CURRENT STATE OF SMARTPHONE SURVEY METHODS

Annotated Bibliography

2015-09-30

Transportation Tomorrow Survey 2.0

Mohammed Rashed, Siva Srikukenthiran

Khandker Nurul Habib & Eric J. Miller

UNIVERSITY OF TORONTO
FACULTY OF APPLIED SCIENCE & ENGINEERING
Transportation Research Institute

TABLE OF CONTENTS

	PAPER TITLE	PASSIVE (LOCATION)	PASSIVE (MODE)	PASSIVE (ACTIVITY)	PASSIVE (TRIP START/STOP)	ACTIVE / VALIDATION / APP DESIGN / INSTRUMENT BIAS	BATTERY / PERFROMANCE / DATA TRANSFER	SAMPEL FRAME	CORE / SATELLITE	HOUSEHOLD / INDIVIDUAL	MULTI-DAY/WEEK	RESPONSE RATES / RECRUITMENT / INCENTIVES / PRIVACY
14	*Opportunities and Problems with Automated Data Collection via Smartphones*											✓
15	*GPS-Based Daily Context Recognition for Lifelog Generation Using Smartphone*	✓		✓								
16	*Smart Diary: A Smartphone-Based Framework for Sensing, Inferring, and Logging Users' Daily Life*			✓			✓				✓	
17	*Tracking Daily Travel: Assessing Discrepancies between GPS-Derived and Self-Reported Travel Patterns*					✓		✓	✓		✓	✓
18	*Does the Use of Mobile Devices (Tablets and Smartphones) Affect Survey Quality and Choice Behaviour in Web Surveys?*					✓						
19	*ATLAS Project – Developing a Mobile-Based Travel Survey*	✓				✓						
20	*Design and Implementation of a Smartphone-based System for Personal Travel Survey: Case Study from New Zealand*	✓			✓	✓	✓	✓	✓	✓	✓	✓
21	*Trip Analyzer through Smartphone Apps*	✓	✓	✓	✓		✓					
22	*Public Works and Government Services Canada Report – Secondary Research into Cell Phones and Telephone Surveys*							✓		✓		✓
23	*The Impact of a Mixed-Mode Data Collection Design on Response and Non-Response Bias on a RDD Landline Telephone Survey*											✓
24	*Residential Telephone Service Survey*							✓				

	PAPER TITLE	PASSIVE (LOCATION)	PASSIVE (MODE)	PASSIVE (ACTIVITY)	PASSIVE (TRIP START/STOP)	ACTIVE / VALIDATION / APP DESIGN / INSTRUMENT BIAS	BATTERY / PERFROMANCE / DATA TRANSFER	SAMPEL FRAME	CORE / SATELLITE	HOUSEHOLD / INDIVIDUAL	MULTI-DAY/WEEK	RESPONSE RATES / RECRUITMENT / INCENTIVES / PRIVACY
25	*Optimizing Surveys for Smartphones: Maximizing Response Rates While Minimizing Bias*					✓						✓
26	*Comparison of Smartphone and Online Computer Survey Administration*					✓						✓
27	*Comparing Survey Results Obtained via Mobile Devices and Computers: An Experiment with a Mobile Web Survey on a Heterogeneous Group of Mobile Devices Versus a Computer-Assisted Web Survey*					✓						✓
28	*Encouraging Survey Response via Smartphones: Effects on Respondents' Use of Mobile Devices and Survey Response Rates*					✓						✓
29	*Improving Response to Web and Mixed-Mode Surveys*											✓
30	*Trends Report: Mobile Participation in Online Surveys*					✓						✓
31	*Human Behaviour Cognition Using Smartphone Sensors*	✓			✓		✓					
32	*UbiActive: A Smartphone-Based Tool for Trip Detection and Travel-Related Physical Activity Assessment*	✓			✓	✓		✓			✓	✓
33	*Participation and Diligence in a Multi-Day, Multi-Year Survey: Impact of Recruitment Methods and Demographics*					✓		✓			✓	✓
34	*Social Media in Public Opinion Research: Report of AAPOR Task Force on Emerging Technologies in Public Opinion Research*							✓				✓
35	*A Simulation Study on Automated Transport Mode Detection in Near-Real Time using a Neural Network*		✓									

	PAPER TITLE	PASSIVE (LOCATION)	PASSIVE (MODE)	PASSIVE (ACTIVITY)	PASSIVE (TRIP START/STOP)	ACTIVE / VALIDATION / APP DESIGN / INSTRUMENT BIAS	BATTERY / PERFROMANCE / DATA TRANSFER	SAMPEL FRAME	CORE / SATELLITE	HOUSEHOLD / INDIVIDUAL	MULTI-DAY/WEEK	RESPONSE RATES / RECRUITMENT / INCENTIVES / PRIVACY
36	*Overcoming Battery Life Problems of Smartphones when Creating Automated Travel Diaries*	✓	✓		✓		✓				✓	
37	*Dutch Mobile Mobility Panel (Hoe mobiel zijn we nu eigenlijk? Eerste inzichten uit het Mobiele Mobiliteitspanel)*	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
38	*SmarTrAC: A Smartphone Solution for Context-Aware Travel and Activity Capturing*	✓	✓	✓	✓	✓	✓			✓	✓	✓
39	*"In the Moment" Travel Study: A GPS Smartphone Application*	✓			✓	✓		✓	✓	✓	✓	✓
40	*Can Your Smartphone Do This: A New Methodology for Advancing Digital Ethnography*										✓	✓

1. A Web-Based Diary and Companion Smartphone App for Travel/Activity Surveys

Greaves, Stephen, Adrian Ellison, Richard Ellison, Dean Rance, Chris Standen, Chris Rissel, and Melanie Crane. 2014. "A Web-Based Diary and Companion Smartphone App for Travel Activity Surveys." *The 10th International Conference on Transport Survey Methods*. Leura, Australia.

Categories	Passive (Location), Active, Battery, Household/Individual, Multi-day/week, Response Rates
Applications	Recruitment methods, reminder system for improving completion rates for validation/diary tools Peak access time of the survey by the respondents was 11am, which was the time the daily email reminders were sent out
Methods Used and/or Summary	▪ An online 7 day travel diary with a companion smartphone app ▪ Features included to simplify process of data entry from the user: auto-fills (previous trip's destination set as new trip's origin), prompting (for example for public transportation access mode to capture incidental walking and cycling), save and recall favourite trips, provide maps of daily travel to assist with recalling if respondent uses the smartphone app ▪ Tips and questions relating to each page of the web survey could be accessed always from any page ▪ Sample consists of 847 residents of a specific area in Sydney, Australia, aged between 18-55 and capable of riding a bike ▪ 75% of participants said they had no issue with the diary once they became familiar with it, 90% willing to do the study again in 12 months' time ▪ Over half the participants used the app, strong indications that it improved recall of trips as well as accuracy of details ▪ Literature review discusses that in traditional surveys (such as mail-back), short walking or cycling trips are inadequately captured but on web surveys, can prompt users for this specifically ▪ Daily email reminders were crucial for getting a high completion rate for each day of the survey ▪ Hard to recruit respondents, even with AUD 50 incentive ▪ For smartphone, cellular network and Wi-Fi for location determination rather than GPS as the latter's effect on battery drain was too high ▪ Smartphone app kept as simple as possible and provided the bare minimum information required ▪ Negative reactions about the web-based survey mainly had to do with functionality issues and compatibility with different browser versions and devices ▪ Peak access time of the survey by the respondents was 11am, which was the time the daily email reminders were sent out ▪ Participants took around 10 minutes per day ▪ Data cleaning: largest task was identifying locations that were the same but spelt differently ▪ App had to be designed for a the various smartphone models available, taking into account different usage patterns and behaviours ▪ Largest hurdle was getting participants to start the diary and complete the first day; once this was done, very few participants failed to complete all 7 days ▪ Those who chose to download the app and looked at the maps reported the highest number of trips, while also making the fewest errors. No statistical difference between smartphone users who looked at the maps and those that did not.
Strengths	▪ Daily email reminders to get high completion rate ▪ Comprehensive discussion about using a web-based diary and smartphone app for collecting information ▪ Literature review provides a brief but good overview of challenges and developments ▪ Smartphone app collects location automatically ▪ Discusses results between those who used the app and those who did not, as well as those who used the maps to recall trips and those who did not
Weaknesses	▪ Smartphone app does not detect mode or purpose automatically ▪ No detailed discussion on how sample frame of residents living in that specific area was obtained

2. Personalisation in multi-day GPS and accelerometer data processing

Montini, Lara, Nadine Rieser-Schussler, and Kay W. Axhausen. 2014. "Personalisation in multi-day GPS and accelerometer data processing." *14th Swiss Transport Research Conference*. Ascona: STRC

Categories	Passive (Activity), Sample Frame, Multi-day/week
Applications	High median accuracy for purpose achieved. Finding that including distance to home and work is increases accuracy slight could be used in TTS activity detection method. Using personal data has no effect on detecting trip mode
Methods Used and/or Summary	▪ Trip purpose detection using random forests by personalization during processing ▪ In previous GPS-based surveys, observed that accuracy of detections regarding trips details (purpose, location, etc.) depended on the participant and their daily schedules ▪ Collected second-by-second GPS and accelerometer data using dedicated GPS device ▪ Collected GPS and accelerometer using GPS devices from 156 respondents randomly selected from address pool. Respondents were asked to validate an automatically generated travel diary, including mode and trip purpose. These were all double checked by the survey team. ▪ Required personal data collection of respondents as well ▪ 17 variables are used, including: age, education level, trip start time, trip end time, day of the week, distance to work, etc. In the personalization strategy, subsets of this available data are used to generate different classifiers, which are compared for accuracy. Classification is better the more data is used, but there is a point of diminishing returns. ▪ Including distance to home and work is important to increase accuracy of results ▪ Collecting annotated data from participants for three days of personal data that is then included in the training set obtains a median accuracy of 80% for trip purpose, a 5.5% increase compared to the base scenario (where no personal data is included) ▪ Using personal data has no effect on detecting trip mode ▪ Concludes that 1 week of smartphone data is not enough to highly personalise trip purpose detection routines. The variance between participants is still very high, and so per person analysis of automatically processed data is problematic. ▪ Next steps: apply the classifiers in a 6 week smartphone study
Strengths	▪ Includes a brief overview of how the random forest algorithm works ▪ Promising potential
Weaknesses	▪ Results not conclusive, work in progress ▪ Requires second-by-second GPS and accelerometer data possible only from dedicated GPS device, likely significant impact on battery if used in smartphones

3. Trip Purpose Identification from GPS Tracks

Montini, Lara, Nadine Rieser-Schussler, Andreas Horni, and Kay W. Axhausen. 2014. "Trip Purpose Identification from GPS Tracks." *Transportation Research Record: Journal of Transportation Research Board* (No. 2405): 16-23.

Categories	Passive (Activity)
Applications	Features in random forest classifiers that improved accuracy the most include: transport mode after activity, duration of activity, transport mode before activity, distance to work, start time, walk percentage, and distance to home. This information could be used for developing the TTS activity detection method
Methods Used and/or Summary	▪ Same authors as #2 ▪ GPS gives many coordinate points even if user is at one location, so need to find a proper representative coordinate – then an activity is assigned to this location ▪ Three aggregation approaches: unweighted point cloud centroid (mean of all points), median x and median y coordinates, and coordinate with the highest density (density is computed as the number of coordinates within a 20 m radius around the candidate coordinate) ▪ Found best representation is achieved using highest density coordinate approach ▪ Discusses location-based vs activity-based identification of trips (activity-based uses information about the trip itself, such as time, duration, walk percentage, occurrences per day, etc. – whereas location-based uses land use information to try to predict trip activity) ▪ Found that location-based approach not as accurate (74%) as activity-based approach (80-85%), inclusion of person-specific data improves results (example: distance to home and work, age, income, etc.). Inclusion of just distance to home and work (and not including age, income, etc.) shows an improvement also. ▪ Overall accuracy of more than 80% for trip purpose ▪ Features in random forest classifiers that improved accuracy the most include: transport mode after activity, duration of activity, transport mode before activity, distance to work, start time, walk percentage, and distance to home.
Strengths	▪ Compares location-based vs. activity-based approaches to identify trip purpose ▪ Overall accuracy of more than 80% for trip purpose
Weaknesses	▪ Requires second-by-second GPS and accelerometer data possible only from dedicated GPS device, likely significant impact on battery if used in smartphones

4. Using Smartphones and Sensor Technologies to Automate Collection of Travel Data

Abdulazim, Tamer, Hossam Abdelgawad, Khandker M. Nurul Habib, and Baher Abdulhai. 2013. "Using Smartphones and Sensor Techologies to Automate Collection of Travel Data ." *Transportation Research Board* (No. 2383): 44-52.

