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Possibilities to Use Existing Data Sources to Replace Traditional Travel Survey Methods

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Abstract

Travel surveys are used for better understanding of individual travel behaviour as a basis for transport planning and decision making. In Norway, travel surveys are done by telephone interviews with a declining response rate from 77 to 20 percent since its inception in 1985. In addition to decreased participation, the reported trips are likely to be over- and underreported. The purpose of this paper is to investigate if emerging methods could overcome these limitations. In order to evaluate this, a comparison between a telephone travel survey and location-based data from smart phones was performed. Results show that the applications identified approximately 1,2 fewer daily trips than the traditional method. Transportation modes were correctly identified in approximately 48 percent of the cases for the active method, compared to 21 percent for the passive registration method. However, the participants favour passive collecting methods due to lower personal burden. This study shows that smart-phone based travel-surveys seem to be a promising alternative to contribute to or replace traditional travel survey methods. However, implementing smart-phone based surveys may create under-reported groups due to privacy concerns and the necessity of compatible smart-phones.

Introduction

Transport projects and policies aim to improve people's daily lives. Therefore, knowledge on people's travel behaviour is essential to simulate their reactions beforehand. When people's reactions are very uncertain, the projects may have undesired consequences. Nevertheless, collecting travel behaviour data is a complex process due to the potential uncertainty in both the sample and the method. Traditionally, the methods used are Paper-and pencil interviews (PAPI), Computer-assisted telephone interviews (CATI), Computer-assisted selfinterviews (CASI), Mail-back questionnaires, Web-based questionnaires and traffic counting.

CATI interviews are carried out over telephone and recorded on a computer. This method has major challenges such as low response- and completion rate (Stopher and Greaves, 2007) and underestimation of short trips (Bohte and Maat, 2009; Wolf, 2004). Technological problems, difficulties obtaining contact and lower willingness to respond are the main reasons to explain the response rate decrease. An increasing proportion of market-call screening is one of the reasons that one of four fall out during the first calling attempt (Hjorthol et al., 2014; Tuckel and O'Neill, 2002). Furthermore, the non-respondents are harder to contact, due to being less available (NCHRP, 2006). Wolf et al. (2003) and Stopher and Greaves (2007) explained that the under-reporting of trips is caused by length of the survey, forgetfulness of respondents, or respondents considering the trips unimportant, and selective omission on the part of the respondent. Also incorrect understanding of trip or activity definitions is pointed out as a problem.

The seventh Norwegian National travel survey was conducted by CATI in 2013/2014 and about 60.000 of the population were interviewed. Since 1985, the response rate for the chosen respondents has dropped from 77% to 20% (Hjorthol et al., 2014). Older and younger people have the highest dropout rates, where up to 90 % do not complete the survey. In addition, the CATI method is costly and time intensive. Therefore, such large scale surveys are only conducted every fourth year. According to the accuracy of trip-attribute estimation, such as travel-time and distance, Stopher and Greaves (2007) explain that people tend to round to the nearest five minutes. This also applies to the precision for route and location information which may affect time and distance travelled. Stopher and Greaves (2007) discuss the use of incentives to increase the response rate. Paid survey panels may lead to under-representativeness for the entire population, but this could be solved by using ”split panels” to check for representative-ness. Incentives in terms of invitation letters, gift cards and motivation conversations have been tried to increase the response rate in Norway. Yet, it does not seem to have had much effect (Hjorthol et al., 2014).

There are several new approaches for collecting and processing travel data. Continuous data collection with GPS-units has been used to supplement travel data for decades, either as a supplement to the traditional survey or as stand alone surveys. Several studies have found that GPS-based surveys have a potential to replace or supplement traditional methods (Bohte and Maat, 2009; Chen et al., 2010). GPS-positioning enables possibilities to capture short trips, which helps to overcome the underreporting of trips in paper- or phone based travel diaries (20-30%) (Nitsche et al., 2014; Shen and Stopher, 2014). In relation to under- and overestimation of travel time, Bohte and Maat (2009) showed promising results to overcome these issues with the use of location based data. Also other trip attributes, such as trip purpose, are derived with high accuracy from GIS or known places (Rasmussen et al., 2015; Xiao et al., 2015).

In a study by Forrest and Pearson (2005), only 44% of the trips reported in CATI were matched correctly with the GPS-survey. Nevertheless Barbeau et al. (2009) stated that use of GPS in travel surveys has a great potential, which may enable large scale surveys at low cost.

Recent work by Xiao et al. (2015) showed a precision between 80-97% for automatically identifying modes by analysing call detail records (CDR) from the telephone company. A location estimate can be provided from cell tower triangulation and tower ID‘s. By using CDR-data there is no need for users to do anything during the survey, and it is the most battery efficient method. There is still some uncertainty linked to this method for collecting travel data, for example due to precision level in non urban areas, since the location precision depends on the tower density (Liu et al., 2016). Alexander et al. (2015) showed a representative result for creating daily origin–destination matrices by purpose using data from this method.

