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Enriching Activity-Based Models using Smartphone-Based Travel Surveys

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Abstract

Smartphone-based travel surveys have attracted much attention recently, for their potential to improve data quality and response rate. One of the first such survey systems, Future Mobility Sensing (FMS), leverages sensors on smartphones, and machine learning techniques to collect detailed personal travel data. The main purpose of this research is to compare data collected by FMS and traditional methods, and study the implications of using FMS data for travel behavior modeling. Since its initial field test in Singapore, FMS has been used in several large-scale household travel surveys, including one in Tel Aviv, Israel. We present comparative analyses that make use of the rich datasets from Singapore and Tel Aviv, focusing on three main aspects: (1) richness in activity behaviors observed, (2) completeness of travel and activity data, and (3) data accuracy. Results show that FMS has clear advantages over traditional travel surveys: it has higher resolution and better accuracy of times, locations, and paths; FMS represents out-of-work and leisure activities well; and reveals large variability in day-to-day activity pattern, which is inadequately captured in a one-day snapshot in typical traditional surveys. FMS also captures travel and activities that tend to be under-reported in traditional surveys such as multiple stops in a tour and work-based sub-tours. These richer and more complete and accurate data can improve future activity-based modeling.

Transportation planners and travel demand modelers utilize a variety of data sources, the most important source being household travel surveys. Household travel surveys, conducted in many metropolitan areas, are administered to collect detailed information about the characteristics of the household, and each household member's travel and activity for some period of time. High quality data collected from these surveys are essential for estimation of travel and activity models.

Traditionally, household travel surveys have been interview-based, either face-to-face or by telephone. Typically, the interviewers first collect socio-economic and demographic information on the household and individual members. Next, for each participating household member, a detailed travel diary that includes all trips and activities on the previous day(s) is recorded or documented. Due to limitation of memory, such surveys usually collect only one day's data, or at most two days, from each participant. Some known issues for such surveys include inaccuracy in reported times and locations, under-reporting of short trips/activities, and inability to capture variability in user's behavior over a longer period of time.

Several recent household surveys have used GPS and/or other devices to improve data accuracy and reduce non-response (*1–3*). However, passive GPS tracking alone is insufficient to provide the details needed for activity-based models. Therefore, the challenge is to combine both automatic detection of trips and activities, together with reliable user-reported information.

Future Mobility Sensing (FMS) is a smartphone-based platform that can be used for automated household travel surveys. It leverages advanced sensing technologies, machine learning techniques and a user-friendly interface to collect personal travel data (*4*). An initial field test of FMS conducted in Singapore in 2012/2013 showed great potential to provide accurate and rich travel behavior data (*5*). Subsequently, FMS has been employed in large-scale household travel surveys (Phoenix, Arizona, 2016; Tel Aviv and Haifa, Israel, 2016/2017; Singapore 2016/2017) as well as in small

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demonstration or research projects (Melbourne, Australia, 2015; Dar es Salaam 2015; London 2016/2017) (*6*).

FMS is designed to overcome key issues faced by traditional travel survey methods such as: oversimplification of trips in a day, under-reporting of short trips, overestimation of travel times, and imprecise reporting of locations and times. It is also more cost-effective than GPS logger-based surveys, since participants use their own smartphones, and it avoids the problems of loggers left uncharged or not carried all the time. In addition, multi-day data can be collected easily at minimal marginal cost.

In this paper, we perform a comparison of data collected by FMS and by traditional surveys in two cities, Singapore and Tel Aviv, and discuss the implications of the enhanced data collection methods for travel behavior modeling. The remainder of this paper is organized as follows. First, a literature review is presented followed by a brief description of the FMS platform. We then describe the four data sets used in this paper, and present the data analysis results. We conclude the paper with a discussion of future directions.

Literature Review

In recent research projects, the feasibility of replacing or complementing the traditional travel diary with a suite of tools that make use of travel data collected smartphone has been studied; for overviews, see Zhao et al. (*5*) and Berger and Platzer (*7*). There have been attempts to make the completion of the whole data collection process on respondents' mobile (cell) phones either manual or semi-automatic (*8–10*). In the past two years, more smartphone-based travel surveys were field evaluated and documented (*11*). SmartMo is a system that is manually completed on respondents' mobile phones and was field-tested in 2013 in Austria (*7*). Another example is MEILI, a system that includes a smartphone application for capturing the movement of users and a web application that allows the users to annotate their movements; it was tested in Stockholm in 2015 (*9*). These systems, although smartphone based, required heavy involvement of participants by providing/verifying the entities and their attributes. An example of a semi-automatic smartphone app is rMove which was used as a multi-day smartphone-based GPS household travel diary survey over a seven-day period in the U.S.A. rMove experiments took place in Indiana, in 2015 (*10*), Ohio in 2016 (*11*), and Washington, D.C., in 2017 (*12*). These studies demonstrated the advantages of technology-based data collection tools; however, their full capabilities and advantages over traditional survey methods, and the implications for travel behavior modeling, are yet to be studied. This paper aims to fill this gap by comparing the travel information collected using traditional surveys and FMS in Singapore and Tel Aviv.

Future Mobility Sensing

FMS is a smartphone-based automated travel survey system (*5*, *13*). It consists of three separate but interconnected 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 mobile/web interface that users access to view and verify the processed data and answer additional questions to supplement the verified data. The FMS software platform is provided for commercial applications by Mobile Market Monitor (MMM) and has been applied in large-scale surveys in the U.S.A., Singapore and Israel. The Tel Aviv data described in the remainder of this paper was collected using the MMM platform.

The Data Sets

Four data sets were analyzed for the comparison of traditionally collected travel and activity data to data collected via FMS. These data sets include two from Singapore and two from Tel Aviv.

Singapore HITS

The Singapore Land Transport Authority's Household Interview Travel Survey (HITS) is a face-to-face interview-based household travel survey conducted every four years since 2004. The survey collects one day of activity and travel data for each participating household member. It also collects socio-demographic and other information about the households and individuals within the household. The format of the survey follows the standard trip diary-based approach, with travel defined as a one-way journey completed for a purpose. The survey includes walk segments taken as part of a trip (e.g., walking to a bus stop), and walking trips before or after a trip with at least one motorized mode (e.g., walking to work, leaving work using a taxi). Walk-only trips are recorded if they are longer than 10 minutes. The data set used in this paper, HITS 2012, has a sample size of roughly 10,500 households, approximately 1% of Singapore's resident population. The HITS 2012 follows similar format, methods, and objectives to other metropolitan-wide travel surveys.

