport, trip purpose, fellow travellers, parking costs and delays, which makes the data imputation process easier. Finally, a respondent need not complete a separate web survey; all procedures can be completed in the app, which benefits the user-friendliness and hence the response burden.

[11] As based on personal communication with Harry Timmermans (6 May 2015) and David Strnad (8 September 2015).

7 Practical experiences with GPS-loggers and smartphone technology

Chapter 6 concluded that from a theoretical perspective GPS-loggers and smartphones are most promising for the OViN. This chapter explores the various practical experiences encountered using GPS-loggers and smartphones; this involves examining the design of case studies, response rates, response burdens, and other relevant issues. As previously stated in Chapter 1, the reasons for considering alternative collection methods include the increasing unwillingness of people to participate in travel surveys and the higher burden that traditional approaches place on respondents. These insights are discussed below.

7.1 Practical experiences with GPS-loggers

This section addresses the various practical experiences encountered when using GPS-loggers as a method for collecting trip data. The focus is on the design, response rate, response burden, and other relevant issues.

7.1a Overview of case studies

Various case studies are used to examine the practical experiences, although they do not provide a comprehensive overview of the various applications of GPS loggers, which is consistent with the stated aim of revealing various insights and experiences. We used the following case studies to provide an overview of GPS-logger experiences. The case studies were selected partly owing to the availability of comprehensive reporting.

- **Case Study A: United Kingdom.** Conducted in the United Kingdom by the Department for Transport in 2008-2009 (Anderson et al., 2009);
- **Case Study B: United States of America.** Conducted in Cincinnati, Ohio Region, United States of America by the Ohio Department of Transportation and the US Department of Transportation (Stopher & Wargelin, 2012),
- **Case Study C: Innovation OViN.** A pilot project that was conducted as part of the OViN's innovation program (no further documentation available). This pilot was conducted using GPS-loggers, software and an online environment at Eindhoven University of Technology. The fieldwork was performed by TNS NIPO.

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Table 7.1 provides an overview of the design of these case studies, whereby trip data was collected using GPS-loggers. The table shows that the manner in which the data was collected and processed differs greatly among the various case studies. In *Case Study B (United States of America)*, respondents were only expected to manually enter part of their trip data for one day. In *Case C (Innovation OViN)*, respondents were asked to upload their data for all the days and subsequently correct the data. Finally, in *Case Study A (United Kingdom)*, the respondents were asked to not only to carry their GPS loggers with them for the full seven-day period, but also to complete a written diary; in this case study, the emphasis was on testing the feasibility, for which comparisons with the findings from a written diary were important.

Tabel 7.1 Overview of GPS-logger case studies

	Case Study A: United Kingdom By the Department for Transport	**Case Study: United States of America** By the Ohio Department of Transportation, US Department of Transportation	**Case Study: Innovation OViN** By the KiM Netherlands Institute for Transport Policy Analysis and Statistics Netherlands
BACKGROUND INFORMATION			
Year	2008 -2009 (2 waves)	2009 -2010 (continuous for 12 months)	2016 (1 wave)
GPS-logger	Atmel BTT08 GPS Data Logger	A specially developed GPS-logger	BT747 Logger
PROCESS			
Distribution of GPS-loggers	Delivered to respondents and picked up after the study's completion, in combination with interviews	Mailed to the respondents with the request to return after the study's completion	Mailed to the respondents with the request to return after the study's completion
Data collection and processing	• Collecting GPS-data during 7 days and collecting in a printed diary for the same 7 days • The GPS-loggers were collected at the end of the fieldwork stage, after which the data was collected by an external party for GPS-loggers • The processing of trip information was partly automated (with imputation algorithms) and partly manually with the help of mapping material • The resulting trip data was compared with the trips recorded in the printed diaries	• Collecting GPS-data for 3 days • The respondents returned their GPS-loggers, after which the data was collected by an external party of the GPS-loggers • The information was converted into trip information, including trip mode and trip purpose, with the help of software (including imputation algorithms) • The respondents were shown the trips for one day and asked to indicate the transport mode and trip purpose. This was checked with automatically generated trip information	• Collection of GPS-data during 10 days • Respondents were asked to download the information from the GPS-logger and then to upload on the server of an external party • The information was converted into trip information, including trip mode and trip purpose, with the help of software (including imputation algorithms) • Respondents were asked to check the data and correct if necessary
RESPONDENTS			
Invited respondents	The household members aged 16 and over, from 90 households, randomly selected from an address database	The household members aged 12 and over, from more than 5,564 households, randomly selected from an address database	160 households, selected from interested Netherlands Mobility Panel (MPN) panel members
Respondents' tasks	• Carry GPS-logger during trips • Complete diaries • Participate in interviews	• Carry GPS-logger during trips • Indicate for each trip for one day every transport mode and trip purpose, so that the imputed data could be checked • Completing questionnaire or telephone interview • Return the GPS-logger	• Installing of various software • Carry GPS-logger during trips • Upload the data every couple days, check and if needed correct the data • Completing questionnaire • Return the GPS-logger
Contact with respondents by organisation	Two interviews at home (start and end), letters and telephone interviews	Letters, telephone interview and e-mails	E-mails and letters

7.1b Response rates, response burden and other relevant issues

The response rate, response burden and other relevant issues are examined for each case study.