Today’s technology makes it possible to collect travel data by smart-phones with customised applications. Smart-phones are ideal to collect travel data, due to increasing popularity and the fact that ”everyone” is travelling with an unit. A rich data set can be derived and computed from multiple built-in sensors, such as motion sensors (accelerometer, gravity sensor and gyroscope), environmental sensors (barometer, photometer and thermometer) and position sensors (GPS and magnetometer) (Google, 2016). Ferrer and Ruiz (2014) processed travel modes by using raw accelerometer data from Android smart-phones, with over 89% match for all modes. Several studies have used both active and passive applications for data collecting. Passive collection among users by using algorithms to automatically detect travels has been carried out by Barbeau et al. (2009) and Chen et al. (2010). The project TRAC-IT is an example of an active application which prompted an instant post-questionnaire survey (PRS) to validate the trips generated. Besides GPS-locations, input data such as mode, purpose and occupancy were added in the user interface before the trips started. Corrections were made afterwords by the user in the PRS (Barbeau et al., 2009). Another advantage of using smart phones to collect travel data is that data is immediately ready in digital format for further processing (Bohte and Maat, 2009). This also eliminates human errors in relation to the CATI method.

As a result of an increased sensor usage, Liu et al. (2016) and Xiao et al. (2015) point out high battery power consumption as a disadvantage which has to be solved before these new methods can replace traditional CATI surveys. Loss of GPS-signal in urban or indoor areas is possible to overcome with use of accelerometer sensors or connection to GSM Cell Ids or Wi-Fi acces points (Ferrer and Ruiz, 2014; Liu et al., 2016). For passive methods, a limitation is that users forget to activate and deactivate the application before and after the trip (Xiao et al., 2015). Passive tracking of peoples behaviour also introduce privacy concerns that set restrictions for data handling and survey design (Datatilsynet, 2012). From a user perspective, the new methods (GPS, CDR, smart phone) make it possible to examine trips over a longer period without exhausting the respondents, due to lower interactivity and personal burden (Chen et al., 2010; Xiao et al., 2015).

The above review raises some fundamental questions: Which technological challenges are introduced by using smart phones to collect data from travel surveys? Do smart-phones provide better and more accurate data compared to traditional methods in travel surveys? Do the new registration methods influence respondents behavior?

This paper aims to explore these concerns by comparing existing smart-phone travel diary’s with traditional CATI-surveys over a continuous period of 10 workdays. The paper is organized as follows: The methodology section defines the approach for the research and reviews the collection of travel-data from the applications. Section 3 presents the investigation results before a discussion in section 5 interprets the data. A conclusion with a recommendation for possible future work follows in section 6.

Methodology

In this paper we use four different methods of data collection; unassisted (CATI A) and assisted interviews (CATI B), Google Location History (GLH) and Smooth Mobility in Oslo (SMiO). The data collection was conducted in Trondheim April 4–15, 2016. Monday to Friday was chosen to avoid public holidays and weekends, since the travel behaviour differs among these and weekdays. In order to identify trends and effects, the duration was set to 10 days. Personal background variables such as home and work address, demographic and smartphone information were collected through an internet based recruitment survey. Completion of thissurvey confirmed experiment participation. A description of general travel surveys was sent out before the registration period. Finally, each volunteer was asked to complete a final feedback survey.

Sample

The sample size of 20 persons was chosen with regard to practical implementation of the telephone interview. The sample set consisted of a relatively homogeneous group; high level of education, approx 20-50 years and work/studying in Trondheim. Among the 25 that were contacted, 13 participants fulfilled the initial survey and they were invited to download and install two apps; Google NOW and SMiO. In order to compare traditional and new methods, the participants were divided into two groups based on phone type. Group A completed the telephone interview corresponding to traditional form, while group B were assisted by data from GLH through the interviewer. Of these, 6 had iOS as operation system while 7 had Android. Other operative systems were not suitable due to software restrictions. Two participants with elderly iPhones (produced mid. 2010) could not install and launch the GLH application. To overcome issues with high battery power usage, each participant was given a battery pack as an incentive to complete the survey.

Data collection

Telephone interview (Assisted and unassisted)

For the traditional data collection method, a structured telephone interview was chosen. The interview design was based on The National Travel Survey 2016-2019. Only questions about purpose, travel-mode, duration, distance and start time of the activity were asked to hold the burden to the bare minimum. To reduce the duration of registration, the trips were registered continuously in a pre-coded database during the interview. Assisted and unassisted interviews were merged as CATI (A&B) in the travel data analysis due to low number of respondents.

