The potential of smartphone data for national travel surveys

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Abstract

Large scale travel surveys are important to understand travel demand and are a necessary input for efficient transport policies. The Swiss government collects travel data since 1974. The last data collection took place in 2015 using computer assisted phone interviews (CATI). A large literature has identified disadvantages of these surveys (respondent fatigue, missing trips, high costs and non-panel nature) and suggests using data from an App on the smartphone of the respondent. An App gives access to sensor data, including GPS. The prevalence of smartphones in the population is large (78% of the population between 15 and 74 years old in Switzerland in 2016) but challenges still exist before using smartphone data in an official representative large scale survey. In this paper, we study the advantages and disadvantages of this approach in the framework of the Mobility and Transport Microcensus (MTMC), including the usage of prompted recall; the detection algorithms used; existing Apps; the response rate and the quality of the collected data. As a conclusion, we provide a roadmap for a large scale application in national travel surveys.

Keywords

travel survey, smartphones, Mobility and Transport Microcensus (MTMC), computer assisted phone interviews (CATI)

1 Introduction

In 2015, the Swiss administration ran a national travel survey, the "Mobility and Transport Microcensus" (MTMC), using a computer assisted telephone interviewing (CATI) procedure, contacting about 106'889 people and interviewing on the phone 57'090 participants. In this introduction, we present the MTMC (Section 1.1) and describe its limitations (Section 1.2).

Further in this paper, we describe the potential and limitations of collecting and analyzing smartphone data for national travel surveys. The first attempt to use mobile phones with GPS capabilities took place in 2001 (Hato and Asakura, 2001, Murakami *et al.,* 2012). Is enough research done to integrate smartphone data in official statistics?

1.1 The Swiss Mobility and Transport Microcensus (MTMC)

Data about mobility behavior are regularly collected by the Swiss government, using the MTMC or stated preference surveys. The MTMC takes places every 5 years since 1974. It is conducted by the Swiss Federal Statistical Office (FSO) and the Swiss Federal Office for Spatial Development (ARE). The last data collection took place in 2015 (OFS/ARE, 2017) and the next one will happen in 2020.

The MTMC data are collected with the following objectives:

Understanding behavior Based on the MTMC data, behavioral models can be built to better understand the behavior of the population and the factors influencing this behavior.

Detecting trends Detecting time trends in mobility behavior. It requires a stability in the questions, in order to be able to compare the different editions of the MTMC.

Providing input data for decision-aid tools Decision-aid tools are built for policy questions about transport and land use from the MTMC data. A typical example is the national passenger transport model[1] developed by the Federal Office for Spatial Development. This kind of models helps developing transport outlooks, forecasting future traffic and testing scenarios. A typical example here is the Transport Outlook 2040. It draw up scenarios for passenger and freight development up to 2040, based on the MTMC data of 2010 (Federal Office for Spatial Development, 2016).

[1] "Modèle national du trafic voyageur" (MNTP) en français, "Nationales Personenverkehrsmodell" (NPVM) auf Deutsch, "modello del traffico viaggiatori a livello nazionale" (MTVN)

Evaluating past decisions By determining the passenger transport performance, strategies and policies in the field of mobility and transport are evaluated and adapted.

The questions of the MTMC are about:

- socioeconomic characteristics of the households and the individuals;
- mobility tools (number of vehicles, driving license, season tickets, ...);
- trips and activities for a reference day (usually the day before the phone interview);
- occasional trips;
- political opinions about transportation and mobility in Switzerland.

A sample of more than 57’000 interviewed persons and the large list of questions makes it one of the largest and most complex surveys in Switzerland. The MTMC data are used by the public administrations at the national and local levels, by the transport industry and by researchers (see e.g. recently Bucher *et al.,* 2016, Cellina *et al.,* 2016, Ciari *et al.,* 2016, Fernández-Antolín *et al.,* 2016, Joly and Vincent-Geslin, 2016, Kowald *et al.,* 2016, Vincent-Geslin and Ravalet, 2016, Bruderer Enzler, 2017).

The MTMC uses a CATI data collection procedure since 1994. Detailed trips are collected for one specific reference day. Since 2005, the destinations of the trips are geocoded during the interview. Since 2010, the chosen itinerary is collected during the phone interview using a mapping tool for trips by public transport and by car, but not for pedestrians nor trips by bike. In 2015, the interviews took place all along the year and the interview took about 26 minutes on average.

Participants were randomly selected. In 2015, only one person per household was questioned (minimum age: 6 years old). Once selected, this person first received a letter and then only was called. Some socioeconomic data were already known by the BFS from official registers before contacting the person, allowing to focus on additional information during the telephone interview. Participants without known phone numbers were asked to provide one by answering to the letter.