Categories	Passive (Location, Mode, Activity), Battery
Applications	Method for mode detection is very accurate, but needs to be tested and developed further as data processing/transfer and battery requirements are too high for practical use
Methods Used and/or Summary	▪ Framework for a smartphone app that does mode, location and activity detection over a long period of time ▪ Mode detection done through using various sensors in the smartphone (including accelerometer, gyroscope, magnetometer, etc). Used machine learning (random forests) to identify the different patterns in the motion signals of the different modes (6 modes: subway, bus, car, walking, running, bike). ▪ Determining activity through using Foursquare (a location-based social network) database – using forward sortation area to create clusters of activity, therefore if someone travels to a particular cluster, the activity can be surmised from the land use information. Can also incorporate number of check-ins and user count at each location. ▪ If a location has been visited before, the app records just the start of a visit to this location; otherwise, it will run the land use discovery module to collect information about nearby locations that can be used to classify the new location. The user will be prompted to verify or correct the current location, which is then stored as a known location. ▪ When the application recognizes that the location is constantly changing, it will start the transportation mode detection module to classify the mode of travel. ▪ Location detection done using both GPS and network-based location services (i.e. triangulation via cellular network and Wi-Fi) – achieved accuracy of 100 m in urban areas using network-based location services ▪ 5 out 6 participants reported no significant change in battery life ▪ To reduce the dependency on the Internet and to limit battery drain, the location logger module maintains a small-scale database of landmarks such as cell identification and Wi-Fi network for frequently visited locations ▪ Activity and location not determined with high accuracy, requires users to correct and validate
Strengths	▪ High accuracy detection for various different modes – does not require GPS or network information (i.e. transit routes), relies simply on smartphone sensors ▪ Stores frequently visited locations and activities in a database on the phone, so does not need to validate trip purpose with user for every trip ▪ The use of machine-learning techniques allows the framework to be transferred to different transportation systems or deployed in other regions.
Weaknesses	▪ Very small sample size – only 6 participants ▪ Only developed for Android thus far, still requires further development for support and optimization on various devices as well as other platforms

5. The Use of Smartphone Applications in the Collection of Travel Behaviour Data

Vlassenroot, Sven, Dominique Gillis, Rik Bellens, and Sidharta Gautama. 2015. "The Use of Smartphone Applications in the Collection of Travel Behaviour Data." *International Journal of Intelligent Transportation Systems Research* 13 (1): 17-27.

Categories	Passive (Location), Active, Multi-day/week, Response Rates
Applications	
Methods Used and/or Summary	▪ Using MOVE (which has different mobile applications developed for the purpose of monitoring crowd behaviour through cell phone localization and activity), survey was done with people who were given electric cars to test for 2 weeks with the condition that they participate in the survey ▪ Purpose was to collect data on origins and destinations, travel times and distances, mode shares, trip purposes, etc. to analyse specific subgroups, either based on geographic selection (for example traffic on a particular link or network segment), or trip properties (example deducting typical user profiles per travel mode, or typical travel patterns per trip purpose). ▪ Users required to input the start and end of each trip, as well as activity and mode ▪ Used GPS and Wi-Fi for location detection ▪ The accuracy of individual tracks was enhanced by collating data from multiple trips on the same route by developing a technique based on fuzzy voting and image processing. "In the first stage tracks are plotted in a multi-dimensional grid with a fuzzy buffer. In the second stage of the process, the multi-dimensional grid is processed with morphological image processing techniques adapted to three dimensions and fuzzy values, in order to extract the skeleton of the road network." ▪ Developing the app further to move towards a more passive application
Strengths	
Weaknesses	▪ Sample not representative of entire population, as it consisted only of car users with access to a free electric cars ▪ Active data collection – if user forgets to input trip end, requires manual correction by researchers which is not feasible for large datasets ▪ Battery life shortened through continued use of GPS

6. A GPS/GIS method for travel mode detection in New York City

Gong, Hongmian, Cynthia Chen, Evan Bialostozky, and Catherine T. Lawson. 2012. "A GPS/GIS method for travel mode detection in New York City." *Computers, Environment and Urban Systems* 36: 131-139.

Categories	Passive (Mode)
Applications	Describes ways in which GIS information of the road and transit network could be used to detect modes
Methods Used and/or Summary	▪ Develops a GIS algorithm that automatically processes the data from GPS-based travel surveys and detects five travel modes (walk, car, bus, subway, commuter rail) in New York. The mode detection results from the GIS algorithm are checked against the travel diaries from two small handheld GPS surveys ▪ Uses GIS for matching GPS traces with transport links in mode detection, similar to previous studies. However, they also build connectivity into their multimodal transportation network in GIS to recognize when mode transfers within a trip are feasible. Important in NYC where it is common to have streets crossing spatially but not connecting (such as bridges and overpasses) or underground subway tracks, streets, and elevated train tracks available at different levels of the same transportation corridors ▪ Also uses the network of bus routes and stops to help identify bus mode or transfers ▪ The overall success rate is 82.6%, ranging from 35.7% for commuter rail to 92.4% for walk mode
Strengths	
Weaknesses	▪ Does not detect underground subways routes since using only GPS ▪ Difficult to differentiate between bus, car or walk

7. Supporting Large-Scale Travel Surveys with Smartphones – A Practical Approach

Nitsche, Philippe, Peter Widhalm, Simon Breuss, Norbert Brändle, and Peter Maurer. 2014. "Supporting Large-Scale Travel Surveys with Smartphones – A Practical Approach." *Transportation Research Part* C 43: 212-221.

Categories	Passive (Location, Mode, Trip Start/Stop), Battery
Applications	Compression technique to reduce size of data collected and sent could be tested and used in TTS pilot
Methods Used and/or Summary	▪ Individual trips of users are automatically reconstructed and trip legs are classified into one of eight different modes of transport. This task is performed by an ensemble of probabilistic classifiers combined with the Discrete Hidden Markov Model (DHMM) ▪ Classification is based on motion trajectory recorded by the phone's positioning system and signals of the embedded accelerometer ▪ Also uses positioning data from the mobile phone cell network, and relies solely on accelerometer features when the trajectory cannot be reconstructed with sufficient accuracy. To train and evaluate the models, 355 hours of probe travel data were collected in Vienna, Austria by 15 volunteers over a period of 2 months ▪ Does not detect trip purpose automatically, users are required to input this manually ▪ Suggests implementing a semi-automatic trip survey using the client-server model. Therefore the extensive computation of the trip legs and travel modes can be performed on server hardware and will not drain the user's battery, but this introduces data transfer issues. ▪ Mentions a protocol that was designed and implemented to reduce traffic usage of the app, which compresses the sensors data size from more than 30 MB to approx. 6 MB per hour ▪ Suggests that if want a semi-automatic survey, users can use a browser to login to the web interface, which shows the user's personal trips and legs based on the reconstruction algorithm, where they can add information such as personal data or trip purpose and correct wrong or missing legs. The corrections are then used to improve the reconstruction algorithm by personalizing the general model towards the special user characteristics
Strengths	▪ Can distinguish between 8 different transportation modes ▪ Compression protocol for data transfer and upload from 30 MB per hour to 6 MB per hour ▪ Includes discussion on integrating the method into existing travel survey procedures
Weaknesses	▪ Classification results range from 65% (train, subway – since these two are similar in terms of velocity and accelerations) to 95% (bicycle) ▪ Requires constant logging from GPS and accelerometer ▪ Mode detection method: relies on GPS signal for greater accuracy, so when GPS signal is not available, this reduces accuracy

8. A Strategy on How to Utilize Smartphones for Automatically Reconstructing Trips in Travel Surveys

Nitsche, Philippe, Peter Widhalm, Simon Breuss, and and Peter Maurer. 2012. "A Strategy on How to Utilize Smartphones for Automatically Reconstructing Trips in Travel Surveys." *Procedia - Social and Behavioral Sciences* 48: 1033-1046.

Categories	Passive (Location, Mode, Trip Start/Stop), Core/Satellite
Applications	
Methods Used and/or Summary	▪ Probabilistic classifiers for automatically reconstructing individual trips of a tour and the mode used. Uses 72 features for classification (7 from GPS data, 64 from accelerometer signals). Results range from 80% (railway modes) to 92-98% (walks and bike rides). ▪ Uses GPS and accelerometer data, the latter only when there is no GPS data available. Recognizes specific patterns in the frequency and time domain of the accelerometer to identify transportation mode ▪ Sensor and GPS data collected in background, major computational tasks carried out in server ▪ Suggests that data collection using a smartphone app will not obtain results representative of the general population, as there may be a bias towards younger people or people with a personal technical interest. Due to this, suggests using smartphones as a supplement to conventional methods as opposed to a replacement of them.
Strengths	▪ Provides a brief discussion of advantages and limitations of a smartphone-based survey method with respect to representativeness, comparability, precise detection of trips, user acceptance and data protection
Weaknesses	▪ Relies on GPS data for trip purpose identification, accuracy drops when GPS data not available

9. Future Mobility Survey

Cottrill, Caitlin D., Francisco Camara Pereira, Fang Zhao, Ines Ferreira Dias, Hock Beng Lim, Moshe E. Ben-Akiva, and P. Christopher Zegras. 2013. "Future Mobility Survey." *Transportation Research Board* (No. 2354): 59-67.

Categories	Passive (Location, Mode, Activity, Trip Start/Stop), Active, Battery, Sampling Frame, Core/Satellite, Household/Individual, Multi-day/week, Response Rates
Applications	Lessons learnt from pilot implementation with regards to use of smartphone app, web validation tool, general logistics and user behaviour would be vital to learn from for TTS

Methods Used and/or Summary	▪ Smartphone-based travel survey developed and deployed in Singapore, subset of nationwide Singaporean Household Interview Travel Survey conducted every 4-5 years.
	▪ Pilot study using a voluntary convenience sample, plan to survey 1000 participants in 2012 household survey
	▪ Is an effort to develop a "core" survey that can be used as a standalone survey, as a well a platform for development of additional surveys as more sensors and applications are developed
	▪ User input at 4 stages:
	  o registration (HR – household responsible – provides basic household information),
	  o presurvey (HR provides more detailed info about household, including socioeconomic information and vehicle ownership),
	  o activity diary (validate activity on FMS website which is detected through use of FMS smartphone app)
	  o exit survey: feedback on survey experience, additional preference information
	▪ Survey for 2 weeks, activity validation required for at least 5 of those days
	▪ Incentive: $25 upon completion
	▪ Presurvey inputs, prior validations, frequently visited places, points of interests, all used to create a contextual knowledge base to improve detection accuracy and to help with trip purpose identification
	▪ Each member of household asked to participate in the survey – therefore survey still at the household level, not limited to only one individual from household

	▪ Prioritized accuracy of data collection in the following order: activities, modes, locations, routes. Reason for this is that it is harder to determine activities and mode from sensory data itself while route identification can be performed via post-processing, for example by using probabilistic map matching and filling gaps with route planning algorithms (eg Google Maps API).
	▪ Pilot suggested that presurvey questionnaire, which was similar to the regular household survey, was too lengthy and burdensome for participants, so information required for background processing and identification was retained in presurvey while other questions were moved to exit survey.
	▪ 74 people completed presurvey, 50% of which installed the app, 36% actually validated the data
	▪ For mandatory questions, would disallow participants from proceeding to the next question if they did not provide an answer. In order to not put users off from the survey entirely, an option to "prefer not to answer" was provided. Sensitive questions such as income and ethnicity were asked only once the participant was invested in the survey.
	▪ Battery issues: focused on "phased sampling" which means turning the GPS off for long periods to conserve energy. During the sleep periods, only GSM, Wi-Fi and accelerometer data would be collected. Various sleep/wake configurations were tested, with the trade-offs being between resource efficiency and data accuracy. These methods still remain under testing and refinement.
	▪ Battery life: range of 10 to 24 hr, depending on user's travel pattern
	▪ Users were given the option to upload continuously using data or only when Wi-Fi was available
	▪ Designed a simple and non-intrusive interface for the app, decided not to keep the activity diary on the app itself to keep it as simple and resource efficient as possible.
	▪ Activity diary: online interface was kept consistent with design of smartphone app. Interface uses maps to help recall of participants trips, allows for editing as needed.
	▪ Conclusions from usability tests (10 participants) regarding the activity diary:
	    o Match map to user interactions with diary (consistent numbering, icons, highlighting when interacting)
	    o Readability based on color and font should be maintained
	    o Content should be clearly organized
	    o Questions should be presented clearly, with limited but sufficient options
	▪ Some users preferred map interaction, others text for validation – both options were available
	▪ Developed responses to FAQs and a tutorial video which was constantly updated
	▪ had call center support during business hours to respond to any queries from respondents.
	▪ Lessons learnt from pilot:
	    o Users tend to forget about the app if it is non-intrusive, and need reminders to turn the GPS on, use the website, etc.
	    o Battery life is a major issue – requires frequent recharge
	    o Even with exact same type of phone and settings, data quality may differ considerably – due to GPS noise, interference, etc.
	    o People can relatively easily recognize past locations and activities when looking at their traces
	    o Some users prefer map interaction while others prefer text, ideally should provide same type of interactions with both approaches
	    o Zoom level: a low zoom level provides context but no a precise location, while a high zoom level allows users to carefully verify location but loses context. Needs to be carefully designed
	    o Users that use this for the first time will need a more information-intensive interface than those who are familiar with it, therefore the interface should gradually change according to the user's expertise – less guidance per visit.
	▪ Next steps involve improving the app, providing automatic email reminders, step-by-step tutorials
	▪ FMS being deployed (at the time of writing the paper) as part of Singapore's latest household travel survey, with an expected 1000+ participants

Strengths	▪ Performed usability tests for web interface and provides good recommendations ▪ Well-designed overall framework suggestions. Includes lessons learnt, methods of improvement and considerations of usability ▪ Each member of household required to use the app, therefore still capturing household level information
Weaknesses	▪ Voluntary convenience sample, no measure of sample coverage, sampling or non-response error – was skewed towards younger and more educated people, with low automobile ownership rates ▪ No conclusive result with regards to phased sampling to limit battery issues, still under testing

