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Behavioral Modeling of On-Demand Mobility Services: General Framework and Application to Sustainable Travel Incentives

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ABSTRACT
This paper presents a systematic way of understanding and modelling traveler behavior in response to on-demand mobility services. We explicitly consider the sequential and yet inter-connected decision-making stages specific to on-demand service usage. The framework includes a hybrid choice model for service subscription, and three logit mixture models with inter-consumer heterogeneity for the service access, menu product choice and opt-out choice. Different models are connected by feeding logsums. The proposed modelling framework is essential for accounting the impacts of real-time on-demand system's dynamics on traveler behaviors and capturing consumer heterogeneity, thus being greatly relevant for integrations in multi-modal dynamic simulators. The methodology is applied to a case study of an innovative personalized on-demand real-time system which incentivizes travelers to select more sustainable travel options. The data for model estimation is collected through a smartphone-based context-aware stated preference survey. Through model estimation, lower VOTs are observed when the respondents opt to use the reward system. The perception of incentives and schedule delay by different population segments are quantified. The obtained results are fundamental in setting the ground for different behavioral scenarios of such a new on-demand system. The proposed methodology is flexible to be applied to model other on-demand mobility services such as ride-hailing services and the emerging MaaS (Mobility as a service).

Keywords: smart mobility, on-demand, incentives, travel behavior, stated preference, sustainability, smartphone app

1 INTRODUCTION

In recent years, emerging new mobility services, including ride-hailing, ride-sharing, bike-sharing, and carsharing systems have gained popularity worldwide. Uber, which operates in 600 cities across 78 countries, gave four billion rides worldwide in 2017 alone, while it has just hit five billion total rides in May 2017 since its first appearance (*1*). In China, DiDi Chuxing completed 7.43 billion rides for 450 million users in more than 400 cities in the same year (*2*). The French-born peer-to-peer carpooling digital platform BlaBlaCar claims to have 60 million members in 22 countries and serves over 18 million travelers every quarter (*3*). The attempts to design, test and implement MaaS (Mobility as a service) platforms which vend travel packages integrated from different service providers have also emerged in the last 5 years.

The success and the still growing interest in these new mobility solutions are largely due to the advancement of Information and Communications Technologies (ICTs) in that these services usually enable on-demand, efficient, convenient and personalized usage through mobile applications. All these mobility services usually require users to (i) subscribe (register) to a given service, (ii) request a service menu with product option(s) through a mobile application and (iii) select the preferred product. We refer to this broad group of mobility services as on-demand services.

When designing a new transportation service/mode, predicting its demand and its sensitivity with respect to service attributes is critical. Currently, the state-of-the-art approaches rely on disaggregate behavioral modelling and activity-based models or ABM (*4*, *5*). These models are commonly based on discrete choice methodology and random utility maximization (*6*, *7*). Since on-demand mobility services are often dynamically tailored to different individual preferences and contexts (time-of-day, supply demand matching), disaggregate behavioral models are essential for the accommodation of their complex dynamics which enables the quantification of user benefits and overall transportation impacts (such as congestion and other externalities). Constructing and understanding these models are thus of great interest to researchers, practitioners and service providers.

Current research on the behavior side of on-demand mobility services mainly focuses on exploring the behavioral insights qualitatively based on aggregate analysis of surveys (e.g. *8,9)*. As indicated by Jittrapirom et al. (*10*), models for MaaS or other on-demand mobility services have been limited so far.

To the best of our knowledge, discrete choice models for on-demand mobility service have been focusing only on either the subscription choice or the product choice. In both cases, usually the service access action (i.e., opening the app) and its impact are not considered. To name a few efforts put in these two streams, Ghose and Han (*11*) investigated the demand (number of downloads) of apps through a 3-level nested logit with consumer taste heterogeneity and nests divided by app attributes. Zoepf and Keith (*12*) estimated a logit mixture with taste heterogeneity to evaluate how carsharing users value each attribute displayed in a product menu. Dias et al. (*13*) used a bivariate ordered probit model for the use of ride-hailing and car-sharing services in terms of weekly usage frequencies. Matyas and Kamargianni (*14*) investigated subscription preferences towards Maas with various product bundles by logit mixtures with taste heterogeneity. Choudhury et al. (*15*) used nested logit to model the mode choice between smart mobility solutions and existing modes, along with other choice dimensions. While the methods in these papers are useful to draw behavioral insights for a specific episode of the decision process, they are missing the connections between the episodes. These segmented treatments could potentially result in inaccurate conclusions and make it hard to engage the models in simulations without placing assumptions on the unmodeled decision stages (e.g. if one has only modelled the mode choice decision, he/she would have to assume a penetration rate for subscription in simulation).

In the greater context of modelling car ownership or service subscriptions, the inter-connections between short-term and long-term decisions have been studied (e.g. *16*, *17, 18*). The uniqueness of on-demand mobility service usage arises from an additional level of decision – whether to access the service menu. This level requires specific treatment to capture the behaviors of travelers who checked the service menu but opted out and who didn't bother checking the menu because they expect unattractive options would had been offered. These behaviors are especially relevant for on-demand services which present their service menu dynamically in real-time.

This paper fills the aforementioned gaps by developing a framework which explicitly considers and integrates all decision-making stages of on-demand service usage, including the real-time and dynamic aspects of such service. Inter-consumer heterogeneity is captured through logit mixtures with distributed taste coefficients. The modelling framework could be either used as a stand-alone or embedded within common ABM frameworks.

Our methodology could be applied to a broad range of on-demand services such as ride-hailing, carsharing and Maas. The capability and flexibility of it are illustrated through a case study on Tripod – an innovative on-demand incentive scheme (*19*). Tripod doesn't provide a mobility service per se but offers incentives for more energy efficient travel options through a personalized real-time travel menu.

The remainder of the paper is organized as follows. In the second section, we propose our modelling framework. In the third section we present the data collection for the case study, followed by model specifications and estimation shown in section 4. Finally, the conclusions are provided in the last section.

2 MODELLING FRAMEWORK FOR ON-DEMAND SERVICES

The decision-making process relevant to an on-demand mobility service is depicted in Figure 1.