The Swiss Confederation (the central government) financed 41’000 interviews and the Swiss Cantons (the local governments) 16’000 on their territory. By doing this, some regions have more data and a better representation of the mobility of their inhabitants. This is particularly common for agglomerations. In order to guarantee the representativity of the MTMC data, households and individuals were weighted according to the different densities of interviews by region and the different participation rates of some groups of the population (e.g., young singles are difficult to contact).

Participation to the MTMC is not mandatory. The response rate was 53.4% in 2015. 106'889 persons were contacted. Among them, 33'367 persons were impossible to contact (letter not distributed, no phone number, etc.) and 16'432 persons refused or were not able to participate (e.g., language or health issues). With a Swiss population of 7'819'119 (6 years old and older) in 2015, this sample size covers 0.7%.

1.2 Critics about CATI surveys in the literature

Answering on the phone about the weather on the reference day, the departure time, the mode (including the type of car and the number of passengers, when the trip has been done by car), the detailed route, the destination, the cost of parking at the destination, the activity at the destination, and the reason why to choose this mode and not another one for all trip segments might prove long and cognitively difficult, in particular when the respondent is very mobile. Respondent fatigue in a CATI surveys is an issue. It leads to non-reported, missing trips and imprecise answers. It also prevents from asking respondents to describe more than one day (non-panel nature).

We describe here five critics about CATI surveys, which are also motivations to test a smartphone-based data collection: non-response rate, missing trips, low precision of the reported trips, the non-panel nature of CATI surveys and the cost.

1.2.1 Non-response rate

Non-response is an issue in all travel surveys. Non-respondents tend to travel more than the average (they are difficult to contact and have high opportunity costs) or are members of larger households (they consider the task as too burdensome) (Stopher and Greaves, 2007). According to Stopher and Greaves (2007), "A typical (good) computer-assisted telephone (CATI) survey in North America will usually achieve about a 60% recruitment rate, followed by a 60% completion rate for recruited households, representing an overall response rate of about 36%". The response rates of such traditional surveys are observed to decline (Bayart and Bonnel, 2012, Liao *et al.*, 2017).

In comparison, the MTMC has high response rates. Still, some groups are underrepresented, such as young singles. The response rates are difficult to compare. Between 1994 and 2010, the sample frame was a list of phone numbers provided by telecommunications providers. Households were selected in this list by geographical strata. Then, one or two members of the household were randomly selected. Participation rates can be compared in this time period (see Fig. 1) In 2015, the sample frame changed: a list of inhabitants of Switzerland was selected, contacted by mail, requested to provide a phone number and then only contacted on this phone number. The global participation rate was 53.4%. It cannot directly be compared with previous editions of the MTMC, but when estimating the participation rate similarly to 1994-2010, it reaches 64.6%.(see Fig. 1 and Appendix).