10. Activity Recognition for a Smartphone-Based Travel Survey Based on Cross-User History Data

Kim, Youngsung, Francisco C. Pereira, Fang Zhao, Ajinkya Ghorpade, P. Christopher Zegras, and and Moshe Ben-Akiva. 2014. "Activity Recognition for a Smartphone Based Travel Survey Based on Cross-User History Data." *22nd International Conference on Pattern Recognition.*

Categories	Passive (Activity)
Applications	Could be used as basis for TTS smartphone app for activity detection. Also includes discussion about using user-specific information (like age, gender, income) for improved accuracy

Methods Used and/or Summary	▪ Based on Future Mobility Survey dataset – improvements for future versions of FMS app
	▪ Paper proposes a learning model that, given a stop location, identifies the most likely activity associated to it.
	▪ Tough challenge as people have heterogeneous patterns within a small area (e.g. shopping malls with a healthcare facility, supermarket, offices) or at the same time (e.g. working at home, shopping while waiting for the train). Also, GPS sensor data quality is poor indoors.
	▪ To alleviate uncertainty of real world data, heterogeneous features are extracted across the population. Given a stop location, algorithm identifies an activity based on spatial, temporal and contextual features. Only assumption is that home location is known (via a presurvey).
	▪ Dataset consists of activity points q_i defined as {*ci, Si, ai*} where a_i denotes an activity. Spatial cell: the location (x_i, y_i) → a cell c_i. The time period (t_{i1}, t_{i2}) →a set S_i. The day type of a time slot *s* is also noted as *W(s)*; *X(c)* retrieves the set of Points of Interest from the database, corresponding to cell c.
	▪ Activity Frequency: for each point, three kinds of activity frequency are determined: temporal, spatial and contextual. Count a normalized frequency of activity *l* within a bin over the total count of all activities within the same bin.
	    o For spatial activity frequency, the bin used is a spatial cell c_i
	    o For temporal activity frequency, each time slot adds 1 (e.g. an activity that spans from 8:00 to 10:00 contributes 12 to the total count, assuming 10 minutes time slots). The bin at activity point *i* is now defined by its entire sequence of time slots (S_i). Inclusion or exclusion of a different activity point *j* in that bin is based on how many common time slots exist between *i* and *j*.
	    o For contextual activity frequency, each Point of Interest category is mapped to one of the activity classes, and then a relative frequency of each activity type in each spatial cell is computed.
	▪ Distance-based empirical probability: For each user, based on Points of Interest, past activity information and their home and work locations (called the "core" activities), the distance to each activity from home and work are calculated
	▪ Activity duration is also collected
	▪ Acceleration and speed variables used to detect stop segments (for example mode transfer, stop at traffic light, etc)
	▪ Decision tree-based methods show best performance using Circular polygon cell. Circular polygon: a spatial quantization method of data points in which a cell is defined within a predefined distance (radius of circle) at each data point. Each data point is a centroid of a cell.
	▪ Overall accuracy: 78%
	▪ Improving process to include user-specific information such as socio-economic information (age, gender, occupation)

Strengths	
Weaknesses	▪ Still work in progress, results not conclusive

11. Exploratory Analysis of a Smartphone-Based Travel Survey in Singapore

Zhao, Fang, Francisco Camara Pereira, Rudi Ball, and Youngsung Kim. 2015. "Exploratory Analysis of a Smartphone-Based Travel Survey in Singapore." *Transportation Research Board 94th Annual Meeting* (No. 15-4343).

Categories	Core/Satellite, Household/Individual, Multi-day/week
Applications	Shows clear measurable differences and advantages of using smartphones to collect more quality data, with better insight into travel patterns over multiple days, and with lower user burden than traditional survey methods,
Methods Used and/or Summary	▪ Research on Future Mobility Survey (FMS) data and comparison with regular household travel survey (called HITS) ▪ FMS had detailed travel activity data, which was validated by participants ▪ This paper discusses revelation of interesting and diverse user daily travel patterns, and how this platform can be used to overcome the challenges of the traditional travel surveys ▪ 793 completed the FMS survey, recruited 1,541 ▪ GSM, WiFi and accelerometer information are used to merge stops that would otherwise be interpreted as distinct stops. Travel modes are detected based on GPS and accelerometer features, as well as public transit location information. Short duration stops that are insignificant from a data validation standpoint (such as stops in traffic or at bus stops or subway stations during their ride) are deleted for the purposes of presentation in the web interface. Non-travel activities (e.g. home, work, shopping, dropoff) are also detected based on previous validations by the user, POI data and other contextual information. ▪ Regular HITS is a paper-based face-to-face survey done every four or five years in Singapore. Sample size of HITS is 10,500 households, about 1% of total household number in Singapore, which is roughly 1 million. ▪ The recruitment process for FMS piggybacked on that of HITS. After a HITS interview, the surveyor introduces and invites the participant to take part in FMS. ▪ While HITS is a household-based survey, FMS is an individual-based survey. The reason for this was because this was the first attempt at using smartphones for doing a travel survey, they wanted to increase participation rate ▪ FMS survey consisted of 14 days, required users to validate at least 5 of those days ▪ FMS participants biased towards younger population. In previous traditional surveys, this younger population was under-represented, so FMS is a good <u>complement</u> (read: satellite) to traditional survey ▪ Clustered the activities of FMS users into 5 travel day patterns. Cluster 1 consists of working days with lunch breaks in mid-day, and many non-work activities after work. Cluster 2 are days that are mainly just working, with few other activities. Cluster 3 has shorter work hours and many work-related activities. No work shows up in Cluster 4, but it has many non-work activities, likely for weekends or off-days. Finally, Cluster 5 are days that are mainly spent at home or traveling. ▪ None of the HITS days fall in Cluster 1, highlighting the low reporting rates of out of work activities in HITS ▪ By analyzing the travel patterns of one user, they see that there is a lot of variability from day to day. A one-day snapshot would not capture this pattern and behaviour ▪ HITS shows narrower travel distribution than FMS, which validates that people tend to report a "typical" day in self-reported surveys, but in reality, the travel times have a wider spread. HITS shows spikes at 20, 30 and 60 minute intervals. ▪ In HITS, most users report that they arrive home in the evening by 8pm, but in fact, a significant portion of the users reach home after 9pm, indicating under-reporting of activities towards the end of the day ▪ Can see three clear peaks in the FMS curve that corresponds to trips to breakfast, lunch and dinner. However, this trend is not clear from HITS data. In fact, the lower values for the HITS curve indicate a much smaller percentage of users reporting Meal/Eating Break activities in HITS. ▪ The amount of Pick-up/Drop-off activities appears to be lower in FMS. Since these activities may have very short durations, and the modes of transportation before and after the stops are the same, they might have been deleted in order to reduce the erroneous detection of "stops" related to traffic lights or traffic jam. Future improvements could be done by incorporating more Points of

	Interest (POI) information of the underlying map, and also from users' past validations ▪ Another observation is that the average travel times recorded in FMS is lower than that in HITS, which again shows that people's perception of travel travel times tends to be longer than reality. ▪ Many problems encountered in traditional surveys, such as under-reporting of short trips, inaccuracy in locations and times, and reporting of the typical day rather than the actual day, can be eliminated via FMS. Also, it is possible to capture large intra-user day-to-day variability in travel and activity patterns according to different types of users, which is not possible in a one-day survey. Marginal cost of collecting additional days with FMS is minimal, and user burden decreases over time as the back-end system learns about the users patterns and can make more accurate predictions over time
Strengths	▪ Shows clear and measurable advantages of using smartphones over traditional methods, such as collecting precise, multi-day data, while not missing on short trips. Additionally, this captures the actual trip behaviour as opposed to the typical day of the user
Weaknesses	

12. Stop Detection in Smartphone-Based Travel Surveys

Zhao, Fang, Ajinkya Ghorpade, and Francisco Camara Pereira. 2014. "Stop detection in smartphone-based travel surveys." *10th International Conference on Transport Survey Methods*. Australia.

Categories	Passive (Trip Start/Stop)
Applications	
Methods Used and/or Summary	▪ Used in Future Mobility Survey (FMS) ▪ Present the Stop detection algorithm used in FMS, from which the user's activity location and start/end times are derived based on the raw data collected from smartphones ▪ With perfect GPS information, the task would be easier, but in densely built up areas, indoors or underground areas, the GPS signal can be noisy, low-accuracy or non-existent, thus making the problem a more challenging one. Additionally, battery life concerns inhibit continued use of GPS. ▪ Takes into consideration inputs from GPS, GSM, Wi-Fi and accelerometer ▪ First round of stop detection based on location and point-of-interest (POI) data. GSM, WiFi and accelerometer information are used to merge stops that would otherwise be interpreted as distinct stops. ▪ Want to detect stops where users change transportation mode or transfer bus/trains, although they can be very short. On the other hand, do not want to include stops at traffic lights, traffic jams, or bus/train stops where the user did not get on/off ▪ 6 steps to the algorithm: filter raw data, generate candidate stops (generated if a user has been within an area of 50 m for one minute), check against frequent location signatures, merge stops, detect still mode (using accelerometer data to revise start and end times of candidate stops or merge them), and remove extra stops after mode detection (remove false positives such as traffic lights, traffic jams, etc). ▪ The last step may remove short drop- off/pick-up stops, which the users will have to add in the activity diary during validation – can be improved by including more POI information like road junctions, bus and train stops, etc. ▪ Based on user validations, the true positive rate of the algorithm is 95.5% and 12.3% percent of the detected stops were false positives (example stops at traffic lights) ▪ Some erroneous stops created when a user is indoors for a long time, but the GPS or GSM signal jumps while the user is not moving, and the system sometimes picks this up as the user making a short trip and returning. Can be partially rectified by utilizing the information from the user's frequently visited locations ▪ Easier to detect users' boarding stops, as they would usually wait for a short period of time before boarding a bus/train. The alighting stops, on the other hand, are very difficult to capture, as passengers would move away immediately after leaving the bus/train. A possible solution may be to examine the accelerometer data more closely ▪ The system can learn from users' personal histories and make better inferences over time
Strengths	▪ 95.5% accuracy of stop detection, which in turn is vital for accuracy of mode detection and activity detection in subsequent steps
Weaknesses	▪ Erroneous stops/trips when indoors for a long time, not detecting pick-up/drop-off stops, alighting from bus/trains. However, paper has suggested ways to improve these aspects as well ▪ Does not specifically address how much data transfer is required, possibly mentioned in other papers

13. An Integrated Stop-Mode Detection Algorithm for Real World Smartphone-Based Travel Survey

Ghorpade, Ajinkya, Francisco Câmara Pereira, and Fang Zhao. 2015. "An integrated stop-mode detection algorithm for real world smartphone-based travel survey." *ResearchGate*. May 6. Accessed August 20, 2015. http://www.researchgate.net/publication/275949958_An_integrated_stop-mode_detection_algorithm_for_real_world_smartphone-based_travel_survey.

Categories	Passive (Location, Mode), Battery
Applications	Similar Location and especially Mode detection methods could be used for TTS
Methods Used and/or Summary	▪ Based on FMS ▪ Both Android and iOS ▪ To preserve battery, have cycles of GPS data collection: collects GPS data for 3 minutes at 1 Hz frequency, then two minutes of no collection ▪ Filter away less accurate location data from network sources (i.e. when GPS unavailable) if accuracy reading is more than 500 m. ▪ Accelerometer readings collected at 2 Hz frequency ▪ Raw location data is segmented such that every location point within 5 minutes or 200 m from the first point is included in the first segment ▪ In the Stage 1 Classifier, each segment is considered for classification into stop, walk or motorized modes – using random forest classifiers. Uses statistical, temporal, GIS features and user history. ▪ The outcome from the first stage is then combined with some new features to build a sequential classification model, where segments are merged such that erroneous mode changes detected in the first stage are smoothed out – uses conditional random fields. Erroneous stop modes detected from Stage 1 are removed here. ▪ In the Stage 2 Classifier, the homogenous trips of motorized modes after merging the segments in Stage 1 are then classified in car, bus or train. Uses contextual features like GIS data of the road and transit networks ▪ 10 volunteers used for data collection for 4 months and annotated every trip to help train the model ▪ 8 different models of smartphones were used
Strengths	▪ 82.5% detection accuracy across 5 modes
Weaknesses	▪

14. Opportunities and Problems with Automated Data Collection via Smartphones

Bouwman, Harry, Mark de Reuver, Nico Heershcap, and Hannu Verkasalo. 2013. "Opportunities and problems with automated data collection via smartphones." *Mobile Media Communications* (1): 63-68.

Categories	Response Rates
Applications	Could use information discussed here as an overview of privacy considerations
Methods Used and/or Summary	▪ Paper provides suggestions in dealing with privacy ▪ Respondents were from Netherlands, but researchers had to also comply with Finnish regulations as the information was stored on a server in Helsinki, in addition to Dutch regulations ▪ Data must be collected with informed consent, privacy regulations should be published on a website related to the study, as well as a user-agreement and privacy-related FAQ. ▪ Data needs to be collected and analyzed by separate entities. The information was made available to the researchers and deleted by the company collecting the information after a prescribed period of time, as well as by the research company. ▪ Data should be stored and accessed using a password-protected login ▪ Finally, only aggregated level data must be reported. ▪ In the exit survey, most respondents stated that they were satisfied with the privacy warranty and trusted the researchers, and more than 70% of respondents indicated that they would be willing to participate again. ▪ Non-response due to privacy concerns can therefore be reduced significantly through proper communication regarding privacy considerations.
Strengths	▪ Good suggestions on how to deal with privacy considerations and to minimize non-response due to privacy concerns
Weaknesses	▪ Focuses more on marketing applications, uses a panel to select sample ▪ Were only able to collect usable data from 128 respondents

15. GPS-Based Daily Context Recognition for Lifelog Generation Using Smartphone

Tanaka, Go, Masaya Okada, and Hiroshi Mineno. 2015. "GPS-Based Daily Context Recognition for Lifelog Generation Using Smartphone." *(IJACSA) International Journal of Advanced Computer Science and Applications* 6 (2).