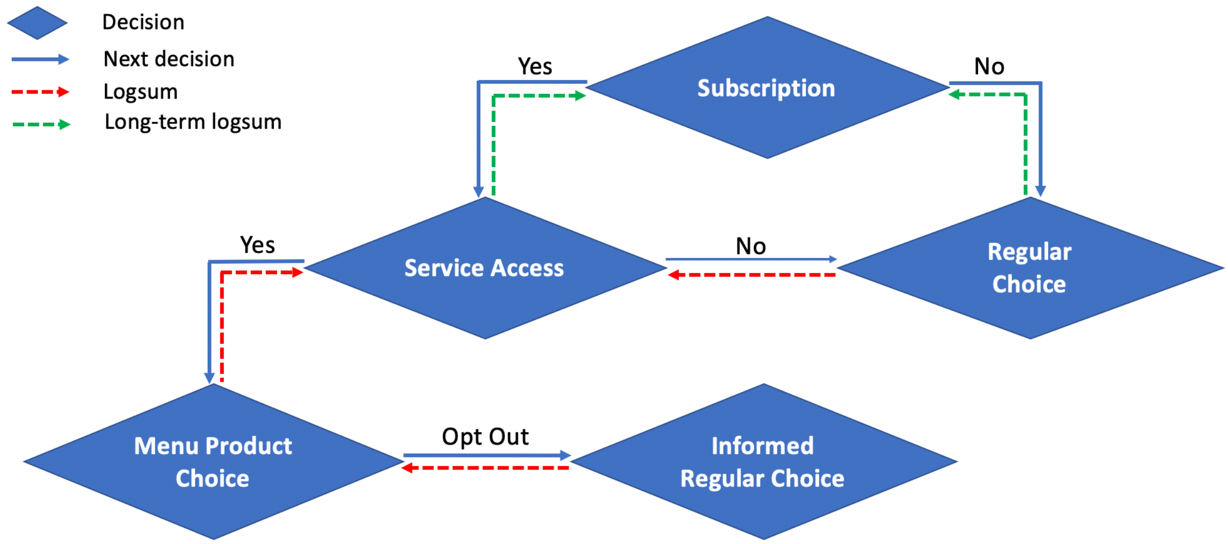


Figure 1 Conceptualized decision-making process in on-demand app usage

First of all, a person needs to decide whether to subscribe to a given service. This choice is represented by the *subscription model*. It typically involves downloading the app (if app-based) and registering. With the goal to model the behavior in service usage, the subscription here refers to people who actually consider to use the service on a regular basis. If a traveler doesn't subscribe to the on-demand service of interest, then upon travel, he/she makes a *regular choice*, i.e., the choice set excludes options offered by this service.

For a subscriber, the first decision prior to trip-making is whether to access the service and view the offered products at all, which is represented by the *service access* model. This may be conditional on the context (e.g., trip purpose, traveling party) or the user's past experience with the service. Sometimes travelers don't consider using a service as they expect the operator to offer unattractive terms (for example they might expect higher price in rush hours) and therefore do not check the menu – while what is offered in the menu might actually be attractive. The explicit modelling of service access model captures this behavior.

In Figure 1 we represent the choice situation of a subscriber who doesn't access the service and that of the non-subscribers by the same model, however, it doesn't mean that the traveler should behave identically under these two situations. This potential behavioral difference could be incorporated in the model specification by segmentation.

If the user decides to access the service, a service menu would be presented and the user would evaluate the products through a *menu product choice model* (see an example of a product menu in Figure 2 (b)). If the user likes one of the products in the menu, he/she would select it and execute the trip. The user may also reject the entire menu (*opt-out*) and choose some other alternative outside the on-demand service at stake.

For subscribers, the choice situation after opt-out (*informed regular choice* in Figure 1) is different from the one without opening the app (*regular choice* in Figure 1) in that the options offered by on-demand mobility services usually also provide users with real-time information (e.g., availability of alternatives, travel time estimates). The impact of information is discussed in

Ben-Akiva et al. (*20*) and Mahmassani and Lin (*21*). For example, if a traveler checks a car-based ride-hailing app prior to travel during a congested period and opts out, she/he may be more likely to select non-road modes.

Based on the sequential nature of the above-described decision process, higher level choices influence lower level ones. However, lower levels have significant impacts on the upper levels as well. When a traveler makes the subscription decision, the major consideration is whether the mobility service is attractive, which is reflected through the experience and perceived benefits of using the corresponding mobility service, including the app. Furthermore, whether to access the service for a given trip depends on users' perceptions of the attractiveness of the menu given the context of the trip, the attributes of the potential service products and the user's sensitivities towards them. To capture this bottom-up dependency, a multi-level nesting structure is proposed. The logsums feedings between levels provide measurements of attractiveness of the lower levels, and their coefficients show the corresponding sensitivities.

In conclusion, five choice models should be considered in order to model an on-demand mobility service: (1) a *subscription model*, (2) a *service access model*, (3) a *menu product choice model*, (4) an *informed regular choice model* for those who opts out, (5) a *regular choice model* for uninformed users.

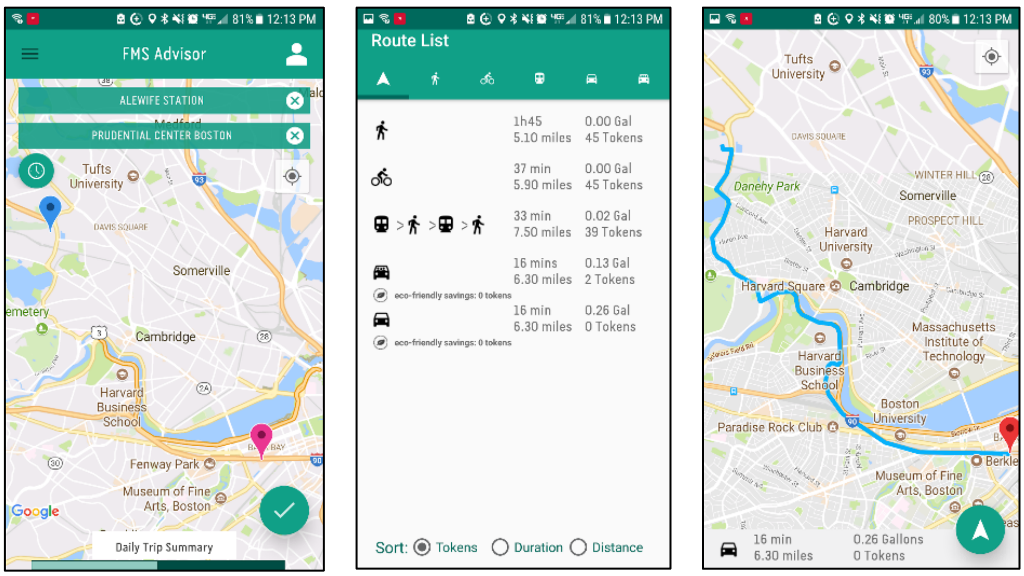
The logsum passing directions are illustrated in Figure 1 by dashed lines. By definition, logsum represents the expected maximum utility from the corresponding lower level. We want to stress two logsum computations that require additional attention. First, the logsum from the *menu product choice model* to *service access model* should depend on what the users expect to see, rather than what would be truly offered. An example of how this is handled in the context of our case study could be found in section 4.1. Second, the long-term logsum (green dashed lines in Figure 1) should be computed based on corresponding lower level models applied to multiple trip contexts pertinent to the traveler and weighted according to their frequency and/or importance.

