Exploratory Analysis of a Smartphone-Based Travel Survey in Singapore

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1   **Abstract**

2   Future Mobility Survey (FMS) is an innovative smartphone-based travel survey system, that was
3   field tested in 2012/2013 together with the Household Interview Travel Survey (HITS) in Singa-
4   pore. In this paper, we present findings of exploratory analysis of the data collected in this test.
5   Clustering of day patterns from FMS data reveals large day-to-day variability of user behavior,
6   which cannot be captured by taking a snapshot with a one-day survey. We show that even if we
7   take advantage of cross-sectional variability of a larger sample size from a traditional survey, we
8   would not have achieved the comprehensive set of heterogeneous patterns as provided by FMS.
9   Some common problems in traditional surveys, such as under-reporting of trips, over-estimation
10   of travel times, in accuracy of location and time, can be significantly reduced by FMS. The FMS
11   data, as compared to HITS, has higher resolution and better accuracy. In addition, FMS is well-
12   suited to collect multi-day data as additional cost is marginal and user burden reduces over time.
13   Therefore, it is a promising technology for next generation travel data collection.

1 INTRODUCTION

The unprecedented and increasing penetration rate of smartphones together with advances in mobile sensing technology have greatly expanded the means of collecting various forms of personal transportation data. While traditional self-reported travel surveys typically suffer from problems such as limited sample size, the under-reporting of total completed trips, an imprecision of trip start and end times (1), smartphone based surveys present the opportunity to collect more detailed and precise data needed for emerging agent and activity-based behavioral models. Developments in this field (2, 3) suggest that location-enabled technologies can reduce the number of erroneous "no travel" days and missed trips; improve accuracy of reported trip times, locations and paths; and reduce respondent burden.

The usage of mobile technologies for automatic surveying is not new. GPS-based logging surveys have been widely implemented worldwide and largely successful as a supplement to household travel surveys (4, 5, 6, 7). However, pure GPS logging suffers from some limitations. Financially, the agencies conducting travel surveys are required to purchase and distribute the GPS collection devices, which can be a significant investment. Also, the participants may forget to carry the GPS loggers with them for the duration of the travel survey, and they will face a recollection problem when completing their travel diary. In contrast, smartphones provide some clear benefits. For instance, users are accustomed to carrying their phones with them constantly and as such, there is a decreased likelihood of missing trips. They are almost always charged, and smartphones contain a combination of sensors not limited to positioning data. The sensors are capable of providing spatial, temporal and proximity data, which can be used to infer activity and mode information. These attributes make smartphones ideal "life-loggers".

To capitalize on these "life-loggers", our team has developed the Future Mobility Survey (FMS) system, which is a smartphone and web prompted-recall based travel survey system (8). The FMS is a next-generation travel behaviour survey system that leverages pervasive smartphones, advanced sensing and communication technologies and machine learning architecture. It delivers previously unobtainable range of data reflecting what people *do*, not what they *say* they do. We field tested FMS in Singapore in conjunction with Singapore Land Transport Authority's (LTA's) Household Interview Travel Survey (HITS) 2012. The test recruited more than 1500 users and produced a large set of rich and detailed travel/activity data that has been validated by the respondents (9). In this paper, we present results on the exploratory analysis of this unique dataset, and demonstrate the capabilities of this kind of survey platform to reveal interesting and diverse user day patterns and overcome some of the known issues of traditional travel surveys.

The remaining part of this paper is organised as follows. Section 2 gives an overview of the FMS system. Section 3 describes the field test with the HITS survey in Singapore and data collected. We then present an example to illustrate the difference between the data collected in HITS and FMS in Section 4. Exploratory analysis results are presented in Section 5 followed by conclusions and future work in Section 6.

2 FMS SYSTEM

FMS consists of three seperate but inter-connected components - the smartphone app that collects the sensing data; the server that includes the database as well as the data processing and learning algorithms; and the web interface that users access to view and validate the processed data and
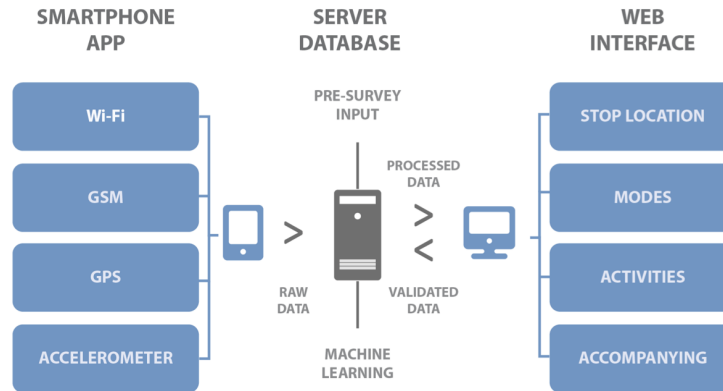
FIGURE 1 FMS architecture

1 respond to additional questions to supplement the validated data. The three components and the
2 flows of data among them are shown in Figure 1.

Smartphone app

4 The smartphone app, available for both Android and iOS platforms, collects data from a multitude
5 of sensors available on the phones including GPS, GSM, accelerometer and WiFi. One of the
6 main objectives of the FMS app design is non-intrusiveness, i.e., the app runs in the background
7 of the phone and silently collects the sensor data without user intervention. Participants would
8 therefore not be influenced in anyway by the application during their normal daily activities. In
9 addition, the application is designed to be light-weight and easy to use. A major concern for
10 location based applications is battery consumption, and we have made various efforts to minimize
11 battery consumption (10). The sensor data collected on the phone are transferred to the back-end
12 server through either the cellular network or WiFi, based on the user's preference.