Categories	Technology (Location, Activity)
Applications	
Methods Used and/or Summary	▪ Paper provides a method for recognizing activities of daily human life based on a person's location ▪ Can recognize several contexts (activities) at the same location by extracting features from GPS data – this is then used to generate classification models by machine learning ▪ 5 classification models developed: mobile or stationary, transportation recognition, and three daily context recognition models ▪ Method can distinguish between shopping, eating a meal, seeing a movie at a shopping mall ▪ Mobile or stationary: machine learning used. User is considered to be mobile if the speed or variance of location (distance moved) is greater than a threshold. ▪ Location recognition: By registering information of locations in a database beforehand, possible to easily estimate a user's location when stationary. If in an unregistered position, it is possible to obtain information from nearby facilities by a place search API ▪ Transportation mode: using speed, location variance, weather as explanatory variables ▪ Investigated optimal machine learning algorithm for mode, mobile or stationary, and activity ▪ Daily context (activity) recognition done for a tavern (F-measure 0.954) and a university location (F-measure 0.920) only
Strengths	▪ Attempts to identify activity by incorporating highly specific information such as location, weather, motion, transportation mode of access and egress from a location, etc.
Weaknesses	▪ Only applicable in two specific locations (i.e. a tavern and a university location)

16. Smart Diary: A Smartphone-Based Framework for Sensing, Inferring, and Logging Users' Daily Life

Liao, Jilong, Zhibo Wang, Lipeng Wan, Qing Cao, and Hairong Qi. 2015. "Smart Diary: A Smartphone-Based Framework for Sensing, Inferring, and Logging Users' Daily Life." *IEEE Sensors Journal* 15 (5).

Categories	Passive(Activity), Battery
Applications	Idea behind mining model method could be considered in development of TTS smartphone app activity prediction algorithm
Methods Used and/or Summary	▪ Analyzes mobile sensors to infer people's daily activities, which is then used to create a digital diary of the user. ▪ By observing and analyzing a user's smartphone usage and motion (SMS, call history, app usage, etc.) throughout the day, the user's activities can be automatically determined. This is then presented to the user in the form of a readable diary. ▪ To address privacy concerns, all activity recognition is done on the smartphone side rather than on a centralized server. ▪ The paper presents an event mining model as well as the logic language for rule-based inferences. Also developed a feedback loop so that users can provide preferences and choices so that the system can continually learn over time and provide more relevant information to the user. ▪ Uses: motion activity, location data, app usage, calendar events, phone calls or SMS history, and web history. ▪ Events are classified into three classes: entertainment activities, social activities and health conditions. ▪ As an example, to detect when a person is exercising, it will use a combination of the motion mining component and the location mining component to determine this. Existing location-based services like Google Maps and Yelp maintain a large database that can be queried. To determine a user's favourite restaurant, the phone usage mining component will analyze app usage, and the location mining component will be used as well. ▪ Rule-based inferences tailored to individual users can also be used: for example a particular user can be considered as shopping if the location detected is a shopping mall, motion detected is mostly walking, the day is not Monday or Tuesday, and the duration is longer than 10 minutes. ▪ Uses decision trees to identify between walking, driving and running. ▪ 90% detection accuracy of 4 different motion types: sit, walk, drive, and run ▪ Battery life stays more than 11 hours before dropping down to 30%
Strengths	▪ Requires no user intervention, mining components are modular and can be reused for multiple different functions ▪ 90% detection accuracy of 4 different motion types: sit, walk, drive, and run ▪ Battery life stays more than 11 hours before dropping down to 30%
Weaknesses	▪ Not directly related to travel surveys

17. Tracking Daily Travel: Assessing Discrepancies between GPS-Derived and Self-Reported Travel Patterns

Houston, Douglas, Thuy T. Luong, and Marlon G. Boarnet. 2014. "Tracking Daily Travel: Assessing Discrepancies between GPS-Derived and Self-Reported Travel Patterns." *Transportation Research Part C: Emerging Technologies* 48: 97-108.

Categories	Active, Sample Frame, Core/Satellite, Multi-day/week, Response Rates
Applications	Gives an idea of differences in durations reported via self-reported vs. passive methods
Methods Used and/or Summary	▪ Comparisons of data from travel diaries and corresponding GPS monitoring. Rate at which trips not reported in travel surveys that are identified in GPS data varies. ▪ Researching the discrepancies in reporting by using alternative measurement instruments such as daily travel logs, ▪ Daily travel logs do not ask for details of each trip, just total daily travel by mode. User is only required to indicate the total number of trips and total minutes they traveled by each mode every day. ▪ 7-day survey of residents in Los Angeles in two phases ▪ Sampling frame: identified potential participants by purchasing a list of all household addresses within the study area (27,275) from InfoUSA, a marketing information firm. Mailed each household an invitation letter, and all households who indicated they were interested in participating (651) were invited into the study. 279 households provided complete response – 1% response rate overall. ▪ Conducted post-processing of GPS data using a classification procedure to identify periods during which participants were at a specific location, and periods during which they were traveling. ▪ In contrast to typical audit studies of trip reporting, which evaluate information from a one-day travel survey, this paper evaluates using an instrument that reduces participant response burden by not requiring input of trip-level details (start and end times, purpose, etc.) and takes place over multiple days ▪ Results show that participant-reported daily travel patterns and GPS-derived patterns are in substantial agreement. ▪ Average difference between daily GPS and log-derived walking duration was about 11.8 mins – participants tended to self-report more minutes per trip than were identified through GPS tracking. This discrepancy could be due to participants rounding travel times to the nearest 5 or 15 minute interval. ▪ Participants who were older, had lower education or household income, or were employed had a lower likelihood of producing a good trip reporting on a given day. Could reflect differences in participant understanding or willingness to follow survey instructions
Strengths	▪ Uses travel log, which minimizes user burden, in order to gauge accuracy of GPS trip reporting
Weaknesses	▪ Specific to certain areas, neighbourhoods and demographics which cannot be readily applied to general population

18. Does the Use of Mobile Devices (Tablets and Smartphones) Affect Survey Quality and Choice Behaviour in Web Surveys?

Liebe, Ulf, Klaus Glenk, Malte Oehlmann, and Jürgen Meyerhoff. 2015. "Does the use of mobile devices (tablets and smartphones) affect survey quality and choice behaviour in web surveys?" *The Journal of Choice Modelling* 14: 17-31.

Categories	Active
Applications	
Methods Used and/or Summary	▪ Tests whether using a mobile device affects survey responses and stated choices in a web-based survey ▪ Finds that survey characteristics such as interview length are affected, mobile device users spend more time to answer the survey ▪ Mobile device users also less prone to acquiescence (acquiescence tendency is present if respondents agree in a survey regardless of what the question is) ▪ Total sample: 3182. 12% (378) of respondents answered on mobile devices that they owned. Of these, 53% used a tablet and 47% used a smartphone. ▪ Survey was optimized for mobile versions, but still required zooming and scrolling for seeing all the choice set options ▪ Mobile device user characteristics: more likely to be female, younger, slightly lower educated and have higher income compared to users who chose to use desktop/laptops. ▪ Selection bias present regarding use of mobile device, and socio-demographic variables such as gender, education and income affect choices. ▪ Used propensity scoring to overcome selection bias, by creating a control group of desktop/laptop users that are not prone to selection bias. ▪ Users more likely to respond later in the day, with mobile device users responding later than non-mobile device users ▪ Found that the smaller the screen size, the longer the survey took to complete
Strengths	▪ Compares responses of mobile versus non-mobile users in a stated choice web-based experiment
Weaknesses	▪ Selection bias regarding use of mobile device, may affect the survey characteristics such as interview length – comparison cannot be readily made between the instruments (mobile vs desktop) since characteristics of the respondents for each are not the same. Required using propensity scores to create a control group which may not be an adequate solution.

19. ATLAS Project – Developing a Mobile-Based Travel Survey

Safi, Hamid, Mahmoud Mesbah, and Luis Ferreira. 2013. "ATLAS Project - Developing a mobile-based travel survey." *Australasian Transport Research Forum 2013 Proceedings*. Brisbane, Australia.

Categories	Passive (Location), Active
Applications	
Methods Used and/or Summary	▪ A framework for smartphone-based survey data collection ▪ iPhone/iPad application developed and available on the App Store for those interested in the research ▪ Still in development phase, not in use for surveys as yet ▪ Uses an active data collection approach to ensure accuracy of data captured and trip-leg detection. This means that users have to input trip mode, duration and purpose. ▪ In order to save time and decrease burden, questions were designed in multiple choice format ▪ Collects GPS data every 10 meters in order to increase accuracy and precision ▪ Includes a brief socioeconomic questionnaire, including questions on age, gender, income, vehicle ownership and usual mode choice during weekdays and weekends ▪ Future work will focus on increasing participation rate, minimizing battery depletion, and testing prompted recall approach as opposed to an active collection method in order to minimize user burden
Strengths	▪ Uses an active method to determine accuracy of data collection and detection algorithms and methods which can then be compared with ground truth
Weaknesses	▪ No discussion on sample frame, selection or size, as well as no specific results published – still a work in progress ▪ Requires users to input details for each leg of the trip ▪ Users required to manually stop the process of tracking in order to minimize battery depletion through continued GPS use.

20. Design and Implementation of a Smartphone-based System for Personal Travel Survey: Case Study from New Zealand

Safi, H., B. Assemi, M. Mesbah, L. Ferreira, and M. Hickman. 2015. "Design and Implementation of a Smartphone-based System for Personal Travel Survey: Case Study from New Zealand." *Transportation Research Board 94th Annual Meeting* (No. 15-1462).

Categories	Passive (Location, Trip Start/Stop), Active, Battery, Sampling Frame, Core/Satellite, Household/Individual, Response Rates
Applications	▪ A full-fledged smartphone survey used a satellite to the regular household travel survey similar to what TTS might, could be used to design pilot or field tests for TTS
Methods Used and/or Summary	▪ Smartphone based system for travel data collection. System called SITSS (Smartphone-based Individual Travel Survey System) – designed to deal with challenges associated with smartphone-based travel surveys, including battery, response rates, and privacy concerns. ▪ Uses prompted-recall ▪ Was employed as part of national household survey in New Zealand to investigate various aspects of performing a national level travel survey using smartphones. ▪ 71% of participants continued participation beyond expected data collection interval. 94% of them required no support to use the app and follow the data collection procedures. ▪ Participants invited to recall and label their travel activity through the smartphone interface, unlike other studies where users are asked to use a desktop/laptop web interface. Allows participants to more conveniently record, recall and report their travel behaviour through using the smartphone only. ▪ Client-server application. Server supports data collection but has no direct interaction with participants during data collection. ▪ Smartphone app itself is called ATLAS II. Can automatically detect start and stop trips. Can function throughout the day by using battery optimization algorithms that only operate the GPS when an

	actual trip is being made and returns to low battery consumption mode when a trip is finished. ▪ Works only on iOS devices, app designed to be simple, tested over multiple screen sizes. ▪ Uses GPS and GSM to detect location. ▪ Five tabs in the app. First tab, “Today” allows users to visualize (via Apple Maps API) and see detailed information about trips made so far that day. Second tab, “History”, contains all previous trips and allows users to upload to SITSS server. “Profile” tab – user’s account detail and a section for various questionnaires. “Help” tab contains tutorials and FAQ. “Info” contains information regarding the research team and goals of the research. ▪ Changes in GSM signal beyond a particular threshold used to detect participants movements and stops. When a significant movement is detected, GPS switched on to record location until a stationary condition lasting beyond a threshold is reached. ▪ Details about the server architecture (3 components: web-server, database-server, web-portal) and ATLASS II app components provided in the paper ▪ Surveys and the relevant questions are stored and managed on SITSS servers. Functionality is provided to allow researchers to add, remove or change surveys at any time – personalized questions/choices can be added for each individual participant. ▪ Experimental study: 186 potential participants who had iPhones and were participants of household travel survey in New Zealand were approached to be surveyed using SITSS. Only requirement was that they needed to have an iPhone. Of 186 approached, 77 installed the app and created a profile. ▪ 71% of participants continued past the required three days, showing an interest in the experiment by continuing to upload data. ▪ May miss up to 400 m of the initial sections of the trip, since relies on GSM/accelerometer to detect large movements before GPS is switched on, logs GPS data every 10 meters ▪ Average working duration of the app was 36.6 hours, therefore did not impact the participant’s interaction with the smartphone or the battery life.
Strengths	▪ Employed as part of an existing household survey, addressing many challenges faced by using smartphone-based survey methods ▪ No significant impact on battery ▪ Users could understand how to use app easily using tutorials in app itself ▪ Users interested in using app and uploading data beyond 3 day requirement
Weaknesses	▪ Does not automatically detect mode and trip purpose ▪ Small sample size - 77 ▪ Works only on iPhones

21. Trip Analyzer through Smartphone Apps

Li, Ming, Jing Dai, Sambit Sahu, and Milind Naphade. 2011. "Trip Analyzer through Smartphone Apps." Chicago, IL: ACM SIGSPATIAL GIS '11.