To estimate the modelling framework we described, a dataset which covers the complete decision sequence is desired. While the *menu product choice* and *subscription choice* are straight-forward to elicit, the *service access choice* is intricate. If revealed preferences (RP) data is used, besides the trips and the choice that are common to most RP datasets, it has to contain information regarding service access actions. These could be acquired by tracking the respondents' smartphones or by including related questions (e.g., "did you access Uber App for this trip?") in the RP survey. While the first one requires additional efforts in the data collection, the second may cause under-reporting of the access-then-opt-out behavior. On the other hand, if SP data is used, service access process needs to be presented and the corresponding choice needs to be recorded. In sections 3 and 4 we describe how we addressed this by smartphone-based SP in the context of Tripod.

3 CASE STUDY: TRIPOD BACKGROUND AND DATA COLLECTION

3.1 Tripod Overview

Tripod is an app-based on-demand system that influences individuals' real-time travel decisions by offering them information and incentives with the objective of achieving system-wide energy savings (*19*). The travel decisions of interest are mode, route, departure time, trip-making and driving style. In response to any changes in any of the above dimensions, users receive incentives in the form of *tokens* that can then be redeemed in a market place for a variety of goods and services. Like in the above-mentioned decision process, a Tripod user has to subscribe to the app and decide whether to request a Tripod menu before each trip. The menu is presented to the user (see Figure 2) with information about the recommended options and their tokens. The tokens for each alternative are calculated based on the energy savings from the expected choice and the menu is personalized according to the user's preferences, characteristic and network attributes (*22*). The user may select an option from the menu and use the Tripod app to navigate to the destination or opt out. In the first case, the app monitors the travel of the user and rewards her/him at the end of the trip if the guidance was followed.



(a) (b) (c)

Figure 2 User interface of the Tripod app

*From left to right: (a) filling in destination and requesting a menu with options (b) menu displayed (c) guidance provided and trip being monitored

3.2 Data Collection Method

In this section we describe the data collection for Tripod, which is based on the methodology proposed by Atasoy et al. (*23*).

The core data collection platform is the smartphone-based Future Mobility Sensing (FMS) (*24*, *25*, *26*). It overcomes the main limitations associated with the traditional "paper-and-pencil" or purely web-based questionnaires, such as under-reporting of trips, inaccurate time and location information, high cost, and lack of detailed route information (*25*). FMS typically collects high quality RP data. In this study, a context-aware SP was integrated into FMS for preferences towards Tripod. Pre- and post-surveys (also integrated within the app) elicit information on socio-demographics and long-term preferences and perceptions, respectively.

Data collection was carried out in Boston-Cambridge region and its vicinity where 1940 observations from 202 participants were obtained, out of which 154 participants have finished the required 14 days of responses and exited the survey at the time of writing this paper (July 2018). Each respondent who had provided 14 days of RP data and completed the corresponding SP was rewarded with a 100-dollar Amazon gift card[1].

3.2.1 Pre-survey Data

Upon downloading the app and registering, respondents were asked to fill out the pre-survey. They were asked about their socio-demographic characteristics, such as age, gender, working status, income, car ownership, bike ownership, and how frequently they use different transportation modes.

3.2.2 Revealed Preferences Data

After completing the pre-survey, RP data was collected in the form of trip and activity diaries. The app collects location data (GPS, WiFi, GSM) on a continuous basis. The data is processed in the backend for stop detection and inference for trip mode and activity type. The app interface presents partially filled activity diaries and reminds the respondents to validate their trip and activity diaries at the end of each day. For activities, the data included activity purpose, location, start and end times. For trips, the origin, destination, travel mode, arrival and departure times were obtained. Figure 3 shows an example of a validated trip/activity diary. More details available in Cottrill et al. (*24*) and Zhao, et al. (*25*).

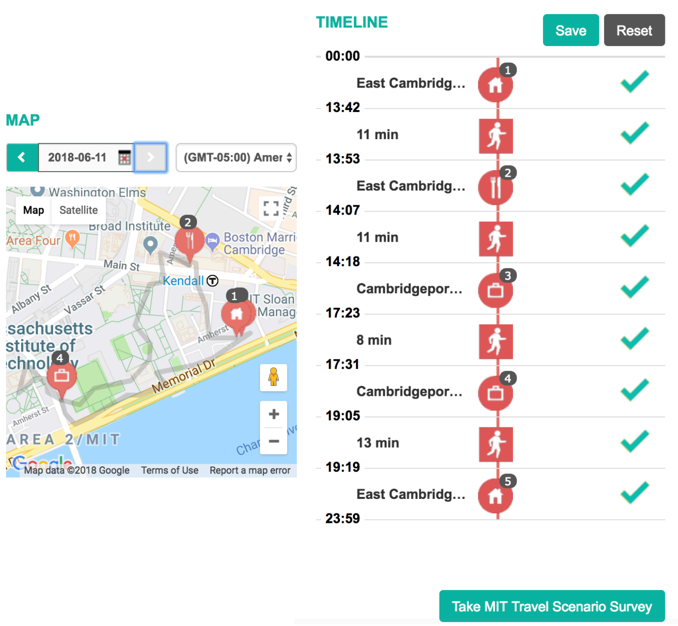


Figure 3 Trip/activity diary validation

[1] In the same data collection effort, SP surveys were also generated for another mobility survey (*23*). The 14 surveys required for each respondent are a mixture of the two (randomly presented with a higher frequency of Tripod appearance).

3.2.3 Stated Preferences Data

Upon validating their diaries, respondents were presented with daily SP questions. For each validated day, a trip is randomly selected and the respondent is asked about his/her choice if the trip had to be repeated under a hypothetical scenario (Figure 4 (a)).

The context-aware SP we adopted is different from the conventional SP's in that the context of the experiments, although being still hypothetical, is coming from the accurately collected RP data. Furthermore, the respondent-specific information collected in advance through the pre-survey, such as, vehicle ownership, usage of car/bike sharing services, etc. is used in the SP survey generation process as constraints. Google Maps API is used on the fly in order to obtain the travel times and distances associated with different modes corresponding to the specific trip. As a result, we expect our SP to be closer to the true decision-making scenarios and hence able to elicit more realistic responses compared to alternative state-of-the-art SP approaches (*23*).