Singapore FMS

Between October 2012 and September 2013, FMS was field-tested together with LTA's HITS 2012 survey. The FMS recruitment piggybacked on the HITS recruitment

Table 1. Data Sets Information

	Singapore FMS	Singapore HITS	Tel Aviv FMS	Tel Aviv HTS
Year	2012/2013	2012/2013	2016/2017	2014
Valid person-days	3,217	26,209	35,534	8,454
Persons	319	26,209	11,928	8,454
Multiple days?	Yes	No	Yes	No
Weekends included?	Yes	Yes	Yes	Yes

process. Following a HITS interview, the surveyor introduced FMS, and invited the participant to take part. Unlike HITS, which required all members of households to participate, household members could participate in the FMS survey as individuals, to increase the participation rate in the pilot. An FMS participant was considered to have completed the FMS survey after collecting at least 14 days of data and validating at least five of those days. Of the 1,541 recruited users, 793 completed the FMS survey. Cleaning and post-processing of the collected data were performed to eliminate days with data gaps and logical errors. The resulting dataset with 319 participants has been used for the analysis in this paper.

Tel Aviv HTS

A household travel survey (HTS) was carried out in 14 major cities of the Tel Aviv metropolitan area between December 2013 and June 2014. Weekdays and weekend days were surveyed. The survey method was similar to the Jerusalem HTS (*14*), and it is briefly outlined as follows.

The survey was conducted in two phases, both of them with surveyor in-home visits. In the first (recruiting) phase, a surveyor visited the household, collected general information, and provided household members older than 14 with a GPS data logger. In the second phase, the interviewer returned to the household to retrieve the GPS readings and complete the questionnaire about the activities recorded by the GPS logger. The GPS data was retrieved with the use of laptop computers, which assisted the surveyor and the household members to identify their trips and activities.

Tel Aviv FMS

A comprehensive survey of 10,000 households in the Tel Aviv metropolitan area conducted using FMS started in late 2016 (and was on-going at the time of the writing of this paper). The software platform was provided by MMM. In-person recruitment was performed by a local survey research company, which sent interviewers to the sampled households. The interviewers contacted an adult person living in the household and explained the data collection process.

Household members who agreed to participate in the survey were given two options for mobile sensor data collection: they could either install the MMM smartphone app on their phones or carry programmable GPS loggers with them for the duration of the survey. The loggers transmit data to MMM's backend where the data are processed and displayed on the user interface in a similar way to the smartphone-based data. The logger option mitigated the problems of incompatible smartphone models, non-ownership of smartphones, or refusal to install the app on personal phones. Each participant was required to complete at least two days of data collection and verification.

Table 1 summarizes the sample information for each of the data sets; the numbers for FMS data are post-cleaning, after removing days with data gaps. These data were used in the analysis described in the following section.

Data Analysis Results

Comparative analysis was performed on the Singapore and Tel Aviv datasets. FMS data has been shown to overcome several major issues pertaining to traditional surveys: (1) imprecision of locations and times, (2) inability to capture day-to-day variability in individuals' travel patterns, and (3) under-reporting of trips. In this section, we use detailed analysis to demonstrate the richness, completeness, and accuracy of FMS data.

FMS Captures Rich Travel Behavior Data, and Reveals Large Day-to-Day Variability

To group similar daily activity patterns together and identify different types of behavior, we performed clustering analysis on person-day activity records for all four datasets. The unit of analysis is "person-day," a person's activity record during one day. In Singapore HITS and Tel Aviv HTS, each participant has one person-day observation, whereas in FMS, a person can have multiple person-day observations. For each person-day, we divide the 24 hours into 288 five-minute windows. Each window is labeled with its activity type. There are 13 types of activities ("Home," "Work," "Work-related business," "Education," "Shopping," "Personal errands/Prayer," "Medical/Dentist," "Sports/Exercise," "Entertainment/ Meals out," "Social visit with friends or family," "Transport/Accompany someone," "Other," and "Missing") coded consistently across the four datasets. Note that "Travel" (change mode/transfer) is a travel activity and was not considered as type of activity for clustering.

The common hierarchical, agglomerative clustering methods share the same algorithmic definition but differ in the way in which inter-cluster distances are updated after each clustering step (*15*). To compute distance between observations, we code each person-day activity pattern into a binary vector. For each activity *i*, A_i is a vector of length 288, which represents whether a person performed activity *i* during time window *t* of the day: $A_i[t] = 1$ if activity *i* is performed at time window *t*, and 0 otherwise. We then concatenate A_is over all activity types to have the final binary representation of the person-day activity pattern.

We choose Jaccard distance, a dissimilarity measure for binary data, as the distance metric for clustering. Given two binary activity patterns *A* and *B*, Jaccard distance is defined as:

$$d_{AB} = \frac{M_{01} + M_{10}}{M_{01} + M_{10} + M_{11}} \tag{1}$$

where M_{ij} is the total number of time windows where the value of *A* is *i* and the value of *B* is *j*. Unlike binary distance, Jaccard distance does not include M_{00} in the denominator, meaning the absence of an activity in both sequences at a given time does not contribute to the similarity of two sequences.

Agglomerative hierarchical clustering algorithm is used for clustering the binary activity sequences. It is a well-established clustering algorithm fit for non-Euclidean distance. The algorithm starts by assigning each observation to its own cluster. Until one single cluster is left, repeatedly merge two clusters *G* and *H* such that distance between *G* and *H*, $d(G,H)$, is the smallest. The distance $d(G,H)$ can be computed in different ways, termed as types of linkage: single linkage, complete linkage, and average linkage. We choose complete linkage (furthest-neighbor linkage), in which the distance between *G*, *H* is the largest dissimilarity between two points in opposite groups:

$$d_{\text{complete}}(G,H) = \max_{i \in G,\, j \in H} d_{ij} \tag{2}$$

We chose complete linkage because it generates the most compact and interpretable clusters (*16*). Single linkage and average linkage generate too many small clusters because of the way they compute distance between clusters: closest-neighbor distance (single linkage) or average distance (average linkage).