Backend server

14 Raw data collected via the app are uploaded to a database where a series of algorithms are used
15 to process the data and make inferences about stops, travel modes and non-travel activities (11).
16 To minimize the user's interaction burden, the backend algorithms translate raw data into trips and
17 activities. The first round of stop detection is made based on location and point-of-interest (POI)
18 data. GSM, WiFi and accelerometer information are used to merge stops that would otherwise be
19 interpreted as distinct stops. Travel modes are detected based on GPS and accelerometer features,
20 as well as public transit location information. Short duration stops that are insignificant from a data
21 validation standpoint (such as stops in traffic or at bus stops or subway stations during their ride)
22 are deleted for the purposes of presentation in the web interface. Non-travel activities (e.g. home,
23 work, shopping, dropoff) are also detected based on previous validations by the user, POI data and
24 other contextual information.

Web-interface

26 The web interface provides a platform that enables users to review their processed data in the form
27 of a daily timeline or activity diary and "validate" their data for a limited number of days (Figure
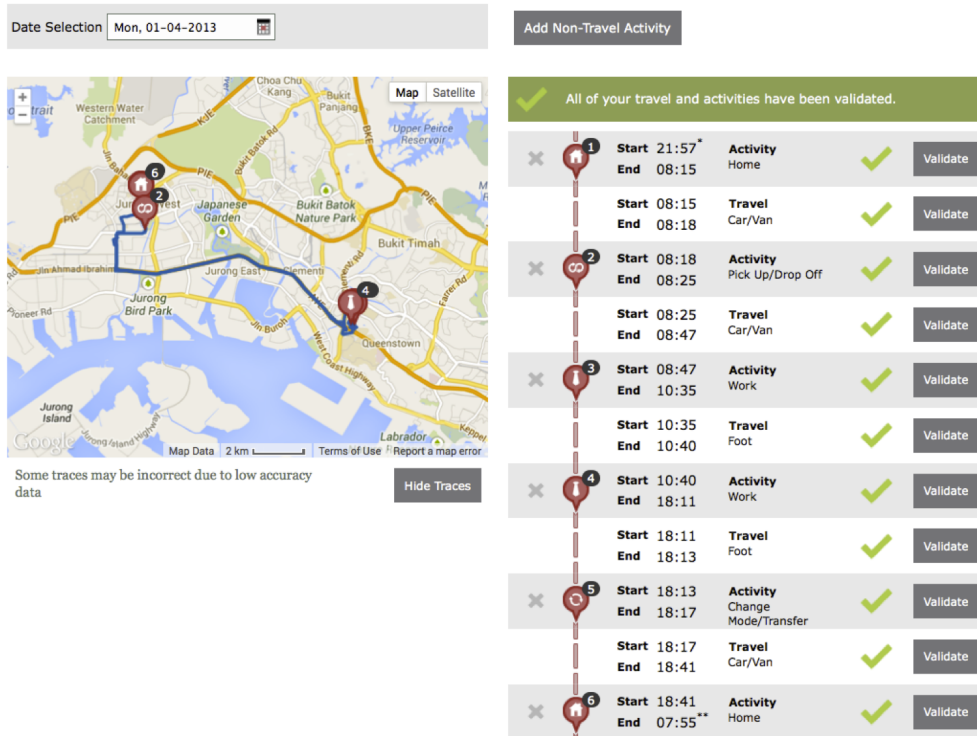
FIGURE 2 FMS web-interface – activity diary

1   2). Validation involves filling in missing information and amending incorrectly inferred data about
2   modes of travel used for particular trips, and specific activities engaged in at locations deemed
3   to be non-travel time segments or "stops". The validated data are uploaded and the algorithms
4   learn to make better inferences as the user interacts with the interface. The website also is flexibly
5   designed to enable supplementary data to be collected from users. Supplemental data pertaining
6   to a specific trip (e.g. how many people the user traveled with or what, if any, fee was paid for
7   parking) are collected within the activity diary validation stage. A helpdesk was available for
8   users to interact with through chat or phone call and users are encouraged to have a session with a
9   helpdesk representative for assistance during their first data validation.

10 **3   FMS FIELD TEST**
11 Between October 2012 and September 2013, we field tested FMS together with Singapore LTA's
12 HITS 2012 survey. HITS is a paper based survey conducted within Singapore every four or five
13 years. The survey collects activity and mobility data for a typical weekday (Monday to Friday)
14 for an individual. It also collects the socio-demographic characteristics of the households, and
15 the individuals. The data is collected through face to face interviews. A local subcontractor is
16 responsible for the recruitment and interviewing of participants. The format of the survey follows
17 the standard trip diary-based approach. Travel was defined as a one way journey completed for a
18 purpose. The survey includes walk segments taken as part of a trip (e.g. walking to a bus stop),
19 and walking trips before or after a trip with at least one motorized mode (e.g. walking to work,
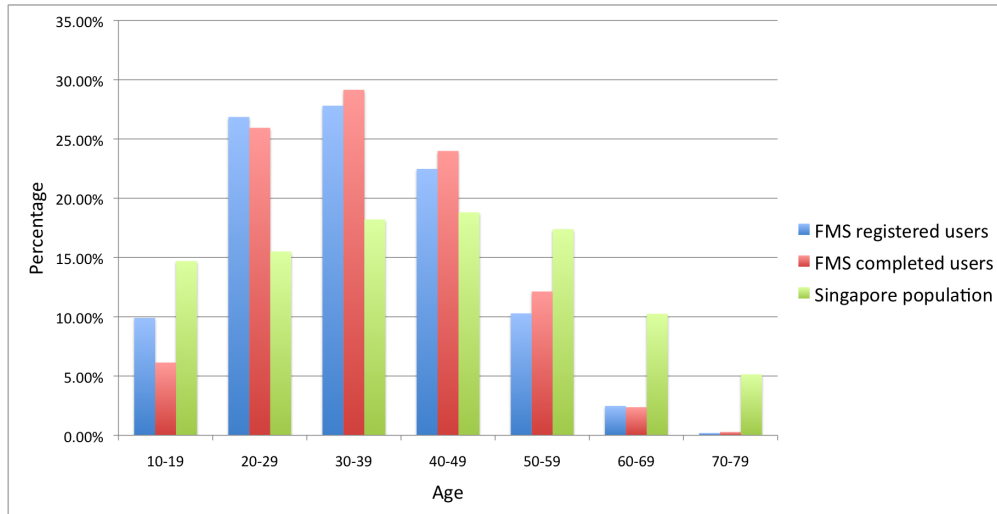
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FIGURE 3 Age distribution of FMS users and Singapore population.