Case Study A: United Kingdom

In this case study, respondents were recruited via random selection from an address database. As such, 90 households were approached, for which the following applied:

- 66 households (73 percent) indicated that one or more household members were willing to participate in the research and thus carry a GPS logger.
- The remaining 24 households (27 percent) did not participate in the research study. The main reason for this was that the households were simply unwilling to participate. However, some households could not be contacted.

In the 66 responding households, a total of 121 household members agreed to participate; each of the household members received GPS-loggers and were asked to take them with them when taking trips. When the research study was completed, the GPS-loggers were retrieved. This study revealed the following:

- Approximately 74 household members (61 percent) indicated that they had carried the GPS-logger with them during all the trips they made on all the days of the research period.
- Approximately 33 household members (27 percent) indicated that carried the GPS-logger, but did not indicate on which days of the research period and/or for all trips.
- 14 household members (12 percent) were unwilling to participate. They indicated that they did not use the GPS- logger. However, it was later discovered that data was recorded on some of these GPS-loggers.

No data was available for six of the 107 household members who indicated that they carried the GPS-loggers with them, because the GPS-loggers were lost or defective.

In a subsequent evaluation conducted among respondents, 94 percent stated that they found it easy to use the GPS-loggers. Moreover, 53 percent stated that they did not experience any problems. The remaining respondents did experience problems, of which the most cited was a ‘talking GPS-logger’, whereby the GPS-logger emitted a signal when searching for a satellite, and this could not be completely deactivated. Other common problems cited included forgetting to take GPS-loggers with them, and that it was unpleasant to carry the GPS-logger. The respondents in this research study were asked to refrain from carrying the GPS-loggers in their bags, but rather to wear them around the neck, for example.

This case study also revealed a problem with the GPS loggers’ software, which altered the intervals by which the GPS data was recorded; this in turn made the data processing more difficult and hence had a detrimental effect on processing the recorded trips.

Case Study B: United States of America

In this large-scale case study, respondents were recruited via random selection from an address database. Ultimately, 5,564 households were recruited. This case study’s published reporting did not indicate how successfully the recruitment process transpired.

GPS-loggers were subsequently sent to 4,238 households. However, because not enough GPS-loggers were available, it proved impossible to provide all the recruited households with GPS-loggers. The household members of these 4,238 households were asked to take the GPS-loggers with them when taking trips and to then return the GPS-loggers. This study revealed the following:

- For 2,059 households (49 percent), there was a minimum of one day in which the GPS data was recorded for all household members or the household members had indicated that they had not travelled on that day.
- For 737 households (17 percent), GPS data was also recorded, but not for all household members.
- The other 1,442 households (34 percent) did receive GPS-loggers, but did not participate.

Some respondents were subsequently asked to check the resulting trip data; in fact, these were the respondents who had relatively quickly returned the GPS-loggers and whose email addresses were

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available. The report did not cite how many respondents were asked to check the data, but did report that 601 households ultimately checked the data.

The users' experiences were not discussed in the reporting of this case study.

Moreover, a practical problem of a more logistical nature emerged in this case study. In this large-scale project, providing all potential respondents with GPS-loggers proved to be a major challenge. The project ran continuously for a period of 12 months, and during that time span a GPS-logger had to be used by multiple respondents, which led to problems when the respondents either lost their GPS-loggers or returned them slower than expected.

Case Study C: Innovation OViN
For this case study, participants were recruited from the Netherlands Mobility Panel (MPN; see Hoogendoorn-Lanser et al., 2015). In another related research study in this panel, respondents were asked if they were interested in participating in a panel using GPS-loggers for a specific period of time. 67 percent indicated that they were interested.

Of these interested respondents, 160 people were selected, representative of gender, age and social class. Each of these 160 people were sent a GPS-logger. Compared to the other case studies, here the respondents had a larger role to play; they were asked to download software, to carry the GPS-loggers during their trips, to download data from the GPS-loggers, to upload these data in an online environment, and to then correct the data. This resulted in the following:
- 87 people (54 percent) uploaded data in the online environment for a minimum of ten days.
- 14 people (9 percent) also did this, but for a shorter period of time.
- 59 people (37 percent) did not upload any data in the online environment.

Some of these respondents also corrected the data.

This non-response was partly due to technical problems. Of the 160 people who had received a GPS-logger, 68 people (43 percent) contacted the help desk. The main reasons for contacting the helpdesk were problems with installing the software and problems with uploading the data. In some cases these problems could be solved, especially for those respondents who lacked the technical know-how required to install the software. Assisted by the help desk, in some cases it was still possible to install the software. However, there were also many cases in which the problems could not be solved, because the software was unsuitable for all operating systems; for example, respondents who used Windows 10 could not participate.

