CONTEXT-AWARE STATED PREFERENCES SURVEYS FOR SMART MOBILITY

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1. INTRODUCTION

The pervasiveness of smartphones coupled with enhanced computing performance has changed the way transportation surveys are conducted *(1)*. Location-enabled devices has greatly expanded transportation data collection options *(2)*. Smartphones are used to collect travel diaries *(2,3,4)* in a cheap and non-intrusive manner *(5)*. While these technologies have been well established in collecting trip diaries - or revealed preferences (RP) data, they have not yet been fully utilized for stated preferences (SP) data.

SP surveys are critical to test hypothetical scenarios such as new transportation services or attribute ranges beyond those observed in RP data. However, SP surveys suffer from many limitations related to realism, response bias, validity, and efficiency *(6)*. They may not be realistic if they do not account for market, personal, or contextual constraints. Indeed, the importance of contextual stimulus in the decision process has long been identified *(7)* and frameworks for modeling and including them in SP experiments have recently been proposed *(8)*. Yet, leveraging both individual-specific smartphone-based data together with online contextual data for better SP data hasn't been explored.

This paper presents a generic method for context-aware SP surveys leveraging state-of-the-art smartphone-based RP methods, and presents its application to mode choice of future smart mobility solutions. We illustrate the idea in Figure 1. The context is coming from the observed RP data, e.g., weekly activity pattern or a selected trip for a given day, together with individual specific information, e.g., vehicle ownership, usage of car/bike sharing services etc. In addition to the direct information obtained from the individual, we collect external contextual data such as the available activity or transportation alternatives for the user through online sources. The experimental design uses those data in order to generate SP choice experiments with reasonable alternatives and attributes. The preferences can then be estimated based on both RP and SP data.

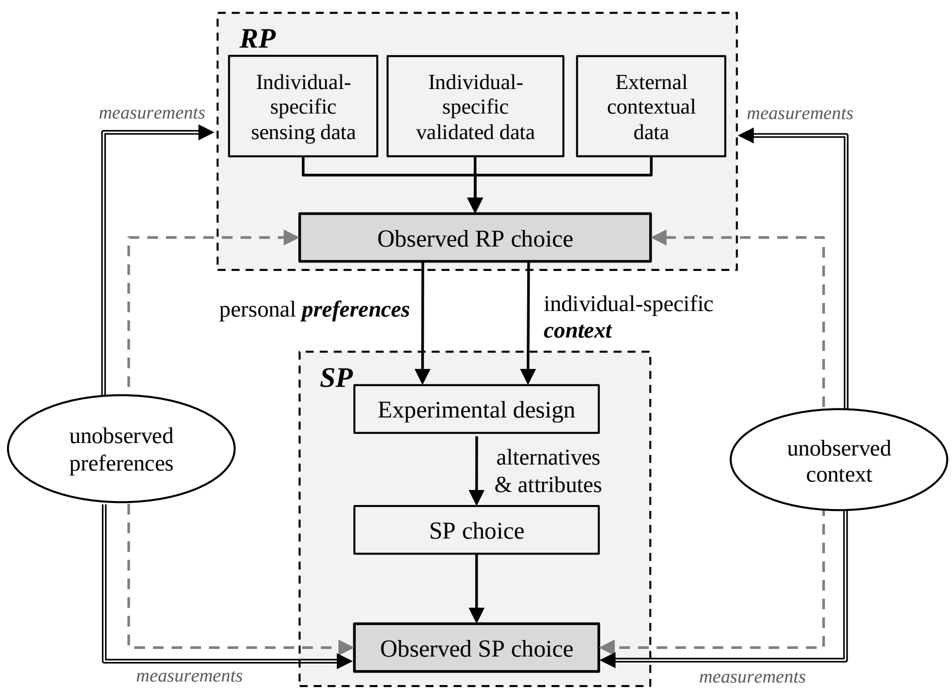

Figure 1 Context-aware SP methodology

2. METHODOLOGY

In this study, we leverage Future Mobility Sensing (FMS) platform *(3,4)*, which is primarily used to collect RP data in the form of activity diaries. FMS overcomes the main limitations associated with traditional surveys such as under-reporting of trips, inaccurate or incomplete time, location and route information *(4)*. FMS app collects location (GPS, WiFi, GSM), accelerometer data and other information (e.g. battery level) on a continuous basis. FMS backend system processes the collected data in-real time in order to detect stops, infer the trip mode and activity type using machine learning algorithms. A web interface presents partially filled activity diaries to users where they can verify and validate their trips and activities periodically.

