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Behavioral modeling of on-demand mobility services: general framework and application to sustainable travel incentives

Yifei Xie[1] · Mazen Danaf[1] · Carlos Lima Azevedo[2] · Arun Prakash Akkinepally[1] · Bilge Atasoy[3] · Kyungsoo Jeong[5] · Ravi Seshadri[4] · Moshe Ben-Akiva[1]

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Abstract
This paper presents a systematic way of understanding and modeling 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 modeling 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 values of time are observed when the respondents opt to use the reward system. The perception of incentives and schedule delay by different population segments are quantified. These 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 mobility as a service.

Keywords Smart mobility · On-demand · Incentives · Travel behavior · Stated preference · Sustainability

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

✉ Yifei Xie
yifeix@mit.edu

Extended author information available on the last page of the article

المنارة للاستشارات

has just hit five billion total rides in May 2017 since its first appearance (Bhuiyan 2018). In China, DiDi Chuxing completed 7.43 billion rides for 450 million users in more than 400 cities in the same year (Xinhua 2018). 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 (BlaBlaCar 2019). The attempts to design, test and implement mobility as a service (MaaS) 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. These mobility services usually require users to (1) subscribe (register) to a given service, (2) request a service menu with product option(s) through a mobile application and (3) 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 modeling and activity-based models (ABM) (Rasouli and Timmermans 2014; Viegas de Lima et al. 2018). These models are commonly based on discrete choice methodology and random utility maximization (McFadden 1974; Ben-Akiva and Lerman 1985). Since on-demand mobility services are often dynamically tailored to different individual preferences and contexts (e.g. 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 (for example, Rayle et al. 2016; Clewlow 2016). As indicated by Jittrapirom et al. (2017), 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 (2014) investigated the demand (number of downloads) of apps through a 3-level nested logit with consumer taste heterogeneity and nests based on app attributes. Zoepf and Keith (2016) estimated a logit mixture with taste heterogeneity to evaluate how carsharing users value each attribute displayed in a product menu. Dias et al. (2017) 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 (2018) investigated subscription preferences towards various product bundles in a MaaS setting by logit mixtures with taste heterogeneity. Choudhury et al. (2017) 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 hamper the engagement of the models in simulations in that assumptions on the unmodeled decision stages would have to be made (e.g. if one has only modeled the mode choice decision, he/she would have to assume a penetration rate for subscription in simulation).

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In the greater context of modeling car ownerships or service subscriptions, the interconnections between short-term and long-term decisions have been studied (e.g. Pinjari et al. 2011; Le Vine et al. 2014; Plevka et al. 2018). 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 expected that unattractive options would have been offered. These behaviors are especially relevant for on-demand services which generate their service menu dynamically in real-time.

This paper fills the aforementioned gaps by developing a framework which explicitly considers and integrates all the 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 modeling 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 systems. The capability and flexibility of it are illustrated through a case study on Tripod—an innovative on-demand incentive scheme (Azevedo et al. 2018). 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 formulate our modeling framework. In the third section we present the data collection for the case study, followed by the model specifications and estimation shown in the fourth section. Finally, the conclusions are provided in the last section.

Modeling framework for on-demand services

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

First of all, a person needs to decide whether to subscribe a given service. This choice is represented by the *subscription model*. It typically involves downloading the app (if

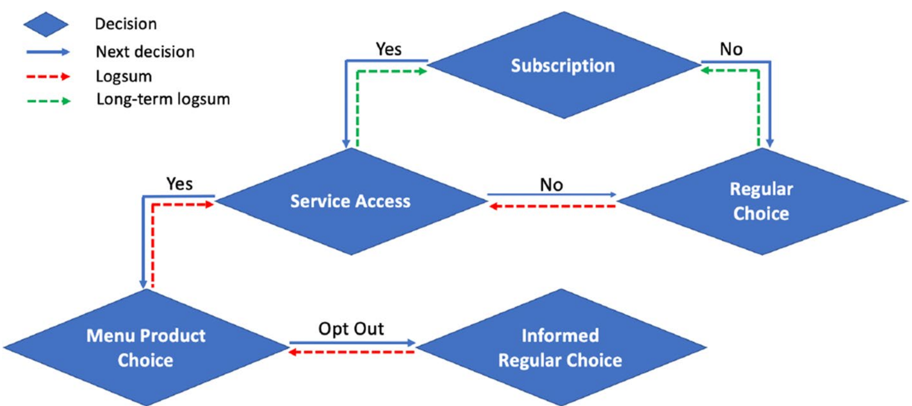

Fig. 1 Conceptualized decision-making process in on-demand app usage

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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 the 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, which is represented by the *service access* model. This may be conditional on the trip 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 that the operator would offer unattractive terms (for example travelers 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 modeling of service access captures this behavior.