At the conclusion of the test period, the 160 people to whom GPS-loggers were sent were asked to complete an evaluation. Only 13 percent of the 134 people who subsequently participated in this evaluation indicated that they had not experienced any problems. In addition to problems with installing software and downloading data, other issues also arose, including, for example, that the GPS-loggers constantly made peeping sounds, the battery ran down too quickly, and the GPS-loggers proved uncomfortable to carry.

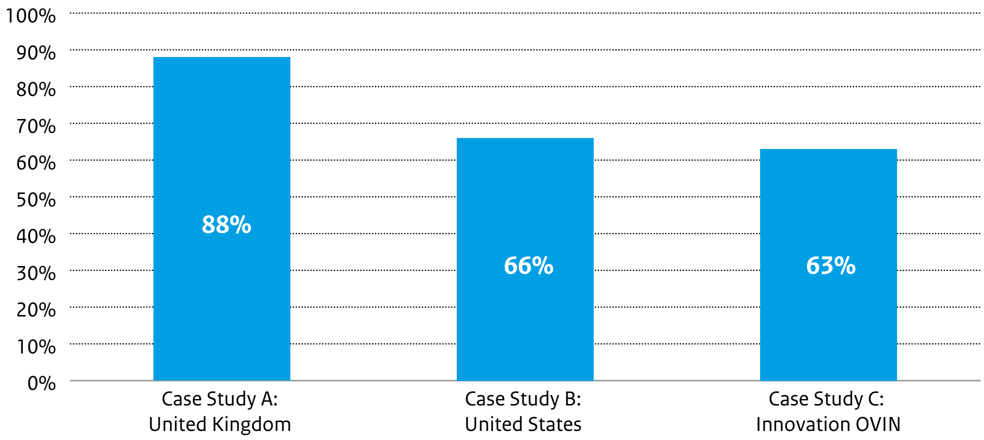
This case study encountered many technical problems, resulting in a high response burden that negatively impacted the data quality. Moreover, it transpired that the only people who could be invited to participate were those whose computers ran a Windows operating system, but even then software proved over the course of the research to be incompatible with all versions of Windows.

The three case studies in succession
Although the response rates in all three case studies were reported differently, this nevertheless provides a rough overview. There was reasonable degree of willingness to participate: for Case Study A (United Kingdom), of the 73 percent of households recruited via random selection from an address database, at least one household member agreed to participate. For Case Study C (Innovation OVIN, Netherlands), 67 percent of the MPN's invited panellists were willing to participate.

Each to the participants received a GPS-logger. Figure 7.1 provides an overview of the participation rates in the research study after receiving the GPS-loggers. These are defined per research study as follows:

- *Case Study A (United Kingdom):* 88 percent of those who had received a GPS-logger indicated that they had carried the GPS-logger with them for at least some of their trips.
- *Case Study B (United States):* for 66 percent of households who had received GPS-loggers, a minimum of one household member had recorded GPS data
- *Case Study C (Innovation OVIN):* 63 percent of the people who received a GPS-logger uploaded GPS data in the online environment.

Figure 7.1 Participation rate in the research study after receiving the GPS-loggers



The respondents' evaluations revealed a host of problems, including peeping and 'talking' GPS-loggers, the inconvenience of carrying GPS-loggers during trips, empty batteries, and software installation issues.

In addition to the technical problems, a practical problem of a more logistical nature also emerged. In the only large-scale project, providing all potential respondents with GPS loggers proved to be a major challenge, as the respondents either lost the GPS loggers or were slower to return them than expected.

7.2 Practical experiences with smartphones

This section details the various practical experiences encountered when using smartphones to collect trip data. The focus is on the design, response rate, response burden, and other relevant issues.

7.2a Overview of case studies

The various case studies revealed the practical experiences of using smartphones. As with the overview of the GPS-loggers, this does not entail a comprehensive overview of the various smartphone applications. Rather, the purpose of the overview is to highlight the insights and experiences, rather than to provide a comprehensive overview of all applications.

The following case studies were examined:

- **Case Study D: The Mobile Mobility Panel *(Mobiele Mobiliteitspanel)*** of the *University of Twente* (Thomas et al., 2014; Thomas & Geurts, 2015).
- **Case Study E: The SPOT project** of the *KTH Royal Institute of Technology, Sweco and Linköping University* and financed by the Swedish Transport Administration (Allström et al., 2016).

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- **Case Study F: In the Moment (ITM) Travel Study project.** This was a project of the *Madison 9 County Council of Governments (MCCOG) in Anderson, Indiana and the Federal Highway 10 Administration (FHWA) Office of Planning and Office of Transportation Policy Studies* (Greene et al., 2016).

