LEVERAGING INFORMATION TECHNOLOGIES AND POLICIES TO INFLUENCE SHORT- AND LONG-TERM TRAVEL DECISIONS

by

Yuntao Guo

A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Lyles School of Civil Engineering

West Lafayette, Indiana

August 2019

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Samuel Labi, Co-Chair

Lyles School of Civil Engineering

Purdue University

Dr. Srinivas Peeta, Co-Chair

School of Civil and Environmental Engineering

H. Milton Stewart School of Industrial and System Engineering

Georgia Institute of Technology

Dr. Jon D. Fricker

Lyles School of Civil Engineering

Purdue University

Dr. Fred L. Mannering

Civil and Environmental Engineering Department

University of South Florida

Dr. Tonglin Zhang

Department of Statistics

Approved by:

Dr. Dulcy Abraham

Head of the Graduate Program

Dedication to my beloved parents and wife

ACKNOWLEDGMENTS

First of all, I would like to express my special appreciation to my advisor Dr. Srinivas Peeta for his continuous support of my Ph.D. study and related research. I am deeply grateful to him for his support, motivation, patience, guidance, and immense knowledge. His dedication and work ethic for research and education have been and will always be an inspiration in my life.

I am also indebted to my co-advisor, Dr. Samuel Labi for his support and invaluable comments on my dissertation and other research. I was fortunate to learn from him, and I am thankful for his advice. He is an inspiring mentor and a caring friend.

I would also like to thank my committee members Dr. Jon D. Fricker, Dr. Fred L. Mannering, and Dr. Tonglin Zhang. Their expertise in transportation planning and statistics are extremely valuable sources. Their guidance and encouragement helped me to expand my research horizon and motivated me to improve every day.

I would also like to thank my coworkers and collaborators throughout the years for their support and company. They made my time at Purdue University and interesting and precious journey.

My deepest gratitude goes to my beloved parents and wife. They made me who I am and drive me to be a better person. I could not have finished my Ph.D. without their support, sacrifice, and love.

This work is supported by the NEXTRANS Center and the Center for Connected and Automated Transportation (Region 5 University Transportation Center).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Author: Guo, Yuntao. PhD
Institution: Purdue University
Degree Received: August 2019
Title: Leveraging Information Technologies and Policies to Influence Short- and Long-term Travel Decisions
Committee Chair: Samuel Labi and Srinivas Peeta

Growing automobile dependency and usage continue to exacerbate traffic congestion, air pollution, and physical inactivity in metropolitan areas. Extensive efforts have been made to leverage advanced technology and related policies to influence short- (within-day and day-to-day) and long-term (mobility and lifestyle) travel decisions to address these issues from the system operator and individual traveler perspectives. However, most studies have yet to address system operator and individual traveler needs together; provide sufficient understanding of the impacts of such technologies on safety and health; and consider the impacts of distinctive regional and political characteristics on responses to different policies among population subgroups.

This dissertation seeks to facilitate the leveraging of information technologies and related policies to influence short- and long-term travel decisions by: (1) developing a framework for apps that integrate augmented reality, gamification, and social component to influence travel decisions that address multiple user- and system-level goals, (2) understanding the safety and health impacts of these apps, (3) developing strategies to influence residential location decision-making to foster sustainable post-relocation travel behavior, (4) investigating the impacts of economic and legal policies on travel decisions by considering distinctive regional and political characteristics.

This dissertation can provide insights to system operators for designing a new generation of apps to dynamically manage traffic in real-time, promote long-term mode shifts from single-occupancy driving to carpooling, public transit use, walking and cycling, and address individual traveler needs. The dissertation also presents app mechanisms for providing feedback to legislators and app developers for designing policies and apps geared towards safe usage and promoting the physical and mental health of its users.

In addition, by considering the impacts of distinctive regional and political characteristics on population subgroups in terms of their responses to information technologies and economic and

legal policies, additional measures can be deployed to support and facilitate the implementation of such technologies and policies.