1   and leaving work using a taxi). Walk-only trips are recorded if they are longer than 10 minutes.
2   Furthermore, the sample size of this survey is targeted for roughly 10,500 households. This is
3   about 1% compared to the total household number Singapore, which is roughly 1 million. The
4   HITS 2012 follows a similar format, methodology, and objective to other metropolitan-wide travel
5   surveys found in the Metropolitan Travel Survey Archive (http://www.surveyarchive.org).
6   The recruitment process for FMS piggybacked on that of HITS'. After a HITS interview,
7   the surveyor introduces and invites the participant to take part in FMS. Unlike in HITS, where
8   participants are required to register in complete households, FMS users can join as individuals.
9   This is to increase the participation rate in this first attempt of smartphone based travel survey.
10 An FMS participant is considered to have completed the FMS survey after collecting at least 14
11 days of data, and validating at least 5 days of them. In total, we have recruited 1,541 users, and
12 among them, 793 participants have completed the FMS survey. The total amount of data collected
13 is 22,170 user-days, and 7,856 of them are validated by the users.
14   As the use of FMS requires ownership of a smartphone and familiarity with web-browsers,
15 it is expected that the FMS participants will have a bias towards younger population, which is
16 reflected in Figure 3. This issue can be rectified by distributing GPS loggers to users who do not
17 have smartphones, and also providing help (over the phone or in person) to validate for the users
18 who are less tech-savvy. These elements fits into the FMS methodology naturally, and do not
19 require additional development work. In addition, it has been noted in previous traditional travel
20 surveys that the response rates are generally lower in younger generations and it is relatively easier
21 to get good quality data from the elderly groups. Therefore, FMS would be a good complement to
22 traditional travel surveys to achieve a balanced overall sample.
23   While smartphones are capable of collecting increasingly accurate data, it is still possible
24 that some geolocation points may be erroneous due to sensory errors and/or a limited sample
25 of points. For example, GPS location accuracy is reduced when participants travel indoors. In
26 addition, by closely examining the collected data, we find two main types of errors:

27   1. **Data gaps** – Occurs when participants' smartphones run low on battery power, user

logs off from the app, or devices are turned off. Such scenarios have the possibility of producing gaps in data (presenting non-continuous data). Although the users can reconstruct their days fully despite these gaps by adding activities during their validations, many users fail to do that properly, leading to incomplete days of data.

2. **Validation errors** – Unlike in traditional surveys, where an interviewer is present to perform some quality control while collecting the data, FMS' web-based validation is totally controlled by the user. Mistakes can happen especially when the user is unfamiliar with the interface.

Throughout the test period, we continuously worked on adding real-time checks for the collected and validated data, including maximum gaps in data to allow validation, ranges of travel speed, activity duration, change of location as compared to collected raw data etc, in order to minimize the above errors. In addition, post-processing was performed to further clean the collected data.

4   AN ILLUSTRATIVE EXAMPLE

Before diving into the exploratory analysis, we first present a sample of HITS and FMS data collected from the same user to highlight some of the properties of FMS data. The travel/activity information of the user are presented in two formats. Firstly, on a map showing her stops, activities at each stop, and her traces. And secondly, in a timeline below the map, which shows the times associated with each activity.

The HITS data (Figure 4 (a)) indicates that the user left home for work at around 7am and returned home before 7pm. On both ways, she travelled by bus, and as HITS does not capture the exact routes, we plot out all the likely bus routes between these two locations based on Google Maps. One thing to note is that for both trips, the reported travel time are exactly the same, 35 minutes. In fact, we see many cases in HITS where users round the travel times to the nearest 5 or 10 minute blocks, and there is a large spike in travel time of 60 minutes for bus trips. In this example, the user reported a simple working day, and there is a lot of uncertainty in the data due to lack of detailed information. In Figure 4(b), we see a much richer set of data for the same user collected in FMS on four weekdays. In the first one, the user only worked half-day, and went out for dinner in the evening. FMS captured the exact bus routes that the user took. On the second day, although the activity sequence is the same as that in HITS (Home-Work-Home), we do see that the work hour is very long, from around 7am in the morning all the way to past 9pm at night. Also, she took two different buses to and from work, which took 18 minutes and 20 minutes, respectively. In the third graph for FMS, the user did not go to work on this day. Instead, she went for some sports activities in the morning, and social/meal activities in the afternoon. We observe yet another day pattern in the fourth graph, where she goes shopping in the morning, and working in the afternoon/evening. In fact, in these four days, none of her trips to or from work took more than 20 minutes. Of course, it might have been that, for the day she reported in HITS, the traffic condition was exceptionally bad, but we believe it is reflective of the fact that people tend to over-estimate travel times (5).