Agglomerative clustering algorithm generates a dendrogram that shows a hierarchy of where merges happen at what distance. To generate the clusters, we need to select a cutoff distance. The maximum distance within each cluster is below or equal to this cutoff. The smaller the cutoff, the larger the number of clusters. There is no pre-defined optimal value for this cutoff distance. A good choice is the point where there is a large jump between the distances of two successive merges. We noticed a big gap around 0.7, and tried cutoff ranging from 0.6 to 0.8. According to the visualization of each cluster's activity patterns, we found cutoff 0.7 is good because it displays clusters having distinctive interpretations and high similarities within clusters. Most importantly, we chose the same cutoff criteria for both traditional surveys and FMS; within cluster similarity and the number of clusters are comparable across datasets.

Note that cluster membership is not directly comparable between different travel surveys as the sample sizes are very different, that is, a pairwise cluster comparison between survey and FMS is not straightforward as there is no direct correspondence between a survey cluster and an FMS cluster, unless we use some similarity measures. Since this is an exploratory analysis, in this paper we focus on the number of clusters and their diversity that could be discovered from traditional survey versus FMS given the same similarity metrics and similarity cutoffs.

The clustering results show that FMS reveals a much larger set of activity patterns than traditional surveys in both Singapore and Tel Aviv. For example, for full-time workers in Tel Aviv, HTS data lead to a total of 12 clusters, while FMS uncovers 44 clusters overall.

In addition to clusters that represent more common activity behavior and that are captured in both surveys, such as working full days, partial days, or night-shifts, FMS uncovered clear patterns of out-of-work activities, which could not be found in HTS. This analysis supports the hypothesis that traditional surveys under-report out-of-work activities. Figure 1 shows three such clusters from FMS that include sports, social visits, and entertainment/meals out after work, respectively. The *x*-axis represents time of day, and each user-day is represented by a horizontal stripe. The activities performed in each time window are color-coded, with the *y*-axis representing the number of user-days belonging to the cluster.

Similarly, for retired people in Tel Aviv, HTS has three activity clusters overall, while FMS uncovers 14 clusters. Figure 2 shows some of the FMS clusters for

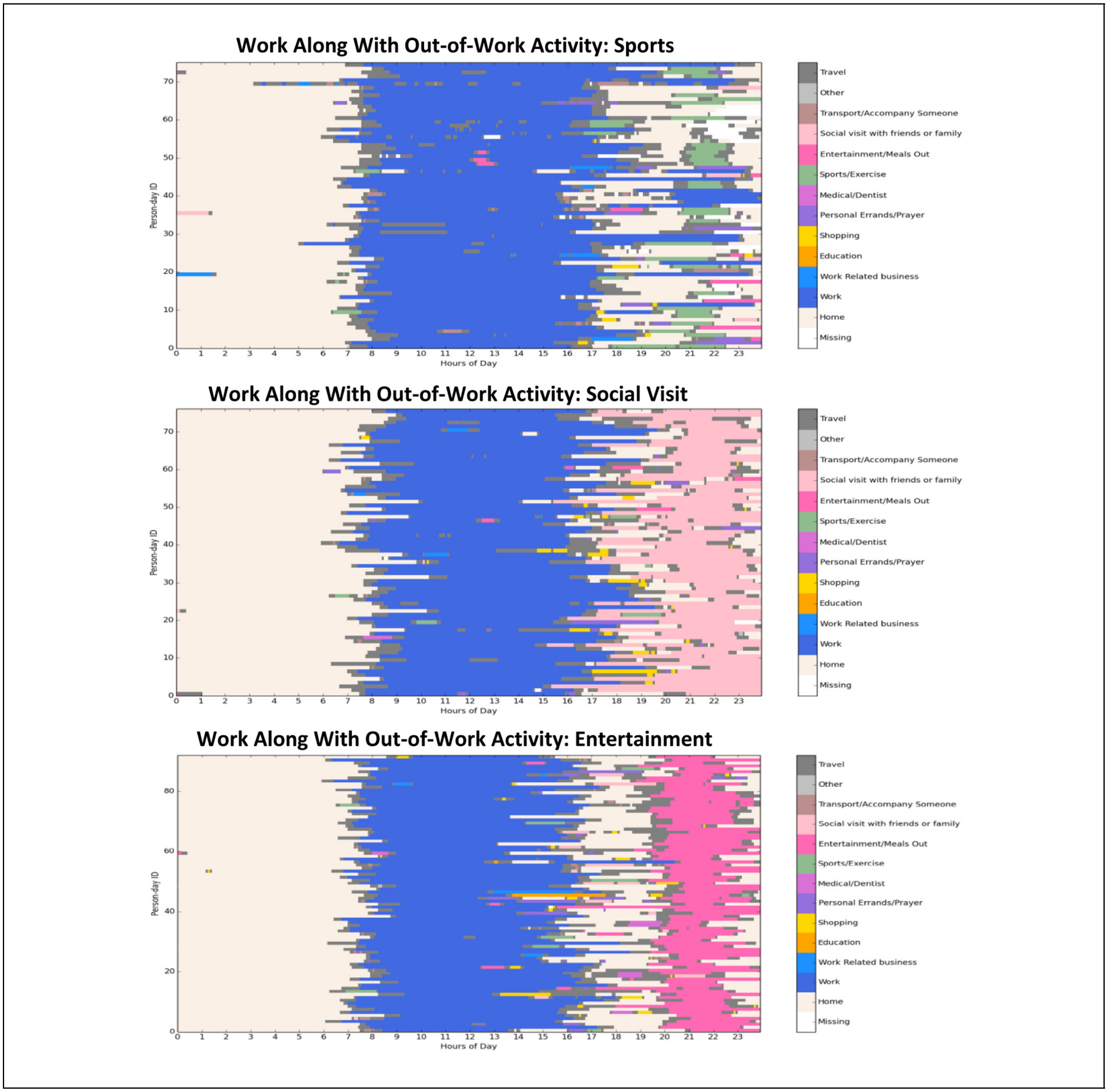

Figure 1. Cluster examples obtained from Tel Aviv FMS: out-of-work activities.

retired individuals in Tel Aviv that are not found in HTS clusters. These activity patterns include sports activities during the day, and social visits or entertainment in the evening.

Besides clustering for each socio-demographic group (employed, retired, etc.), we also performed overall clustering of the whole sample. Figure 3 shows clear activity patterns of leisure activities revealed using FMS. Apart from entertainment activity in the evening, other activities, such as personal errands/prayer in the morning and shopping at noon, are missing in HTS. In activity-based modeling, we usually have work, education, shopping, and "other" as a main purpose of the tour (e.g., *17*, *18*); using detailed data collected in FMS, the "other" can be further divided into well-defined purposes such as prayer, sports, and entertainment.