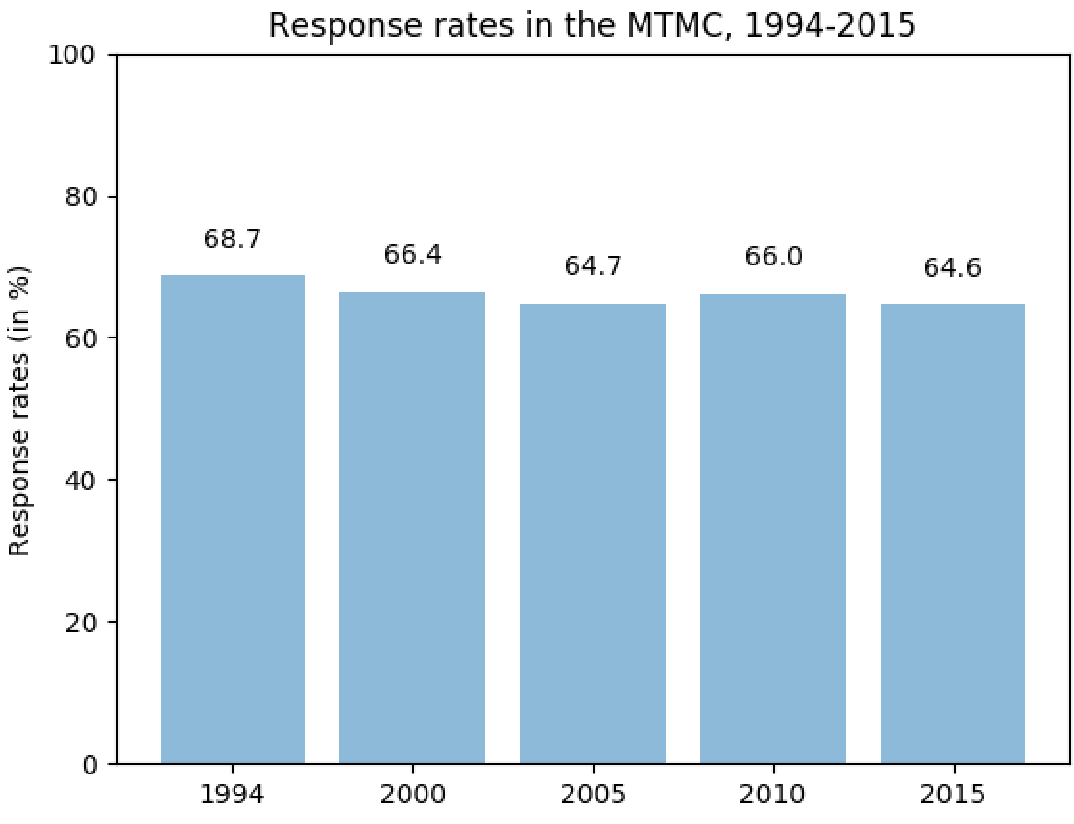

Figure 1: Participation rates in the MTMC, 1994-2015

The participation rate of the MTMC shows a very small decrease between 1994 and 2010. In 2015, the sample frame was modified in order to reach people on their mobile phones. A data collection using a smartphone App might still help to contact very mobile persons and assure high participation rates also in the future.

1.2.2 Missing trips

Respondents do not declare all their trips (Forrest and Pearson, 2005, Wolf *et al.,* 2003a). In comparison to data from dedicated GPS devices, standard trip-based CATI surveys are underreporting 20-25% of trips in the US and 7% in Australia (Stopher *et al.,* 2007). Short trips are particularly underreported (Stopher and Greaves, 2007), walking trips or trips in the afternoon. Missing trips are a bigger problem than imprecision in the characteristics of trips for modeling, since trip rate and trip generation are key elements in a traffic demand model (Wolf *et al.,* 2003a,b). A bias in a traffic demand model leads to a bias in investment decisions for transport infrastructures and to a wrong allocation of public money.

Smartphone data might help collecting these missing trips. In recent studies, 20% more trips are detected on average using an App (see Section 4.1.1). However, missing trips are still an issue with smartphone data.

1.2.3 Low precision of reported trips

In addition to failing to report all their trips during the day, respondents tend to round the departure or traveling times. Rounding to the nearest 5 or 15 minutes might have a large impact for short trips (Stopher *et al.,* 2007). More generally, even simple routes are sometimes difficult to report in detail (Stopher and Greaves, 2007).

The MTMC uses a mapping tool during the CATI interview to improve the quality of the routing data. GPS data from a smartphone might help collecting the exact routes and more precise departure times. A comparison between CATI data and GPS data showed a better precision for the latter (Bricka *et al.,* 2009). A better precision might impact the modeling of departure time and in particular the modeling of peak hours.

1.2.4 Non-panel nature

A CATI survey does not easily allow to collect data for more than one day. Panel data are however used in transportation research for a long time (Golob *et al.,* 1997). They are important in the development of choice models (Carrel *et al.,* 2016, McFadden, 2001). Dynamic models using panel data inscrease statistical efficiency, improve prediction and allow to study behavioral dynamics (Kitamura, 1990). Habits in mobility behavior can be detected (Gärling and Axhausen, 2003), in particular in route choice (Aarts and Dijksterhuis, 2000, Bamberg *et al.,* 2003, Eriksson *et al.,* 2008, Gardner, 2009, Schwanen *et al.,* 2012, Thøgersen, 2006, Verplanken *et al.,* 2008). Panel data are also important for the development of activity-based models covering several days (Nijland *et al.,* 2014).

The MTMC collects trips for one day. Smartphone data would allow to collect trips for a longer period.

1.2.5 High costs

The cost of a CATI survey is high. In the US, the average cost of a survey is about 487'000$, including design, sampling, training, conduct, documentation, some coding and processing. It corresponds to an average cost of 150$ for a completed survey for one household (Hartgen and San Jose, 2012). For the MTMC, more than 100'000 people were contacted and more than 50'000 answered questions on the phone for about 26 minutes. Smartphone data might decrease the marginal cost of collecting data about an individual, even when considering support for using the App and data preparation.

This article is decomposed in three parts reviewing the literature and enlightening the opportunities of smartphone data for national travel surveys. First, we review the existing tools to perform such a data collection (Section 2). Then, we consider the sample: who would participate to this survey, what are the existing experiences and the resulting answer rates (Section 3). Finally, we analyze the possible outcomes of these tools (Section 4). A conclusion wraps up the different elements and provides a directions for a possible application of an App in a national travel survey (Section 5).