CHAPTER 1. INTRODUCTION

1.1 Background

Growing automobile dependency and usage have led to increased traffic congestion, air pollution, productivity loss and physical inactivity in many metropolitan areas (Kenworthy and Laube, 1999; Williamson, 2016; Guo et al., 2018). Extensive efforts have been made to develop strategies that curtail the amount of travel by influencing short- and long-term travel decisions. These strategies serve to address goals from the perspectives of the system operator (such as a traffic control center, or a public or private transportation system management agency) and/or individual travelers. Some strategies aim to influence short- to medium-term travel decisions like within-day and day-to-day travel decisions (such as route, departure time and non-work trip destinations) of individual travelers in order to improve system performance. Other strategies focus on influencing long-term travel decisions such as mobility and lifestyle decisions to meet system-level goals (e.g., gradually reducing travel-related emissions) and/or individual-level goals (e.g., adopting green lifestyle and improving personal health). In such contexts, it has been found that structural measures, behavioral intervention strategies, market-based solutions, and legal policies have been widely used to successfully influence travel decisions (Steg, 2003; Bamberg et al., 2011).

Structural measures involve physical infrastructure changes, such as adding new lanes or road links. While such measures can enable limited or short-term success in addressing goals from the system operator's perspective (such as managing travel demand and/or congestion), they alone may not be effective in the long-term. Further, structural measures can entail high investment costs, negative environmental impacts, and political resistance (Stopher, 2004).

Behavioral intervention strategies provide information and feedback to travelers so that they voluntarily change their short- and long-term travel decisions (Ben-Elia and Shiftan, 2010; Guo and Peeta, 2017; Sunio and Schmöcker, 2017). Recent advances in communication technology and the proliferation of smartphones have led to several efforts in academia and industry to design mobile apps or investigate their use to influence users' short- and long-term travel decisions in order to achieve some system level goals. The insights from implementing the aforementioned strategies illustrate that they influence within-day and day-to-day route choice decisions and/or reduce automobile usage (e.g., travel distance and time) during the initial implementation period, such as one month. However, they also show that these apps have limited ability to influence long-term travel decisions, such as inducing mode shifts from driving alone to alternative modes. Furthermore, strategies based on up-to-the-minute transportation information, while desirable for multiple reasons, have demonstrated limited ability to significantly alter travel behavior, particularly regarding habitual travel decisions (e.g., habitual commuting mode choice), towards a more sustainable direction (Chorus et al. 2006; Guo 2011; Zhou 2012; Andersson et al. 2018).

Market-based solutions include various types of price-based (e.g., tolling) and quantity-based (e.g., tradable credits) instruments. Legal policies such as vehicle registration lottery system, road space rationing system (i.e., each work day about one-fifth of all vehicles are prohibited from using the road network), the license plate auction system, and other legal policies, have sharply curtailed new vehicle registrations in metropolitan cities including Beijing and Shanghai (Yang et al., 2014; Xie et al., 2017). However, such solutions can raise issues of public acceptance and equity (Miralinaghi and Peeta, 2016). Furthermore, in the past, several many market-based solutions and legal policies were implemented without considering the distinctive regional and political characteristics. This may lead to potential social exclusion and financial burden to certain population subgroups.

1.2 Research Objectives

On the basis of the research background discussed above, the objectives of this dissertation are five-fold: (1) develop a framework for a new generation of incentivizing behavioral intervention strategies to influence travel decisions that address multiple user- and system-level goals. The framework utilizes the increasing ubiquity of mobile devices, the level of comfort that Millennials and generations thereafter have with technology and interactions thereof, the advances in augmented reality (AR) and virtual reality technologies, and the emerging trend of virtual socialization; (2) evaluate the safety and health (both physical and mental) impacts of apps that adopt the framework proposed in (1); (3) develop a personalized accessibility information tool for behavioral intervention strategies to influence people’s residential location decision-making process to foster more sustainable travel behavior after relocation; (4) investigate the impacts of economic policies (congestion pricing and reward) and (5) legal policies (motorcycle ban policies) on travel mode shift responses and capturing the differences among these responses among population subgroups by factoring distinctive regional and political characteristics.