In Fig. 1 we represent the choice situation of the subscribers who don't access the service and that of the non-subscribers by the same model, however, it doesn't mean that these two types of travelers should behave identically. This potential behavioral difference could be incorporated into 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*. 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 an alternative other than the on-demand service at stake.

For subscribers, the choice situation after opt-out (*informed regular choice* in Fig. 1) is different from the one without opening the app (*regular choice* in Fig. 1) in that the options offered by on-demand mobility services usually also provide the users with real-time information (e.g., availability of alternatives, travel time estimates). The impact of information is discussed in Ben-Akiva et al. (1991) and Mahmassani and Liu (1999). 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, the higher level choices influence the lower level ones. However, the 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 the 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 and non-subscribers.

The logsum passing directions are illustrated in Fig. 1 with the 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 "Model formulation and

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specification" section. Second, the long-term logsum (green dashed lines in Fig. 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 modeling 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 preference (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 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 stated preference (SP) data is used, service access process needs to be presented and the corresponding choice needs to be recorded. In "Case study: tripod background and data collection" and "Case study: model formulation and estimation" sections we describe how we addressed this by a smartphone-based SP in the context of Tripod.

Case study: tripod background and data collection

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 (Azevedo et al. 2018). The travel decisions of interest are mode, route, departure time, trip-making and driving style. In response to any changes in any of these 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 Fig. 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 without Tripod and the menu is personalized according to the user's preferences, characteristic and network attributes (Song et al. 2018; Danaf et al. 2019). 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 trip of the user and rewards her/him at the end of it if the guidance was followed.

Data collection method

In this section we describe the data collection for Tripod, which is based on the methodology proposed by Atasoy et al. (2018).

The core data collection platform is the smartphone-based Future Mobility Sensing (FMS) platform (Cottrill et al. 2013; Zhao et al. 2015; Seshadri et al. 2019). 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 (Zhao et al. 2015). 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

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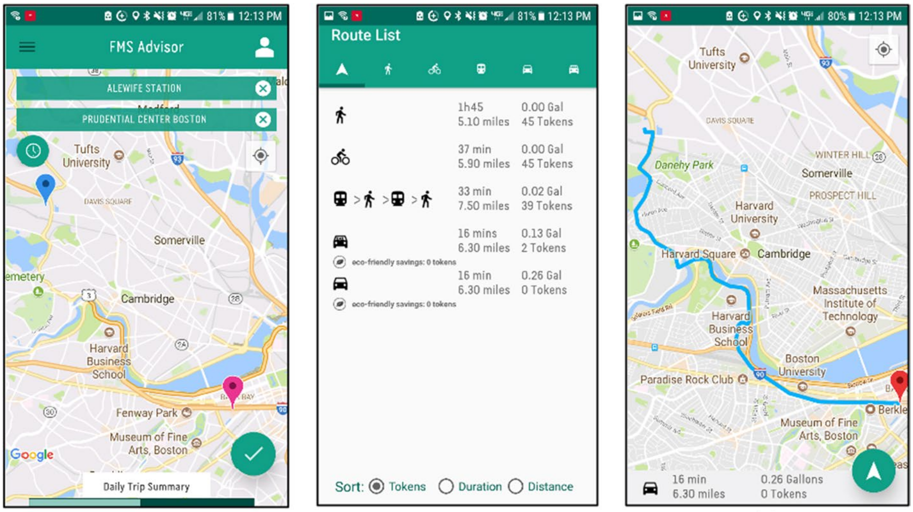

(a) (b) (c)

Fig. 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

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]

Pre-survey data

Upon downloading the app and registering, respondents were asked to fill out the pre-survey. They were asked about their socio-demographics, such as age, gender, working status, income, car ownership, bike ownership, and how frequently they use different transportation modes. Examples of the interface are shown in Fig. 3a, b.

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

[1] In the same data collection effort, SP surveys were also generated for another mobility survey (Atasoy et al. 2018). The 14 surveys required for each respondent are a mixture of the two (randomly presented with a higher frequency of Tripod appearance).