Categories	Passive (Location, Mode, Activity, Trip Start/Stop), Battery
Applications	Can use the methods of mode detection and rules for activity detection in TTS
Methods Used and/or Summary	▪ Describes a trip analysis system comprised of a mobile app and a centralized analyzer. This is used to identify trip mode and purpose. Travel modes detected include cars, buses and walking. Trip purposes are classified based on the location, time, day, and stop time at the destination (duration). ▪ Uses GPS and accelerometer in smartphone to detect travel mode. ▪ Tested with 70 people volunteered to participate. ▪ Only raw data is collected about the user's movement from GPS and accelerometer, a trip management component identifies trips, travel mode and purpose for each trip. ▪ GPS is used to track people's location and speed, accelerometer is used to detect intensity of movement. ▪ To minimize the effect on the battery, an adaptive sensing policy that reduces the sensing frequency of the GPS automatically with minimum impact on accuracy is developed and described in the paper. ▪ Similarly, accelerometer data is passed through a low-pass filtering algorithm in order to not introduce heavy load on the smartphone processor and memory. ▪ To differentiate between car and bus modes, accurate locations of all bus stops are first obtained, and if a user's travel mode change is detected within close proximity to a stop, this trip is classified as a bus trip, else it is classified as a car trip ▪ This achieves an 80% accuracy. ▪ Trip purpose classification: o Home/work/school location identification: End points of the last trip of the past 5 days is identified as the home location for each individual. Work and school locations are identified as locations that have a stop time between 3-9 hours or being visited more than 3 times a day. If that location is a school as identified in local Points of Interest (POI) data, then it is labeled a school trip. Else it is labeled as a work trip. o A rule-based trip purpose identification is used to provide initial trip purposes. Criteria include arrival time, day, stop time, nearest POI, distances between origin/destination and home/work/school. o User feedback can be collected by validation of the trip purposes. These verified trip purposes are then used as training data to build the trip purpose classifier. ▪ Process still continuing at the time the paper was written.
Strengths	▪ Provides details on algorithms and methods used to minimize impact on smartphone battery, processor and memory while still maintaining data quality ▪ Uses a rule-based identification method to identify trip purposes ▪ 80% mode accuracy
Weaknesses	▪ Small sample size, volunteers, so no discussion about usability and acceptability by various demographics ▪ Range of travel modes detected limited to bus, car and walking, while not achieving highest accuracy ▪ No decisive results provided for trip purpose identification as process was still ongoing.

22. Public Works and Government Services Canada Report – Secondary Research into Cell Phones

and Telephone Surveys

Phoenix Strategic Perspectives Inc. 2012. *Secondary Research into Cell Phones and Telephone Surveys*. Public Works and Government Services Canada.

Categories	Sampling Frame, Household/Individual, Response Rates
Applications	
Methods Used and/or Summary	▪ Report prepared by Public Opinion Research Directorate (PORD) which provides coordination and advisory services for Government of Canada public research. ▪ Documents current practices of survey research via cellphones, impacts and implications of using cellphone sampling frames, best standards and practices, how frames are created and how representative they are. ▪ Focuses on dual sample frames of cellphones and landlines. ▪ Number of cell phone only households in Canada is expected to reach 20% by the end of 2015. ▪ Impact of not including cell phone only (CPO) households is coverage error resulting from an incomplete sampling frame. ▪ Younger Canadians more likely to be cell phone users. Conservatively, at least half of all 18-34 year olds use only a cell phone. ▪ CPO (cell phone only) respondents in Canada are younger, more likely to be male and to live in smaller households, and more likely to be lower-income compared to the general population. ▪ Dual frame surveys have become standard practice in the U.S., both Pew Research Center and Gallup (two leading survey organizations) include cell phone samples. ▪ Leading association for market and public opinion research in Canada is MRIA (Marketing Research and Intelligence Association) who have started to investigate cellphone sampling frames. Newspaper Audience Databank (NADBank), the research arm of the Canadian daily newspaper industry, augments its telephone sample frame with CPO households as well. ▪ Two approaches: overlapping and non-overlapping. If screening cell phone sample for cell phone only households, then it is a non-overlapping sample frame design. While this is less complex to statistically analyze, it is much more costly. The cost per completed interview for the overlapping design is less than half of the non-overlapping design. ▪ Non-overlapping design may lead to nonresponse bias. If dual users are unlikely to be reached on their landline, they will not be reached since they would be removed from the cell phone sample frame, thus increasing nonresponse bias. ▪ Data quality: the belief is that data quality obtained through cell phone surveys will be lower as the respondent could easily be distracted and might be multi-tasking. However, there has been no conclusive studies done to support this definitively. There have been studies that show that the difference in data quality is not that large between cellphones and landlines, but the sample sizes for these studies have been small. ▪ “With an overlapping design, weights must take into account the multiple probabilities of selection. Weighting is simpler when working with a non-overlapping design. Essentially the design is treated as a stratified sample with three strata: landline only, dual users (‘wireless-mostly’ and ‘landline-mostly’), and cell only. Weights are first calculated for the landline sample (which includes dual users and must factor in response propensity by service) and the cell sample separately, and then combined.” ▪ There have also been studies that show no evidence that respondent break-offs occur more frequently will cell phone samples. ▪ Response rates tend to be lower on cell phones compared to landlines. • Associations leading this research: American Association for Public Opinion Research (AAPOR), the Marketing Research and Intelligence Association (MRIA), the European Society for Opinion and Marketing Research (ESOMAR), and the Marketing Research Association (MRA). AAPOR has taken a lead role in this area, with the MRIA even referring to AAPOR as the most comprehensive source of information on this topic. • 2010 AAPOR *Cell Phone Task Force Report* concludes that it is premature to establish standards or

	'best practices' to address the issues surrounding cell phone survey research. ▪ Major sample providers in Canada do not yet provide cell phone samples, very few firms offer these for purchase (two at the time the paper was written). ▪ Three ways to construct cell phone sample frames: RDD (random digit dialing), pre-screened cellphone numbers, and cellphone only households. The cost for obtaining these samples increases from RDD, pre-screened and CPO, with the latter being the most expensive. The pre-screened numbers have been "pre-dialled" and those not in service are removed. CPO samples are those that have been verified to not have a landline as well. While convenience samples of the latter two are available, these two are not random probability samples and cannot be considered representative of the target population.
Strengths	▪ Comprehensive review of standards using dual sampling frames of cellphones and landlines ▪ Includes suggestions and recommendations for cell phone surveys including incentives, remuneration, ethics and privacy, overlapping vs non-overlapping frame and the design and consequences of each, and more.
Weaknesses	

23. The Impact of a Mixed-Mode Data Collection Design on Response and Non-Response Bias on a RDD Landline Telephone Survey

Hu, S. Sean, Carol Pierannunzi, and Lina Balluz. 2011. *The Impact of a Mixed-mode Data Collection Design on Response and Non-response Bias on a RDD Landline Telephone Survey*. Centers for Disease Controls and Prevention, AAPOR 2011.

Categories	Response Rates
Applications	Using a mail follow up to landline telephone survey improves response rates
Methods Used and/or Summary	▪ A mail follow-up survey was sent to non-respondents of a landline telephone survey and was implemented in 4 states. ▪ Using the mail follow-up survey boosted response rate by 10%. ▪ No substantial difference among demographic characteristics between landline and mail respondents.
Strengths	
Weaknesses	▪ Households with cell-phone only coverage and without residential telephones were not included ▪ No steps taken to reduce instrument bias between the two modes

24. Residential Telephone Service Survey

Statistics Canada. 2013. "Residential Telephone Service Survey 2013."

Categories	Sampling Frame
Applications	
Methods Used and/or Summary	▪ In 2013, 21% of households reported using a cell phone exclusively, up from 13% in 2010. ▪ Exclusive cell phone use is more pronounced in young households where all of the members are under 35 years of age. In 2013, 60% of these households reported using a cell phone exclusively, up from 39% in 2010 and 26% in 2008. Although exclusive cell phone use is less common in households composed only of those aged 55 and over, it is on the rise, up from 2% in 2008 to 6% in 2013. ▪ In 2013, 83% of Canadian households had an active cell phone, up from 78% in 2010. The proportion of households with an active cell phone was highest in Alberta (91%), Saskatchewan (86%), British Columbia (85%) and Ontario (85%). ▪ The share of households with a traditional landline fell from 66% in 2010 to 56% in 2013. ▪ Share of households in Ontario without a landline in 2013: 27%
Strengths	
Weaknesses	

25. Optimizing Surveys for Smartphones: Maximizing Response Rates While Minimizing Bias

Lattery, Kevin, Gloria Park Bartolone, and Ted Saunders. 2013. *Optimizing Surveys for Smartphones: Maximizing Response Rates While Minimizing Bias*. Maritz Research.

Categories	Active, Response Rates
Applications	Design tips suggested could be incorporated in smartphone app
Methods Used and/or Summary	▪ Purpose of the research was to identify enhancements in mobile survey designs to increase response rates as well as differences in responses between mobile and non-mobile/traditional PC respondents. ▪ The number of points to use in rating scales: best option is to use the 5 point scale across both types of data collection (mobile and non-mobile), since the use of more points would require the options to be very close to each other on smaller screens, requiring more effort to accurately select an option. Mobile respondents tended to rate lower than PC respondents overall – most noticeably when more point scales were used. ▪ Grid format: regular grid format (with text to the left and the options to select on the right) showed marginally lower ratings for mobile when compared to non-mobile users. High correlation between mobile and non-mobile responses across the 10 attributes. New grid format (with text above the individual attribute) improves this relationship. ▪ Radio Button Spacing and Label Alignment: Avoid using longer scales (more than 5 points) on mobile devices since these lowered survey satisfaction and decreased completion rates. ▪ Use of background image: Mobile respondents who received the heavy (i.e. large) background image took significantly longer than the mobile optimized light or no image respondents and had a significantly lower completion rate. However, using a background image significantly increased the likelihood of taking a similar survey in the future for mobile survey respondents. ▪ Completion rates: mobile: 79.%, non-mobile: 89.5% ▪ Completion time: mobile: 15.3 min, non-mobile: 14.1 min
Strengths	
Weaknesses	▪ No discussion of number of respondents and socioeconomic breakdown of respondents

26. Comparison of Smartphone and Online Computer Survey Administration

Wells, Tom, Justin T. Bailey, and Michael W. Link. 2014. "Comparison of Smartphone and Online Computer Survey Administration." *Social Science Computer Review* 32 (2): 238-255.

Categories	Active, Response Rates
Applications	Design tips suggested could be incorporated in smartphone app
Methods Used and/or Summary	▪ Survey 1500 online panelists – all smartphone users who were randomly assigned to mobile app or computer mode of survey. $5 incentive. ▪ Tested whether mobile app survey respondents are sensitive to particular experimental manipulations similar to other modes. Also tested whether responses collected in both modes are similar. ▪ Short questions and sets of responses so that vertical scrolling is minimized or eliminated, taking into account smaller sizes of screens. ▪ Low vs High Frequency Scales: high-frequency scales produce higher reported frequencies, as respondents use the answer options as a cue (Example question: "How many hours per day do you use the internet?") Mobile app respondents were not more or less likely than PC web respondents to report higher frequencies of behaviour. ▪ Closed-Ended vs Half-Open "Other" Category: Alongside the "other" category, unlikely responses were provided, which were intended to drive respondents to the "other" category. No significant differences in response distributions between the two versions of the survey. Mobile app respondents not found to be reluctant to type short open-ended responses. ▪ Small vs Large Text Box: Size of text box affects the length of open-ended responses. While mobile respondents willing to provide short responses to open-ended items, their responses are consistently and significantly shorter in length ▪ Randomized vs Alphabetized Response List: testing for primacy effects i.e. the tendency for respondents to select responses at the top of a list, which may be due to respondents' focusing more on the first few items in a response list or the tendency of respondents to quickly select the first satisfactory response they encounter without seeing all the options available carefully. This research found no evidence of primacy effects or of response-order effects in general. ▪ 7.8 % response rate. Completion rates: mobile: 58%, Web: 61% ▪ <u>Median completion time (min):</u> mobile: 5.5, Web: 5.8
Strengths	▪ App was tested on and optimized for various mobile devices ▪ Since all respondents were users of smartphones (even those assigned to use the non-mobile mode of survey), the results avoid bias with regards to respondent characteristics.
Weaknesses	▪ Survey was short and only included short sets of responses in order to minimize scrolling, results could vary for longer surveys (i.e. noticeable primacy effects)

27. Comparing Survey Results Obtained via Mobile Devices and Computers: An Experiment with a Mobile Web Survey on a Heterogeneous Group of Mobile Devices Versus a Computer-Assisted Web Survey

Bruijne, Marika de, and Arnaud Wijnant. 2013. "Comparing Survey Results Obtained via Mobile Devices and Computers: An Experiment With a Mobile Web Survey on a Heterogeneous Group of Mobile Devices Versus a Computer-Assisted Web Survey." *Social Science Computer Review* 31 (4): 482-504.