The process of the data collection is straightforward: upon registering to FMS platform, user's socio-demographic data as well as attitudes and perceptions are collected. The app starts to track the user and the user validates the activity diaries with trip and activity information every day. After a full day is validated, an SP is presented based on a selected trip. For a given validated day, any realized trip recorded by FMS can be selected for the SP question as long as it satisfies a set of pre-defined conditions. Here we select home-based half-tours, since the goal is to estimate mode choice models in an activity-based model *(9)*.

SP includes a wide range of alternatives: walk, bike, bike-sharing, drive alone, carpool, car-sharing, taxi, on-demand services, and transit. In this paper, we also consider an app-based smart mobility solution, Flexible Mobility on Demand (FMOD) *(10)*. FMOD provides an optimized menu of travel options including taxi, shared-taxi, and minibus in real-time. FMOD taxi provides door-to-door service in a private vehicle. FMOD shared-taxi serves multiple passengers and travel time may increase due to the pick-up and drop-off of other passengers. FMOD minibus runs along fixed stops but adapts to passengers' schedule. The user has the option of opting-out in case the presented alternatives are not preferable. Figure 2 presents a sample activity diary validated through the FMS web interface and a screenshot from SP. In this example, the user clicked the FMOD tab to see the options.

Choice situations in SP are generated based on a random design. Random design does not require any priors on parameter values, and can outperform efficient designs when dominated alternatives are removed. It typically includes choice tasks that are randomly chosen from a full factorial design *(11)*. Normally, a uniform distribution is used such that each level has an equal probability of being selected for inclusion in a choice situation. However, in our case, some attributes are chosen from a pre-defined set of levels such as waiting times, while others are calculated as interactions of input data and random design parameters. For example, the taxi waiting time is equally likely to be 2, 5, 8, 10, or 15 minutes, while travel time by car is calculated as the travel time obtained from Google Maps multiplied by a design parameter that is equally likely to be 0.85, 0.95, 1, 1.05, 1.15, 1.2, or 1.5 in order to represent the uncertainty. The extent of uncertainty is another design parameter in the experimental design, e.g., the transit headway can range between 5 and 10 minutes.