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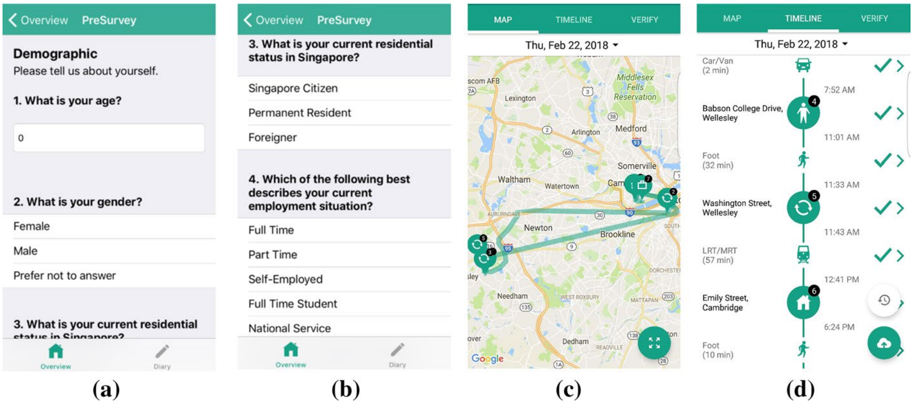

Fig. 3 Pre-survey and RP Trip/activity diary validation

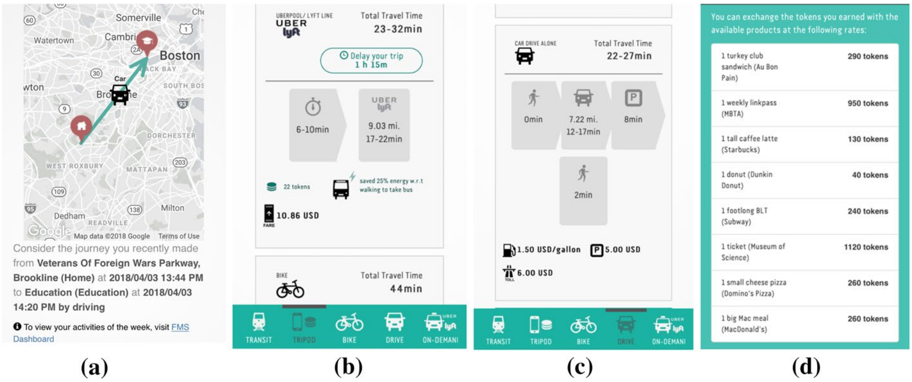

Fig. 4 Tripod SP: trip context options and market place. From left to right: **a** recall of trip context; **b** an option in Tripod tab; **c** an option in Drive tab; **d** the market place for a respondent

activities, the data included activity purpose, location, start and end times. For trips, the origin, destination, travel mode, arrival time and departure time were obtained. Figure 3c, d show an example of trip/activity diary validation. More details are available in Cottrill et al. (2013) and Zhao et al. (2015).

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 (Fig. 4a).

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.

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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 (Atasoy et al. 2018).

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 examples in Fig. 4b, 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. (2018). Each of these sets is shown in a separate tab, alongside the tab for Tripod menu (Fig. 4b, c). Furthermore, respondents are presented with ranges that reflect the 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 min), 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 (Needell et al. 2016). 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 (Fig. 4d). 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.

Post-survey data

Upon completing 2 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 as well as 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 "Case study: model formulation and estimation" section for more details).

Sample characteristics

After data cleaning, sessions completed within 10 s 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 employment status, number of household vehicles, age and household income compared to the population distributions in the