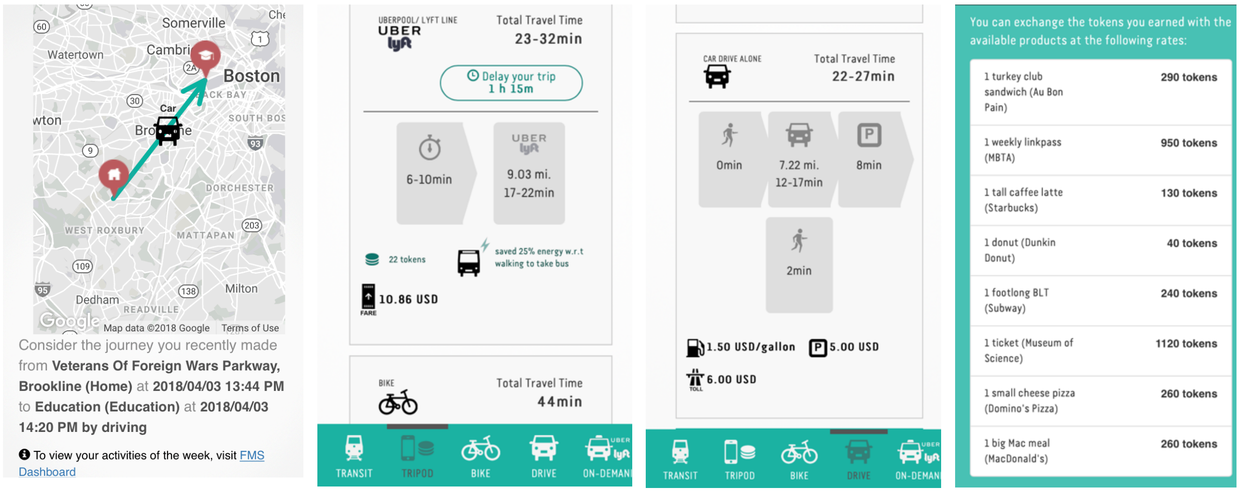
Each SP choice task is presented through a "profile", defined as a menu that includes all travel alternatives available to the respondent (along with their attributes), with the addition of a Tripod menu including options provided by Tripod (see example in Figure 4 (b), (c)).

The set of alternatives might include non-motorized modes (walking, biking, and bike-sharing), private motorized modes (car and carpooling), on-demand modes (e.g. Uber/UberPool, Lyft/Lyft Line, carsharing, and taxi), and transit (with walk, bike, or car access). The attributes of these alternatives are presented in Atasoy et al. (*23*). Each of these sets are shown in a separate tab, alongside the tab for Tripod menu (Figure 4 (b), (c)). Furthermore, respondents are presented with ranges that reflect uncertainty in the attributes such as travel time and waiting time.

The Tripod menu presents a subset of the existing alternatives with changes across multiple dimensions that generate energy savings, e.g., the departure time may be delayed (between 15 and 90 minutes), a different route or driving in an eco-friendly way may be presented. Information on energy savings (relative to the RP choice) and *tokens* assigned to alternatives are also presented. Energy consumption values are obtained from TripEnergy (*27*). Only alternatives with positive energy savings could be included in this menu.

Upon accessing the SP for the first time, respondents are presented with a "marketplace" showing the items that can be purchased with tokens (Figure 4 (d)). The redemption value of tokens is fixed for each individual. The marketplace is accessible to the respondents throughout the SP.

SP Profiles are generated based on a random design and validated using validity checks that eliminate dominant and inferior alternatives or unrealistic attribute combinations. The profile generation algorithm was validated using Monte-Carlo simulations. During each SP session, respondents' actions on the app are tracked.



(a) (b) (c) (d)

Figure 4 Tripod SP: trip context options and market place
*From left to right: (a) recall of trip context; (b) an option in Tripod tab; (c) an option in Drive tab; (d) the market place for a respondent

3.2.4 Post-survey Data

Upon completing two weeks of data collection, respondents are presented with the post-survey, which collects feedback on the potential use of Tripod if it existed in real life, attitudes and perceptions towards energy consumption, environment, mobile apps and technology in general. As an example, respondents rate statements like "I would use Tripod if it were available today" on a 5-point Likert scale (see section 4 for more details).

3.3 Sample Characteristics

After data cleaning, sessions completed within 10 seconds were excluded (likely correspond to random selections), as well as profiles corresponding to trips with very long distances (e.g. flights and inter-city trips). As a result, 1155 surveys from 183 individuals are used in the analysis. Figure 5 shows the sample distributions of age, number of household vehicles, gender, household income, and employment status compared to the population distributions in the survey region based on American Community Survey (ACS) (*28*). For employment status distribution in the population, we only considered population 16 years old and over because younger population is not considered as the market of Tripod (limited discretion and not allowed to drive). Since the survey is smartphone-based, the sample is biased towards young respondents as expected. In addition, females and household income group $50k to $99k (annual) are slightly oversampled.