From this example, we can observe some typical issues with traditional travel surveys, i.e.,

- people tend to report a simple (typical) day;

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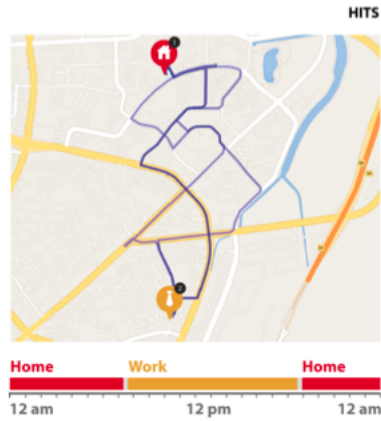
(a) HITS data for an unspecified weekday
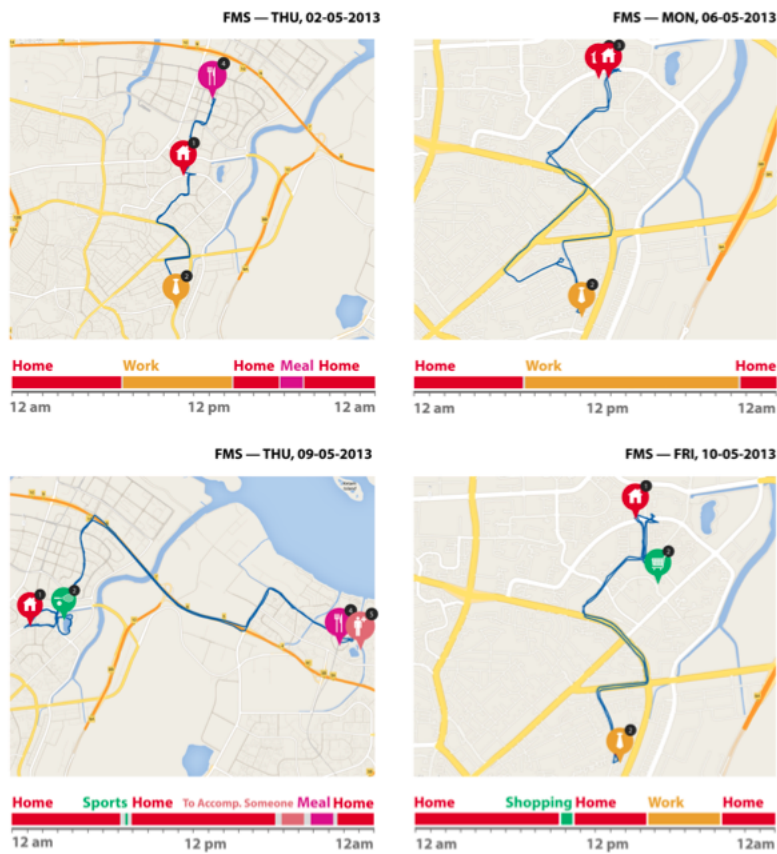
(b) FMS data for four weekdays

FIGURE 4 HITS and FMS data from one user on different days

1   • short activities are under-reported;

2   • travel times are over-estimated for short trips; and

6

- people have large day-to-day variabilities, which cannot be captured by a one-day survey.

On the contrary, FMS is capable of collecting more detailed and accurate data, and capture the variability in user's travel/activity patterns. In the next section, we will examine the overall FMS dataset in various ways to demonstrate these points in more details.

5   DATA ANALYSIS

For the exploratory analysis, after post-processing and cleaning of the data, we selected a subset of 319 users who have, on average, a larger number of validated days, which is useful for studying the intra-user variability of travel/activity patterns. With a total number of 2350 days, we have on average 10.5 validated days from each user.

Clustering of user day patterns

To examine the day-to-day variability of user behaviour, we first perform clustering of FMS user day patterns for the 233 employed participants (full-time or part-time). The day pattern is generated by dividing each day into 5-minute slots and assign to the slot the activity (including travel) associated with it. This transforms each user day into a vector of 288 elements. Weighted clustering algorithm is used to group the day patterns into 5 clusters.

Figure 5 shows the day patterns that belong to each cluster. 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. As most errors in FMS data are related to data gaps, which can lead to excessive travel times (since we mark all non-stop segments as traveling) or home activities (as we merge home stops before and after a gap, assuming they are home all the time), many of the days with errors fall into Cluster 5. The distribution of days of weeks in each of these clusters (Table 1) are consistent with our expectation. Clusters 1, 2 and 3 are mostly on weekdays, where Cluster 4 is mainly on weekends. Clusters 5 also has a higher concentration on weekends, but the day patterns with errors throughout the week also contribute to the high number of days in this cluster.

Clusters	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	**Total**
Cluster 1	113	110	112	121	94	26	11	587
Cluster 2	86	89	85	85	66	14	9	434
Cluster 3	17	28	28	33	20	7	6	139
Cluster 4	39	38	48	28	52	145	132	482
Cluster 5	95	88	83	90	94	106	137	693

TABLE 1 Breakdown of user days in each cluster and each day of week.