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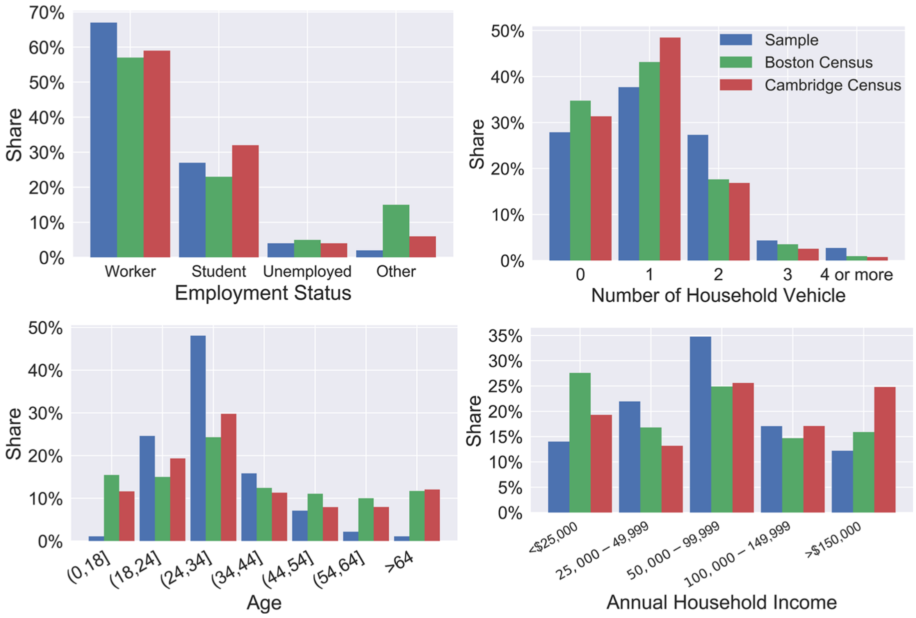

Fig. 5 Sample characteristics

survey region based on American Community Survey (ACS) (United States Census Bureau 2018). For the 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, household income group \$50k to \$99k (annual) are slightly oversampled.

Case study: model formulation and estimation

In this section, we apply the model structure proposed in "Modeling framework for on-demand services" section to the case of Tripod and we formulate and estimate each model component with the data described in "Case study: tripod background and data collection" section.

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 that 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 the *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 the *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 are required for the estimations

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of higher-level models. The model specifications and results are presented in this order as well.

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.

Regular choice model

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.

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

Menu product choice model

Equation (2) shows the utility specification for an option in the menu while Eq. (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 Fig. 4d).

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

$$U_{out} = ASC_{out} + \beta_{Iout} I_{RC} + \epsilon \tag{3}$$

Service access model

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

$$U_{nac} = ASC_{nac} + \beta_{Inac} I_{RC} + \epsilon \tag{4}$$

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

As mentioned in "Modeling framework for on-demand services" section, the logsum entering Eq. (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 from 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 included 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

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Table 1 Notations in utility specifications

Variable	Unit	Description	Inter-consumer distribution of corresponding parameter
t_{IVTT}	Minute	In-vehicle travel time	Lognormal distributions[a]
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	
p	US dollar	Cost	
r	US dollar	Reward in monetary token	
t_{delay}	Minute	Schedule delay	Lognormal distribution
D_{RP}	Binary	Dummy for whether the mode of SP option is the same as the RP mode	Normal distributions
$D_m, m \in M$	Binary	Mode dummies. *M* includes walk, bike, bikeshare, car and carpool, Uber and Uberpool, taxi, and public transit accessed by walk, bike and car	
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

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Table 1 (continued)

Variable	Unit	Description	Inter-consumer distribution of corresponding parameter
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"

[a]The distributions of the parameters of travel time and cost are segmented by full-time workers and other populations (different means and standard deviations)

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single trip-specific menu. This provides us with an optimistic approximation of the 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.

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

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

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

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

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

The responses to the indicators of measurement equations and whether to subscribe are in a 5-point Likert scale ranging from "strongly disagree" to "strongly agree". As the error terms in Eqs. (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 Eq. (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 "Estimation results" section, the estimated thresholds are subscripted according to the measurement equations' subscripts.

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

Estimation results

We estimated the set of models by BIOGEME (Bierlaire 2003). The models with inter-consumer heterogeneity were estimated with maximum simulated likelihood. Halton draws (Halton 1960) 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 experiments. 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".

المنارة للاستشارات

To clearly identify the click action on the Tripod tab, the surveys where the default tab (the tab shown when the 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 which attempts 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 "Model formulation and specification" section. 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. (2012).

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.

Value of travel time (VOT)

Using the parameter estimates of the *menu product choice model* and the *regular choice model* shown in Table 2, inter-consumer distributions of the values of in-vehicle, out-of-vehicle, and non-motorized travel time could be obtained for both population segments (full-time workers and others). As such, there are twelve distributions in total.