These case studies were selected based on the fact that they were recently conducted and reporting was available. The Mobile Mobility Panel was also cited in a previous chapter of this report. As noted, this is not an exhaustive overview. The *Fietstel-app*, an app used to record bike rides[12], is another recent example. This app was developed by Mobidot, which also developed the app for the Mobile Mobility Panel. Further, various international developments include the Future Mobility Survey in Singapore (Zhao et al., 2015), a project of the Singapore-MIT Alliance for Research and Technology, the Massachusetts Institute of Technology. However, compared to the selected case studies, these case studies contain relatively few user experiences.

Table 7.2 provides an overview of the design of the case studies, in which smartphones were used to collect trip data. The table reveals that the amount of data collected automatically differs per case study. As such, respondents in *Case Study F (In the Moment Travel Study project)* were asked to indicate the transport mode and trip purpose. In *Case Study D (The Mobile Mobility Panel)* and *Case Study E (the SPOT project)*, software was used to automatically determine objective and purpose. Hence, logically, the respondents' roles also differ in the various case studies.

Tabel 7.2 Overview of smartphone case studies

	Case Study D. The Mobile Mobility Panel Conducted by the University of Twente	**Case Study E. SPOT project** Conducted by KTH Royal Institute of Technology, Sweco and Linköping University	**Case Study F. In the Moment Travel Study project** Conducted by the Madison 9 County Council of Governments (MCCOG) and the Federal Highway 10 Administration (FHWA) Office of Planning and Office of Transportation Policy Studies
BACKGROUND INFORMATION			
Year	2013, 2014 and 2015 (2 waves per year)	2015 (1 wave)	2015 (1 wave)
App	MoveSmarter app	Meli MCC app	rMove™ app
PROCESS			
Data collection and processing	• Collecting data via the smartphone of the respondent or with a loaner smartphone for a period of 2 to 6 weeks • Automatic processing of the data into trip information • Respondents were asked to check the trips and if needed correct in an online environment • On the first day of participation the respondents also filled in the online diary	• Collecting data via the smartphone of the respondent for a period of 7 days • Automatic processing of the data into trip information • Respondents were asked to check trips and if needed correct in an online environment • On the first day of participation the respondents also filled in the online diary	• Collecting data via the smartphone of the respondent for a period of 7 days • Locations and times were automatically collected using the smartphone • Each time a trip ended, the respondent was asked to indicate the transport mode and trip purpose in an app • At the end of each day the respondents were asked to complete a questionnaire in the app

[12] See http://fietstelweek.nl/ for more information.

	Case Study D. The Mobile Mobility Panel Conducted by the University of Twente	**Case Study E. SPOT project** Conducted by KTH Royal Institute of Technology, Sweco and Linköping University	**Case Study F. In the Moment Travel Study project** Conducted by the Madison 9 County Council of Governments (MCCOG) and the Federal Highway 10 Administration (FHWA) Office of Planning and Office of Transportation Policy Studies
RESPONDENTS			
Invited respondents	Approximately 800 people, selected from the Longitudinal Internet Studies for the Social Science (LISS) panel of CentERdata. It specifically involved panel participants who had expressed interest in smartphone research	1,559 people who had expressed interest were approached via a traditional diary-based travel study	478 people, selected from respondents who in a previous survey had expressed interest in participating in future research and who had completed a selection questionnaire for this specific research
Respondents tasks	• Downloaded the app • Took smartphone when taking trips • At least once during the 3 days to check the trips and if needed correct them	• Downloaded the app • Took smartphone when taking trips • Check and correct the data • Complete an online diary for one day • Complete questionnaire	• Downloaded the app • Took smartphone when taking trips • After each trip and at the end of the day answered various questions in the app • Complete a questionnaire (before and after as evaluation)

7.2b Response rates, response burden and other relevant issues

The response rate, response burden and other relevant issues are examined for each case study.

Case Study D: The Mobile Mobility Panel

This case study provides relatively little information about the response rate. Recruitment occurred among members of the LISS panel who had indicated an interest in smartphone research. In 2013, the first year of research study, approximately 800 people were invited, of which some 600 people (75 percent) ultimately participated. The participants downloaded an app, took their smartphones with them during their trips, and partially verified and corrected their imputed trip data.

A users' evaluation in 2015 revealed the following:

- 11-13 percent of respondents who used their own smartphones indicated that they had forgotten to bring their phones with them, compared to 22 percent of respondents using loaner smartphones.
- According to 57 percent of respondents, at least 70 percent of the recorded trips were correctly displayed by the app. According to 10 percent of respondents, this accounted for at least 90 percent of the recorded trips.
- 30-42 percent of respondents indicated that the app had detected the correct mode of transport. This percentage differed per type of smartphone: 30 percent for the Samsung Gio loaner smartphones, 32 percent for respondents using their own personal Android phones, and 42 percent for respondents using their own iPhones.
- 24-52 percent of respondents indicated that the battery usage was (very) high. This percentage differed per type of smartphone: 24 percent for the Samsung Gio loaner smartphones, 32 percent for respondents using their own Android phones, and 52 percent for respondents using their own iPhones. However, for 31-60 percent of respondents, the battery usage was (extremely) irritating. This percentage also varied per type of smartphone: 60 percent for Samsung Gio loaner smartphones, 48 percent for respondents using their own Android phones, and 31 percent for respondents using their own iPhones.