Clustering done on the Singapore datasets reveals the same trends. Since the traditional Singapore HITS is purely based on user recall, unlike in the Tel Aviv HTS where a GPS logger was used for prompted recall, the

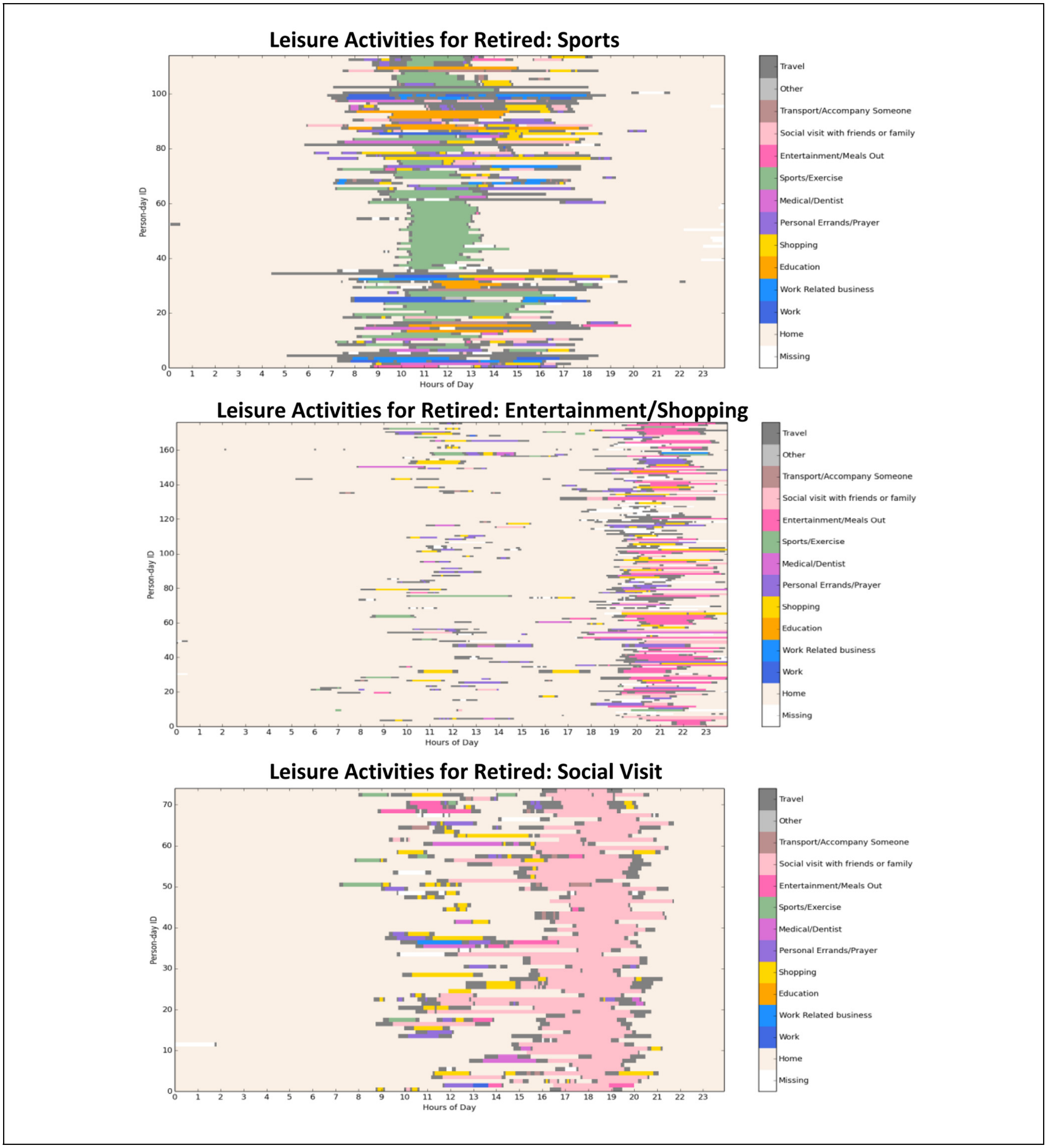

Figure 2. Example of clusters using Tel Aviv FMS data: leisure activities for retired persons.

reported activity patterns are even more uniform and simple. For example, for full-time employed participants, Singapore HITS only has five clusters, as opposed to 12 in the Tel Aviv HTS. The Singapore FMS clustering results can be found in Zhao et al. (*5*); however, due to the small sample size, we cannot perform a comprehensive comparison of clustering results for Singapore.

In many datasets used for model estimation and forecasting, each individual generally represents a single activity pattern. This is because in most traditional