Categories	Active, Response Rates
Applications	Design tips suggested could be incorporated in smartphone app
Methods Used and/or Summary	▪ Compares the results between a survey done on a mobile device and a computer. Total of 661 panel members aged 14 and older who all had a smartphone or tablet device. ▪ Three versions of the survey designed and the panelists sub-divided into the corresponding groups: web/computer (Condition 1), mobile (Condition 3) and a hybrid (Condition 2) which used the mobile layout but for use on a computer. ▪ In the mobile and hybrid versions, each question was presented on a separate screen to minimize scrolling ▪ Response in the mobile condition was lower than the others, possibly because the panelists are used to completing it on their computers ▪ When comparing the means of the responses from the three groups, the authors found very few differences ▪ The mobile group users estimated the survey to be longer than respondents who completed the survey on a computer, and indeed they took longer to complete it as well ▪ Interestingly, users of the hybrid version of the survey completed the survey slightly quicker than the web version ▪ When asked about their preferred device, respondents who completed the survey on a mobile device reported that they used these devices significantly more than those who responded on a computer. When asked the same question a few weeks later but on a computer device, this disparity disappeared. It appears that the response mode affected their behaviour when the question relates to the mode itself.
Strengths	▪ Multiple versions of a survey tested and optimized for different devices, both mobile (including smartphone and tablet) and computers
Weaknesses	▪ Panelists are used to completing the survey on the computer, and so when asked to use their smartphone or tablet instead they still opted for the web version

28. Encouraging Survey Response via Smartphones: Effects on Respondents' Use of Mobile Devices and Survey Response Rates

Millar, Morgan M., and Don A. Dillman. 2012. "Encouraging Survey Response via Smartphones: Effects on Respondents' Use of Mobile Devices and Survey Response Rates." *Survey Practice* 5 (3).

Categories	Active, Response Rates
Applications	Could consider testing or using strategies recommended in the paper to improve response rates for TTS
Methods Used and/or Summary	▪ "Email augmentation" – combining postal mail contacts (with a cash incentive) and follow-up email messages doubles the response rate that achieved using only emails (without the cash incentive). ▪ Paper presents an experiment designed to build upon email augmentation by encouraging respondents to use their smartphones. Compares the overall response rate as well the proportion of smartphone respondents. Objective was to see whether it would be possible to drive respondents to use their smartphones in responding. ▪ Designed a smartphone-friendly website ▪ Study conducted on 1800 college undergraduates – 3 groups of 600 each. The first group was asked to respond to an online questionnaire. The second group was also told of the online questionnaire, but were highly encouraged to use their smartphones if they had one. The third group was given a choice between the online questionnaire and a paper copy. ▪ Anyone who accessed the survey website could opt for either the standard or the smartphone-optimized questionnaire, but only the second treatment group's messages mentioned this option. ▪ Attempted to standardize appearance of paper and online versions, but used the mobile one optimized for smartphone screens ▪ $2 incentive, contacted 5 times, alternating between mail and email ▪ Similar response rates for the standard online questionnaire and mobile (49.7% and 50.0%) – therefore encouraging smartphone option did not achieve a higher response rate ▪ The third group (offered a choice of online or paper) achieved the highest overall response rate (56.3%) – consistent with prior research that showed email augmentation strategy increases response when offering a choice of mail or Web. ▪ Only 40 students in the entire study responded using a smartphone. This equates to 4.3 percent of all respondents. ▪ Interestingly, the third group had a similar response rate via smartphone as the second group (which was encouraged to use the smartphone). ▪ "Although it may be possible to push some respondents to use smartphones, more work is needed to improve upon these results. We obtained more mobile responses when encouraging smartphone response, but the overall number of smartphone responses we received was still rather low." ▪ 46.4 percent of all respondents reported owning a smartphone. Therefore, a majority of students who had a smartphone did not use it to respond, even when encouraged to do so. ▪ Only 6.6% of all respondents indicated that they would prefer using their smartphones to respond to a survey. ▪ "Pew study on smartphone usage implies that this may change as more people replace traditional computers with phones for accessing the Internet."
Strengths	▪ Provides a good discussion on how email augmentation (mail and email reminders including incentives) helps drive response rates up
Weaknesses	▪ Focused only on undergraduates as sampling frame ▪ Overall number of smartphone responses was still rather low

29. Improving Response to Web and Mixed-Mode Surveys

Millar, Morgan M., and Don A. Dillman. 2011. "Improving Response to Web and Mixed-Mode Surveys." *Public Opinion Quarterly* 75 (2): 249-269.

Categories	Response Rates
Applications	Could consider testing or using strategies recommended in the paper to improve response rates for TTS
Methods Used and/or Summary	▪ The purpose of the paper was to find ways to improve response rates in a web-based survey ▪ Sampled 2800 and 4300 undergraduate students in two different experiments ▪ In previous studies, found that improving trust that the survey is legitimate and useful and provides some sort of benefit to the respondent leads to higher response rates ▪ Providing a choice of response modes does not improve response rates (when compared to only providing a mail response option) as the additional burden of switching modes discourages respondents ▪ Web plus email augmentation group (contacted and reminded via postal mail and email alternatively) produced the highest response rate of all (59.7%) ▪ Highest response rate: 59% ▪ Response rates generally increased after the implementation of mode switch, when different groups in the experiment were offered an alternate mode of response ▪ Most effective strategy is the combined use of multiple response-inducing techniques (i.e. contacting/reminding through both mail and email and offering different modes of response or choice of mode at different stages) – takes advantage of both contact modes by establishing memorability and presence through postal mail and reduces burden of responding by providing a link to the website directly through email ▪ "Offering modes in sequence (following requests for Web response with a final request to respond by mail) can significantly increase the overall response rate, making it equivalent to the response rate when mail is the only response option." ▪ If email addresses in sample frame are not available, suggest that an effective method is to request Web response initially and then finally request a response by mail ▪ Advance cash incentives not possible through email, only mail, and show that this can increase response rates by 17% (offered $2 advance cash incentive to each person contacted in sample) ▪ Previous studies show that advance cash incentives more effective than "raffle draws" or gift certificates
Strengths	▪ Suggests means of improving response rates with populations accessible by postal mail only or by both mail and email ▪ Web and paper surveys were designed identically to minimize response differences between modes – one question per page for both web and paper survey
Weaknesses	▪ Focused only on undergraduates as sampling frame who are all familiar with internet use ▪ Survey was sponsored by an organization affiliated with the university – this relationship may have increased the legitimacy of the study in the eyes of the respondents that may not be possible to repeat in other situations ▪ Main findings and methods require access to both postal and email addresses of sample population

30. Trends Report: Mobile Participation in Online Surveys

Jue, Aaron. 2014. *Trends Report: Mobile Participation in Online Surveys*. FocusVision.

Categories	Active, Response Rates
Applications	
Methods Used and/or Summary	▪ Completion rates for smartphone users have improved over the years as smartphones become easier to use and more widespread, thus users are more familiar with the device ▪ However, because of the issues like scrolling, pinching, etc. it takes longer to complete survey on smartphone and smartphone users abandon surveys at a greater rate than devices with larger screens ▪ Two common problems are that the text is too small or cluttered and input areas are not large enough to select with precision ▪ Instead of radio buttons, button boxes should be used, such that the entire row is selectable and not just a single point ▪ Completion rates: Desktop: 73%, Tablet: 74%, Smartphone 64% ▪ Recommendations for mobile surveys: o Ensure text size is readable and is no text is cut off from the screen o Button and input sizes should be large enough to not require zooming o Should be functional in both vertical and horizontal orientation o Performance: try to minimize loading between different pages
Strengths	▪ Good overview of mobile survey design issues and provides recommendations for mobile survey design
Weaknesses	

31. Human Behaviour Cognition Using Smartphone Sensors

Pei, Ling, Robert Guinness, Ruizhi Chen, Jingbin Liu, Heidi Kuusniemi, Yuwei Chen, Liang Chen, and Jyrki Kaistinen. 2013. "Human Behavior Cognition Using Smartphone Sensors." *Sensors* 13 (2): 1402-1424.

Categories	Passive (Location, Trip Start/Stop), Battery
Applications	
Methods Used and/or Summary	▪ Focuses on sensing context (activity) by modeling human behaviour and developing a new architecture for a cognitive phone platform. ▪ Context pyramid includes six levels: raw sensor data, physical parameters, features/patterns, simple contextual descriptors, activity-level descriptors, and rich context. ▪ Three technologies used: positioning, motion recognition, human behaviour modeling ▪ Location accuracy is 1.9 meters in corridor environments and 3.5 meters in open spaces ▪ For positioning, uses GPS and Wi-Fi data. When GPS signal-to-noise ratios are high, considered to be outdoors and thus GPS kept on. When GPS signals drop and Wi-Fi signals strengths are high, this is considered to be indoors. Thus battery life is not unnecessarily depleted. ▪ Fingerprinting Based Wireless Positioning: Received signal strength indicators (RSSIs) of Wi-Fi networks are used for determination of position using the routers are reference points in an indoor location. ▪ In a specific context, actions are performed in particular patterns. For example, to determine that an employee is fetching coffee, the location of the employee in the break room standing in front of the coffee machine can be determined, as well as sensing the movements moving to and from the break room and pouring the coffee. ▪ Test results also indicate that the motion states are recognized with an accuracy rate up to 92.9% using a Least Square-Support Vector Machine (LS-SVM) classifier. ▪ Tested in a very specific environment (workplace scenario) in order to validate the positioning algorithms and motion recognition methods using a set of dedicated tests. ▪ Activity-Level accuracy is 90.3%
Strengths	▪ Location and motion methods presented in the paper can be used to infer some human activities, as level of activity specificity targeted in the paper may not be required for TTS 2.0 purposes.
Weaknesses	▪ Tested only in a very specific environment (i.e. a university). In order to reduce complexity, tester always kept the phone in their pocket to fix the orientation of the phone. ▪ Each different activity has its own set of features, difficult to develop a universal model to classify activities. Undefined contexts are not able to be handled in the proposed model yet.

32. UbiActive: A Smartphone-Based Tool for Trip Detection and Travel-Related Physical Activity Assessment

Fan, Chen, Liao & Douma. 2012. "UbiActive: A Smartphone-Based Tool for Trip Detection and Travel-Related Physical Activity Assessment." *Transportation Research Board 92st Annual Meeting.*

Categories	Passive (Location, Trip Start/Stop), Active, Sampling Frame, Multi-day/week, Response Rates
Applications	
Methods Used and/or Summary	▪ Smartphone based collection tool for recording people's daily travel behaviour as well as the associated amount of physical activity ▪ Requires participants to input trip details after completion of trip ▪ Used 30 meters as the threshold from GPS signal to determine change of location and start of new trip, end of trip was determined if a stationary status was observed for 5 minutes ▪ GPS receiver was programmed to generate outputs every 30 seconds ▪ Immediately after the trip is determined to have ended, the app prompts the user to first confirm that they have indeed just ended a trip, then proceeds to ask basic information about the trip including start and end time, trip purpose, travel modes used and people accompanying the user. A second set would ask about travel psychological experience. ▪ If a trip was missed by the app, users could add a trip manually. ▪ Recruitment method included posting flyers around campus and sending emails to departmental listservs. Respondents were invited to an orientation meeting which would explain the scope of the study and the participant's responsibilities, and the app was installed by the researchers themselves. ▪ Participants were also required to fill in a pen-and-paper diary in addition to their smartphones, so that the two modes could be compared at the end of the survey. ▪ 23 participants surveyed for three weeks. ▪ Only 6 participants were satisfied by the app's ability to detect trip starts and ends. ▪ Trips between buildings not detected effectively. ▪ Users reported higher willingness to use smartphone rather than pen-and-paper survey ▪ Very few participants filled in trips manually that were missed by the app
Strengths	▪ App user interface was well designed, users found it quick and easy to navigate. ▪ Users also generally happy with length and amount of after-trip survey questions
Weaknesses	▪ Very small sample size ▪ Users required to fill in most information (very active survey) ▪ Required researchers to meet users personally to explain the procedures and install app on their phone ▪ Was only used to detect trips longer than 10 minutes because it deemed shorter trips to not be important ▪ Impact on battery was significant – shortened by a range between 25% - 83% ▪ Detection of trip start and end times not effective.

33. Participation and Diligence in a Multi-Day, Multi-Year Survey: Impact of Recruitment Methods and Demographics

Greaves, Stephen P., Adrian B Ellison, and Richard B. Ellison. 2015. "Participation and Diligence in a Multi-Day, Multi-Year Survey: Impact of Recruitment Methods and Demographics."