SMiO

SMiO is an active data collector. It is a special developed application to collect travel data and to better understand public transport patterns in Oslo community. The app aims to retrieve travel information, actively generated by the traveller. Derived information such as purpose and mode were added by the participants before each trip or leg-change. Raw data was transferred instantly to a dedicated server and may be retrieved after the experiment for further processing.

Google NOW (GLH)

Google NOW is a passive data collector that enables automatic mode detection connected to the time-stamped location in the raw data takeout. Some timestamps contain a mode- and confidence estimate set by Google. Regarding the data transfer, group B were asked to take out log files from GLH after each registration day. The KML format was chosen due to easier visualisation for the interviewer and less burdensome takeout for the respondents. KML is missing mode estimate, therefore it was necessary to extract JSON from the whole registration period after finishing the experiment.

Both applications switch automatically between GPS, WiFi and CDR to improve start-up performance and location accuracy. Location data was recorded with a non-uniform sampling interval, depending of speed and mode. To save battery, GLH decrease the sampling intervalwhen the battery is close to empty.

Data processing

This study was partly based on the method of Schuessler and Axhausen (2009) for processing the GPS data. The method consisted of four steps: GPS data cleaning, trip identification (TI), trip segmentation (TS) and mode identification (MI). TS was not taken into account in this study.

1) GPS data filtering

Since the raw format of location data was of varied quality regarding accuracy and altitude, the first step was to clean and smooth the data. The following three conditions should be satisfied for validating the data, thus the rest of the data was not included to avoid potential errors during the analysis.

- Altitude levels between -10 m and 2000 m.
- Point accuracy below 50 m/100 m for respectively Android and iOS devices to get suitable tracks (Accuracy between 5 and 10 m are considered as ideal (Wolf, 2004).)
- Maximum point acceleration below 12 m/s^2 to avoid impossible jumps in time, as Wolf (2004).
- Trips with no duration.

2) Trip identification (TI)

For the GLH data-set a TI-algorithm was applied to link the locations together. The algorithm is based on one of three criteria adopted from Rasmussen et al. (2015) and Schuessler and Axhausen (2009). The algorithm flags an activity if:

- The smartphone has been stationary within a location for a period of 60 seconds.
- The velocity was under 0,01 m/s for 60 seconds.
- The gap between two consecutive time-stamped locations was over 120 seconds.

The departure time for GLH was chosen to be the point before the first location with speed greater than 0,5 km/h. Start and end timestamps for SMiO were set when activating or deactivating the application.

3) Mode identification

This step was not necessary to calculate, since the apps should provide mode information. MATLAB and manual identification were used to extract mode-estimate information from SMiO and GLH.

4) Matching the data-sets

Matching the data sets is crucial to examine the differences between the four methods. To avoid low matching rate between trips recorded by GPS and the corresponding CATI trips, a manual comparison and matching was performed in this study. Location Visualizer PRO was used to interpret the GLH-data. The criteria for match was primarily based on the time-stamp for the start of the journey, then by purpose and mode if they existed.

Results

Data processing

In the data filtering procedure, about 4% of the location points from SMiO were filtered out before the matching. These points did not satisfy the criteria for acceleration and accuracy. For GLH the share of filtered trips were 95%. 99% of the data-set was filtered out if we include the weekend and days before and after the survey. For the CATI method, 118 of 130 scheduled interviews were completed. This is equivalent to an answering rate of 91%.

Regarding the trip identification step, 451 trips were stated through the CATI method, 51% with assisted information from GLH. 349 trips were manually registered through the SMiO application and 560 trips were found from the GLH data.

When looking at the mode identifications, all of the trips from the interviews have one or more modes connected to the trip. 5% of the total trips registered in the SMiO application were without mode. GLH contains a mode estimate in about 30% of all entries, but there was also observed an unknown amount of timestamp repeats for the Android data. Further examination of the GLH modes showed that there were three different values for moving by foot. These were merged before the matching. The value ”inVehicle” in GLH does not distinguish between public transport and car mode, and was merged with car for the analysis.

A comparison of trip matching for all data-sets is shown in table 1. In total 43% of the recorded trips in SMiO were found in the CATI survey. The proportion was highest in group B with half of the trips recorded. Of these matched trips in CATI and SMiO, 79% were found in GLH. Here the proportion was also higher for group B with 95%. From the CATI B survey we know that eight trips were detected with the use of assisted interview method. CATI B discovered two more trips than GLH during the interviews.

Table 1 – Identified SMiO trips in CATI and identified GLH trips in SMiO and CATI.