2 Tool: What technology?

In this section, we first describe technologies allowing to locate a device (Section 2.1). Then, we describe the necessary interactions with the user (Section 2.2) and we list the existing Apps and their characteristics (Section 2.3).

2.1 Data from Apps, GPS and GSM antennas

Locating a device on the user could be done with three different technologies. One is providing a separate, dedicated GPS device to the participants (Section 2.1.2) and two are using smartphones as devices: either using data from the smartphone using an App (Section 2.1.3) or using data from the GSM antennas (Section 2.1.1).

2.1.1 Collecting data using GSM antennas

GMS network administrators can locate the users of their GSM network. This includes mobile phones, but also sometimes tablets and laptops. The advantages of such data collection techniques are:

The possibility to use an existing network: No need to install new antennas in most cases, in opposition to other localization technologies (e.g., Bluetooth), where no existing network can be used and additional antennas must be installed.

Large coverage: In the study area, the coverage is usually large. GSM networks are largely available in Switzerland.

No need to install anything on the smartphone: A simple connection to the network is enough.

No need to distribute devices: Unlike with dedicated GPS devices.

No reactivity: The user does not change his behavior, since he doesn't know he is tracked.

Sample size: The samples are usually large.

Panel data: The data can be collected for a long period.

The disadvantages are:

No socio-economic data: These data must be collected separately, which makes it difficult.

No opt-out possible: It is difficult for the user to refuse to participate to the data collection. The user can also not delete a single trip or only part of the data. This causes significant problems to assure privacy.

Representativity: The users of mobile phones are not representative of the full population. Without socioeconomic variables, it is difficult to correct the sample bias.

Multiple devices: When someone has several devices, it is difficult to count them only once.

Frequency of measurements The frequency of localization measurements depends on the usage of the device. Some stops might not be detected for some users (using less their mobile phone), while there would have been detected for another user (using more his mobile phone).

Semantics is missing: Transport mode detection is not entirely possible yet. The activity at the destination is difficult to detect.

Precision for itineraries: The precision is not good enough for itinerary detection.

This type of data can be used to estimate road congestion or study long-distance mobility. They do however not provide the type of behavioral data a national travel survey collects to fulfill the objectives outlined under Section 1.1.

2.1.2 GPS data collection with dedicated devices

The first experiment took place in 1996. It was managed by the US Department of Transportation in Lexington (Wagner, 1997). The advantage of such a data collection is the better precision of a dedicated device compared to a GPS in a smartphone. The disadvantages are:

- The logistics and costs of the distribution of the device;
- The risk of forgetting the device is larger than forgetting a smartphone (which is directly useful for the user);
- The data transfer is often more complicated than with a smartphone;
- The low precision of the GPS indoor and in urban canyons;
- The sample size is often small: a maximum of 4882 respondents is reported in a recent literature review (Shen and Stopher, 2014).

The expected sample size and the difficulty of distributing devices make this approach unattractive for the MTMC. From the viewpoint of the user, dealing with an extra device, charging its battery and sending its data make the data collection complex (Safi *et al.,* 2016a). However, if a high resolution for localization is needed, GPS devices are still relevant (Montini *et al.,* 2015).

2.1.3 Data from an App on a smartphone

Smartphone data have several advantages:

- Privacy issues can be addressed. The user knows he is tracked and can stop the data collection when he wants.

- Several technologies can be used: WiFi, GPS, GSM and Bluetooth for the localization, accelerometer and ambient noise for the context (Bierlaire *et al.,* 2013*,* Chen*,* 2013*,* Chen and Bierlaire*,* 2015). These sensors might save the battery when replacing the GPS and improve the precision of the localization in certain contexts (indoor, urban canyon).
- Smartphones can directly transfer the collected data (unlike a dedicated GPS device).
- No distribution of devices is needed (unlike with a dedicated GPS device).

The disadvantages are the following:

- The user needs to install an App on his smartphone.
- The smartphone users are not representative of the Swiss population.
- The data collection heavily uses the smartphone's battery.
- The smartphone's GPS is less precise than the GPS of a dedicated device.

Based on a small sample, a comparison between a data collection using an App on a smartphone and a data collection using a dedicated GPS device shows that using an App is more precise, if the data collection on the smartphones uses prompted recall (Safi *et al.,* 2016a). A smartphone App improves the collection of non-motorized trips, in particular if used with prompted recall.