Of note in this case study is that the findings differed between respondents who used their own smartphones and respondents who used loaner smartphones. As such, the respondents using loaner

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smartphones recorded significantly fewer rides per person than did the respondents using their own smartphones. In addition to the loaner smartphones, only respondents with Android phones or iPhones participated.

Case Study E: SPOT project

For this case study, the respondents were approached via a traditional national travel study, resulting in 1,559 people who expressed interest in participating in a research study. It was found that people were more likely to express interest if they could provide their email addresses at the conclusion of an online questionnaire, instead of having to send an email to an email address included in a printed letter.

Subsequently, 495 of these 1,559 people (32 percent) ultimately decided not participate in the project. The following reasons were cited for their dropping out:

- Some of these people seemingly only wanted more information about the project rather to actually participate.
- Only people with Android phones and iPhones could participate.
- Because the app was not available on time in the Appstore, iPhone users were initially told they could not participate. When the app became available a day later, the iPhone users were informed that they could still participate. However, this may have lowered the response rate.

Ultimately, only 293 of the 1,559 people (19 percent) collected trip data with their smartphones. The primary reason indicated for dropping out was that the iPhone version of the app did not work properly due to the installation of a newer version of the operating system (iOS 9.0). This new installation only became known a few days before starting the data collection, leaving no time to modify the app.

An evaluation among the 303 participants revealed the following insights:

- 87 percent experienced no problems installing the app.
- 62 percent did not experience any major differences in their smartphones' battery use as result of participating in the travel survey. Further, 21 percent indicated that they had to uploaded somewhat more frequently on their smartphones, while 17 percent indicated that they had do this much more than otherwise.
- 60 percent indicated that they had collected their trip data throughout the entire week. Those who failed to do this gave the following reasons, ranked from frequently to infrequently cited: 1) The app did not work as expected, 2) The app used too much battery, 3) reasons of integrity, 4) the trip app slowed down their smartphone. The integrity reasons were not specified; this was perhaps due to privacy-related concerns.
- Around 70 percent gave a negative score to the online environment they used for checking and correcting data; this turned out to be primarily due to the speed of the website and other technical glitches, as well as a lack of user-friendliness.
- As for the question of what people found 'more intrusive', collecting trip data with a smartphone or via an online diary, 43 percent indicated that they found the using the smartphone 'more intrusive', while 55 percent found no difference between the two methods.

Participation in the project was limited to people who had Android phones or iPhones. However, problems with the iPhone app occurred, thus limiting the participation.

Case Study F: In the Moment Travel Study project

The potential respondents in this case study were selected based on their interest in travel research and their willingness to participate in this specific research study. Consequently, 478 people were invited, of which 295 people (62 percent) actually downloaded the app. Of all the invitees, 240 people (50 percent; 240 out of 478 people) delivered data for all the days and answered questions.

During the study, the respondents were specifically asked about uninstalling the app and the reward they were offered as compensation for their participation. A third topic involved technical questions, for example, relating to the uncertainty about how to turn off the app.

Respondents were asked for feedback, from which comparisons were made with the completing of an online or telephone survey conducted the year previous. 87 percent of respondents indicated that it was easy to participate in the smartphone research, while this figure was 66 percent for the more traditional methods. In terms of time spent, 52 percent indicated that the smartphone study required less time than the more traditional research study (in which data was collected for only one day). However, 23 percent did not agree that the smartphone survey required less time

The users were also asked about switching off the GPS or WiFi on their smartphones. 31 percent indicated that they had occasionally switched off the GPS or Wi-Fi in order to save their batteries, while 6 percent indicated they had occasionally switched off the GPS or Wi-Fi due to privacy concerns. The respondents were also asked about what could be done to improve the research, and battery use was most commonly cited.

Respondents could only participate if they had Android phones or a newer iPhone.

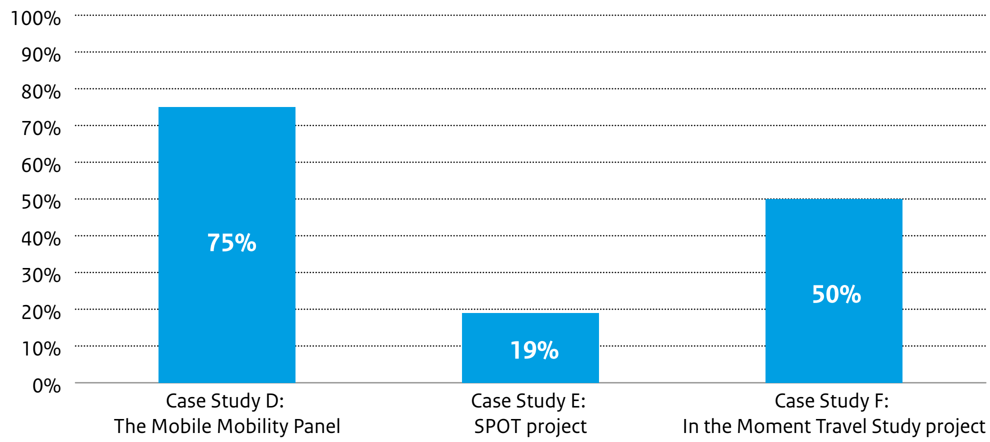
The three case studies in succession

Although the response rates in all three case studies were reported differently, this nevertheless provides a rough overview.