As the cost parameter (β_p) and the relevant time parameter (here generally denoted as β_{time}) enter utility Eqs. (1) and (2) on the exponent (for lognormal distributions), the VOT in US dollars per hour could be calculated as shown in Eq. (12).

$$VOT\left[\$/\mathrm{h}\right] = \frac{e^{\beta_{time}}}{e^{\beta_p}} * 60\left[\mathrm{min}/\mathrm{h}\right] = e^{\beta_{time}-\beta_p+\ln(60)} \tag{12}$$

Since β_p and β_{time} are normally distributed and uncorrelated whose means and standard deviations are denoted by μ_p, μ_{time}, σ_p and σ_{time} correspondingly, the distribution of VOT follows the lognormal distribution shown in Eq. (13), the mean and median of which could be computed with Eqs. (14) and (15) respectively.

$$VOT \sim Lognormal\left(\mu_{time} - \mu_p + \ln(60), \sigma^2_{time} + \sigma^2_p\right) \tag{13}$$

$$\mu_{VOT} = e^{\mu_{time}-\mu_p+\ln(60)+\left(\sigma^2_{time}+\sigma^2_p\right)/2} \tag{14}$$

$$Median_{VOT} = e^{\mu_{time}-\mu_p+\ln(60)} \tag{15}$$

After applying this procedure for all the VOTs, the means and medians of the above-mentioned twelve VOT distributions are summarized in Table 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

Table 2 Estimation results

Regular choice model

Name	Mean	Robust SE	SD	Robust SE
β_p full-time worker	−3.29	0.360**	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	0.720
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**	0.220	0.173
β_{NMM} full-time worker	−3.01	0.187**	0.321	0.176*
β_{NMM} other	−2.40	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**	0.110	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	0.900**	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	0.430**	0.337	0.333
β_{NMM} full-time worker	−2.42	0.158**	0.00734	0.236
β_{NMM} other	−2.40	0.234**	0.00734	0.236
β_{delay}	−1.99	1.09*	1.31	1.67
$\beta_{inertia}$	1.14	0.250**	0.403	2.51
ASC_{out}	0		2.29	0.523**
β_{bike}	5.63	1.29**	2.35	0.821**
β_{PT}	4.66	1.21**	0	
β_{car}	4.86	1.15**	1.45	0.620**
$\beta_{bikeshare}$	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**		

المنارة للاستشارات

Table 2 (continued)

Menu product choice model

Name	Mean	Robust SE	SD	Robust SE
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	1.10*	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	0.300
β_E	0.710	0.548			

Thresholds for the choice model

Name	Value	Robust SE	Name	Value	Robust SE
$\delta_{S,1}$	0.970	0.129**	$\delta_{S,2}$	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}	3.00	1.65*
λ_{E1}	1		λ_{A1}	0.149	0.087*
λ_{E2}	3.14	1.03**	λ_{A2}	0.392	0.193**

المنارة للاستشارات

Table 2 (continued)

Subscription model—measurement equations					
Name	Value	Robust SE	Name	Value	Robust SE
λ_{E3}	1.67	0.883*	λ_{A3}	1	
Thresholds for the measurement equations					
Name	Value	Robust SE	Name	Value	Robust SE
$\delta_{E1,1}$	0.560	0.101**	$\delta_{E1,2}$	2.39	0.275**
$\delta_{E2,1}$	0.881	0.217**	$\delta_{E2,2}$	4.59	0.882**
$\delta_{E3,1}$	0.905	0.132**	$\delta_{E3,2}$	2.23	0.279**
$\delta_{A1,1}$	0.362	0.0791**	$\delta_{A1,2}$	2.08	0.223**
$\delta_{A2,1}$	0.960	0.219**	$\delta_{A2,2}$	3.77	0.538**
$\delta_{A3,1}$	2.21	0.904**	$\delta_{A3,2}$	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

Table 3 Value of travel time

Unit: $/h	Regular choice			Menu product choice		
	IVTT	OVTT	NMM	IVTT	OVTT	NMM
Full-time worker mean	59.5	54.1	83.7	43.5	35.6	63.1
Full-time worker median	58.8	53.2	79.4	26.2	23.9	44.9
Other mean	28.7	56.9	85.3	17.4	39.9	42.5
Other median	17.4	34.3	52.7	14.6	37.5	42.3

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 are in search for low-cost alternatives.