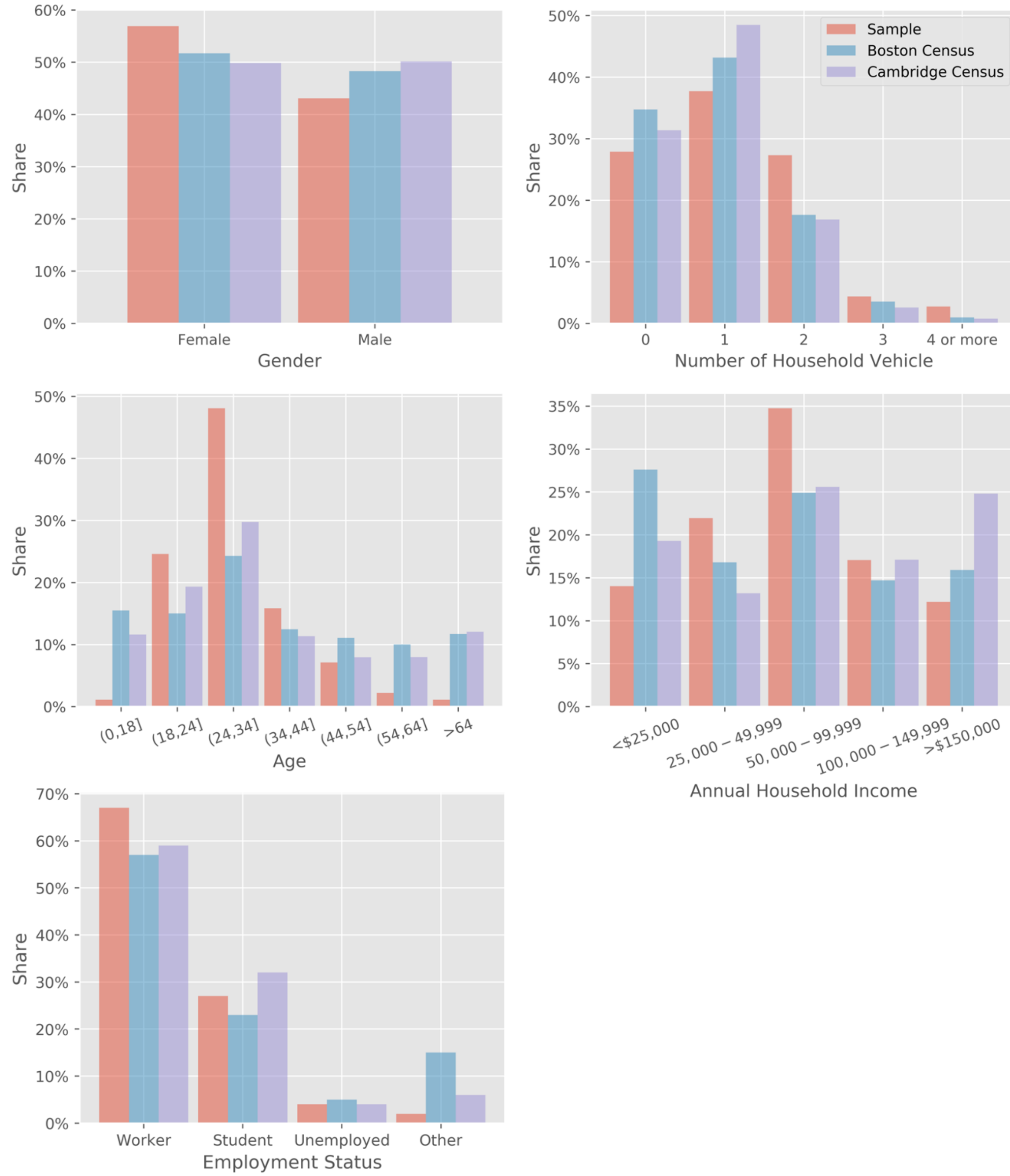


Figure 5 Sample characteristics

4 CASE STUDY: MODEL FORMULATION AND ESTIMATION

In this section, we apply the model structure proposed in section 2 to the case of Tripod and we formulate and estimate each model component with the data described in section 3.

In our SP setting, we present attributes (such as travel time and cost) of all the alternatives to the respondents and expect them to assume the values are real. As a result, the *regular choice model* which should be based on expected attributes under uninformed conditions cannot be estimated using the SP data. To circumvent this difficulty, we estimated the *informed regular choice model* and used it as the *regular choice model* in the logsum calculations for model estimation as an approximation. We refer to this model as *regular choice model* in the rest of the paper. Due to the limited sample size, the behavioral of subscribers and non-subscribers are not differentiated in *regular choice model*.

The models are estimated sequentially from the bottom in the following order: *regular choice model*, *menu product choice*, *service access model* and *subscription model*. This allows us to compute the logsums of the lower levels which is required for the estimations of higher-level models. The model specifications and results are presented in this order as well.

4.1 Model formulation and specification

The utility equations of each model are specified below. The notations are explained in Table 1. β, α, δ, λ, σ, and ASC are the coefficients to be estimated. Selected mode in the corresponding RP trip is considered in the utility equations to capture inertia. Binary variables are denoted as D's.

<u>*Regular choice model*</u>

Equation (1) shows the utility specification for an alternative in the *regular choice model*. The travel time is divided into in-vehicle travel time, out-of-vehicle travel time and non-motorized travel time.

$$U_{option} = -e^{\beta_{IVTT}} t_{IVTT} - e^{\beta_{OVTT}} t_{OVTT} - e^{\beta_{NMM}} t_{NMM} - e^{\beta_p} p + \beta_{inertia} D_{RP} + \sum_{m \in M} \beta_m D_m + \epsilon \quad (1)$$

<u>*Menu product choice model*</u>

Equation (2) shows the utility specification for an option in the menu while equation (3) shows it for the opt-out option. To capture respondents' perceptions of the value of the tokens, we include the tokens as monetary value ($) converted by the token exchange rate that had been randomly assigned to the respondents upon their registration of the survey (the rate is implicitly indicated to them by the price of goods in the marketplace, see Figure 4 (d)).

$$\begin{aligned} U_{menu\ option} = & -e^{\beta_{IVTT}} t_{IVTT} - e^{\beta_{OVTT}} t_{OVTT} - e^{\beta_{NMM}} t_{NMM} - e^{\beta_p} p + \beta_{inertia} D_{RP} + \sum_{m \in M} \beta_m D_m \\ & + e^{\beta_r} r - e^{\beta_{delay}} \log\left(t_{delay} + 1\right) + \epsilon \end{aligned} \quad (2)$$

$$U_{out} = ASC_{out} + \beta_{Iout} I_{RC} + \epsilon \quad (3)$$

<u>*Service access model*</u>

Equations (4) and (5) show the utilities of accessing and not accessing the mobile app in the *service access model* respectively.

$$U_{nac} = ASC_{nac} + \beta_{Inac} I_{RC} + \epsilon \quad (4)$$

$$U_{ac} = ASC_{ac} + e^{\beta_{TER}} X_{TER} + \beta_{Iac} I_{MC} + \epsilon \quad (5)$$

As mentioned in section 2, the logsum entering equation (5) should be based on what the respondents expect to see rather than what is truly offered. Tripod's personalization algorithm limits the number of offered alternatives (currently to 5). Based on past experience, a respondent might be expecting a different set of alternatives than the one that is generated from the personalization algorithm for a trip. In this case, he/she would still access the service in the first place. Thus, in our estimation we used all the possible alternatives (the ones with energy-savings and hence positive incentives) from Tripod before the personalization for logsum calculation rather than what would truly appear on the single trip-specific menu. This provides us with an optimistic approximation of respondents' expectations. Ideally a behavioral expectation model would be necessary to couple with the logsum transfer. This modeling and data collection effort is however left for future work. The same practice should be carried out accordingly when applying the estimated model in simulation.

Subscription Model

We formulate the *subscription model* as a hybrid choice model. Equations (6) and (7) show the structural equations for the latent variables "app-lover" and "environmentalist". Equations (8) and (9) show the measurement equations of the latent variables with their corresponding questions specified in Table 1. Equation (10) shows the utility of app subscription.

$$A = ASC_A + \beta_{BS}X_{BS} + \beta_{TNC}X_{TNC} + \sigma_A z \tag{6}$$

$$E = ASC_E + \beta_{VEH}(X_{VEH} > 1) + \beta_{HI}X_{HI} + \sigma_E z \tag{7}$$

$$i_{An} = \alpha_{An} + \lambda_{An}A + \epsilon, \qquad for\ n = 1,2,3 \tag{8}$$

$$i_{En} = \alpha_{En} + \lambda_{En}E + \epsilon, \qquad for\ n = 1,2,3 \tag{9}$$

$$U_{subscribe} = ASC_{sub} + \beta_A A + \beta_E E + \beta_{Isub}I_{sub} + \beta_{Insub}I_{nsub} + \epsilon \tag{10}$$

The responses to the indicators of measurement equations and whether to subscribe are in 5-point Likert scales ranging from "strongly disagree" to "strongly agree". As the error terms in equations (8), (9) and (10) follow the Gumbel distribution, the models of the responses are in forms of ordinal logit. Due to the limited sample size and the answers being framed as symmetric, we assumed the to-be-estimated threshold values to be symmetric as shown in equation (11) using the ones for the whether-to-subscribe question as an example. The thresholds for each question of each latent variable are estimated separately. In section 4.2, the estimated thresholds are subscripted according to the measurement equations' subscripts.