Next, we focus only on the weekdays, as HITS data are all for weekdays, and study the variability in people's day patterns. Figure 6 shows the number of users having different numbers of distinct clusters of their day patterns during the week. Almost all users (97%) have at least two clusters observed, and majority of them (73%) have at least three patterns. Traditional surveys,
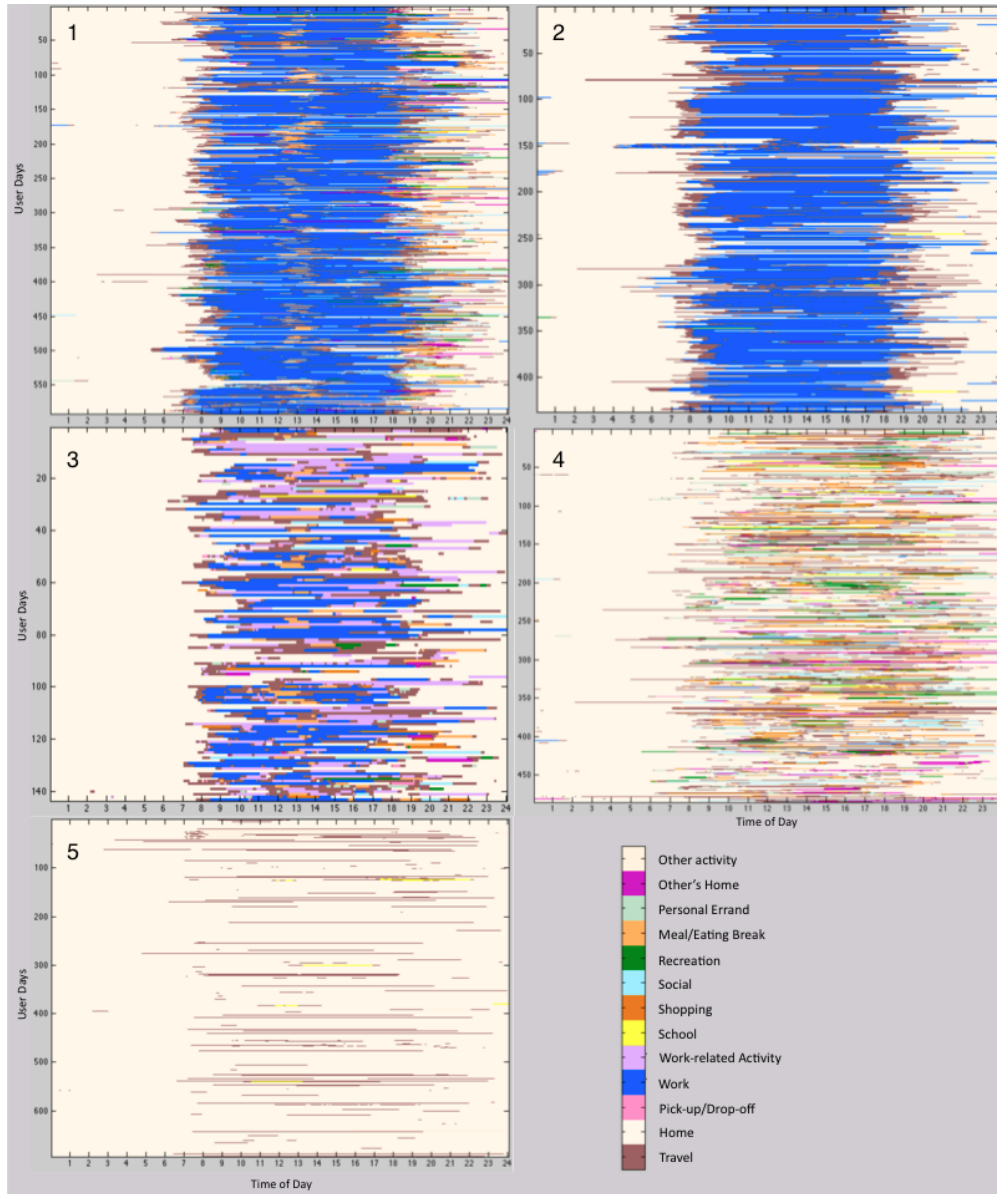
FIGURE 5 Results of clustering FMS user day patterns into 5 clusters (employed users).

1 like HITS, typically only take one or two days of samples, and are clearly insufficient to capture
2 the full patterns. We have also linked the day patterns generated by these 223 users' HITS data
3 to the 5 clusters shown above, and 208 of them (93%) falls in Cluster 2 with simple work tours.
4 This agrees with our observation of the example in Section 4. In fact, none of the HITS days fall
5 in Cluster 1, highlighting the low reporting rates of out of work activities in HITS. This indicates
6 that, even if we took advantage of cross-sectional variability in HITS to overcome the single day
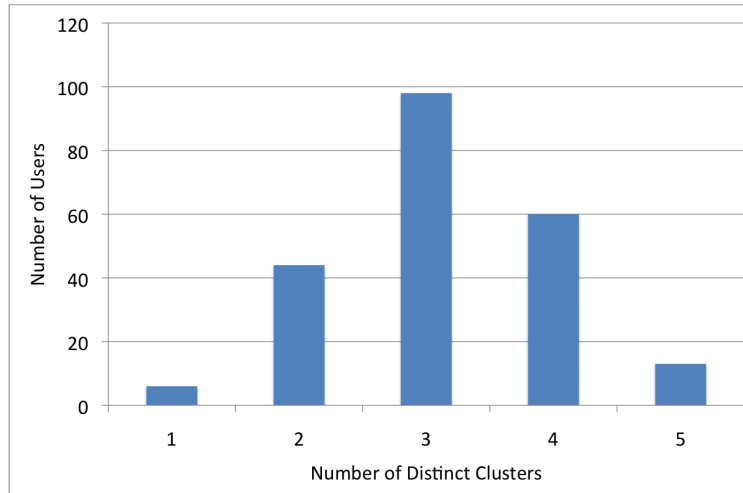7 limitations, we would not achieve a comparable set of heterogeneous patterns as FMS provides.