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 h schedule delay has a median of $5.5 and a mean of $18.3 for the full-time worker

المنارة للاستشارات

Fig. 6 Value of schedule delay

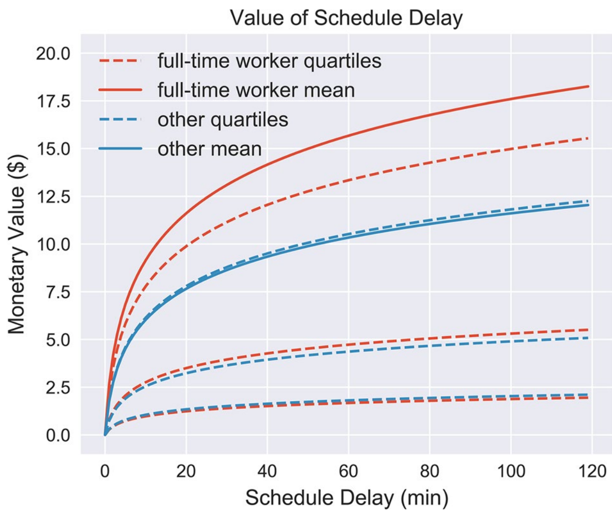
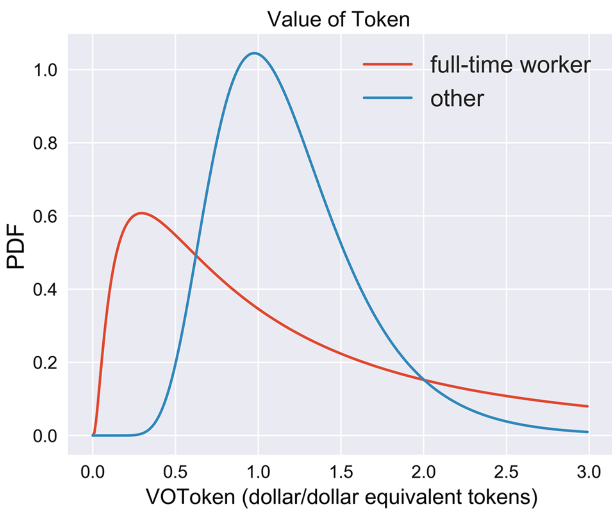


Fig. 7 Distributions of value of token



segment, while it has a median of \$5.1 and a mean of \$12.1 for the other population segment. The value of schedule delays within 2 h is visualized in Fig. 6.

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.

Value of incentives (tokens)

The probability density function of the value of tokens is shown in Fig. 7, segmented by full-time worker and other population segments. The value of token represents how much the respondents value the amount of tokens that has the purchasing power of 1 dollar.

المنارة للاستشارات

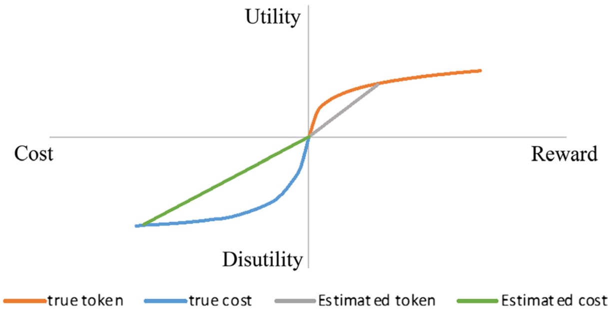


Fig. 8 Hypothesis explaining the higher perception of tokens

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.

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 decrease as gain and loss (cost) increase respectively (Kahneman and Tversky 1984). Under this hypothesis, with the simplification of utility being linear in token and cost might cause the current observation in cases shown in Fig. 8. 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.

Conclusion

In this paper, we presented a general framework for modeling 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 modeling of on-demand mobility services.

The framework is applied to model 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

المنارة للاستشارات

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 that have less time constraints.

One main difficulty we 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 "Case study: tripod background and data collection" section (or acquire such data from the service operator). 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 modeling 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 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.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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Yifei Xie is a Ph.D candidate in transportation at the Massachusetts Institute of Technology (MIT). His research focuses on the innovation of econometric choice modeling methods and their applications to travel behavior.

Mazen Danaf received the B.E. and M.E. degrees in Civil and Environmental Engineering from the American University of Beirut in 2011 and 2013, and the Ph.D. degree in Transportation from the Massachusetts Institute of Technology in 2019. He specializes in new and innovative applications of behavioral models such as recommender systems, smart mobility, web- and smartphone-based applications, and stated preferences methods.