$$Answer = \begin{cases} \textit{strongly disagree} & & -\infty < & U & < -\delta_{s,1} - \delta_{s,2} \\ \textit{disagree} & & -\delta_{s,1} - \delta_{s,2} < & U & < -\delta_{s,1} \\ \textit{neither agree nor disagree} & \text{if} & -\delta_{s,1} < & U & < \delta_{s,1} \\ \textit{agree} & & \delta_{s,1} < & U & < \delta_{s,1} + \delta_{s,2} \\ \textit{strongly agree} & & \delta_{s,1} + \delta_{s,2} < & U & < \infty \end{cases} \tag{11}$$

Table 1 Notations in utility specifications

Variable	Unit	Description	Inter-consumer Distribution of corresponding parameter
t_{IVTT}	minute	In-vehicle travel time	
t_{OVTT}	minute	Out-of-vehicle travel time, including access time, egress time and waiting time	
t_{NMM}	minute	Non-motorized travel time, used in the bike, walk and bikeshare options	Log-normal distributions*
p	US dollar	Cost	
r	US dollar	Reward in monetary token	
t_{delay}	minute	Schedule delay	Log-normal distributions
D_{RP}	binary	Dummy for whether the mode of SP option is the same as the RP mode	
$D_m, m \in M$	binary	Mode dummies. M includes walk, bike, bikeshare, car and carpool, Uber and Uberpool, taxi, and public transit accessed by walk, bike and car	Normal distributions
I_{RC}		Inclusive value calculated from the regular choice model	Fixed
I_{MC}		Inclusive value calculated from the menu product choice model	Fixed
X_{TER}	US cent/token	Token exchange rate	Truncated lognormal distribution
I_{sub}		Inclusive value calculated from the service access model	Fixed
I_{nsub}		Inclusive value calculated from the regular choice model	Fixed
X_{BS}	binary	Whether a member of (using) any bikeshare service	Fixed
X_{TNC}	binary	Whether a member of (using) any ride-hailing app	Fixed
X_{VEH}	cars	Number of household vehicles	Fixed
X_{HI}	binary	Whether annual household income > 100k	Fixed
z		random variable with i.i.d standard normal distribution	
ϵ		random variable with i.i.d Gumbel distribution	
Latent variable			
A		app-lover	Fixed
E		environmentalist	Fixed

Measurement Equations			
indicator	**intercept**	**slope**	**Corresponding question asked in the post-survey**
i_{E1}	α_{E1}	λ_{E1}	"I am aware of the energy impact of my daily travel"
i_{E2}	α_{E2}	λ_{E2}	"I am interested in knowing how much energy I can save in my commute"
i_{E3}	α_{E3}	λ_{E3}	"I would like to share my energy savings with friends and family"
i_{A1}	α_{A1}	λ_{A1}	"I am a regular customer of eCommerce services"
i_{A2}	α_{A2}	λ_{A2}	"I am interested in the latest technological advancements"
i_{A3}	α_{A3}	λ_{A3}	"I am interested in mobility apps"

*the distribution of the parameters of travel time and cost are segmented by full-time workers and other populations (different means and standard deviations)

4.2 Estimation results

We estimated the set of models by BIOGEME (*29*). The models with inter-consumer heterogeneity were estimated with maximum simulated likelihood. Halton draws (*30*) were used and the number of draws was decided based on the stationarity of the parameters.

The *regular choice* and *menu product choice* models are estimated with the chosen alternatives in individual SP experiment. The action of clicking on the Tripod tab in a SP is recorded and considered as a service access action for the estimation of the *service access model*. Finally, the *subscription model* is based on the degree of agreement on the post-survey statement "I would use Tripod if it were available today".

To clearly identify the click action on Tripod tab, the surveys where the default tab (the tab shown when respondent opened the page, randomly assigned in survey generation) is Tripod had to be excluded. In addition, we noticed that in 30% of the surveys the respondents viewed only 1 tab. To nudge the respondents to make the choice of which tab to click, we recommend that future studies trying to elicit this action do not provide a default tab so that the respondent has to make a choice of which tab to click before selecting the final option.

The estimation results are presented in Table 2 with the notations specified in section 4.1. In the *menu product choice model*, due to the sample size, the standard deviations of the travel time coefficients' logarithms are fixed to be the same across population segments. Normalized parameters are shown without standard errors. The normalization in the hybrid choice model is done according to Daly et al. (*31*).

Table 2 Estimation results

Regular choice model

Name	**Mean**	**Robust SE**		**SD**	**Robust SE**	
β_p full-time worker	-3.29	0.36	**	0.0614	0.155	
β_p other	-2.27	0.339	**	0.982	0.432	**
β_{IVTT} full-time worker	-3.31	0.318	**	0.144	0.72	
β_{IVTT} other	-3.51	0.569	**	0.206	0.286	
β_{OVTT} full-time worker	-3.41	0.361	**	0.174	0.791	
β_{OVTT} other	-2.83	0.231	**	0.22	0.173	
β_{NMM} full-time worker	-3.01	0.187	**	0.321	0.176	*
β_{NMM} other	-2.4	0.197	**	0.0215	0.182	
$\beta_{inertia}$	0.944	0.181	**	0.696	0.308	**
β_{taxi}	0			0		
β_{PT}	1.59	0.298	**	0.0515	0.0784	
β_{car}	-1.37	0.494	**	1.72	0.299	**
β_{bike}	2.12	0.372	**	0.678	0.267	**
β_{uber}	1.61	0.259	**	0.0552	0.427	
$\beta_{bikeshare}$	1.46	0.376	**	0.11	0.282	
β_{walk}	1.89	0.483	**	1.25	0.358	**
Sample size	664					
Null log-likelihood	-1539.31					
Final log-likelihood	-1281.74					

Menu product choice model

Name	**Mean**	**Robust SE**		**SD**	**Robust SE**	
β_p full-time worker	-2.13	0.369	**	0.825	0.245	**
β_p other	-2.05	0.481	**	0.0917	0.514	
β_r full-time worker	-2.03	0.769	**	0.798	0.471	*
β_r other	-1.94	0.9	**	0.354	0.359	
β_{IVTT} full-time worker	-2.96	0.469	**	0.578	0.238	**
β_{IVTT} other	-3.46	0.734	**	0.578	0.238	**
β_{OVTT} full-time worker	-3.05	0.475	**	0.337	0.333	
β_{OVTT} other	-2.52	0.43	**	0.337	0.333	
β_{NMM} full-time worker	-2.42	0.158	**	0.00734	0.236	
β_{NMM} other	-2.4	0.234	**	0.00734	0.236	
β_{delay}	-1.99	1.09	*	1.31	1.67	
$\beta_{inertia}$	1.14	0.25	**	0.403	2.51	
ASC_{out}	0			2.29	0.523	**
β_{bike}	5.63	1.29	**	2.35	0.821	**