FIGURE 6 Distribution of users with different numbers distinct clusters.

Distance-from-home diagrams

To visualise the travel/activity pattern of a user over multiple days, we use distance-from-home diagrams, which show user's distance from his/her home against time over the duration of the survey. Color markers are used to represent the non-home activities the user performed at each stop. If the activity lasts for a long time, the marker is placed at the start time of the activity. These graphs reveal interesting patterns for different types of users, and here we show three representative examples, with different social-demographic background.

Figure 7(a) is the distance-from-home diagram for a full-time employed user who works long hours. Although she goes to work almost everyday, we do see large day-to-day variability in her work hours and in the other activities she performs on these days. Also, there are large variances in her time spent in each type of activity and each mode of transporation, which cannot be possibly captured by a one-day survey.

Figures 7(b) is based on data collected by a part-time employed user. He goes to work on some days, and performs other activities on the others. His main modes of transportation are car and trains, and there is a large variation in the travel times.

In contrast, a very different activity pattern can be seen in Figure 7(c) for a homemaker. One marked difference between her data and the previous two users is that she typically makes multiple short home-based tours per day. And again, one snapshot of her day wouldn't be able to capture the full spectrum of her patterns.

Time of travel

Next, we compare the time of travel for different activities captured in HITS and in FMS for weekdays (Figure 8) . We plot the percentage of users who are traveling for Work, Home, or Meal/Eating Break at different times during the day. For travel to work and to home (Figure 8 (a) and (b)), as expected, most of the trips take place around the morning and evening peak hours. In these two graph, 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. In addition, in HITS, we note that most users report that they arrive home in the evening by

9

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.

Figure 8(c) shows the time of travel to Meal/Eating-Break activities. We 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. This is also reflected in Table 2, which lists the top three purposes of home-based tours reported in HITS and FMS for users of different employment status. For all categories of users, except those self-employed, Meal/Eating Break activity is among their top three purposes in FMS. In contrast, this activity only appears once in the list on the left for HITS. This agrees with the observation that short trips tend to be under-reported in self-reported travel surveys. On the other hand, the rank of Pick-up/Drop-off activities appears to be lower in FMS. This is the due to the fact that these activities may have very short durations, and the modes of transportation before and after the stops are typically the same. When this kind of stops are detected in FMS, they are normally deleted in order to reduce the erroneous detection of "stops" related to traffic lights or traffic jam. The detection accuracy will improve in this aspect when we incorporate more Points of Interest (POI) information of the underlying map, and also learn from users' past validations.

	HITS	FMS
Employed Full-time	Work Pick-up/Drop-off Work-related	Work Meal/Eating Break Personal Errand
Employed Part-time	Work Pick-up/Drop-off Shopping	Work Meal/Eating Break Personal Errand
Self-employed	Work-related Work Pick-up/Drop-off	Work Personal Errand Shopping
Homemaker	Pick-up/Drop-off Shopping Meal/Eating Break	Meal/Eating Break Shopping Personal
Full-time student	Education Shopping Work	Education Work Meal/Eating Break
Retired	Other's Home Pick-up/Drop-off Social	Meal/Eating Break Personal Errand Recreation

TABLE 2 **Top three purposes of home-based tours.**

Travel time by mode

As the analysis of travel time is more sensitive to errors in our collected data, we have selected a subset of 1100 days from the 319 users, and manually checked them to ensure data quality. This dataset is used in this and the next subsection.

Figure 9 compares the histograms of travel times by car in HITS and FMS. While the distribution of travel time in FMS is smooth and continuous, the HITS graph is more rugged, with spikes at 20 minutes, 30 minutes, and 60 minutes. As we know, survey participants tend to round their travel time estimations. The resulting data may not reflect the true shape of distribution of the travel times, and can create difficulty when used in modelling. FMS avoids this problem by deriving the real "continuous" travel times from sensory data. 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, as we mentioned in Section 4. For other modes of transportation such as bus or train, we observe similar issues in HITS data. However, the definition of trip time in FMS and HITS are not entirely consistent for these modes, and thus, we do not present the comparisons here. Specifically, for public transport, HITS trip time is the door-to-door time from origin to destination, which includes access time, waiting time, egress time etc. On the other hand, FMS' data separates each leg of the trip and change mode/transfer stops. Thus, direct comparison of travel times of these modes between the two surveys is not straightforward.

Figure 10 is the box plots of travel times for each mode in FMS. The box shows the range of values between the first and third quantile, while the top and bottom whiskers represent $1.5 \times IQR$ (Inter-Quantile Range) from the upper and lower quantiles, respectively. We see that, on average, trips by train (MRT/LRT) are the longest, and those by foot or bicycle are the shortest. Also, a significant number of walk trips are recorded in FMS, which are not registered in HITS.

6 CONCLUSIONS AND FUTURE DIRECTIONS

Exploratory analysis of the data collected by FMS in Singapore demonstrates that FMS is capable of producing accurate, detailed, and rich data for travel surveys. It senses what people do, rather than asking them to report what they do. This eliminates many problems that traditional self-reported surveys face, such as under-reporting of short trips, inaccuracy in location and times, and reporting of a typical day rather than the actual day. Also, large intra-user day-to-day variabilities in the travel/activity patterns have been observed across different types of users, and taking a snapshot by a one day survey is inadequate to reflect the true patterns. An advantage of FMS is that the marginal cost of collecting additional days of data is minimal, and as a user provides validations (which our backend can learn from) and familiarizes with the web-interface, the participation burden reduces significantly over time. Therefore, smartphone based travel surveys, such as FMS, are viable and superior alternatives to traditional travel surveys.