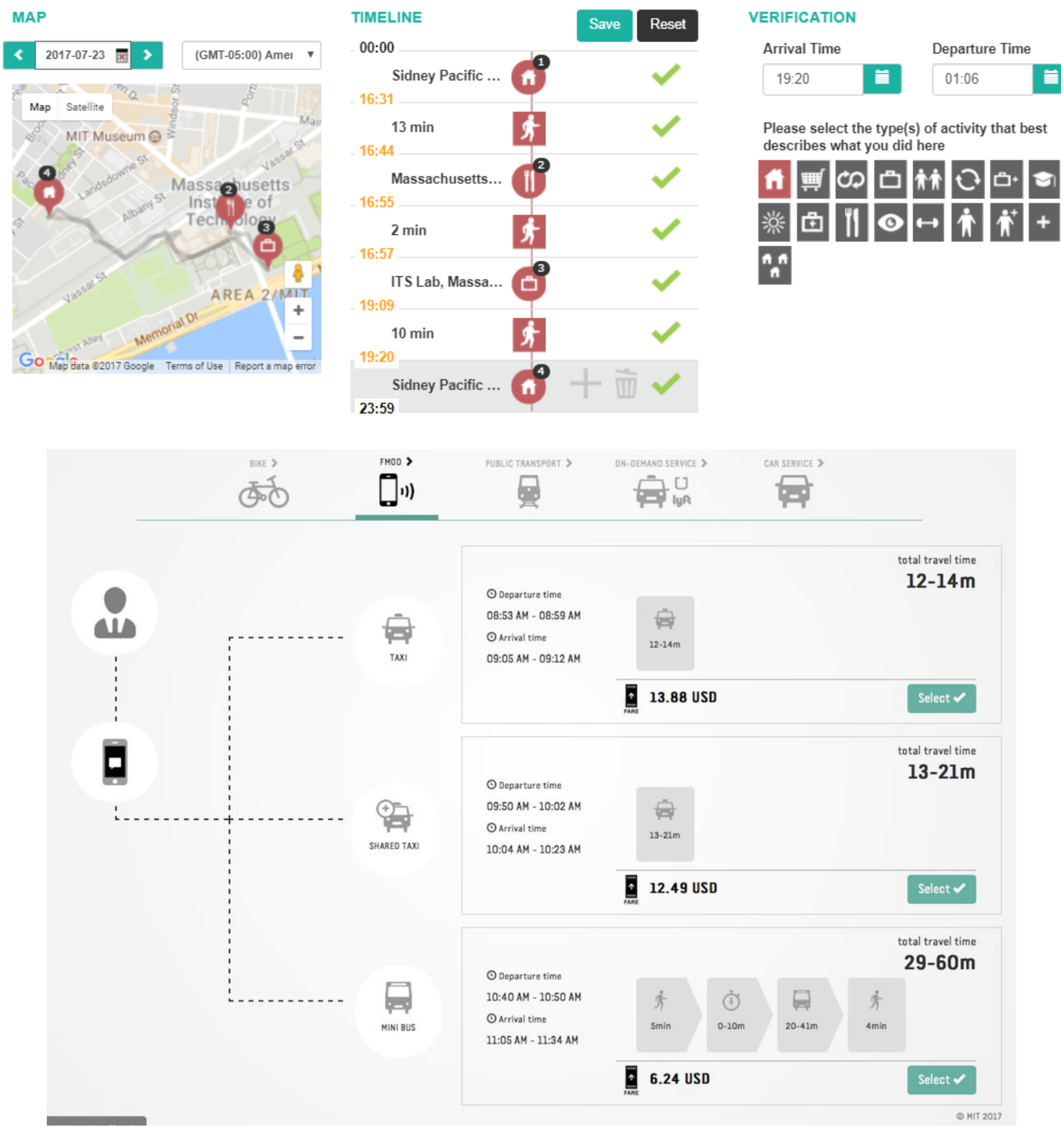

Figure 2 Screenshots of trip validation and SP

Considered attributes across all modes are listed in Table 1. Under non-motorized modes, bike-sharing has additional attributes of access and egress times (as users pick-up (drop-off) bikes at the stations), annual subscription and time-based rental costs. The availability for those modes is determined by pre-specified maximum walking and biking distances. Bike availability is contingent on bike ownership; however, bike-sharing is always displayed given that maximum biking distance is not violated.

For drive alone and carpool alternatives, the existence of toll and parking costs are randomly decided. If there is a non-zero parking cost, it is calculated based on the activity duration.

The experimental design ensures that the drive alone travel time is not greater than carpooling travel time. Drive alone availability is determined by car ownership and a valid driving license. Otherwise, only carpool "as a passenger" is available.

For on-demand services, the design ensures that travel time for shared alternatives (e.g. UberPool) is never less than that of the private ones (e.g. UberX). They are assumed to be always available except car-sharing which necessitates a valid driving license. Since FMOD is a schedule-based service, users are asked about their preferred arrival or departure time window. Due to operational constraints, it is possible that the user is not provided service within the specified window which leads to schedule delay. Schedule delay is not directly presented and it is reflected in the estimated pick-up and drop-off times. FMOD is assumed to be always available to users (except for very short trips, in which FMOD minibus is not available).

Finally, transit modes include bus and train, with walk or car access (i.e., park-and-ride). = The number of transfers is randomly determined in a time-based manner, e.g., trips shorter than 10 minutes have no transfers, those between 10 and 20 minutes may have up to one transfer, and trips longer than 20 minutes may have up to two transfers. The fares include a fixed and a distance-based component for flexibility (e.g., setting the distance-based component to zero results in a flat fare). A transit alternative may include bus, train, or a combination of the two. The availability is either based on the existing conditions (referring to Google Maps), or defined by the researcher in order to test hypothetical scenarios.

