Transportation Research Part C 79 (2017) 207–223

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services ☆

Feras El Zarwi [a,*], Akshay Vij [b], Joan L. Walker [c]

[a] Department of Civil and Environmental Engineering, University of California at Berkeley, 116 McLaughlin Hall, Berkeley, CA 94720-1720, United States
[b] Institute for Choice, University of South Australia, Level 13, 140 Arthur Street, North Sydney, NSW 2060, Australia
[c] Department of Civil and Environmental Engineering, University of California at Berkeley, 111 McLaughlin Hall, Berkeley, CA 94720-1720, United States

ARTICLE INFO

Article history:
Received 28 June 2016
Received in revised form 6 December 2016
Accepted 3 March 2017

Keywords:
Technology diffusion
Dynamics
Latent class choice models
Social influences
Spatial effect
Demand forecasting

ABSTRACT

Major technological and infrastructural changes over the next decades, such as the introduction of autonomous vehicles, implementation of mileage-based fees, carsharing and ridesharing are expected to have a profound impact on lifestyles and travel behavior. Current travel demand models are unable to predict long-range trends in travel behavior as they do not entail a mechanism that projects membership and market share of new modes of transport (Uber, Lyft, etc.). We propose integrating discrete choice and technology adoption models to address the aforementioned issue. In order to do so, we build on the formulation of discrete mixture models and specifically Latent Class Choice Models (LCCMs), which were integrated with a network effect model. The network effect model quantifies the impact of the spatial/network effect of the new technology on the utility of adoption. We adopted a confirmatory approach to estimating our dynamic LCCM based on findings from the technology diffusion literature that focus on defining two distinct types of adopters: innovator/early adopters and imitators. LCCMs allow for heterogeneity in the utility of adoption for the various market segments i.e. innovators/early adopters, imitators and non-adopters. We make use of revealed preference (RP) time series data from a one-way carsharing system in a major city in the United States to estimate model parameters. The data entails a complete set of member enrollment for the carsharing service for a time period of 2.5 years after being launched. Consistent with the technology diffusion literature, our model identifies three latent classes whose utility of adoption have a well-defined set of preferences that are significant and behaviorally consistent. The technology adoption model predicts the probability that a certain individual will adopt the service at a certain time period, and is explained by social influences, network effect, socio-demographics and level-of-service attributes. Finally, the model was calibrated and then used to forecast adoption of the carsharing system for potential investment strategy scenarios. A couple of takeaways from the adoption forecasts were: (1) placing a new station/pod for the carsharing system outside a major technology firm induces the highest expected increase in the monthly number of adopters; and (2) no significant difference in the expected number of monthly adopters for the downtown region will exist between having a station or on-street parking.

☆ This article belongs to the Virtual Special Issue on "Emerging Mobility Servi".

* Corresponding author.
E-mail addresses: feraselzarwi@gmail.com (F. El Zarwi), vij.akshay@gmail.com (A. Vij), joanwalker@berkeley.edu (J.L. Walker).

http://dx.doi.org/10.1016/j.trc.2017.03.004
0968-090X/

1. Introduction

The growth in population and urban development has impacted societies in one way or another from air pollution to greenhouse gas emission, climate change and traffic congestion. This made policy makers more inclined towards the development of smart cities that promote sustainable mobility, connectivity and multimodality. As such, major technological and infrastructural changes are expected to occur over the next decades such as the introduction of autonomous vehicles, advances in information and communication technology, California high speed rail, carsharing and ridesharing. This will induce potential paradigm shifts in the cost, speed, safety, convenience and reliability of travel. Together, they are expected to influence both shot-term travel and activity decisions, such as where to go and what mode of travel to use, and more long-term travel and activity decisions, such as where to live and how many cars to own. This transformative mobility, whether in the form of sharing economy, connected vehicles, autonomous and app-driven on-demand vehicles and services will revolutionize travel and activity behavior.

Travel demand models are the commonly-used approach by metropolitan planning agencies to predict 20–30 year forecasts of traffic volumes, transit ridership, walking and biking market shares across transportation networks. These models try to assess the impacts of transportation investments, land use and socio-demographic changes on travel behavior with the main objective of predicting future mode shares, auto ownership levels, etc. These models focus on a behaviorally richer approach to modeling travel mode choice as opposed to the traditional four step travel demand models. Travel demand models evaluate travel and activity behavior as a series of interdependent logit and nested logit models that entail travel mode choice, vehicle availability, and time-of-day models, etc. However, current travel demand models are unable to predict long-range trends in travel behavior as they do not entail a mechanism that projects membership and market share of new modes of transport (Uber, Lyft, autonomous vehicles, etc.). According to Guerra (2015), “only two metropolitan planning organizations in the 25 largest metropolitan areas mention autonomous or connected vehicles in their long-range regional transportation plans”. That is why current travel demand models lack a methodological framework that caters for those upcoming transportation services and technologies and their impact on travel behavior which will be prevalent in 20–30 years.

Our objective is to develop a methodological framework tailored to model the technology diffusion process by focusing on quantifying the effect of the spatial configuration of the new technology and socio-demographic variables. Moreover, we are also interested in capturing the effect of social influences and level-of-service attributes of the new technology on the adoption process. The methodological framework used in our analysis entailed an integrated latent class choice model (LCCM) and network effect model that was governed by a destination choice model. Our approach was confirmatory as the latent classes used in the analysis (innovators/early adopters, imitators and non-adopters) are rooted in the technology diffusion literature across multiple disciplines. These latent classes are able to capture heterogeneity in preferences towards technology adoption. Our research is motivated by existing work in technology adoption modeling which employs a microeconomic utility-maximizing representation of individuals. This framework is of interest to us as it could be easily integrated with our disaggregate activity-based models. Our proposed disaggregate technology adoption model shall help planners and policy makers gain insight regarding the projected market shares of upcoming modes of transport for various policies and investment strategies at the public and private levels.

Most diffusion models employ an aggregate framework, for example the Bass model (Bass, 1969). While recent aggregate models have further enriched the specification of the Bass model, they still do not account for a range of policy variables (including the spatial configuration) that can be used to rank policies and investment strategies needed to maximize the expected number of adopters of a new technology in future time periods. Our methodological framework is different than other disaggregate models in the diffusion and transportation literature as it accounts for (1) heterogeneity in the decision-making process across distinct market segments that have a different adoption behavior; and (2) the spatial configuration effect of the new technology in terms of quantifying how an increase in the size of the network governed by the new technology will impact adoption.

This study contributes to the existing body of literature in providing a unique methodology to model the adoption behavior and uptake of new products/technologies by various market segments. Our model caters for the effects of social influences, network effect, socio-demographics and level-of-service attributes of the product on the adoption behavior of each of the market segments. The following framework could be used to predict future market shares of upcoming modes of transport as one specific type of application. The paper is organized as follows: Section 2 provides a literature review of existing technology adoption and diffusion models. Section 3 provides the adopted methodological framework used to model technology adoption and details the framework of the dynamic Latent Class Choice Model (LCCM) and the network effect model. Section 4 explains the dataset used in the study. Section 5 discusses model results and model applications. Section 6 concludes the findings of the paper.

2. Literature review

Autonomous vehicles are on the horizon, not to mention the transformative mobility trend that is occurring in our transportation system via the introduction of electric vehicles, ridesharing, carsharing, and many other new technologies. In order