	SMiO	*GLH*
In CATI	*193 (43%)*	
A	*78 (35% of all A trips)*	
B	*115 (50% of all N trips)*	
In SMiO		*152 (79%)*
A		*43 (55% of all A trips)*
B		*109 (95% of all B trips)*

Table 2 summarises the four different data-sets collected by the applications and the telephone interviews through the investigation period. It also shows the final data-set after data filtering and trip matching. After completing the matching step, 152 trips from GLH were identified as trips in both SMiO and CATI which formed the final data-set. The GLH application produces a great amount of data. For the whole registration period, a single GLH file is about 25 Mb/pers. compared to the equivalent SMiO-file which is just about 6 Mb/pers. Additionally, the Android GLH data was almost 67 times greater than data generated by iOS after data filtering. SMiO has the highest proportion of valid trips per megabyte, but the lowest number of valid trips per megabyte.

Table 2 – Overview of collected data, before and after the four data processing steps. Android and iOS produce same type of data in SMiO.

	CATI (A)	*CATI (B)*	*SMiO*	*GLH, Android (n=8) / iOS (n=3)*
Duration interview [min]	*325*	*320*		
Size data-set [Mb]			*74*	*400/0,3*
Number of points			*166434*	*158460/1581*
Number of trips			*359*	
Size data-set [Mb]			*71*	*18/0,1*
Number of valid points			*161405*	*7756/587*
Number of valid trips	*221*	*230*	*359*	*219/94*
Valid points per [mB]			*2273*	*430/5870*
Valid trips per [mB]			*5*	*12/940*
Valid trips per [min]	*1,5*	*1,4*		

The final data-set was further analyzed at different levels (sample, group and individual) to detect variations in the sample.

Travel data analysis

Figure 1 presents identified average number of trips per person each day. After the first registration day, the average number of trips increased rapidly from 1.5 to 3.3 and 1.4 to 2.6 for the SMiO and CATI method. At day 6, GLH produced 52% more trips than the CATI method. Over the whole period, GLH identified most trips in 7 of 10 days. In the second registration week, the gap between automatic detected trips from GLH and manually registered trips in CATI were higher than the first week (except from day one). Before trip matching, average trips per day for the whole period was 4,1 for CATI (A&B), 2,87 for SMiO and 2,84 for GLH (Norwegian RVU=3,26).

As we can see from figure 2, the assisted interviews (CATI (B)) have a lower proportion of registered trips than the unassisted interviews (CATI (A)). The blue marks indicate the average number of trips from GLH. CATI (A) shows in average 0,6 more trips than GLH estimate and CATI (B) shows in average 0.5 trips less than GLH estimate.

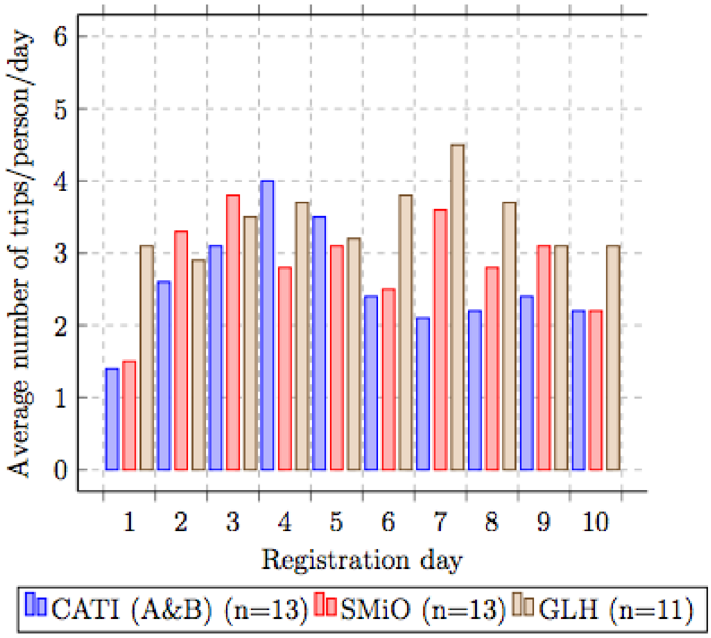

Figure 1 – Average number of identified trips per person per day.