In all the cases studies, the people invited to participate had previously indicated their interest in such a research study. Figure 7.2 provides an overview of the participation in the research. This is defined per research study as follows:

- *Case Study D (The Mobile Mobility Panel):* 75 percent of the invited people downloaded an app, took the smartphone with them during their trips and partially checked and corrected their trip data.
- *Case Study E (SPOT project):* 19 percent of people who expressed interest in the research study downloaded the app, took the smartphone with them during their trips, and likely verified and corrected their trip data.
- *Casus Study F (In the Moment Travel Study project):* 50 percent of invited people downloaded the app, took the smartphone with them during their trips, and answered questions after the trips and at the end of each day.

Figure 7.2 Participation in the research after being invited.



The difference in the response rates between the SPOT project and the In the Moment Travel Study project can partly be explained by the fact that SPOT encountered problems related to the iPhone app.

The evaluations among respondents revealed a variety of different experiences. Both positive and negative experiences were associated with battery use. These experiences differed according to the type of smartphones the respondents used: a loaner smartphone or their own personal smartphones, and an Android phone or an iPhone. Respondents were also asked to compare their experiences with another research study they had previously participated in, in which data was collected in a traditional manner – via online or telephone surveys. Here, too, the experiences varied: the respondents' experiences differed in terms of convenience and the time required when using smartphones and a traditional approach.

7.3 Discussion

This section addresses the following question: does the use of GPS-loggers or smartphones actually reduce the response burden and increase response rates, as compared to the traditional collection methods? Other pertinent issues arising from the practical experiences are also addressed.

The case studies revealed that the use of GPS-loggers and smartphones can result in a considerable response burden. For GPS-loggers specifically, the respondents encountered the following problems: peeping and 'talking' GPS-loggers, the inconvenience of carrying GPS loggers during trips, empty batteries and technical problems related to installing software, and the online environment. For smartphones, different experiences emerged. Thus, both positive and negative experiences pertained to battery use. The respondents' experiences also differed in terms of convenience and the time required when using smartphones as compared to a traditional approach.

More generally, the response burden differs greatly for each application. Overall, GPS-loggers are more burdensome than smartphones, as respondents are unfamiliar with these devices. And this also applies when loaner smartphones are used. What tasks the respondents were expected to perform was another key difference between the case studies. In the OViN innovation program, respondents were required to install various software tools, which was highly burdensome. This was not the case for the other case studies. In all case studies the respondents were asked to check and/or provide supplemental information. The resulting burden varied per case study, depending on the number of days the respondents had to check, and the user-friendliness of the online environment in which this checking occurred. Although the response burden differed greatly per case study, it is unlikely that the use of GPS-loggers and smartphones will significantly reduce the response burden as compared to a traditional approach.

It is difficult to assess whether the use of GPS-loggers or smartphones leads to an improved response rate, as this largely depends on the more traditional case study being compared. Of note is that many case studies recruited people who had previously expressed interest in such research; hence, self-selection occurred, and this applies to all the smartphone-related case studies cited this report. This means that in these case studies the tests were conducted among a specific target group. If random recruitment had occurred from an address database, the response rate may have been lower and other experiences also encountered.

In addition to insights into the response rate and the response burden, other issues also arose. A number of case studies – using both GPS-loggers and smartphones – experienced technical problems, pertaining to the software installation and the online environment in which the trip data was corrected. The GPS-loggers also revealed a practical problem of a more logistical nature: in the large-scale case study conducted in the Cincinnati, Ohio Region, United States, providing all potential respondents with GPS loggers proved to be a great challenge. GPS loggers were lost or returned slower than expected. Of note in the case studies using smartphones was the fact that the findings differed among the respondents using their own smartphones and the respondents who used loaner smartphones. Moreover, it also became apparent that if a loaner smartphone was not used, only the respondents who had Android phones or iPhones could participate. Additionally, not all iPhone owners could participate for several reasons: namely, the app was made available too late, the app was only suitable for the latest model iPhones, and operating system was changed shortly before the data collection began, whereby the app could no longer be adapted.

8
Conclusions

This chapter presents conclusions as to whether the OViN can be switched to a different collection method than the existing one, and, if so, to what extent. Various focal points in a subsequent switch to alternative collection methods are also examined.