As mentioned previously, what we have collected in this field test of FMS is a unique, large, and rich dataset on individual travel behaviour. Besides the exploratory analysis presented in this paper, we plan to further analyze the data, especially in discovering and classifying user patterns over multiple days, associating travel behaviour with other context information, such as weather, events, incidents, etc. The authors are also implementing an analytical framework for comparing the HITS and FMS sample presented in this paper through econometric modelling. This framework features include: controlling the temporal effect (i.e. participants provide data for different days for HITS and FMS); modelling the attrition rate (i.e. participants choose the number of days to validate); panel periods (multiple days of data for FMS); and others.

At the same time, we seek to enhance the capabilities of FMS system with two main goals:

reducing user burden and improving data quality. Two key aspects of reducing user burden are battery consumption and user-friendliness/intuitiveness of the interface. To improve data quality, we focus on using machine learning techniques based on context information and user history. These two goals can have competing needs, and require careful consideration in design and development.

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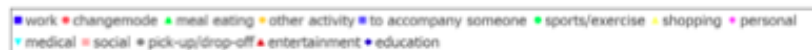9   Methods*, Australia, 2014.
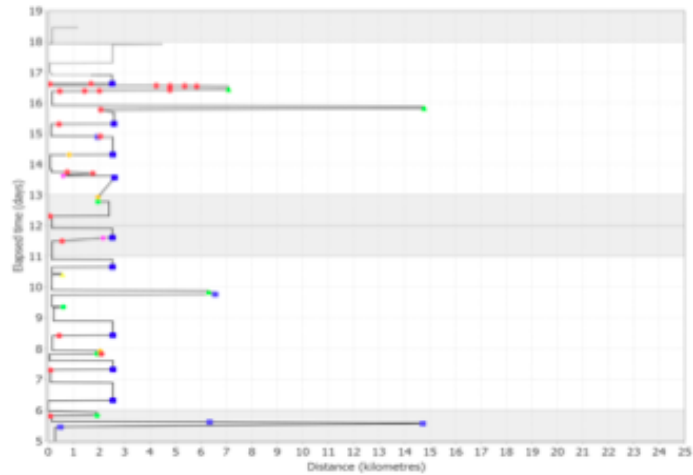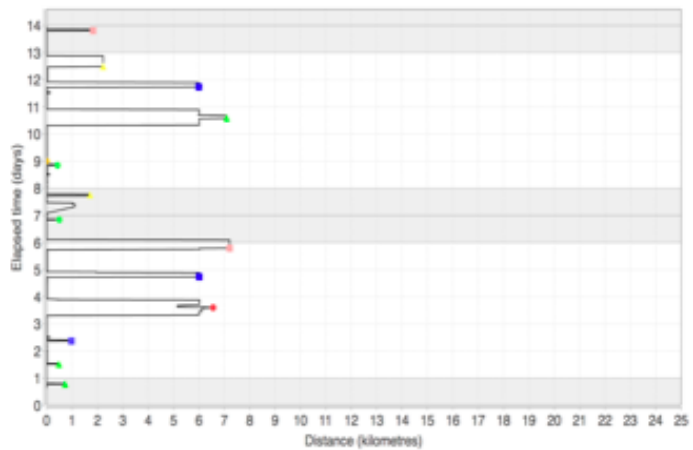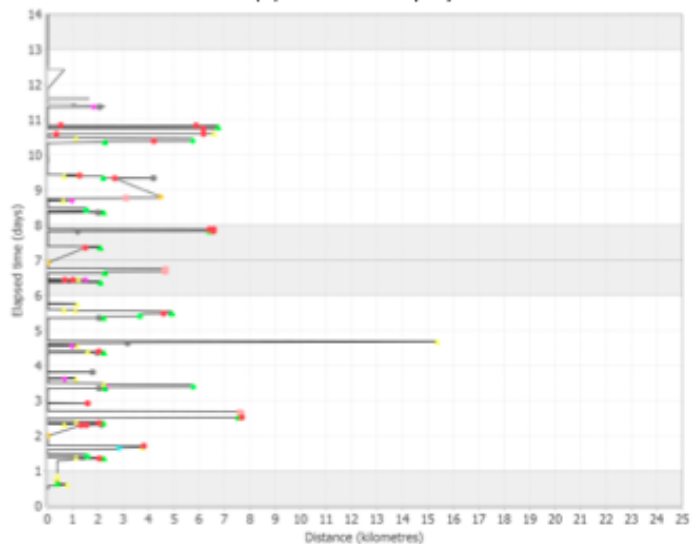
FIGURE 7 Distance-from-home diagram for (a) a full-time employed user who works long hours; (b) a part-time employed user; and (c) a homemaker
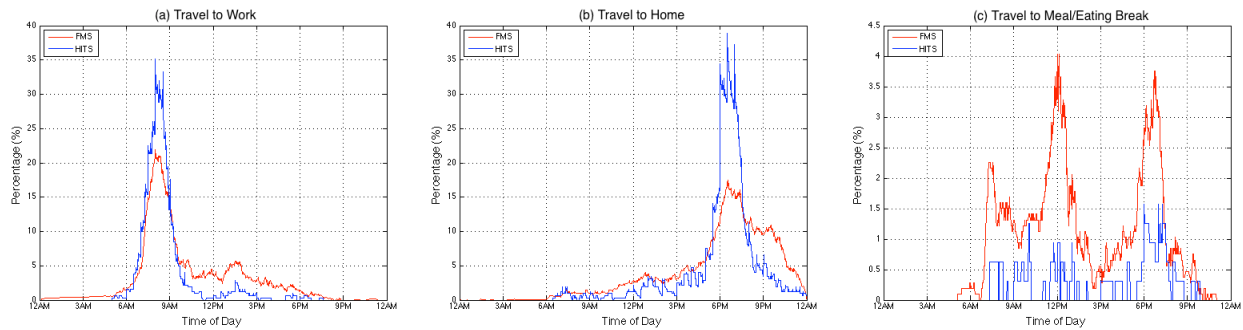
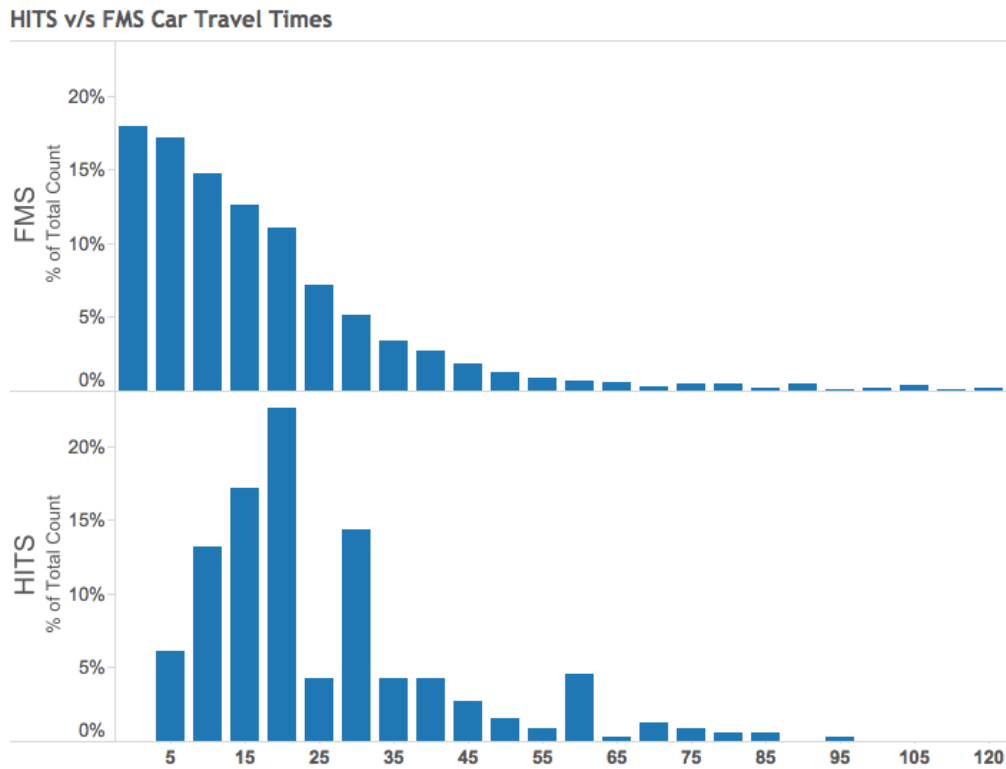**FIGURE 8 Percentage of participants traveling to (a) Work, (b) Home, (c) Meal/Eating Break at different times of day.**
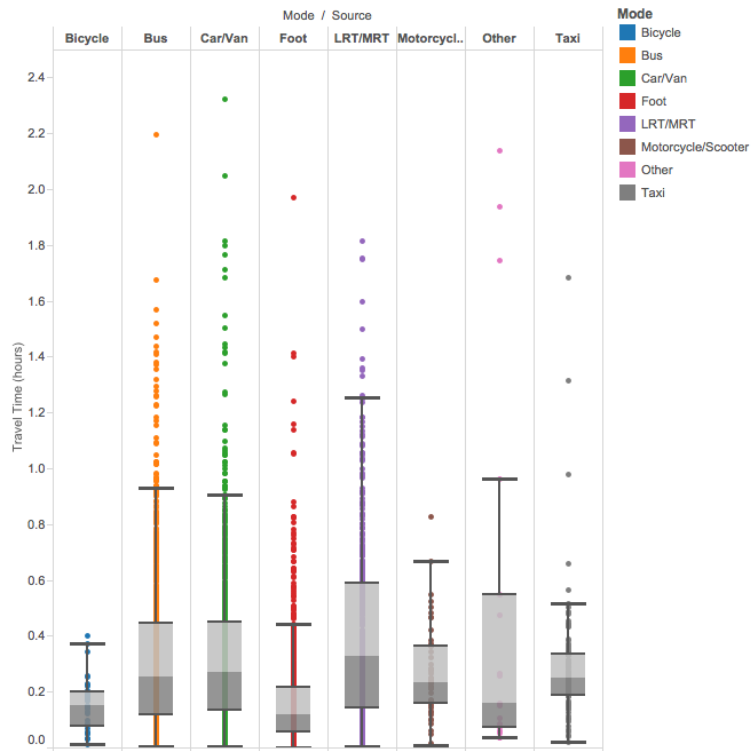

FIGURE 9 Histogram of trip times by car for HITS and FMS.

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FIGURE 10 Boxplot of travel times for each mode in FMS.