2.2 Interaction with the user

When using an App on a smartphone, collected data provide the localization of the device. These data require an interaction with the user for three reasons:

Semantics: Localization data do not directly provide the transport mode nor the activity performed at the destination.

Missing data: Localization data are sometimes imprecise (indoor, in an urban canyon, in a tunnel, etc.). Therefore short trips might be omitted or the exact itineraries might not be detected.

Right to correct or delete data: Data are passively collected. The user must have the right to know what is transmitted, the possibility to delete the data or correct them.

We must therefore offer the user a way to see, modify and possibly delete the data (Section 2.2.1), by automatically detecting in advance most of these information in order to limit respondent fatigue (Section 2.2.2).

2.2.1 Prompted recall

Functionalities In practice, most smartphone apps ask the user to add, check or correct information about transport mode, activities and stop detections. Prompted recall has two advantages in this context:

- A better quality of the data;
- A right to access the data for the user, which is guaranteed in Switzerland (Art. 8, Federal Act on Data Protection).

The user interface must allow to delete a trip, to add one, to group trips (wrongly detected as several trips when they correspond in reality to one single trip) and to divide a trip (wrongly detected as one trip when it corresponds in reality to several trips). It must be noted that it is much easier to delete a wrongly detected stop than to add one (Cottrill *et al.,* 2013). The interface must also allow to change the imputed transport mode. Trips must quickly be processed to be visible on the phone or on a webpage.

According to a study in the Netherlands for 3 years with 600 participants and 18'000 validated trips (Geurs *et al.,* 2015), 20 to 25% of trips are not detected by the smartphone and added by hand. Some research at MIT Singapore also recommends this technique (Cottrill *et al.,* 2013). For the authors, it allows to separate between car and taxi, or to detect the transition between bus and walking when several bus stops could have been used.

Among all the information the user needs to confirm, the activity at destination is a priority, since it is more difficult to detect from the raw data. The itinerary is probably the less important aspect to confirm (less important for modeling, more difficult for the user to confirm and/or correct).

User interface The user interface must be simple (Cottrill *et al.,* 2013). Users are not familiar with these technologies, reading and understanding maps or interacting with a survey on the internet. The interface must be intuitive enough, possibly interesting to use, to compensate the absence of an interviewer, like in a CATI.

Installing two Apps (like with GoEco !, see Section 2.3.1) seems too complicated. The user interface must show trips as a text or as a map, letting the choice to the user of his preferred way to correct his trips (Cottrill *et al.,* 2013). Zooming is also an important question: too broad, the user misses the details; too detailed, the user misses the overview and might forget a trip (Cottrill *et al.,* 2013). Prompted recall can be done directly on the smartphone (Safi *et al.,* 2016b), on a webpage or both.

A hotline must be available, in particular to help for installing the App. The user must be able to define from which percent of the battery the App must stop collecting data, in order to save the remaining battery charge.

2.2.2 Detection algorithm

Detection algorithms has two goals:

minimize the respondent fatigue: by suggesting trips, transportation modes, activities and by asking (possibly not too often) only for a confirmation or correction. Thus, the user only needs to correct mistakes from detection and does not have to enter all information. The detection must therefore be fast, almost in real time and as precise as possible.

provide usable data for the modeling of behavior: Raw data are note directly usable, since they are not associated to categories of activities, a route or a category of transport mode. This coding does not need to be in real time.

There is a trade-off between reducing the noise in the data and biasing the data. Stops, transport mode, activity at destination and itinerary must be detected. The transport mode and the activity at the destination must be quickly detected in order to be confirmed by the user. The itinerary can possibly be detected later, without confirmation from the user (Cottrill *et al.,* 2013).

The confirmation by the user can be done directly on the smartphone using the App or on a dedicated webpage. It can take place once at the end of the day or using pop-ups on the smartphones when needed, all along the day (with the risk of asking the user at an inappropriate time, several times per day).

Stop detection

Since adding an undetected stop on the smartphone or on the webpage is more difficult than deleting a wrongly detected stop, the stop detection must be configured to generate slightly more false positives (type I error) than false negatives (type II error) (Cottrill *et al.,* 2013). A balance must be however found in order not to overload the user interface with wrong stops, which would discourage the user.

Transport mode detection

With MoveSmarter in the Netherlands (Geurs *et al.,* 2015), the transport mode has been automatically detected for 75% of trips. Short trips by car are however often detected as trips by bike. Trips by train are underdetected. Trips by bus, tram or metro are often also difficult to detect. In order to improve detection, the authors suggest to use the accelerometer, to use more contextual data, (bus stops, bus lines, etc.) and to use previous trips to improve the transport mode detection. The difference between private car and taxi must in any case be added by the user (Cottrill *et al.,* 2013).