8.1 Active collection method are more promising for use in the OViN than passive collection methods

From a theoretical perspective, using active collection methods (GPS loggers and smartphone technology; see Figure 8.1 for an overview) is seemingly more promising than using passive collection methods (smartcards, data-and call-traffic, and social media). Active collection methods score well on multiple fronts, as previously stated in Chapter 6 (see Table 8.1 on page 57). The data quality is high and the information need fully covered, provided supplementary questionnaires/prompted recall surveys are used. However, there is a greater (perceived) impact on the respondents' privacy than in the current OViN. Moreover, using these methods in practice results in a high response burden, owing to various technical issues, high battery use (for smartphones), and unfamiliarity with the technology (GPS-loggers), for example.

Various restrictions are associated with using passive collection methods. Firstly, they cover only a limited part of the information need; for example, public transport chipcards only provide insights into the trips made via public transport that were paid for with public transport chipcards. A second limitation is that little information is known about the research participants; they are not personally involved, and consequently cannot answer supplementary questions nor verify their trips (via prompted recall), yet the ability to do so is crucial in terms of explaining perceived trends, for which the OViN is precisely intended.

Although on average the passive collection measures scored lower on the characteristics deemed important for the OViN, they could still be suitable for addressing certain research questions that the OViN is less suited for, or for supplementing observations from the OViN. For example, data- and call-traffic information could be used in traffic and transport models, providing information about those locations in the Netherlands that the OViN does not provide sufficient observations for to conduct detailed origin-destination pattern analysis (OD-patterns). Background information about respondents is less relevant to such research questions.

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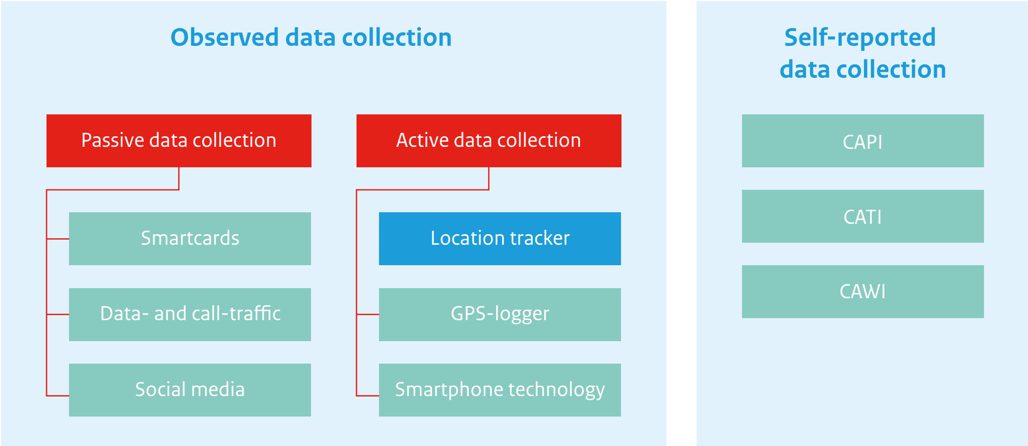
Figure 8.1 Schematic overview of the various types of collection methods.



8.2 Smartphone technology more promising for use in the OViN than GPS-loggers

8.2a Differences in approach when using GPS-loggers and smartphone technology

GPS-loggers and smartphone technology are location trackers. Both technologies can establish a person's location, by means of GPS, GSM, Wi-Fi, gyroscope and accelerometers. These observations are then used in imputation algorithms that determine a person's transport mode and trip purpose. Because algorithms are not always capable of discovering the ground truth, namely the respondent's actual travel behaviour, prompted recall surveys are used as a supplement. The respondent receives feedback on his (imputed) trips and is asked to correct the trips where necessary, and this helps in the process of completing the survey. The use of prompted recall is however no guarantee that the actual trip behaviour will be identified. Respondents make mistakes, whether consciously or not, as is also the case in the current OViN.

There are essentially three main differences between GPS-loggers and smartphones. Firstly, the respondent receives a separate measurement device when using GPS-loggers, while using smartphones only requires an app to be installed. The practical case studies revealed that the respondents occasionally forgot to take the GPS-loggers with them or even lost them. Because smartphones are also used privately, respondents are more likely to take them with them.

Secondly, the use of smartphones allows the respondents to receive direct feedback. For GPS-loggers, feedback occurs indirectly, for example, via a respondent's PC, because the logger has a limited user interface. This direct feedback via smartphones means the respondents can be contacted before, during or shortly after a trip. As such, the respondents can quickly proceed to the prompted recall survey.

Thirdly, battery use differs substantially. A GPS-logger can work well on a full battery for a few days. Conversely, smartphones must contend with increased battery use by the trip app, as was also apparent in the practical case studies. However, that smartphones are also used privately is advantageous, in that respondents are highly incentivised to ensure their smartphones have full batteries.