Carlos Lima Azevedo is an Associate Professor at DTU Management, Department of Technology, Management and Economics Technical University of Denmark (DTU) and a Research Affiliate of the ITS Lab at the Massachusetts Institute of Technology. His research is focused on the development of new models and simulation techniques for smart mobility design and assessment. Previous research includes the development and application of large-scale agent-based urban simulation, its application for the design and evaluation of new mobility management solutions such as shared automated vehicles ondemand and personalized real-time incentive systems; individual behavior experiments and preferences modeling towards new mobility solutions; methods for the calibration and validation of simulation tools and innovative road safety assessment models without accident data. He obtained his PhD (2014) and MSc (2008) in Transportation Systems from the University of Lisbon, IST, Portugal.

Arun Prakash Akkinepally is a Researcher Scientist at Intelligent Transportation Systems Lab at MIT. He earned his Ph.D. in Transportation Engineering in 2016 and B.Tech and M.Tech in Civil Engineering in 2010 from Indian Institute of Technology, Madras India. Prior to joining MIT, he was a postdoctoral associate at Singapore-MIT Alliance for Research and Technology, Singapore. His research and professional interests include network modeling, travel simulation, travel behavior, and future of urban mobility.

Bilge Atasoy is an assistant professor at TU Delft within the Department of Maritime and Transport Technology in section Transport Engineering and Logistics. Her main research interests lie at the intersection of optimization and behavioral models. She applies the scientific methodologies in the field of various transport and logistics problems. Prior to joining TU Delft, Bilge was a research scientist at MIT at the Intelligent Transportation Systems (ITS) Lab where she is now a research affiliate. At MIT she led several research projects in the areas of real-time optimization, travel behavior and choice-based optimization for which she also worked on funding applications. Bilge obtained her Ph.D from EPFL in November 2013 in the area of integrated supply and demand models in transportation problems which received the best PhD Thesis Award from the Swiss Operations Research Society. She received her MSc and BSc degrees in Industrial Engineering from Bogazici University, Istanbul, in 2009 and 2007, respectively.

Kyungsoo Jeong is a researcher at the National Renewable Energy Laboratory (NREL), Transportation and Hydrogen Systems Center. He received his Ph.D. in Civil and Environmental Engineering from the University of California, Irvine. Before joining NREL, he was a postdoc at the MIT ITS Lab. His research focuses on how new mobility services and emerging technologies affect people and goods movement, and how the transportation system increases its efficiency.

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Ravi Seshadri is a Research Scientist at the Singapore-MIT Alliance for Research and Technology. He received his Bachelors, Masters and Ph.D degrees from the Indian Institute of Technology Madras. His research interests include real-time dynamic traffic assignment, agent-based simulation, transportation network modelling and smart mobility.

Moshe Ben-Akiva is the Edmund K. Turner Professor of Civil and Environmental Engineering at the Massachusetts Institute of Technology (MIT), Director of the MIT Intelligent Transportation Systems Lab, and Principal Investigator at the Singapore-MIT Alliance for Research and Technology. He holds a Ph.D degree in Transportation Systems from MIT and was awarded honorary degrees from the University of the Aegean, the Université Lumiére Lyon, the KTH Royal Institute of Technology, and the University of Antwerp. His awards include the Robert Herman Lifetime Achievement Award in Transportation Science from the Institute for Operations Research and the Management Sciences, the Lifetime Achievement Award of the International Association for Travel Behavior Research, the Jules Dupuit prize from the World Conference on Transport Research Society, and the Institute of Electrical and Electronics Engineers ITS Society Outstanding Application Award for DynaMIT, a system for dynamic network management. Ben-Akiva has co-authored two books, including the textbook Discrete Choice Analysis, published by MIT Press, and nearly 400 papers in refereed journals or refereed conferences.

Affiliations

Yifei Xie[1] · Mazen Danaf[1] · Carlos Lima Azevedo[2] · Arun Prakash Akkinepally[1] · Bilge Atasoy[3] · Kyungsoo Jeong[5] · Ravi Seshadri[4] · Moshe Ben-Akiva[1]

1 Massachusetts Institute of Technology, 77 Massachusetts Ave, Cambridge, MA 02139, USA

2 Technical University of Denmark, Anker Engelunds Vej 1 Bygning 101A, 2800 Kgs. Lyngby, Denmark

3 Delft University of Technology, Mekelweg 2, 2628 CD Delft, The Netherlands

4 Singapore-MIT Alliance for Research and Technology (SMART), 1 CREATE Way, #09-02, CREATE Tower, Singapore 138602, Singapore

5 Transportation and Hydrogen Systems Center, National Renewable Energy Laboratory, Golden, CO 80401, USA

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