Menu product choice model – continue

Name	Mean	Robust SE		SD	Robust SE	
β_{PT}	4.66	1.21	**	0		
β_{car}	4.86	1.15	**	1.45	0.62	**
$\beta_{bikeshare}$	4.37	1.24	**	2.62	0.624	**
β_{taxi}	5.25	1.27	**	1.17	1.15	
β_{uber}	6.22	1.21	**	0.946	1.14	
β_{walk}	6.95	1.31	**	0.147	0.669	
β_{Iout}	0.905	0.355	**			
Sample size	455					
Null log-likelihood	-796.831					
Final log-likelihood	-601.226					

Service access model

Name	Mean	Robust SE		SD	Robust SE	
ASC_{nac}	0			0.00713	0.0141	
ASC_{ac}	-1	1.12		0		
β_{TER}	-1.82	1.1	*	2.93	1.38	**
β_{Inac}	0.578	0.229	**			
β_{Iac}	0.201	0.201				
Sample size	369					
Null log-likelihood	-255.771					
Final log-likelihood	-219.805					

Subscription model - structural equations for App lover

Name	Value	Robust SE		Name	Value	Robust SE	
β_{BS}	2.65	1.89		β_{TNC}	3.17	1.75	*
ASC_A	0			σ_A	4.72	2.11	**

Subscription model - structural equations for Environmentalist

Name	Value	Robust SE		Name	Value	Robust SE	
β_{VEH}	0.163	0.194		β_{HI}	-0.535	0.241	**
ASC_E	0			σ_E	0.735	0.301	**

Subscription model - utility in choice model

Name	Value	Robust SE		Name	Value	Robust SE	
ASC_{sub}	0.856	0.791		β_{Isub}	0.0946	0.101	
β_A	0.164	0.0827	**	β_{Insub}	-0.437	0.3	
β_E	0.71	0.548					

Thresholds for the choice model

Name	Value	Robust SE		Name	Value	Robust SE	
$\delta_{\mathrm{S},1}$	0.97	0.129	**	$\delta_{\mathrm{S},2}$	2.18	0.262	**

Subscription model - measurement equations							
Name	**Value**	**Robust SE**		**Name**	**Value**	**Robust SE**	
α_{E1}	1.17	0.223	**	α_{A1}	0.661	0.239	**
α_{E2}	2.87	0.617	**	α_{A2}	2.41	0.602	**
α_{E3}	0.824	0.241	**	α_{A3}	3	1.65	*
λ_{E1}	1			λ_{A1}	0.149	0.087	*
λ_{E2}	3.14	1.03	**	λ_{A2}	0.392	0.193	**
λ_{E3}	1.67	0.883	*	λ_{A3}	1		
Thresholds for the Measurement Equations							
Name	**Value**	**Robust SE**		**Name**	**Value**	**Robust SE**	
$\delta_{\mathrm{E1,1}}$	0.56	0.101	**	$\delta_{\mathrm{E1,2}}$	2.39	0.275	**
$\delta_{\mathrm{E2,1}}$	0.881	0.217	**	$\delta_{\mathrm{E2,2}}$	4.59	0.882	**
$\delta_{\mathrm{E3,1}}$	0.905	0.132	**	$\delta_{\mathrm{E3,2}}$	2.23	0.279	**
$\delta_{\mathrm{A1,1}}$	0.362	0.0791	**	$\delta_{\mathrm{A1,2}}$	2.08	0.223	**
$\delta_{\mathrm{A2,1}}$	0.96	0.219	**	$\delta_{\mathrm{A2,2}}$	3.77	0.538	**
$\delta_{\mathrm{A3,1}}$	2.21	0.904	**	$\delta_{\mathrm{A3,2}}$	8.39	3.17	**
Sample size	149						
Final log-likelihood	-1236.33						

* p-value for robust t-test < 0.1
** p-value for robust t-test < 0.05

4.3 Discussion

All the signs and relative magnitudes of the estimated coefficients are as expected, and most of them are statistically significant. In this section we present and discuss the distributions of the monetary values of travel time, schedule delay and tokens.

4.3.1 Value of Travel Time (VOT)

We present the VOT (in terms of in-vehicle travel time, out-of-vehicle travel time and non-motorized travel time) for the *menu product choice model* and *regular choice model* for the two population segments (full-time workers and others) in Table 3.

Table 3 Value of travel time

	Regular Choice			**Menu Product Choice**		
Unit: $/hr	IVTT	OVTT	NMM	IVTT	OVTT	NMM
full-time worker mean	59.5	54.1	83.7	43.5	35.6	63.1
other mean	28.7	56.9	85.3	17.4	39.9	42.5
full-time worker median	58.8	53.2	79.4	26.2	23.9	44.9
other median	17.4	34.3	52.7	14.6	37.5	42.3

As can be seen, full-time workers have higher VOT in both choice situations which is likely due to their higher income and tighter schedules. For the other segment, the VOT is valued in the order of NMM, OVTT and IVTT from high to low, while for full-time workers, the VOT for IVTT and OVTT are similar, possibly because full-time workers make longer trips, which makes them more lenient towards waiting time and access/egress time.

For each population segment, lower VOTs in the *menu product choice model* are observed as expected. Travelers are more likely to accept one of the Tripod options when they have flexible schedule and in search for low-cost alternatives.

4.3.2 Value of Schedule Delay

In the *menu product choice model*, the log-transformed delay shows a better fit compared to the linear case. This indicates that the marginal disutility caused by schedule delay decreases as delay increases. This sensitivity to delay is specified to be distributed across consumers. From the estimation result, the monetary value of a 30-minute schedule delay has a median of $4.0 and a mean of $13.1 for the full-time worker segment, while it has a median of $3.6 and a mean of $8.6 for the other population segment. The monetary value of 2 hours schedule delay has a median of $5.5 and a mean of $18.3 for the full-time worker segment, while it has a median of $5.1 and a mean of $12.1 for the other population segment. Furthermore, schedule delays cause less disutility than travel times, possibly because travelers may spend the delay time on other tasks. The diminishing marginal disutility of schedule delay also makes sense to the authors since larger periods of such time might be easier to utilize.

4.3.3 Value of Incentives (Tokens)

The probability density function of the value of tokens is shown in Figure 6, segmented by full-time worker and other population segments. The value of token represents how much the respondents value an amount of tokens that has the purchasing power of 1 dollar.

Since the tokens could only be used in the Tripod marketplace to exchange for gift cards and merchandise, we expected that the token is valued less than the equivalent amount of real money. However, contrary results were observed. The lognormally distributed value of token for full-time workers has a median of 1.1 and a mean of 2.1, while the median and mean for other populations are both around 1.2. A bit surprisingly, half of the respondents value the dollars in equivalent tokens more than the real money.