Activity detection

Map data containing points of interest help detecting the activity at destination. They are used in the "Move" App (see Section 2.3.2) and mentioned for the Future Mobility Survey (Cottrill *et al.,* 2013).

In the case of the MTMC, the home address could possibly be introduced in the App before the beginning of the data collection.

Itinerary detection (map matching)

Raw data cannot directly be associated with itineraries; The precision of the localization is not good enough. Several itineraries can be detected and associated to the likelihood to be the real one (Bierlaire *et al.,* 2013*,* Chen and Bierlaire*,* 2015). A balance must then be found between:

- suggesting a unique itinerary (the most likely one) in order to minimize the fatigue of the respondent and
- suggesting several itineraries, without asking too much information.

Traditional travel diaries require the respondent to answer on the phone, when called, in an interview. In the MTMC, this interview took on average 26 minutes. In a smartphone survey, the interactions are multiple, the time of the interactions are chosen by the user and each interaction is short (about 5 minutes). These characteristics allow a longer time period to collect data over multiple days (Murakami *et al.,* 2012).

2.3 Existing Apps

Apps were first developed for research. Recently, the first commercial Apps are coming to the market with the intention to be used in national travel surveys, such as rMove since November 2014[2]. We describe here a list of some existing Apps, either used in research or for commercial purposes. Their main characteristics are described.

2.3.1 Used in research

GoEco ! is an App related to another one, Move (see Section 2.3.2 below). Two Apps need to be installed. 200 persons were followed between March and April 2016 in Zurich and in Ticino using this App. The goal was to observe their mobility behavior et provide them with information about their energy consumption. The transport mode is automatically detected. One of the key information collected is the number of kilometres per mode. A second experiment took place in October 2016. The project is still running.

Modalyzer has been developed in Germany for research. It automatically detects some transport modes (bike, bus, car, metro, walk, train, tram). Trips by plane, boat or bus that are not included in the public transport (private bus shuttles) must be included directly by the user. The user can see his data on a dedicated website. The user can correct the trips and confirm their transfer to the analysts. The App has been used for 14 research projects. The largest number of participants at a project was 730.

PEACOX suggests several itineraries to the user between a departure point and an arrival point. The user is tracked and can confirm the trip directly in the App (no website).

MoveSmarter is an App with a confirmation on a website and visualization of the data on the smartphone, without possibilities to edit the trips. The App has been used by 600 people, including some without a smartphone (Geurs *et al.,* 2015). 18'000 trips have been validated in 2 weeks. The goal of the research was to compare the data from the App with the data from a panel in the Netherlands. The users were satisfied with the precision of the automatic detection, even if 20 to 25% of the trips were not detected by the App. Very short activities are often falsely collapsed to one unique long trip by the App.

Future Mobility Survey or Future Mobility Sensing has been developed at the MIT Singapore. The App was tested in parallel to the Singaporean Household Interview Travel Survey (HITS), the local national travel survey, between October 2012 and September 2013. 1500 persons were surveyed. According to the authors, a comparison between the data from HITS and from the App shows that the App collects richer data, with a better resolution

[2]Source: The Internet Archive

and a larger dataset. A more recent study compares the results of the Korea Passenger Trip Survey (PTS), the Korean national travel survey, with results from the App (Lee *et al.,* 2016). The test was performed with only 46 students. Results show that the App detects more short trips and that the respondents to PTS overestimate the duration of trips. The App was also used for the project Happy Mobility about well-being in transportation (Raveau *et al.,* 2016).

UbiActive is an App from the University of Minnesota (Fan *et al.,* 2012). It uses the accelerometer, the GPS and the magnetic sensor of the phone to detect the duration, speed and direction to evaluate the intensity and duration of physical activity. The App exists only on Android phones.

MEILI was used in Stockholm by Allström *et al.* (2016). It is an App with a webpage for the annotation of the trips. It has the particularity that it was used the same day with the same respondents than a traditional survey. During the reference day, the App was running but the user could not see the collected data. The following day, the user answered a traditional survey, then only received a link to see and possibly correct the data from the App.

2.3.2 For commercial purposes

Move is an App originally developed to monitor sport activities, but it detects the transport mode, the stops, the activity at destination and it allows the user to correct the name of the destination. It was used for the research project GoEco ! (see Section 2.3.1 above).

rMove has been developed by RSG and runs on iOS and Android. Data are encrypted before being sent. The App identifies repetitive trips and adapts the detection based on these repetitions. The App requires a confirmation on the smartphone few minutes after the end of the trip, and not only at the end of the day.