Categories	Active, Sampling Frame, Multi-day/week, Response Rates
Applications	Result shows that method of recruitment does not affect participation, can focus on reaching different demographics through various means without worrying about the effects of the recruitment method
Methods Used and/or Summary	▪ A multi-day, multi-year (panel) travel survey that reports the impact of various recruitment methods on participation, diligence and retention rates ▪ Investigated changes in travel and health indicators of residents before and after the construction of a major cycleway in Sydney, Australia (two waves of surveys done with same participants before and after construction) ▪ A 7-day online travel diary supplemented by an optional smartphone app to passively detect trip details and assist in recall of trips ▪ Previous research, not necessarily related to transportation, shows that different methods of recruitment results in sometimes significant over- or under-representation of different segments of the population ▪ They show that there may be underlying differences in the characteristics of people recruited through each method that cannot be inferred from their demographic characteristics alone ▪ $50 AUD incentive provided ▪ Recruitment done using a professional survey firm, survey link sent to participants through email. Main method of recruitment was cold-calling spatially-targeted home telephone number, where respondents were asked for their emails if they agreed to participate. 20,410 numbers were used, 415 participants completed the questionnaire phase ▪ Also used electronic circulation lists (136 participants recruited), social media (39 recruited), face-to-face recruitment around breakfast events (105 recruited), and mailbox drop ▪ Age of recruit corresponded heavily with recruitment method – younger recruits more likely from electronic recruitment (89%), while older recruits more likely to come from cold-calling (79%) ▪ Reported mode of travel varied significantly by recruitment method – cyclist more likely through intercept and social media ▪ Obtained an attrition rate of 32% (i.e. 32% did not return for Wave 2 of survey) ▪ The highest retention rate were those who were recruited by mailbox drop, while the lowest retention rates were electronic circulation lists, which were mostly comprised of students ▪ One important goal was to determine whether completion and retention rates differed solely because of different demographics obtained by the corresponding recruitment methods, or whether the recruitment methods themselves were responsible in some way and affected the completion and response rates ▪ By studying and surveying those who completed both waves and those who did one but not the other, as well as analyzing diligence (i.e. whether the participants would fill all 7 days of the diary), they found that none of the recruitment methods themselves explained participant attrition (i.e. not returning for the second wave) or diligence ▪ Findings show that, in terms of diligence and attrition, how people were recruited into the study was not a subsequent factor in their participation in the study ▪ Recommend that those undertaking complex surveys efforts should focus on trying to reach those demographic segments that are normally difficult to contact, and not focus on whether the recruitment method itself would affect them
Strengths	▪ Tested wide range of recruitment methods ▪ Result shows that differences in recruitment methods should not be a cause of concern, but rather the focus should be on which recruitment method is best for reaching different demographics
Weaknesses	▪ Did not necessarily target different demographics, but just tried different methods and analyzed what demographics were obtained from each method

34. Social Media in Public Opinion Research: Report of AAPOR Task Force on Emerging Technologies in Public Opinion Research

Murphy, Joe, Michael W. Link, Jennifer Hunter Childs, Casey Langer Tesfaye, Elizabeth Dean, Michael Stern, Josh Pasek, Jon Cohen, Mario Callegaro, and Paul Harwood. 2014. *Social Media in Public Opinion Research: Report of the AAPOR Task Force on Emerging Technologies in Public Opinion Research*. American Association for Public Opinion Research (AAPOR).

Categories	Sampling Frame, Response Rates
Applications	Suggests possible ways to reach certain demographics that are hard to reach via other methods, although sample will not be probabilistic
Methods Used and/or Summary	▪ Reviews how social media is currently being tested or used for recruitment purposes, discusses the demographics of social media users, and what future potential this platform might have ▪ Currently, researchers using social media to obtain qualitative insights, as opposed to recruiting based on probability-based point-estimates ▪ More research is needed to determine whether a sampling frame can be obtained where individuals, who are social media users, can be sampled with a known and non-zero probability ▪ Some concerns are that sometimes users can have multiple accounts, or many accounts belong corporations and businesses as opposed to individuals ▪ Still trying to ascertain whether social media may represent a subset of the general population, and more importantly, what the demographic makeup of that subset is specifically ▪ Popularity of social media websites rises and falls over time, difficult to predict whether one will be the most popular at some future point in time, and each has their own set of rules and protocols in terms of data availability, privacy, which are subject to change any time ▪ Little progress done to show how data collected through social media can represent the general population – so far only non-probability samples can be obtained ▪ Can be bias within the social media frame – individuals who never or rarely post may be missed by certain sampling techniques or might be systematically under-sampled. This can bias results of data collection towards the most heaviest users. ▪ One method of recruitment is to create a group, on Facebook for example, and target specific groups and users of interest to join that group. Easy way to reach a specific demographic without using much resources – but is not a probabilistic sample ▪ Another way to get more diverse set of respondents: pay-per-click ads. The more the researcher pays, the more heavily featured their ad will be to "active" users (i.e. those individuals who click on ads with great regularity). This can also be used to do a targeted campaign, for example if looking for people between the ages of 18-35 only, and the ads will be targeted more towards these demographics ▪ Other factors that can be targeted include education, hometown. ▪ Previously, ads were only shown in the full, desktop version of the Facebook website, but now these are also shown in the mobile versions ▪ Targeted ad-based approach is being used currently: one study obtained a sample of 3,093 eligible individuals with 1,548 completing the survey, at a cost of $4.28 per completed survey ▪ In non-targeted ad-based approach, one study found that the majority of people who clicked the ad different in demographics from those who completed the survey. Majority of those who clicked the ad were between 18-25 years, but the distribution from the demographic questions in the survey showed a more representative age distribution, meaning that the younger individuals were more likely to click the ad but not complete the survey. ▪ Non-targeted approach is slower than targeted and costs more as well ▪ One study found that there are more individuals currently using social media in the United States than those that have a landline
Strengths	▪ Provides a good overview of the current state of social media surveys, including challenges, opportunities and areas of improvement

35. A Simulation Study on Automated Transport Mode Detection in Near-Real Time using a Neural Network

Das, Rahul Deb, Nicole Ronald, and Stephan Winter. 2015. "A Simulation Study on Automated Transport Mode Detection in Near-Real Time using a Neural Network." *CEUR Workshop Proceedings*. March 10-12. Accessed August 20, 2015. http://ceur-ws.org/Vol-1323/paper24.pdf.

Categories	Passive (Mode)
Applications	Mode detection method
Methods Used and/or Summary	▪ A simulated study on detecting travel mode using in near real-time using neural networks. Investigated how spatial information can improve mode detection accuracy. ▪ Model has achieved 87% for 5 modes if included spatial information such as road/train network information ▪ Velocity-only based approach not sufficient – low speed conditions due to traffic or bad weather can cause confusion between modes since bicycle or bus would be going at similar speeds. Therefore, need to use non-kinematic attributes as well. ▪ This research uses a neural network that adjusts in real time to varying movement behaviour to detect modes even at low speeds, as opposed to other research that might detect the mode offline after the fact ▪ Uses data obtained from GPS-enabled smartphones in Beijing central business district and its surrounding suburbs, and users provided ground truth separately ▪ Simulated queries within short temporal windows to detect a given mode instead of on a second-by-second basis, hence “near” real-time ▪ In addition to eight kinematic attributes used (like average speed, acceleration, variance of speed, etc), they also used spatial attributes, like average road/railroad proximity, variance of road/railroad proximity, relevance score for bus/train/traffic stop/parking lot/car wash. In order to estimate POI (point of interest) relevance (i.e. proximity to bus stop, train stop, traffic signal or car wash or parking lot), a density-based clustering kernel was run over each temporal window ▪ Used 2.5 m/s as the walking speed threshold ▪ 5 modes detected: car, walk, bus, train, bike ▪ Results show that including spatial attributes improves accuracy as opposed to just using kinematic attributes ▪ From accuracy measures, there is a trade-off between temporal window size and mode detection accuracy – 300 seconds deemed to be optimal for window size ▪ Did not use bus network information to detect bus, if included then accuracy should increase
Strengths	▪ 87% accuracy over five modes (car, walk, bus, train, cycling)
Weaknesses	▪ No discussion about data transfer requirements or battery drain

36. Overcoming Battery Life Problems of Smartphones when Creating Automated Travel Diaries

Jariyasunant, Jerald, Raja Sengupta, and Joan Walker. 2012. "Overcoming battery life problems of smartphones when creating automated travel diaries." *13th International Conference on Travel Behaviour Research*. Toronto.

Categories	Passive (Location, Mode, Trip Start/End), Battery, Multi-day/week
Applications	Solutions for maintaining battery life in some cases could be implemented or developed further for TTS
Methods Used and/or Summary	▪ Paper attempts to balance the collection of location data from smartphones with battery life. Presents an algorithm to generate trips from sparse GPS data ▪ Suggests six metrics to analyze the quality of the trip determination system ▪ Developed algorithm and app by analyzing user behaviours of 125 users across 20 states and 23 different models of smartphones, but then ran a field test of final app with only 6 users for 3 months ▪ App runs only on the Android system ▪ Trade-off exists between battery consumption and trip inference accuracy ▪ Battery will be drained in 5 hours if a smartphone's GPS sensor is continuously collecting location points ▪ Possible to collect small amounts of location points, thus not draining the battery completely, and then recreate trips using data from various sensors, like GPS, Wi-Fi, and accelerometer. ▪ Detects trip start/ends, locations, route used and travel mode ▪ Challenges include types of phones, geographic locations, topographies, user behaviours, users' phone settings ▪ This research attempts to provide insight into these issues as well as a robust solution to the problem ▪ Determining mode cannot be done with GPS sensor data alone, requires data about underlying transportation network to differentiate between driving and transit ▪ App uses techniques similar to other papers, where a movement detector is implemented using a Wi-Fi and accelerometer, an adaptive sensor selection during movement adjusts the duty cycles of GPS, Wi-Fi and accelerometer, and a mobility predictor based on a person's familiar locations at various times of the day ▪ Main difference between this and other papers is the adjustment of the duty cycling of the GPS sensor while user is in motion. When the user is still, a progression of sensors are used: first the accelerometer gathers data at 5Hz for 3 seconds once per minute. If movement is detected, Wi-Fi beacons are used to detect whether the location change is significant (this data is gather once per minute). ▪ If user is detected to be moving faster than walking speed, GPS is sampled once per minute, until the person begins to move at walking or slower speeds. ▪ From testing 125 users with 21 different types of phones: amount of power consumed while person is in motion is 8.7 mA, while in stasis is 0.7 mA. ▪ Average mobile phone battery capacity is 1500 mAH, the energy consumption of the app allows for 33 hours of energy consumption, assuming 2 hours of traveling each day and average smartphone usage ▪ On average, the app accounts for 3% of total battery consumption at any given time. ▪ If application is killed or the phone restarts, the app is brought back up after a short delay ▪ Sensor data from app uploaded to server once every 3 hours ▪ Under 1% of GPS points lied outside the circle defined by the latitude, longitude and horizontal accuracy, while 51% of network points, with the location sourced from either cell towers or Wi-Fi beacons, lied outside the circle ▪ "Hotspots" developed, defined as locations where a user spends a large amount of time (home, work, gym) – hotspots within 250 m of each other are merged, any hotspots with durations less than 2 hours are eliminated, and if a user visits a location very regularly (even if it is less than 2 hours per trip), that will also be considered a hotspot. Every hotspot identified is annotated with the set of all Wi-Fi access points within a 250 m radius ▪ A location where a person repeatedly drops off or picks up another passenger probably would

	not be captured by the algorithm ▪ Hotspot locations are favoured according to the time of day if there is any ambiguity in terms of location detection ▪ The average error for a hotspot location was 25m with a standard deviation of 101 m. This error increases to 197m with a standard deviation of 599 m for origin/destination locations which were not hotspots. ▪ Once route start and end locations are determined, the route is determined. The route determination algorithm uses start points, raw location points, and Google Directions API ▪ The output of the Google Directions API is a set of shortest paths (by time) between the origin and destination that run through the waypoints detected. Therefore, any trips that use suboptimal routes are not captured accurately. The API also assumes that the start and end locations are exact while the data itself has a range of accuracy – even minor differences like providing a point at the opposite side of a street can affect the route provided by the API ▪ The mode of transport is detected after route determination. Two classifiers used: one to determine between motorized modes, bicycles, and walking, and then a map matching algorithm to differentiate between public transit and driving ▪ While a trip may consist of many mode segments, like walking to a car, then driving home – only the main mode (driving in this example), is classified ▪ Instead of using features that can be observed in real-time, features that are defined over the course of a trip are used, such as the median speed between trip start and end times. ▪ Uses random forest classifiers to determine mode – 10 decision trees with 6 attributes. The classifier predicts between walking, motorized, or biking – an additional one is used to differentiate between walking and motorized. At the start of the survey, the user is asked the frequency of biking, and based on that the appropriate classifier is used. ▪ Database includes transit route configurations – trips are sent to the map matching algorithm to determine the percentage of the route that matches with any bus or train lines. Any trip matching greater than 90% is defined as a transit trip. ▪ Trips that are missed due to insufficient readings from GPS, accelerometer, etc. are normally short trips under 2 km. ▪ Application was tested with 125 users in various states in the U.S. ▪ Found that non-GPS sources return inaccurate readings very frequently, some phones are unable to access accelerometer in the background (so only Wi-Fi could be used to detect movement), location readings in areas with skyscrapers were very accurate (likely due to high density of Wi-Fi access points), most inaccurate readings were in suburban or rural areas when location was attempted to be gathered from non-GPS sources, GPS readings of high accuracy often drift between 20-50 m ▪ Start/end times: 16% of trips could not be identified within a 6 minute window of their true start time ▪ 33 trips missed by the system – all were under 2 km ▪ Passive mode detection accuracy: bike (66%), drive (53%), transit (85%), walk (88%)
Strengths	▪ Battery life – average of 33 hours assuming 2 hours of travel and normal internet use ▪ Conducted tests on various models of smartphones in various locations to test battery impact of app, providing measureable results
Weaknesses	▪ Route and mode detection not very accurate ▪ Developed and tested only on Android phones ▪ Route determination uses Google Directions API, which finds the shortest path, thus not capturing the true route taken by a user ▪ 90% of hotspots discovered by the 3rd week ▪ Travel mode classifier does not detect the mode for each trip segment, only the main mode ▪ No trip purpose inference

37. Dutch Mobile Mobility Panel (Hoe mobiel zijn we nu eigenlijk? Eerste inzichten uit het Mobiele Mobiliteitspanel)

Thomas, Tom, Karst Chargeurs, Marcel Bijlsma, and Salima Douhou. 2014. "The Dutch Mobile Mobility Panel." *The Netherlands Organisation for Scientific Research* (NWO). September. Accessed August 20, 2015. http://www.nwo.nl/en/research-and-results/research-projects/10/2300170410.html.