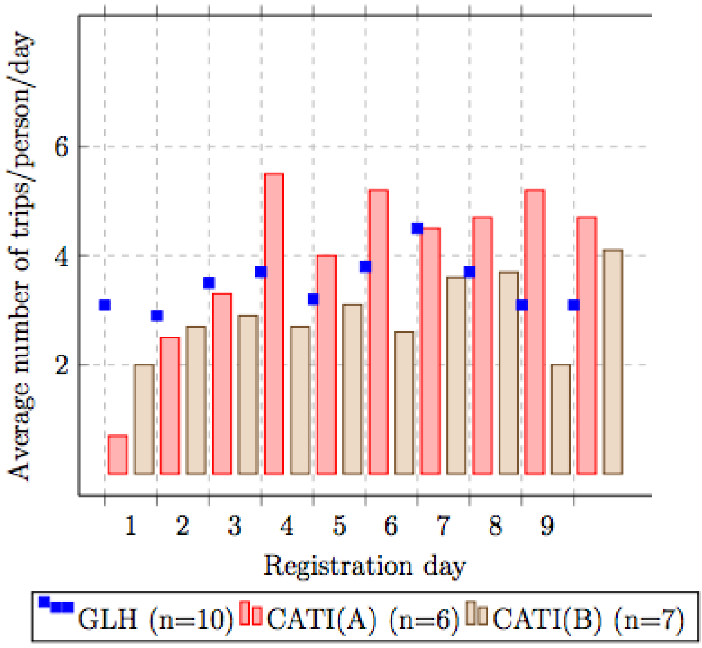

Figure 2 – Average number of identified trips per person per day.

Figure 3 shows the total trip distribution dependent on modes and methods after trip matching. iOS units did not provide a mode estimate and hence the trips were not analysed. For SMiO, each mode registration represents the main transport mode for one trip. There is a great correlation for the walking mode between the methods. GLH identified only seven cyclingtrips, but 53 trips by vehicle. Both applications identify fewer cycling trips than CATI (A&B). The applications also have an equal amount of trips with unknown modes.

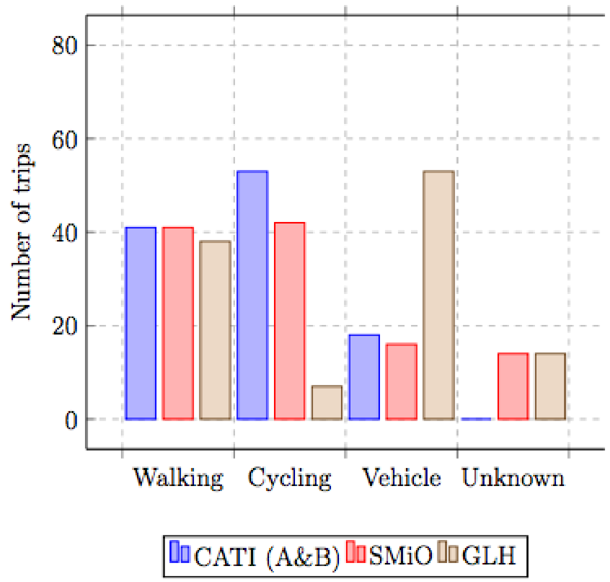

Figure 3 –Distribution of trips by mode (n=112).

Table 3 shows that there is a greater positive relationship between CATI (A&B) and SMiO, with r(112) = 0.48 ($p < 0.05$) for all modes. GLH shows low correlation relative to CATI (A&B) and SMiO.

Table 3 – Correlation-matrix between different modes (n=12).

	CATI (A&B)	*SMiO*	*GLH*
CATI (A&B)	*1,00*		
SMiO	*0,48*	*1,00*	
GLH	*0,21*	*0,21*	*1,00*

100% of the trips registered as a public transport trip in SMiO, only had a walking trip before they travelled by bus, not afterwards. 50% of the reported public transport trips in CATI were identified in SMiO.

A comparison between the two different applications for each operative system is shown in figure 4. The correlation between SMiO and GLH is greater for Android (figure 4a) than iOS (figure 4b) smart-phones. In this case, the iOS participant uses longer time to travel a shorter distance with the GLH application. The GLH logging frequency is about 10 times lower for the iOS system (0,005 Hz) than the Android system (0,050 Hz).

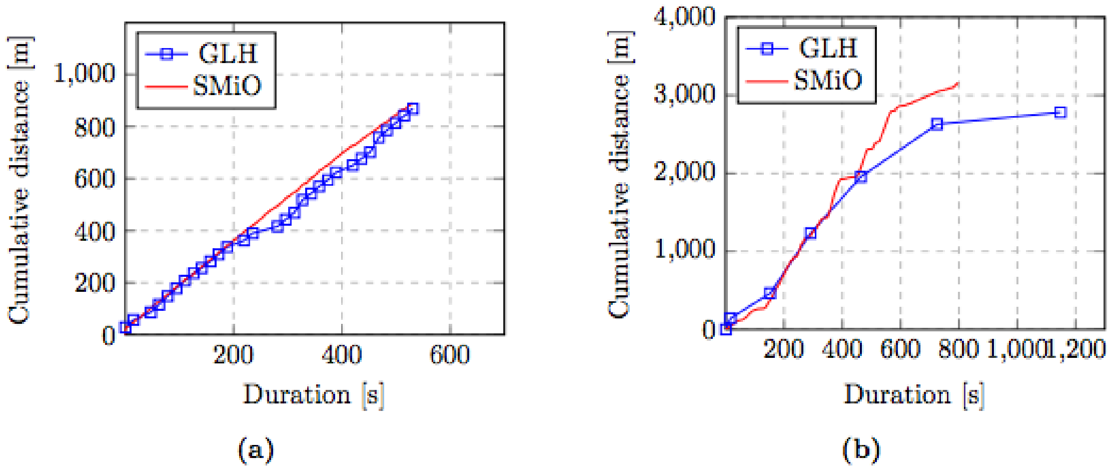

Figure 4 – Relation between cumulative distance and duration dor Android (a) and iOS (b) (n=1).