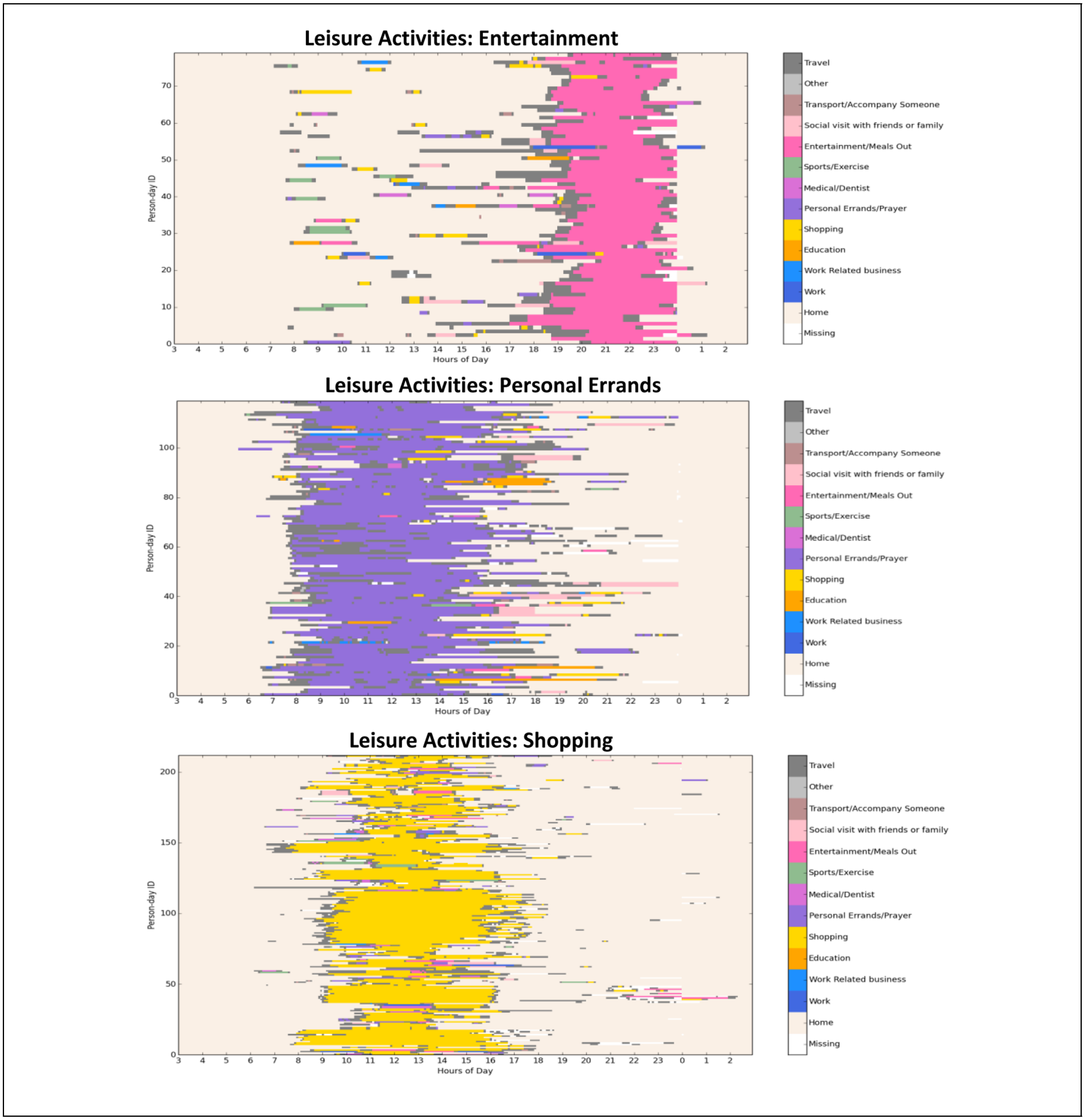

Figure 3. Examples of clusters obtained using Tel Aviv FMS data: leisure activities.

surveys data is collected for a single day, which does not allow day-to-day variability in individuals' activity patterns to be revealed. However, through FMS, we observe significant variability in users' day-to-day activity patterns, which warrants the need for multi-day/long-term data collection. Based on traditional one-day survey data, participants are classified into one main cluster. With multi-day data from FMS, most participants have days that fall into at least two distinct clusters, as shown in Figure 4. Users in Singapore who were tracked for a longer period of time are shown to have a much higher number of clusters. With a single-day sample, the heterogeneity of individuals' daily patterns cannot be identified.

In addition to the clustering analysis, we also identified the activity sequences present in the four data sets. Activity sequence is defined as a sequence of activity

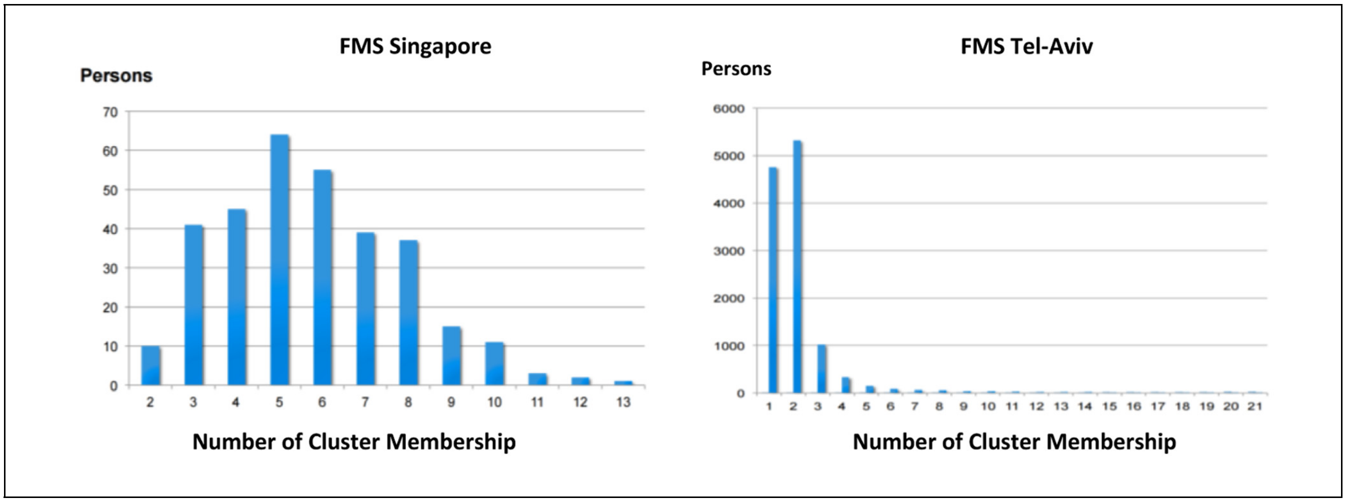

Figure 4. Number of FMS users by counts of distinct cluster membership.

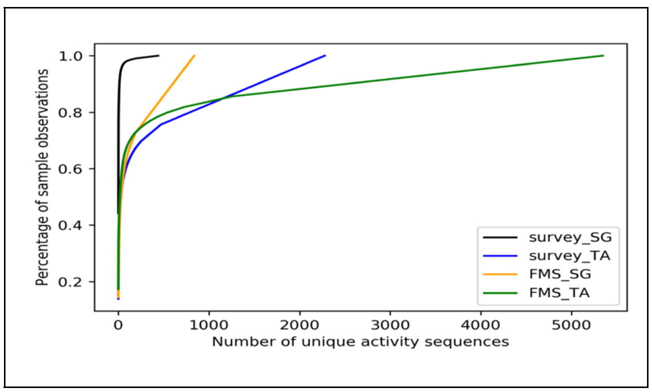

Figure 5. Cumulative percentages of sample covered by different numbers of unique activity sequences.

labels in 24 hours excluding travel (for example, home–work–home, home–work–school–home, and so on). Figure 5 shows the cumulative percentage of observations covered by the unique activity sequences (from most popular to least popular) in the four data sets. In Singapore HITS, more than 90% of the sample is covered by only 10 activity sequences. Despite the much smaller sample size in Singapore FMS, it still covers more unique sequences than HITS. The Tel Aviv HTS data has a large variety of activity sequences, partially due to the GPS-assisted prompted recall, but the data is still not as rich as the FMS data.