Experimental design is validated using Monte-Carlo simulations before implemented for actual data collection. Furthermore, SP choice experiments are automatically validated to reduce the number of dominant alternatives in real-time.

Table 1 Considered attributes across alternatives

	Non-motorized			Motorized		On-demand						Transit
	Walk	Bike	Bike-sharing	Drive alone	Carpool	Taxi	Uber/ Lyft	Car-sharing	FMOD taxi	FMOD shared-taxi	FMOD mini-bus	
Walking time	x											
Biking time		x	x									
Waiting time						x	x		x	x		
Schedule delay									x	x	x	
Access/egress time			x	x	x			x			x	x
In-vehicle travel time				x	x	x	x	x	x	x	x	x
Parking time				x	x							
% Bike lane		x	x									
Annual subscription cost			x					x				
Distance-/time-based variable cost/fare			x			x	x	x	x	x	x	x
Fuel cost				x	x							
Toll cost				x	x			x				
Parking cost				x	x			x				
Transfers												x
Headway												x

3. PRELIMINARY ANALYSIS

An SP study for FMOD was conducted with a convenience sample of 38 MIT researchers in Singapore and U.S. in early 2017. A total of 962 days of data, 345 of which were validated and 194 valid SP responses were collected. In this first experiment, the design was limited with fewer alternative modes: walk, bike, bus, train, car, taxi each having two options of different routes, and three FMOD modes (taxi, shared taxi, and minibus). For the final version of this paper, the analysis will include the full set of alternatives under a revised design and a larger sample.

In these preliminary results, notable differences are seen between the observed travel modes (RP) and the mode chosen in SP. As shown in Figure 3, there is significant decrease in almost all mode shares, which are distributed amongst the FMOD options and bike. The largest drop is observed in car share where it decreases from 18.3% to 7.4%. Overall, 29% of the users chose to utilize an FMOD mode when presented the option. Bike share increased from 8.7% to 15.6%. Due to the convenience sampling characteristics and the limited set of alternatives, a large share of the respondents showed a shift towards on-demand and shared modes available within FMOD.