Mobile Market Monitor uses the technologies from the research App Future Mobility survey (see Section 2.3.1 above).

SBB DailyTracks is the App of the Swiss Railways (SBB). It has been developed by MotionTag, a German company. It has been used with the clients of Green Class, a service offered to a limited number of clients combining a GA travelcard (a yearly ticket proving access to all public transports in Switzerland), an electrical car, and car and bike sharing memberships. A research project is currently undertaken together with the ETH Zurich.

3 Sample: Who participates?

3.1 Proportion of the population with a smartphone

Cellphone adoption varies between countries. In a non-commercial panel for academic research in the Netherlands including 5000 housholds and 8000 persons representing the whole population, 800 persons were selected to participate between 2013 and 2014. 36% had a smartphone (Geurs *et al.,* 2015). In a study about free-floating car-sharing, a control group of 6000 persons, representative of the general population, was asked to answer a survey. 594 persons answered the survey and among them, 73% had a smartphone (Becker *et al.,* 2015). Table 1 summarizes these values.

Country	Smartphone adoption	Year	Source	Sample
United States	77%	2016	Pew Internet Project	~2000
Switzerland	73%	2014	Becker *et al.* (2015)	594
Sweden	36%	2013	Geurs *et al.* (2015)	8000
United States	46%	2012	Pew Internet Project	~2000
Singapore	90%	2011	Armoogum *et al.* (2014)	
Sweden	52%	2011	Armoogum *et al.* (2014)	
Denmark	45%	2011	Armoogum *et al.* (2014)	
Great Britain	40%	2011	Armoogum *et al.* (2014)	
United States	35%	2011	Pew Internet Project	~2000
France	30%	2011	Armoogum *et al.* (2014)	

Table 1: Cellphone adoption by country

3.2 Participation rates

Existing data collections using smartphones show small samples (Safi *et al.,* 2016a).

In the Future Mobility Survey (Cottrill *et al.,* 2013), 74 persons answered an initial survey about socioeconomic characteristics, less than 50% of those installed the App and only 36% validated their data on the internet. The sample was biased (young and educated). Some problems probably lowered the participation rate (the App was not available for a time).

In Stockholm, 130'000 persons were contacted to participate to a study (Allström *et al.,* 2016).

Only 1559 persons answered, 495 persons installed the App and 293 persons collected 2142 trips (participation rate: 0.2%). According to the authors, the reason for this very low participation rate are, among others, the absence of an App for Windows phone, problems with the App and communication issues.

In New Zealand, 186 persons were contacted, partially from the national survey (112) and using commercial panels or classified advertisements (74). Only 73 persons participated (participation rate: 65%).

4 Outcome: What quality of the data?

It is difficult to evaluate the quality of the output when running a data collection using an App on a smartphone. In this section, we present results about the quality of the trip data (Section 4.1), and the cost of such a data collection technique (Section 4.2).

4.1 Quality of the trip data using an App

The existing literature does not provide many examples of experiments comparing more traditional surveys with results from an App. We develop here two elements: the number of trips per day and the trip duration and distances.

4.1.1 Number of trips per day: more frequent

Two recent studies in North Carolina and in Indiana (Bradley and Greene*,* 2016*,* Greene *et al.,* 2016) collect 20% more trips per day than traditional surveys, the same year and the same season, according to the authors. The largest difference appears among young adults and "busy" households (large and large income households).

A data collection in North Carolina used both an App, rMove, and more traditional surveys (phone and internet) in 2016 (Flake *et al.,* 2017). The data collection with an App was used to define weights for trips collected with traditional techniques. The App detected 5.41 trips per day on average and the standard survey 4.35 trips. The extension factor was defined for 7 age groups. The 18-24 years old group shows the largest factor: 5.89 trips per day were detected on average using an App and 3.40 trips using the standard survey in this age group. The number of trips per day also varies with the income: Among the highest income group (>100'000$/year), data from an App reveal 5.77 trips per day, while the standard survey indicate 4.57 trips. The authors suggest that people with a high value of time (e.i. high opportunity costs) show more trips using an App, since the time to introduce a trip is lower compared with a standard survey method.

4.1.2 Trip durations and distances: similar

According to Flake *et al.* (2017), durations and distances of trips collected using an App do not differ from the ones collected using phone interviews or internet surveys.

4.2 Cost

In North Carolina, a data collection with smartphones cost 30% more than collecting the data using telephone and internet (Flake *et al.,* 2017). The increase is due to data cleaning work according to RSG, a consulting firm in transportation planing. The cost per collected day was 50% lower using rMove than a standard survey, since the data collection with the App last 3 days. It means that the increasing cost due to data cleaning might be compensated by the possibility to collect data over multiple days per individual. RSG predicts that the costs will decrease due to the standardization of the characteristics of the Apps, methodological improvements.