Table 4 illustrates the aggregated results for estimated departure times from the interview and matched timestamps from GLH and SMiO. Overall the iOS units show greater variety between the three methods. iOS-users underestimate with approximately 11 minutes in CATI compared with the SMiO application. Also GLH shows a greater negative difference compared with SMiO. Further analysis show that the differences between SMiO and GLH are greater in the morning hours than the rest of the day. Furthermore, except in three cases, all of the CATI-registrations were rounded off to the nearest five minutes.

Table 4 – Relationship between differences in average estimated departure times.

OS		*CATI vs SMiO*	*SMiO vs GLH*	*CATI vs GLH*
Android	*Mean [min]*	*2,32*	*0,71*	*3,03*
(n=112)	*Std. Deviation*	*24,64*	*8,99*	*22,88*
iOS	*Mean [min]*	*-11,45*	*3,81*	*-7,64*
(n=40)	*Std. Deviation*	*44,61*	*21,47*	*44,88*
Total	*Mean [min]*	*-1,30*	*1,52*	*0,22*
(n=152)	*Std. Deviation*	*31,58*	*13,43*	*30,45*

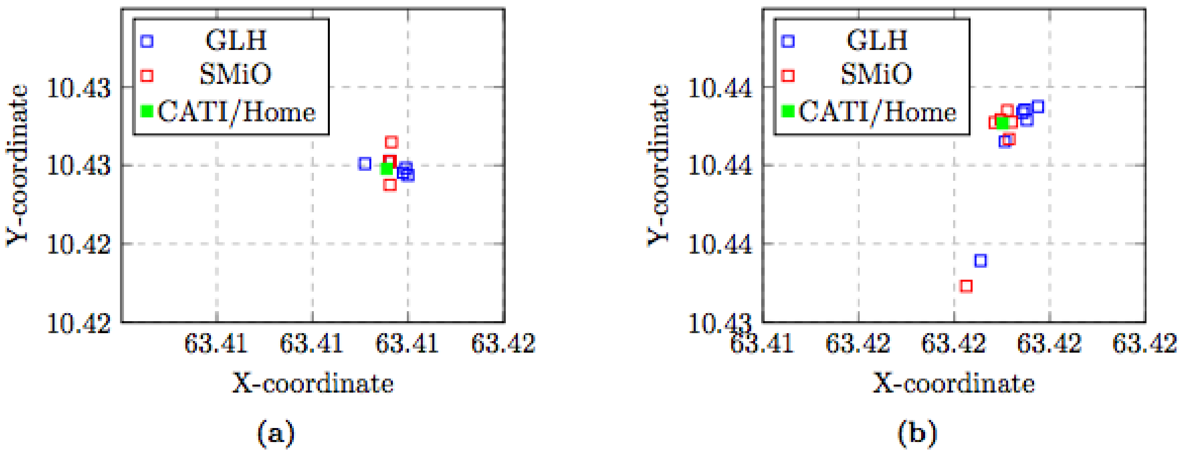

Figure 5 – Start location for Android (a) and iOS (b), related to home (n=1). Each route 10x10m.

A closer look at the start-locations for six work-trips is illustrated in figure 5. The trips are common for both applications. Green marks point out the home location based on public map data. Figure 5a shows that the Android location provides high accuracy and precision with an average offset distance 14, 3 ± 3, 7m for GLH and 8, 8 ± 2, 0m for SMiO. For iOS in figure 5b, the corresponding number is 37, 4 ± 11, 4m for GLH and 26, 2 ± 17, 1m for SMiO. Except from one location by iOS, SMiO shows high accuracy and precision and the GLH-locations indicate lower accuracy.

Figure 6 shows the change in the average duration of the telephone interview. The duration decreased after the first two registration days and it seems to stabilise at four minutes. CATI A use in average 67% longer time than CATI B.