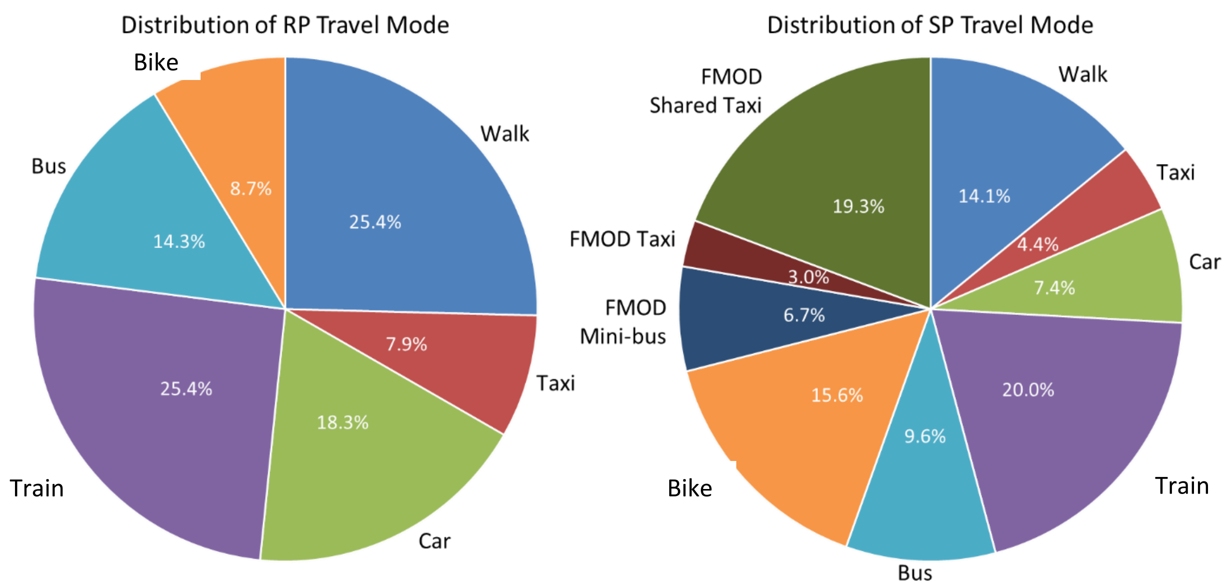

Figure 3 Summary of RP (left) and SP (right) modes

Using the preliminary data, a logit mixture model with panel effects was developed for mode choice. The utility functions are expressed in Equations (1)-(3). A normally distributed error component (EC) is estimated for each mode, which is common for the two options of the same mode (walk, bike, bus, train, car, taxi) and for the three FMOD modes to capture correlation among similar alternatives. The alternative specific constant (ASC) is also the same for the two options of the same mode but are different for the three FMOD modes. A scale parameter is estimated while the cost coefficient is fixed to -1. Therefore, all parameters are in the willingness to pay space. Travel time related coefficients and the scale parameter follow the log-normal distribution to ensure the correct sign. Due to the small sample size, only travel time and cost related parameters are estimated, however, more attributes can be estimated once we collect more data. For car, in-vehicle travel time (IVTT) includes both average travel time and parking time, while for other modes it only includes average travel time. Out-of-vehicle travel time (OVTT) includes access/egress time (car, bus, train, FMOD minibus), and waiting time (bus, taxi, train, FMOD minibus). Non-motorized travel time (NMTT) is the average travel time for walk or bike. Cost is the fare for all modes except for car, which is the sum of fuel cost, parking cost and toll cost.

$$V_i = (ASC_i + EC_i - \exp(B_{IVTT}) * IVTT_i - \exp(B_{OVTT}) * OVTT_i - 1 * COST_i)/\exp(Scale) \quad (1)$$
$$V_j = (ASC_j + EC_j - \exp(B_{IVTT}) * IVTT_j - 1 * COST_j)/\exp(Scale) \quad (2)$$
$$V_k = (ASC_k + EC_k - \exp(B_{NMTT}) * NMTT_k - \exp(B_{NMTT}) * NMTT_k)/\exp(Scale) \quad (3)$$

where:

i: bus, train, car, taxi, and FMOD minibus
j: FMOD taxi and shared taxi
k: bike and walk

The model converged with 5000 pseudo random draws of the random parameters and almost all parameters are significant at 0.9 confidence level. Everything else being equal, walking is the most preferred and car is the least preferred mode. The error component for FMOD alternatives indicates a strong correlation among the three FMOD services. The standard deviations of the travel time related coefficients confirm that the travel time sensitivity is heterogeneous across the population. As everything is in monetary terms, the values of IVTT, OVTT, and NMTT are 20.78 (0.212 $/min * 60 min/hr), 27.95, and 31.28 $/hr respectively. These values seem slightly high possibly because of our small convenience sample. Yet, they could be within a reasonable range since the convenience sample consists of researchers of higher education. The value of IVTT is the lowest indicating participants are more tolerant to IVTT in comparison to NMTT and OVTT as expected.

4. CONCLUSION AND ON-GOING RESEARCH

This paper presented an app-based context-aware SP methodology that enables to infer preferences towards new mobility solutions and transport policies. It is demonstrated with the FMOD service but ongoing applications include automated mobility on demand (AMOD) *(12)* and an app-based travel advisor, Tripod, which incentivizes users to switch towards more environmental friendly alternatives *(13)*.

The preliminary analysis is limited because of a small sample. As we are currently collecting data in Greater Boston for 500 travelers, which will end in early Spring 2018. By the time of the conference we will have a comprehensive analysis and results on our proposed method. As our framework collects both RP and SP data, we are currently designing the estimation procedure based on joint RP-SP data which will be unique in the context of app-based mobility solutions.

Furthermore, the presented SP is trip-based, i.e, considers a single trip to create choice situations. Undergoing research is focusing on activity-based SPs in order to evaluate the impact of new mobility solutions on the full activity pattern of users. An example is the mobility-as-a-service (MaaS) packages *(14)*.

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