5 Conclusion: How to use such tools at the national level?

Almost 20 years after the first data collection using a mobile phone and GPS capabilities, are we ready to use it at a large scale for for an official statistical survey such asthe MTMC 2020?

5.1 A promising data collection technique

This paper shows that using an App on a smartphone could improve the quality of the data (Section 4.1) and answer some critics about CATI surveys (Section 1.2). “Smartphone travel surveys increase the likelihood of recording non-motorised trips” (Safi *et al.,* 2016a). It has already been used in Singapore, in California, in Florida (Cottrill *et al.,* 2013), in Seoul (Lee *et al.,* 2016), in Stockholm (Allström *et al.,* 2016), in New Zealand (Safi *et al.,* 2016b) and in North Carolina (Flake *et al.,* 2017). Consulting companies begin to offer such Apps (e.g., rMove by RSG, see Section 2.3.2) and research projects such as Future Mobility Survey (see Section 2.3.1) enter the market for commercial services.

5.2 Challenges are still existing

Difficulties are also mentioned in the literature. The App heavily consumes the battery of the respondent’s smartphone (Liao *et al.,* 2017). Participation rate is also a clear weakness of this technique (see Section 3.2). Including socioeconomic information on a smartphone is perceived as long and difficult (Cottrill *et al.,* 2013). In a pilot study, respondents’ feedback underlines the difficulties in finding a balance between

- mandatory and optional questions;
- broad categories with a limited choice and entering data for the user.

5.3 Recommendations

It seems to be better to ask socioeconomic questions on the internet or by phone, and not on the smartphone of the user. When doing so, the home address could possibly be included in the system before the beginning of the data collection with the App, in order to improve the detection of the location and the activity performed. Cottrill *et al.* (2013) also insist on the importance of asking sensitive socioeconomic questions, such as income, at the end of the survey, when respondents have already provided the other informations.

To our knowledge, only one experiment collected data with an App and with a standard survey on the same day (Allström *et al.,* 2016). The participation rate was very low (less than 1%, see Section 3.2). This setup seems complicated. Moreover, a CATI survey collects data most often on only one day, while Apps are collecting data for about three days. We would therefore recommend to avoid these difficulties and not collect data on the same day with both techniques.

The App must be available for iOS and Android, and possibly for Windows Phone. For comparison purposes, it must include the same categories for mode, activity, etc. than in the MTMC.

The company providing the App must guarantee a proper management of private personal data. It includes a clear definition of the rights of their employees to access the data, a clear definition of the collected data and of what is received from and provided to the client, a clear list of the hardware used and where it is stored, a backup strategy for the data and the encryption of the connection between the App and the server.

A Appendix

Table 2 shows the detailed participation rates of the MTMC between 1994 and 2015. The detailed numbers for computing the participation rate between 1994 and 2005 come from Gindraux (2007). For 2010, they come from Rebmann (2012). In 2015, only the addresses with known land line numbers are included, in order to be able to compare the participation rates. See Section 1.2.1 for an explanation of the difference of sample framework between 1994-2010 and 2015.

Table 2: Detailed participation rate 1994-2015, respondents with known land lines only

	1994			2000			2005			2010			2015	
	Number	Household response rate	Individual response rate	Number	Household response rate	Individual response rate	Number	Household response rate	Individual response rate	Number	Household response rate	Individual response rate	Number	Individual reponse rate
Delivered addresses to the polling organization				44447			57295							
Not activated				2313			8081							
Activated addresses	23191			42134			49214			96024				
Not valid	599			3480			5026			12267				
Valid addresses	22592	100.0%		38654	100.0%		44188	100.0%		83757	100.0%			
Not reached	2335	10.3%		3799	9.8%		5398	12.2%		10065	12.0%			
Refused or impossible interviews	3687	16.3%		6202	16.0%		6840	15.5%		13721	16.4%			
Valid interviews with households	16570	**73.3%**		28653	**74.1%**		31950	**72.3%**		59971	**71.6%**			
Selected target persons	19297		100.0%	33673		100.0%	37288		100.0%	69220		100.0%	83831	
Not valid										973			6989	
Valid selected target persons													76842	
Refused or impossible interviews	1227		6.4%	3527		10.5%	3898		10.5%	5379		7.8%		
Valid interviews with persons	18070		**93.6%**	30146		**89.5%**	33390		**89.5%**	62868		**90.8%**	49606	**64.6%**
Participation rate			**68.7%**			**66.4%**			**64.7%**			**65.0%**		**64.6%**

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