FMS Collects More Complete Information

Figure 6 presents the distribution of the number of intermediate stops in a home-based tour in each dataset. In both cities, the proportion of tours with no intermediate stops (that is, with a single destination per tour) is lower in FMS in comparison with previous surveys. For example, in the 2014 Tel Aviv HTS, 70% of tours do not include intermediate stops, while in the FMS dataset over 50% of tours include more than one stop.

The same trend is observed for Singapore. In the HITS dataset, 75% of tours do not include intermediate stops, while in the FMS dataset over 60% of tours include more than one stop. It should be noted that, for both Tel Aviv and Singapore, FMS captures tours with more than four stops, all of which are included in the 4 + stops category. Thus, even with the GPS-assisted data collected in the 2014 Tel Aviv survey, more complex tours were missed.

The completeness of FMS data is also reflected in Table 2, which lists the top three purposes of home-based tours, reported in traditional surveys and FMS, for users of different employment status. In Singapore, for all categories of users (except self-employed), meal/eating-break activity is among their top three purposes in FMS. In contrast, this activity only appears once in the list for HITS. In Israel, for all categories of users (except professional soldiers), personal errands/prayer is among the top three purposes in FMS, while in the traditional survey this activity appears only for unemployed and retired participants. This reflects the under-reporting of short trips/stops in traditional surveys, which is alleviated in FMS.

We also studied the distribution of the number of stops in work-based sub-tours in both Tel Aviv and Singapore (Figure 7). In Singapore, just 2.4% of all work activities had work-based sub-tours in HITS, out of which, 12% of the sub-tours included two stops or more. In contrast, in the FMS dataset, 13% of work activities had work-based sub-tours, and more than 44% of them included two stops or more. Similarly, in Tel Aviv, 7% of work-based sub-tours are detected in the 2014 HTS

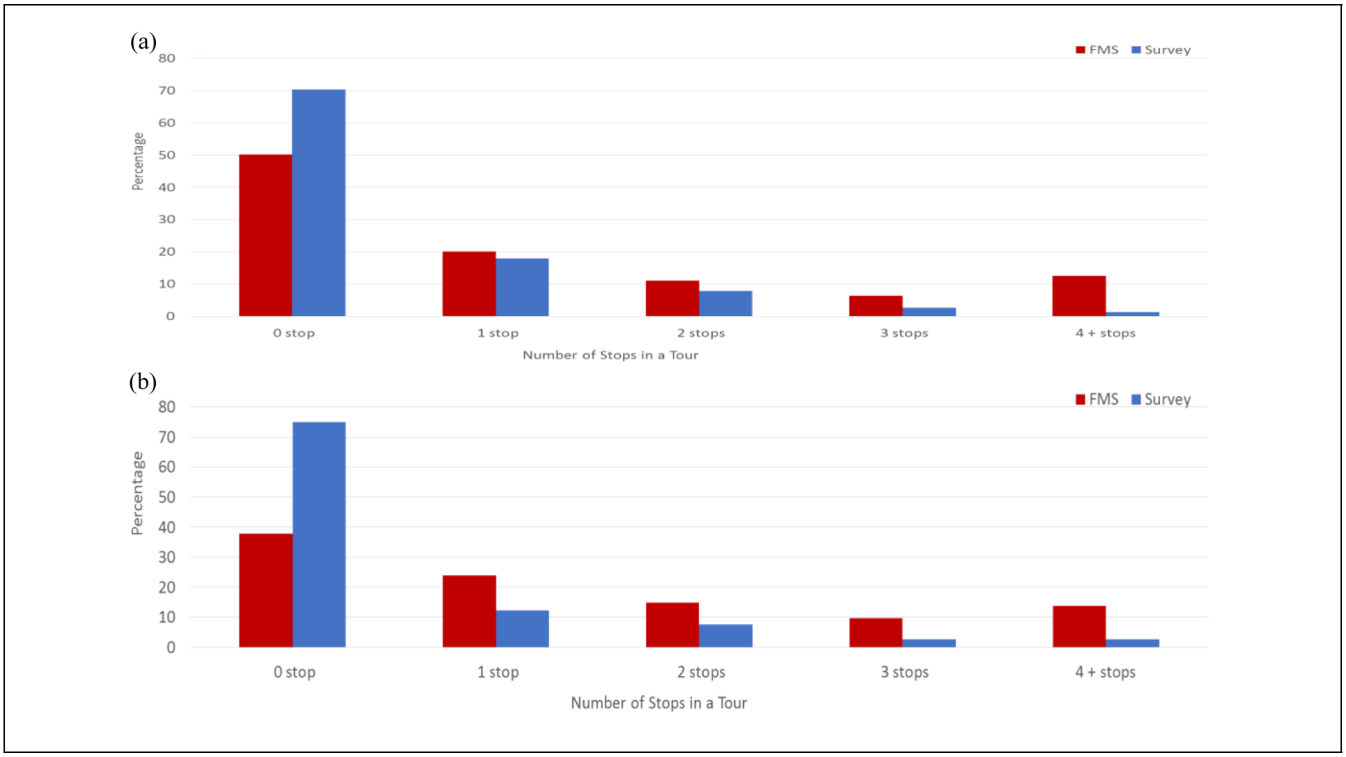

Figure 6. Distribution of number of intermediate stops in a tour: comparison between FMS and traditional survey in (*a*) Tel Aviv and (*b*) Singapore.

