Modeling travel behavior with on-demand systems: the case of real-time sustainable travel incentives

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Extended Abstract

An increasing number of new on-demand mobility services are being proposed and offered to consumers, assuring a growing share in the transportation market. The success of these new solutions is largely due to the advancement of Information and Communications Technologies (ICTs) enabling on-demand, efficient, user friendly or personalized services easily available through mobile applications. Using their smartphones, users are usually required to (i) subscribe (register) to a given service, (ii) request a service offer with product option(s) and (iii) select the preferred product through a single mobile application.

Since on-demand mobility services are often dynamically tailored to different individual preferences and contexts, disaggregate behavioral models are essential to the accommodation of the underlying complex dynamics in their design and assessment. To the best of our knowledge, choice models for on-demand mobility service have focused either on the subscription to the service or the product choice, ignoring the services access and the interactions between these three decision processes (*2*, *3*, *4*, *5*, *6*).

We propose a new modelling framework for traveler's response to on-demand mobility services (see Figure 1). 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 and registering. 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. If the user decides to access the service, a request is triggered and the user is able to evaluate the products presented in the menu through a *menu product choice model*. If the user finds one of the products in the menu attractive, he/she would select it and execute the trip with the selected product. The user may also reject the entire menu (*opt-out*) and choose some other alternative outside the on-demand service at stake.

Based on the hierarchical 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 user makes the subscription decision, the major consideration is whether the mobility service is attractive, which is reflected through the experience and 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 and the sequential nature of the decision process, a multi-level nesting structure (*1*) is adopted. The logsums feeding between levels provide a measurement of attractiveness of the lower levels, and their coefficients show the corresponding sensitivities.

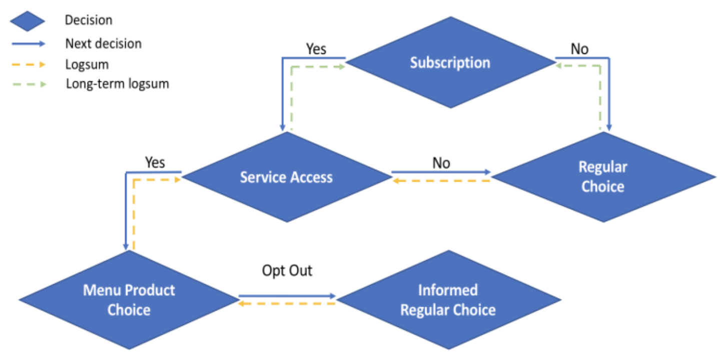

Figure 1 Framework for decision-making process in on-demand app services

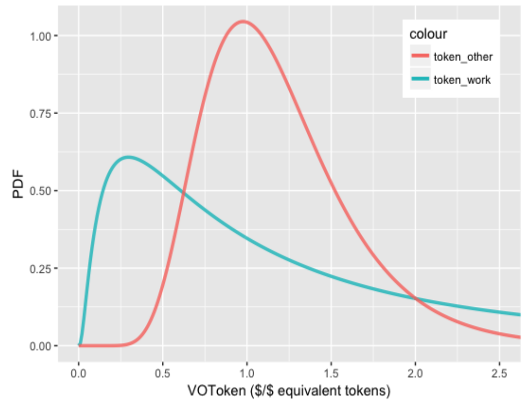

Figure 2 Distributions of value of token

We apply the above framework to the response to a future real-time incentives systems targeting energy efficiency, called Tripod: Sustainable Travel Incentives with Prediction, Optimization and Personalization (*7*). 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. In this presentation, the travel decisions of interest are mode, route and departure time choice. In response to any changes in any of these dimensions, users receive incentives in the form of *tokens* that can be redeemed for a variety of goods and services from third party providers. Data was collected through a full smartphone-based framework using the Future Mobility Sensing (FMS) (*910*) platform. (a) high resolution revealed preferences (RP) data as travel diaries, (b) context-aware stated preferences (SP) towards Tripod (*8*), (c) pre- and (d) post-surveys for, respectively, information on socio-demographics and long-term preferences and perceptions (on, among others, subscribing Tripod) were collected. The data collection was carried out in Boston from 154 participants with the required 14 days of RP, 14 SP responses and pre- and post-surveys (as of July 2018).

The estimated framework for Tripod included a hybrid choice model for service *subscription*, and three logit mixture models with inter-consumer taste variations for the *service access*, *product and opt-out* choice, which are connected by feeding logsums. The models were estimated sequentially from bottom (bottom-up) in the following order: *regular choice model*, *Tripod menu product choice*, *service access model* and at, the end, *subscription model*. This is because of that the logsums of the lower levels need to be computed based on estimation results prior to the estimation of higher level models.

Through model estimation, lower VOTs are observed when the respondents opt to use the reward system. Generally, fulltime workers have a higher estimated VOT in each choice model level, likely due to their higher income and tighter schedules. For the other segments, the VOT is valued in the order of *non motorized travel time*, *out-of-vehicle travel time* and *in-vehicle travel time* from high to low, while for fulltime workers, the VOT for *in-* and *out-of-vehicle travel time* are similar. This is due to the fact that fulltime workers make longer trips in Boston. For each population segment, noticeably lower VOTs in the *menu product choice model* was 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.

The perception of incentives and schedule delay by different population segments were also quantified. We computed the monetary value of a 30 minutes schedule delay with a median of 4.0$ and a mean of 13.1$ in the fulltime worker segment, and a median of 3.6$ and a mean of 8.6$ in the other population segments. The monetary value of 2 hours schedule delay has a median of 5.5$ and a mean of 18.3 $ in the fulltime worker segment, while it has a median of 5.1$ and a mean of 12.1$ in the other population segments. We could conclude from here that the schedule delay causes less disutility compared to the travel times, which might be because of the benefits of other tasks in delay situations.

The pdf for the value of tokens in $/$ is shown in Figure 2, segmented by full time worker and other segments. 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 are observed. For example, the lognormally distributed value of token for fulltime workers has a median of 1.1 and a mean of 2.1. This can be due to the fact that: 1) the process of token redemption is not included in the SP; 2) the perceived token value in Tripod can be associated with energy and environmental gains; or 3) since the tokens are perceived as rewards while travel costs are perceived as out-of-pocket expenses, they could be perceived very differently.

The estimated models are currently being deployed in a simulation based platform (*11*) to test different deployment scenarios for Tripod. Furthermore, several future research directions were identified by the authors and will be discussed in the presentation, including how to incorporate RP data for emerging on-demand mobility services at every choice model level in the estimation process, the extension of the model formulation with revision/dynamic processes, for en-route opt-out and change behavior or the exploration of this model into other decision processes, such as travel planning and the activity-based framework or long-term decision making such as vehicle ownership.

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