Categories	Passive (Location, Mode, Activity, Trip Start/Stop), Active, Battery, Sampling Frame, Core/Satellite, Household/Individual, Multi-day/week, Response Rates
Applications	Larger scale smartphone survey done in Netherlands using panel participants
Methods Used and/or Summary	▪ Trip details detected of 591 participants over two weeks using a smartphone application (Moves Marter) ▪ Works with both Android and iPhone ▪ Detects departure and arrival time, transport mode and trip purpose ▪ Participants were recruited from a panel (LISS panel) ▪ 60% of participants received a loan smartphone, either an Android or an iPhone ▪ Results show that number of trips detected is clearly higher than the traditional surveys, even though app does not capture all trips (15-20% of trips not detected) ▪ Through analyzing user evaluations at the end of the survey, saw that participants generally satisfied with location accuracy, but less so with mode detection and battery consumption ▪ 3 components: 1) the app itself 2) back-end server where data is processed 3) online environment for data validation and correction ▪ Sensors used: GPS, Wi-Fi, GSM and Cell ID ▪ In the back-end server, the GPS, Wi-Fi, and GSM location data and collected, cleaned and analyzed to obtain exact time and location of origins and destinations of trips, the route and distance travelled. ▪ The trip purpose is automatically assigned based on destination and mode of travel. ▪ The mode detection uses pattern recognition via Bayesian statistics to determine most probable mode ▪ Locations specified by the user are then saved, used for more accurate detections if user visits the location again ▪ Participants were asked to monitor and validate detected trip details regularly, include trips missed. They were also asked to choose from a predefined list if certain other circumstances were applicable, like extreme weather, roadwork or public transit delays, or whether they were sick, or travelling with others. This was basically a way to gauge how any of these might have affected their travel pattern that day. ▪ Sample frame: Participants are part of LISS panel which has a pool of 5000 households/8000 participants, provides a representative view of the Dutch population. nearly 800 panelists selected who had previously expressed an interest in have participation smartphone research and authorized for temporary storage of their data to a third party – therefore not random sample from the panel pool either ▪ Panelists given a financial incentive for their participation (although how much the incentive was is not mentioned in the paper) ▪ Mode detection accuracy: 75% ▪ 7 mode categories: walk, cycling, driver, car passenger, train, bus, other ▪ Also did a basic analysis of trips by mode made throughout the week – for example more people go running or biking on Sundays. Also, more passengers trips are made on weekends/holidays as more family trips are presumably made ▪ User evaluation: 21% dissatisfied with accuracy of automatic detection of destination and arrival. 49% dissatisfied with accuracy of mode transport. 50% of users said impact on battery was significant. ▪ Surprisingly, the ones who were loaned smartphone were most critical of battery life. Could be that

	smartphone users are familiar with shorter battery life of smartphones while those who use regular cellphones are used to longer battery life ▪ Issue with loaning smartphones is that they may not be used to carrying them everywhere – 17% of the time, users forgot to take their phones during trips ▪ The longer the app was used, the better it got at accurately detecting trip details – 27% of users indicated that they hardly needed to adjust the data ▪ Also does comparison between smartphone users and those who were loaned smartphones – saw that for those where loaned smartphones, they made fewer trips and that the detection accuracy was lower – possibly because, the more trips they make and validate, the more accurate the app gets ▪ Saw that those who owned smartphones tended to be more mobile. ▪ For those making more or longer trips, battery drained quicker – logging more points through GPS, but also that the percentage of missed trips was lower ▪ Three improvement directions: first, the sensing algorithms will be expanded and will also include accelerometer data. Moreover, where applicable, the enhanced positioning capabilities of the latest versions of the Android and iOS operating systems will be used. Second, will include transit information like location of bus, metro and train stations and routes. Will improve algorithms to help for more accurate detection ▪ Incentive amount not provided
Strengths	▪ ~600 participants ▪ Mode detection accuracy: 75% across a wide range of modes ▪ 27% of users indicated that they hardly needed to adjust the data ▪ Provides insight as to how multi-day data collection can be used to assess more information and travel patterns, for example mode usage over different days of the week ▪ Provides some insight as to how regular smartphone users and those who don't use one (i.e. were loaned a smartphone) differ in their usage of the app and perception of various factors like battery, accuracy
Weaknesses	▪ Activity detection accuracy not mentioned, only talks about user satisfaction with accuracy, which was poor ▪ Battery consumption was a significant factor – 50% of users were unhappy with performance

38. SmarTrAC: A Smartphone Solution for Context-Aware Travel and Activity Capturing

Fan, Yingling, Julian Wolfson, Gediminas Adomavicius, Kirti Vardhan Das, Yash Khandelwal, and Jie Kang. 2015. *SmarTrAC: A Smartphone Solution for Context-Aware Travel and Activity Capturing*. Volpe Center at U.S. Department of Transportation in support of the Intelligent Transportation Systems Joint Program Office.

Categories	Passive (Location, Mode, Activity, Trip Start/Stop), Active, Battery, Household/Individual, Multi-day/week, Response Rates
Applications	Comprehensive with regards to most issues pertaining to smartphone-based survey methods, including discussion of methods and accuracy of various components, although the sample size is very small
Methods Used and/or Summary	▪ Smartphone sensing with machine learning techniques to automatically detect trip details ▪ Did 7-day field tests, where participants were 17 Android users ▪ While running the app, 74% of the phones had a battery life longer than 6 hours, and about half of the phones (47%) had a battery life longer than 8 hours ▪ Produces 50 megabytes of data per day, requiring 350 megabytes of data storage space for a seven-day participation. The associated weekly data transfer needs are roughly 150 megabytes after data compression. ▪ The overall accuracy in classifying travel mode across all six mode options (car, bus, rail, wait, bike, and walk) is 86% ▪ The predicted activity matches the true activity type 25-40% of the time. Correct activity type is among the top two most probable predicted activity types 70-80% of the time, and among the top three 80-95% of the time ▪ Different modules used: *sensor listener module, data filter module, activity/trip separator module, travel mode classifier module* ▪ Some distinct features that set SmarTrAC apart from some of the other smartphone-based methods: real-time, high-accuracy prediction of travel mode, real-time visualization and annotation options for the user, recursive self-improvement (SmarTrAC uses respondent input to optimize its data mining modules which allows for personalization of travel patterns) ▪ Pays special attention to accurately identifying the exact moments when a user is transitioning from a trip to an activity. This is done by comparing the distances between the points logged around a point and seeing when the points start clustering together – if the points are greater than 5 m apart, consider that point as part of the travel, otherwise it is the dwelling episode. Through iteration the exact point of conversion from travel to dwelling is found. A similar method is used to find end of dwelling and new travel episode. ▪ SmarTrAC predicts a change within ± 30 seconds 88% of the time ▪ For the travel mode, obtains GPS and accelerometer data (bearing, speed, and acceleration information) over 30-second and 120-second segments at 30-second intervals, which are used as inputs for classifiers in random forests ▪ *Correction to point-wise mode prediction:* uses a backward-looking smoothing technique to correct point-wise, real-time mode predictions based upon the fact that sudden and brief changes in mode of transportation are highly unlikely. For example, given a sequence of predictions at 30-second intervals such as "Car, Car, Car, Car, Bus, Car, Car, Car, Car", it is very probable that the "Bus" prediction is incorrect and should be replaced by "Car" ▪ Before the start of the survey, SmarTrAC asks users for their home and work locations, and if a location is logged near this location (within 50 m), it is automatically assumed that this is the purpose and location. This achieves an accuracy of 95% for work and home locations. ▪ Prediction of purpose for unvisited locations: uses Google API to list nearest points as training dataset for activity classifiers, which is why it is not very accurate ▪ Random forest purpose categories: Eat out, Education, Shopping, Social/recreation/entertainment/community, or Other personal business – home and work not predicted via random forest as they are typically associated with previously visited locations ▪ Tested a few different smartphone models and varied accelerometer and GPS sampling rate (example 0 Hz, 0.2Hz, 1Hz) - tests show that phone battery life is dramatically shortened by GPS data collection (4.9% - 7% per hour) and is only modestly shortened by accelerometer data collection. Once GPS and accelerometer listening is turned on, sampling rates and file writing rates

	play a minimal role in influencing battery consumption ▪ Decided to have the accelerometer run continuously, and use the accelerometer readings to stop GPS sampling during periods of inactivity ▪ For the field tests, participants were provided access to 9 online tutorials showing how to use the app ▪ 17 participants were recruited via convenience sampling, no compensation for participation provided ▪ Only tested on phones with Android version 4.0.4 or later ▪ Before the use of SmarTrAC, all participants' phones (100%) had a battery life longer than 6 hours and 94% of the phones had a battery life longer than 8 hours. With SmarTrAC running continuously, 74% of the phones had a battery life longer than 6 hours, and about half of the phones (47%) had a battery life longer than 8 hours. ▪ Battery performance varied from model to model, but even if the model was the same the results varied. Two identical Sony Experia phones were tested: one showed no significant change in battery life, while the other saw a decrease of up to two hours
Strengths	▪ Travel mode detection accuracy: 86% over 6 modes ▪ Predicts a transition from trip to activity within ± 30 seconds 88% of the time ▪ Compared battery life of smartphones both before and after usage of the app
Weaknesses	▪ Activity detection is poor – top activity predicted is accurate only 25%-40% of the time ▪ Only tested with 17 participants ▪ Relatively few bike and rail episodes recorded – likely due to small sample size ▪ Battery life can drop significantly for some users

39. "In the Moment" Travel Study: A GPS Smartphone Application

Hathaway, Kevin, Elaine Murakami, Elizabeth Greene, Robert Wertman, and Michael Geilich. 2015. ""In the Moment" Travel Study: A GPS Smartphone Application." *15th TRB National Transportation Planning Applications Conference*. Atlantic City, New Jersey: RSG.

Categories	Passive (Location, Trip Start/End), Active, Sample Frame, Multi-day/week, Core/satellite, Household/Individual
Applications	
Methods Used and/or Summary	▪ GPS-enabled smartphone application for iOS and Android called rMove ▪ Recently tested in Indiana by 300 people – doing further pilots this year ▪ Motivations: data quality and completeness (reducing recall bias, respondent more likely to always have smartphone with them, ability to collect multi-day or –week travel data), reduction in participant burden (faster and easier than completing paper, web or phone surveys long after travel has finished), scalability and cost reduction for agencies (as app matures, incremental costs should be reduced allowing for longer data collection periods and recruitment of more households) ▪ Questions that they are looking to answer: Can smartphones be a 100% replacement for traditional survey methods? Can GPS-based travel information be reliably collected via a low burden smartphone app? Will the resulting data be equal or better in quality? ▪ Automatic trip start and end/stop detection, route recording, duration ▪ Uses GPS, compass, Wi-Fi ▪ Automatically runs in background and on device power-up ▪ Transfer data to server immediately after trip is complete (assuming connection), and issues messages to user if GPS/Wi-Fi turned off ▪ Validation in-app, uses real-time logic based on response ▪ For each trip made, asks from a selection which vehicle (that the user owns) was used and how many persons from household accompanied trip. Can also select other modes. ▪ Daily end of day survey ▪ Trips that have the same start and stop location and distance are matched from a pre-populated list so users can simply accept or change details – 8% of trips were matched in this way ▪ Recruited from 2014 household survey. First, each household does a recruitment survey where they are asked to provide household information and smartphone ownership, then sent info on travel dates assigned ▪ 1417 households invited to study, 171 households (295 people) answered trip survey on smartphone during assigned travel date period. ▪ Response rate is 12%. ▪ Participants recruited for 7 days ▪ Completion rate: 86% of people answered every single trip survey. ▪ Is a household survey (i.e. all participants used app on their own smartphones) ▪ Battery life an issue in some Android devices, also have a wider range of quality
Strengths	▪ Household-level smartphone survey, not individual ▪ Good completion rates ▪ Applies a trip matching method so that users don't need to input all details, will get better over time as app matures
Weaknesses	▪ Does not detect mode or infer activity – users required to provide this info ▪ No specific measurements on battery life and accuracy of detections

40. Can Your Smartphone Do This: A New Methodology for Advancing Digital Ethnography

Bailey, Justin, Michael W. Link, E. Nicole Bensky, Lorelle Vanno, Jennie Lai, Karen Benezra, and Hala Makowska. 2011. *Can Your Smartphone Do This: A New Methodology For Advancing Digital Ethnography*. The Nielson Company, AAPOR

Categories	Response Rates, Multi-day/week
Applications	
Methods Used and/or Summary	▪ Survey of 428 South Africans over a 5-week period during the 2010 soccer World Cup ▪ In previous studies, findings showed that users complete surveys intended for online consumption on a mobile device. The percentage of respondents who do this was estimated to be at only 1-4%, but will likely rise as more people adapt to smartphones and tablets as replacements for their traditional PCs. ▪ Also in previous studies, users attempting to complete surveys intended for desktops on mobile devices are more prone to breakoffs (8% for desktop vs 24% for mobile web users) ▪ Smartphone penetration is highest among 18-24 year old because of the novelty of the technology ▪ This novelty effect can be leveraged by survey researchers to encourage participation and completion ▪ However, as the novelty of the device erodes, it is likely that response rates will fall accordingly. This similar effect was observed with response rates to email surveys.
Strengths	▪ Gives a brief overview of the benefits and uniqueness of smartphones over other methods
Weaknesses	▪