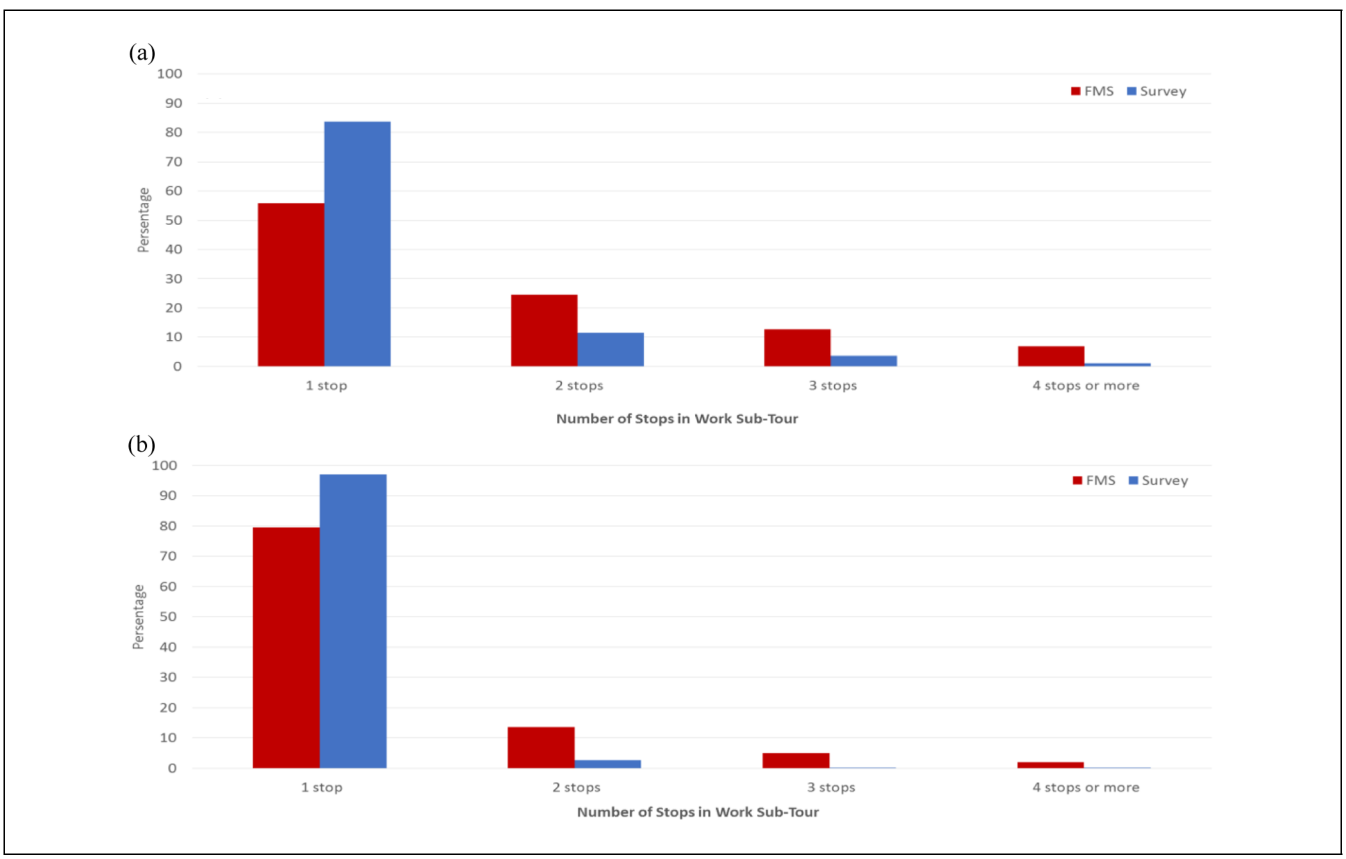

Figure 7. Distribution of number of stops in work-based sub-tours: comparison between FMS and traditional survey in (*a*) Tel Aviv and (*b*) Singapore.

Table 2. Top Three Purposes of Home-Based Tours

Status	HITS	FMS
Singapore		
Full-time worker	Work	Work
	Pick-up/Drop-off	Eating
	Work-related	Personal
Part-time worker	Work	Work
	Pick-up/Drop-off	Eating
	Shopping	Personal
Retired	Others	Eating
	Pick-up/Drop-off	Personal
	Social visit	Recreation
Self-employed	Work-related	Work
	Work	Personal
	Pick-up/Drop-off	Shopping
Homemaker	Pick-up/Drop-off	Eating
	Shopping	Shopping
	Eating	Personal
Full-time student	Education	Education
	Shopping	Work
	Work	Eating
Tel Aviv		
Full-time worker	Work	Work
	Accompany	Accompany
	Shopping	Personal
Part-time worker	Work	Work
	Accompany	Personal
	Shopping	Accompany
Retired	Shopping	Personal
	Personal	Shopping
	Social visit	Social visit
Unemployed	Shopping	Personal
(seeking employment)	Personal	Education
	Accompany	Accompany
Unemployed	Shopping	Education
(not seeking employment)	Social visit	Personal
	Personal	Accompany
Professional soldier	Work	Work
	Shopping	Entertainment
	Education	Social visit
Enlisted soldier	Work	Work
	Other	Social visit
	Social visit	Personal

dataset, compared with 12% of work-based sub-tours in FMS. Out of all work-based sub-tours in 2014 HTS, less than 3% had at least two stops, while in FMS, the number of sub-tours with multiple stops reached almost 20%.

FMS Data Is More Accurate in Location and Time

Location data from FMS are mainly based on GPS sensors, fused with other input data, which are typically more accurate than traditional surveys that are based on user recall and reporting of locations. With regard to time accuracy, Figure 8 compares the time of travel for different activities, plotting the percentage of users traveling for (a) work, (b) home, or (c) meal/eating-break in Singapore (left side) and (a) work, (b) home, or (c) personal errands/prayer in Tel Aviv (right side). For Singapore, HITS data show a narrower travel distribution than FMS, supporting the hypothesis that people tend to report a "typical" day in self-reported surveys, when in reality travel times have a wider spread. In addition, in HITS most users report arriving home in the evening by 8:00 p.m., while, in fact, a significant portion of the users reach home after 10:00 p.m., indicating underreporting of activities toward the end of the day. Also, three clear peaks emerge in the FMS curve (c), corresponding 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.

As already mentioned, unlike Singapore's HITS, the 2014 HTS conducted in Tel Aviv was GPS-assisted and therefore the travel time data are accurate. Note that the curves for both 2014 HTS and 2017 FMS have a very similar shape.

Conclusions

The main purpose of this study was to demonstrate the capabilities of FMS in improving data quality over traditional methods, and the implication of using FMS data for travel behavior modeling. FMS was field-tested in Singapore in 2012/2013 and a large FMS survey is currently being carried out in Tel Aviv metropolitan area. The datasets from these two surveys were used to compare against traditional datasets from HITS conducted in Singapore in 2012 and HTS conducted in the Tel Aviv area in 2014. Results reveal the capabilities of FMS in terms of collecting precise location and time information, uncovering information that was missed using traditional surveys, and revealing day-to-day heterogeneity in individuals' travel patterns that can only be captured by collecting multi-day data. FMS is well suited for this purpose as multi-day data collection can be done with minimal marginal costs and with reduced user burden over time. In addition, it was found that FMS effectively represents out-of-work activities and leisure activities, and alleviates the under-reporting problem in traditional surveys.