8.2b Impact of the various approaches

Observed differences emerge in the process of conducting a national travel survey using GPS-loggers or smartphone technology. First, the fact that respondents do not have GPS-loggers means that these devices must be sent to them. High costs are associated with distributing GPS-loggers; a simple calculation reveals that the shipping costs alone for a survey the size of the OViN will run into the hundreds of thousands. That respondents must also take the GPS-loggers with them also increases the response burden, as the practical case studies revealed.

As stated, when using smartphones, the direct feedback to/from respondents ensures that submitting the (imputed) trips for verification occurs fairly easily, and at a time when the trips are still fresh in the respondent's memory, which benefits the response burden. Moreover, respondents need not upload the recorded data, which is frequently the case with GPS loggers.

In contrast, owing to a smartphone's limited battery capacity, the chosen frequency for recording trips in the trip app is relatively low. GPS is avoided as much as possible to save the battery. The reviewed literature also revealed that respondents occasionally switch off the app in order to save the battery, but then subsequently forget to restart the app when starting a new trip. This can compromise the data quality and increase the response burden when completing the prompted recall survey. Smartphone manufacturers however have an interest in increasing battery capacity; consequently, it is likely that progress will be made in this area in the near future. Additionally, battery use particularly comes into play in long-term research studies. The OViN however currently takes only one day to complete, which is beneficial in terms of the higher response burden associated with higher battery usage.

The overarching OViN innovation program - of which this study is a part - aims to increase the data quality of trip information and/or decrease the associated costs of data collection. Overall, smartphone technology is expected to produce higher data quality and lower response burdens than is the case when using GPS-loggers. Moreover, the cost of using GPS-loggers is likely to be higher. Smartphone technology is therefore considered to be a more promising application in the OViN.

In conclusion, Table 8.1 provides a definitive assessment of the collection methods' various characteristics, as compared to the current collection method. It is an update of Table 6.1, as the practical experiences (Chapter 7) necessitated some downward adjustment of the assessments. At issue are the costs and response burden (indicated in red).

Tabel 8.1 Overview of the definitive assessment of collection methods.

		Passive data-collection			Active data-collection	
Characteristic		**Smartcards**	**Data- en call-traffic**	**Social media**	**GPS-loggers**	**Smartphone-technology**
Information need	Monitoring	0	-	-	0	0
	Explaining	-	-	-	0	0
	Modelling (OD-patterns)	-	+	0	+	+
	Modelling (choice models)	-	-	-	0	0
Quality		+	0	-	+	+
Future sustainability		0	+	-	0	+
Costs		-	-	0	-	-
Quantity		+	+	-	0	0
Privacy		0	0	-	-	-
Response burden		+	+	+	-	0

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8.3 Smartphone technology owns the future

Various parties are engaged in the development and application of smartphone technology, including improving battery use and the imputation algorithms. Large-scale field tests are also being conducted; one such example is the In the Moment Travel Study project (see Chapter 7). Consequently, experience is gained and all manner of practical problems brought to light. If this development and application in practice proves successful, the possibilities for collecting trip data with smartphones will be enhanced. In knowing that the number of people with smartphones continues to increase, it can be said that smartphone technology owns the future.

There are however various focal points to consider when using smartphone technology in large-scale studies, such as the OViN. For example, a wide range of available smartphones and corresponding operating systems exist. This must certainly be taken into account; if not, it could have potential repercussions for the representativeness and hence quality of the data. Work must also be done to keep the software up-to-date, so that the trip apps will function properly on smartphones, which the users keep updated. This must also occur quickly and satisfactorily. In this regard, specialist knowledge and support for the respondents (for example, a helpdesk) is required.

In terms of the representativeness (and corresponding data quality), it is important to take into account the research participants who do not want to or cannot participate in research using smartphones. Using active collection methods has a greater impact on the respondents' privacy, and this could be reason for participants to refrain from participating in the OViN. In order to ensure that these people can still participate, researchers can revert to Computer Assisted Web Interviewing (CAWI), Computer Assisted Telephone Interviewing (CATI) of Computer Assisted Personal Interviewing (CAPI), for the sake of the sample's representativeness. The same holds true for the research participants who do not have smartphones or are unable to install the required software: the standard trip logbook is a suitable fall-back option for these people. The use of smartphone technology, in combination with the traditional types of self-reported data collection (as in the current OViN), is therefore certainly conceivable.

The use of smartphones provides more personal details about the respondents than is currently the case in the OViN. The expected impact on privacy is therefore greater. Communicating with the research participants about (the impact on) privacy is therefore a key focal point of any possible implementation. Of note however is that in the practical case studies, privacy concerns did not appear to be a barrier preventing respondents from participating in the research study.

Finally, implementing this new collection method requires changes to the OViN's organisation. As previously stated, an app (+ updates), tailored to the OViN, must be developed. However, this not a core business of Statistics Netherlands (CBS) nor the Ministry of Infrastructure and the Environment; consequently, collaboration with external partners is required. Moreover, work must be done on integration in the data collection process. All told, much needs to occur. It is advisable to devote the requisite time to this.

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