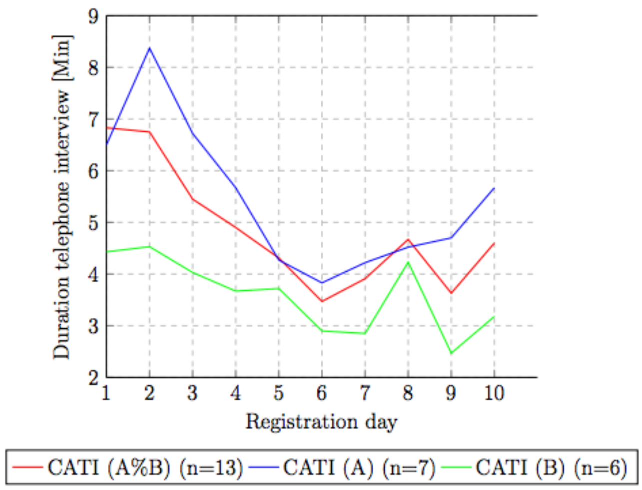

Figure 6 – Average interview duration per day.

End survey

After the registration period, the participants were asked to complete an end survey about their experiences with the applications and the overall procedure. The duration of 10 days seemed to be within acceptance for most of the participants, but it was perceived differently by the various methods. Especially for the CATI method, the participants were divided in their opinions. By some, the method was seen as annoying and complicated on an everyday basis. The others thought it was helpful with a daily reminder.

81% did not prefer the SMiO application. The main reasons were linked to ”Technical problems with app”, such as long start-up time to receive GPS-signals and general usability. As a result of this, one of three did not track at least 10 trips. None of the participants tracked all their trips, which can be explained by the fact that one of two forgot to bring their phone for one to five trips. Nobody mentioned power problems as a reason for the low tracking rate, but it was pointed out that an external battery pack was necessary. An interesting statement was ”The application may provide more accurate data, especially combined with the interview.” The participants were more excited about the GLH application. Two out of three preferred this automatic method, mainly because it was an automatic data collector and therefor less of a burden. Especially not having to change travel mode at each leg was considered as positive. Just one participant was worried about the privacy and how much the receiver could learn from the travel habits.

Discussion

In this study we used crucial travel indicators to compare four different methods to determine if they are suitable to supplement or replace the national travel surveys in Norway. The pilot survey investigation was conducted in the central Trondheim area, with a small homogeneous sample size which may not be representative for a full scale project. Regardless of this, the project might give an idea of the challenges of such methods.

Which technological challenges are introduced by using smart phones to collect data from travel surveys?

The results from the experiment showed major differences between the applications in terms of the data sets sizes. A possible explanation to why GLH produces more data, may be that this passive collector also tracks location points when the phone is still. In GLH, there are also great difference between type of operative system, while in SMiO there is no difference. The filtering process had greater impact for the Android GLH data-set and ended up producing more valid trips per megabyte than SMiO. This seems to be consistent with the higher sampling frequency in SMiO.

The major difference between iOS and Android seems to be the sampling interval. In the distance-duration analysis, reduced sampling interval caused cut off path-corners for iOS in both applications. The consequences are shorter trips and less precise routes. Despite this, reducing the number of data points will be beneficial in terms of reduced data processing time and cost (Shen and Stopher, 2014).

Even if smart phones can calculate most tasks locally, the processing demands efficiency hardware, high storage capacity and battery consumption. Both applications transfer data and stores it on a dedicated server. This requires regular data transfer between the unit and a computing server, which will require more cellular data traffic and operational costs. This may cause time delays where there are slow speed networks, but also no transfer at all in areas with low signal (such as mountains and tunnels). Thus, some trips might not be completed in the data-set.

Feedback from the respondents tells us that long start-up time may explain why SMiO registered fewer trips than GLH. Problems regarding slow GPS-fix should be handled automatically in both SMiO and GLH by connecting to Wi-Fi. In areas without Wi-Fi signal, GLH remembers the last registered position since it tracks continuously. In SMiO, the application must initialise the position before each trip and this may cause longer start-up time. SMiO performed better in the start-location analysis and that may indicate that the respondents are willing to wait for the application to start up.

Assisted CATI did help the participant with some missing trips by using information from GLH. Therefore, the accuracy of the GLH data has direct affect. Anyway, the method seem to give marginal benefit relative to CATI A in this study.

Do smart-phones provide better and more accurate data compared to traditional methods in travel surveys?

The matching rate between SMiO and CATI was 43%. This is in line with the study by Forrest and Pearson (2005), where 44% of the trips reported in CATI were matched correctly with the GPS-survey. This could be explained by the fact that both applications produced fewer trips than CATI. The non-matched trips from the applications might be new trips which could equalize the underestimation of trips.