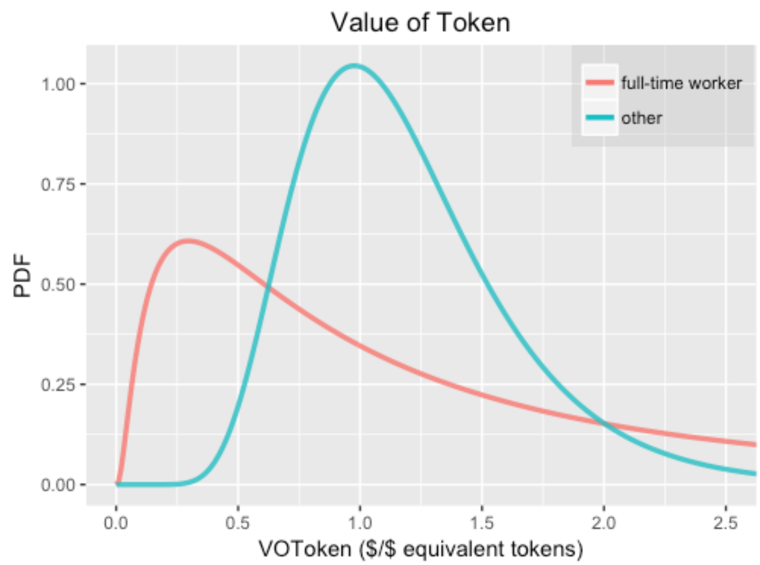


Figure 6 Distributions of value of token

We think there are three potential causes for this. First, the process of token redemption is not included in the SP. Consequently, the potential inconvenience of it might be unrealized by some of the respondents. This effect would no longer be relevant when the RP data regarding Tripod becomes available. Second, since the token value in Tripod is generated based on the energy savings, the valuation of energy savings is partially incorporated through the valuation of tokens. Since Tripod promotes environmentally friendly travel options, we expect a group of environmentalists to appear, in addition to the ones purely motivated by incentives.

Third, since the tokens are perceived as rewards while travel costs are perceived as out-of-pocket expenses, they could be perceived very differently. In the case of Tripod, since energy-efficient and hence highly rewarded options are usually associated with low costs, the situations where the decision maker needs to evaluate a trade-off between token and real money seldom happens. In addition, the marginal utility and disutility of gain and loss (cost) are expected to decreases as gain and loss (cost) increases respectively (*32*). Under this hypothesis, with the simplification of utility linear in token and cost might cause the current observation as shown in Figure 7. To confirm this, it would be interesting to conduct a comparable experiment with rewards being offered in terms of real money. If our hypothesis is true, we expect the respondents to value the monetary rewards even higher compared to the token rewards.

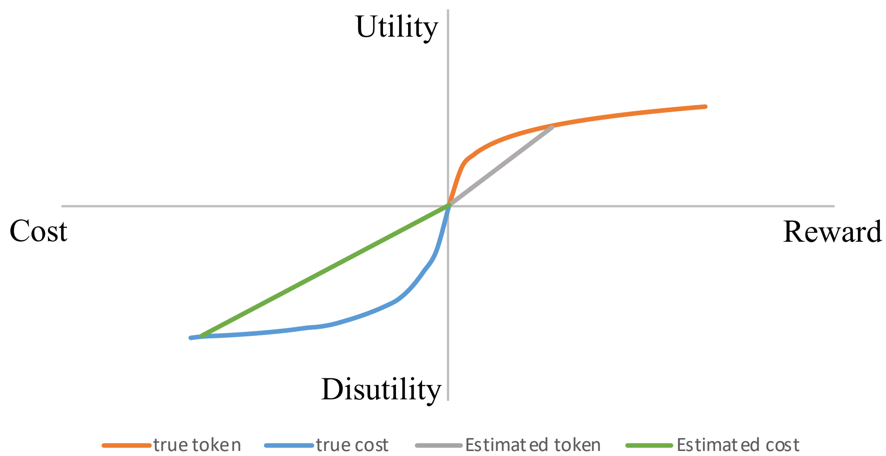


Figure 7 Hypothesis explaining the higher perception of tokens

5 CONCLUSION

In this paper, we presented a general framework for modelling the behavior of on-demand mobility services. The framework uses a nested structure to explicitly account for the subscription, service access, menu product and opt-out choices and their connections. The inclusion of the complete service usage decision process differentiates our work from previous research on the choice modelling of on-demand mobility services.

The framework is applied to modelling the demand of Tripod, which influences individuals' real-time travel decisions by offering information and incentives for system-wide energy efficiency. Context-aware SP data was collected by a smartphone-based data collection platform for the model estimation. Inter-consumer heterogeneity was captured in the model specification. Through estimation and sensitivity analysis, we found that the rewards associated with energy-savings are valued higher than cost savings in real money. As expected, the VOTs in the Tripod *menu product choice model* is much smaller than the VOTs in the *regular choice model* (cases where the traveler is not subscribing Tripod, not accessing Tripod or selecting opt-out), which indicates that Tripod's acceptance would be higher in the lower income population segments and its usage would be likely associated with trips with less time constraints.

One main difficulty faced in the present work is the actual data collection process. Compared to traditional one-time "paper-and-pencil" SP surveys, the higher quality of the data collected by longitudinal RP-SP data collection process is at the cost of longer efforts from the respondents, especially in our case study where the respondents need to first understand what Tripod is.

As suggested by the reviewers, it would be interesting to investigate how the service access action is influenced by other factors such as the ease of access to information. We think these factors are of great relevance and should be included in future related studies. Several other future research directions could be developed based on this paper. The first is to collect RP data for mobility services which meets the data requirements of our framework as mentioned in section 3. Second, the behavior framework could be extended to incorporate a revision process where the en-route opt-out behavior would be handled. The necessity of this additional complexity from a modelling point of view also requires further investigations. Finally, further work needs to be done to fully integrate the models into an ABM simulator and use it for system-wide optimization. This process is essential to on-demand incentivization systems such as the Tripod system.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Yifei Xie, Mazen Danaf, Carlos Lima de Azevedo, Arun Prakash Akkinepally, Bilge Atasoy, Ravi Seshadri, Moshe Ben-Akiva; data collection: Yifei Xie, Mazen Danaf, Carlos Lima de Azevedo, Bilge Atasoy, Kyungsoo Jeong; analysis and interpretation of results: Yifei Xie, Mazen Danaf, Carlos Lima de Azevedo, Arun Prakash Akkinepally, Bilge Atasoy, Kyungsoo Jeong, Ravi Seshadri, Moshe Ben-Akiva; draft manuscript preparation: Yifei Xie, Mazen Danaf, Carlos Lima de Azevedo, Arun Prakash Akkinepally, Bilge Atasoy, Kyungsoo Jeong. All authors reviewed the results and approved the final version of the manuscript.

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