The findings reported in this study have major implications for future activity-based modeling. Not only will the information used to estimate the models be more accurate and reliable, but the heterogeneity dimension will add great complexity to the models, and modeling leisure activities will constitute an important part of modelers' work. For example, for Singapore, much richer information can be used for better modeling of work-

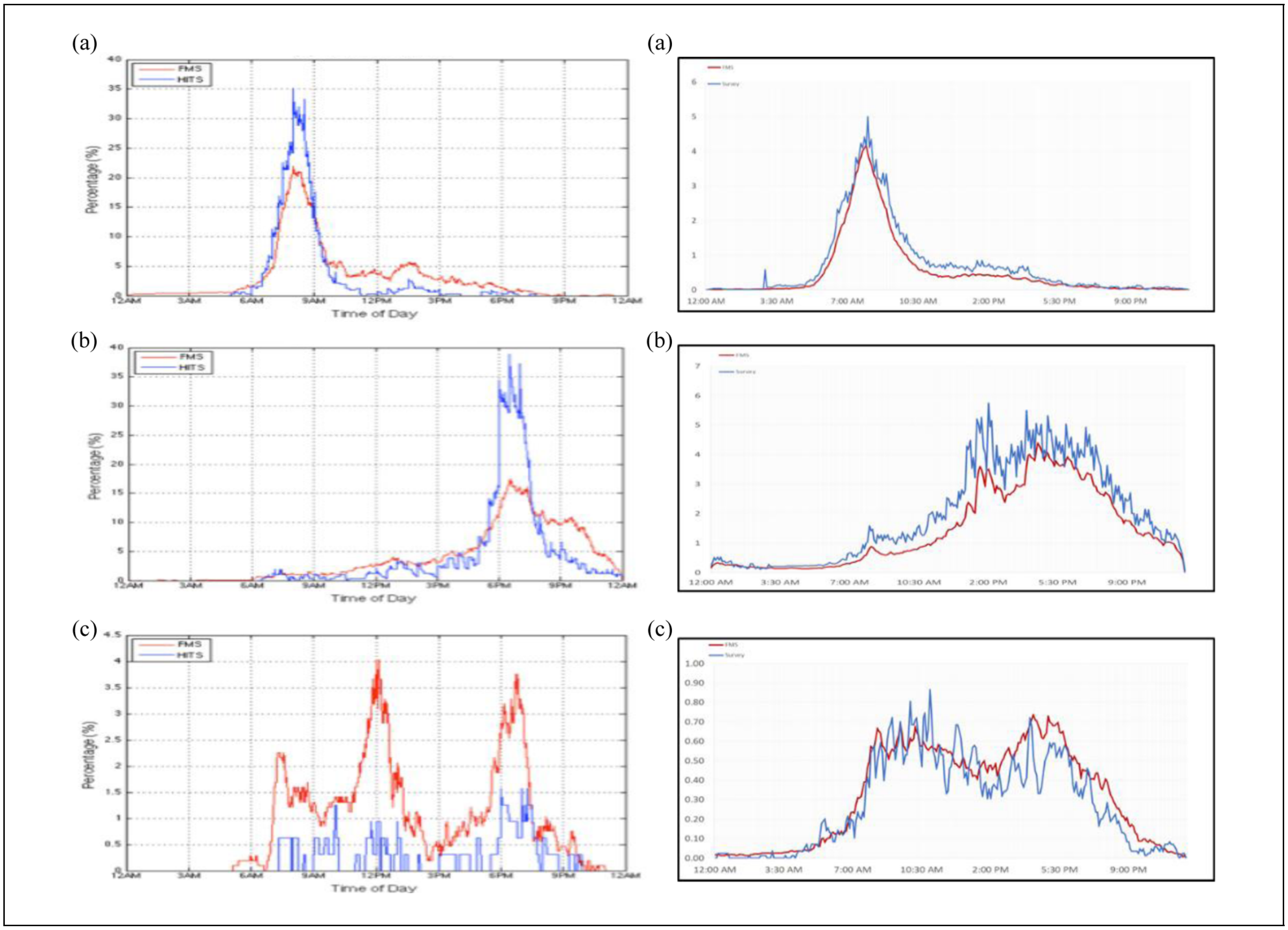

Figure 8. Percentage of participants traveling to (*a*) work; (*b*) home; (*c*) meal/eating-break or personal errands/prayer at different times of day in Singapore (*left*) and Tel Aviv (*right*).

based sub-tours, while in Tel Aviv this dimension, which is missing today, can be added to the Tel Aviv model structure. Likewise, short intra-zone trips could be added to both models using FMS data. Leisure activities can also be added with great detail to both model structures, which are mainly focused on work and education activities. In addition to activity patterns, the enhanced data collection method enables a detailed identification of trip leg modes. Instead of just collecting the main trip mode (e.g., private car, transit, park and ride, and so on), FMS allows the construction of the full mode chain (e.g., walking to the car park, driving, walking to the destination) along with its companions (escorts). Further research will explore the possibilities of including detailed mode chaining and intra-household and social interactions for modeling purposes.

In terms of future improvements for FMS, close examination of FMS data reveals that the quality of the data relies heavily on user verification, and when users are not careful or not familiar with the interface they introduce verification errors. We address this issue by performing cleaning of the collected data. Moving forward, we are continuing to improve the backend inference algorithms, as well as the user interface, in order to minimize user burden and ensure the quality of collected data.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Bat-hen Nahmias-Biran, Shlomo Bekhor, Fang Zhao, Moshe Ben-Akiva; data collection: Shlomo Bekhor, Fang Zhao, Christopher Zegras, Moshe Ben-

Akiva; analysis and interpretation of results: Bat-hen Nahmias-Biran, Yafei Han, Shlomo Bekhor, Fang Zhao, Moshe Ben-Akiva; draft manuscript preparation: Bat-hen Nahmias-Biran, Yafei Han, Shlomo Bekhor, Fang Zhao. All authors reviewed the results and approved the final version of the manuscript.

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