When it comes to the share of transportation mode detection, the applications does not correlate well. The cycling mode tends to be registered as vehicle in the GLH. This may be due to placement of the telephone, since the applications also use accelerometer data to estimate modes. If the phone is in the backpack, it might simulate a vehicle frequency. The low share of public transport trips from the SMiO can be explained by the fact that the users forget to change mode for leg number two. The low correlation between CATI and the applications, show the strength of the CATI method, since CATI provides a mode estimate for all trips. This is in contrast to the high share of ”unknown” modes in the applications.

When decreasing the sampling interval to reduce battery consumption in iOS, the locations become more unsuitable for further analysis. This applies for both applications. Even if we increase the accuracy threshold to 100 m, the distance-duration comparison reveal differences between the operative systems that probably will affect other trip attributes. Both applications provide great precision in the start-location analysis. However, they can not compete with the CATI method where the location was fixed.

Our study shows that iOS users underestimate their departure times compared to the applications, while Android users tend to overestimate. This can be explained by the combination of sampling interval and the definition of departure time (first location with speed greater than 0,5 km/h). The lower standard deviation within the applications tell us that they probably are more close to the real departure time than CATI. Therefore, our study shows that CATI is less accurate for the departure time than the smart-phone based methods. It is likely that this also applies to travel times.

There are differences between the methods regarding the data quality. The active SMiO data collector might be a more accurate trip data collector than the passive GLH. But the passive collection method might be the best in capturing short trips, as these are the ones less reported in CATI. The greatest benefit from the smart-phone based methods may be the time variable. It seems to be more accurate than the traditional method.

Do the new registration methods influence respondents behavior?

The emerging methods must get user acceptance and a way of doing this is to lower the respondents burden. All four methods make it possible to examine trips over a longer period than today's travel survey, with a different grade of interaction by the respondents. Both the CATI methods require high interaction for a short time at daily basis. In this pilot study the interviewer was flexible when it came to the time of the calls. In a large scale survey the answering rate may be much lower than 91% due to decreased schedule flexibility. In the traditional RVU, the telephone interview takes about 23 minutes (Hjorthol et al., 2014). In this pilot, it lasted about 5 minutes. Long duration of the interview could contribute to lying or hasting to finish, which may lead to underreporting.

Passive tracking introduces a major concern due to privacy and security of data. The GLH method requires constant surveillance, but still the majority have no trouble letting themselves be tracked. This may be due to the fact that the respondents are young and technological interested, thus familiar to sharing their lives on social media. Elderly and non technologically people may, for the same reasons, be an under-reported group. Liu et al. (2016) mention ”sensitive zones and times” as a suggestion to protect the personal privacy. The participants may be more willing to be a part of the data collection if they know that they are only on record at certain times or in certain areas. This could be taken into account if one should go further with a passive method such as the GLH.

Like the CATI-method, SMiO has registered fewer trips than the GLH the first registration day. According to Stopher and Greaves (2007), the reason might be that the respondent uses a certain time to get used to operating the application or the correct understanding of the trip definitions. The respondents also found it hard to remember starting the SMiO application. To avoid those factors, a passive method should be selected.

The respondents were more positive towards the passive GLH application than the active SMiO application due to lower interaction and hence less of a burden on a daily basis. There is no doubt that the SMiO application should be more streamlined (clear and simple user interface, aesthetic, responsive, consistent, etc.) to minimize cost and maximize benefits for the users. For an active application such as SMiO, users should feel that they are part of something valuable. Additional services such as travel suggestions, social connected features, calorie or CO2 emission consumption counter could be integrated in the applications to get more enthusiastic respondents (Barbeau et al., 2009). Free data traffic during the survey period could also be an alternative.

Another interesting finding is that this medium/long term travel survey has a larger gap between automatic and manual trip registrations later in the period. Together with the decreasing duration for the telephone interview, this may indicate that the respondents tend to auto-answer when they had learned the questions. This problem could be avoided with use of the new methods.

Conclusion

In this paper we have used four methods to compare crucial indicators within transportation and travel behaviour surveys. The above analysis and discussion indicate that data collected by smart-phones will vary in precision and accuracy depending on sampling frequency. This is related to different types of operative system. iOS seems unsuitable as a data collector for use in travel surveys. By setting advantages up against the disadvantages, continuous passive tracking based on data from SMiO seems to be the way for further investigation. Combined with a smart-phone based recall survey that confirms travel modes, the quality of the collected data should be more precise and accurate than today's diaries.

This paper recommends going further with a passive collecting method, based on a similar sampling frequency as the SMiO application. Although a passive logging method produces more data and raise privacy concerns, the overall travel survey quality may increase due to higher response rates. Smart-phone based travel-surveys seems to be a promising alternative to contribute to or replace traditional travel survey methods. However, it can create some socioeconomic challenges, due to the necessity of compatible smart-phones. Further research should be focused on immediate validation through PRS and improvement of processing algorithms.

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