1.3 Research Tasks

To achieve objectives listed in 1.2, the following tasks are performed:

(1) A framework for integrating augmented reality (AR), gamification and social interactions through mobile apps (hereafter referred to as "LAR apps") is proposed to influence travel decisions. Its potential was studied by understanding the impacts of Pokémon GO, a popular location-based AR gaming app, on route and mode choices. To achieve this, an online survey is designed and conducted that uses the self-reported behavior of a group of Pokémon GO users to explore the impacts of Pokémon GO on the following aspects of travel behavior: (i) potential market penetration of the app (i.e., app usage frequency while driving); (ii) frequency of changing route to interact with virtual objects; (iii) likelihood of carpooling more instead of driving alone for in-app collaboration; and (iv) likelihood of mode shift from drive alone to public transit, walk and bike if provided with additional incentives. The ordered survey responses including frequency and likelihood are analyzed using random parameters ordered probit models to account for the unobserved heterogeneity across users and identify subpopulations of travelers who are more susceptible to the influence of Pokémon GO.

(2) The potential safety and health implications of LAR apps are investigated using an online survey to capture self-reported perception, attitude, and behavior for exploring the impacts of Pokémon GO regarding: (i) perceived risk of using the app while driving and cycling, and opinion of Pokémon GO prohibition while driving and cycling, (ii) self-reported frequency of app-related distracted driving and cycling, (iii) self-reported frequency of app-induced driving (i.e., driving more to use the app) and potentially unsafe driving behavior (i.e., intentionally driving slower than the traffic), (iv) self-reported average daily steps before and after using the app, and (v) perceived physical health benefits (i.e., if using the app makes you physically healthier) and mental health benefits (i.e., if using the app increases social interactions). Multivariate binary probit models and random parameters ordered probit models were estimated to capture sociodemographic and behavioral characteristics that affect these perceptions, attitude and behavior.

(3) A behavioral intervention strategy is developed to understand the impacts of personalized accessibility information on residential location decision-making process of potential relocators and their travel behavior after relocation. Relocators (people who change their residence from one city to another) are used to evaluate the effectiveness of the personalized neighborhood accessibility information because they make more long- and short-term travel decisions that can

be observed compared to the general population. As shown in the literature (Matthies et al. 2002), while travel decisions, in principle, can vary on a day-to-day basis (e.g., driving to work versus using transit), they are more often habitual and are rarely meaningfully reconsidered (e.g., most people know which mode they want to use for work without reconsidering every time). When people relocate, however, they are more likely to form a new set of habits (Rodriguez and Rogers 2014) which makes relocation the ideal time for providing such information to potentially foster more sustainable travel behavior. An experiment was designed and implemented using a sample of persons that were planning to relocate to Tippecanoe County, Indiana, United States. The participants were randomly allocated to either a control or an experimental group. The experimental group participants were provided personalized accessibility information before relocation through an online application that characterizes the ease of access of each neighborhood to potential destinations using walk, bike, transit, or car mode. The control group participants were not given this information. The personalized accessibility is calculated based on a participant's work location and travel needs to potential destinations. Surveys were designed to capture participants' self-reported residential location decision-making process and travel behavior before and after relocation. Simultaneous equation models are estimated to capture the potential interrelationship between the accessibility of participants' residential neighborhood and their self-reported weekly driving time after relocation, and the factors that affect them.

(4) The potential impacts of congestion pricing and reward policies on migrant and resident millennial car travelers' morning commute mode shift responses in China is investigated. A stated preference survey developed for this part of the dissertation was conducted in 2017 among millennial car travelers living or working in Beijing's inner district, and yielded approximately 2,000 responses. Separate random parameters bivariate ordered probit models were estimated for migrant and resident millennial car travelers to capture the potential differences that existed between their mode shift responses. This modeling method can account for unobserved heterogeneity in the data and correlation between their mode shift responses to congestion pricing and reward policies. Several key contributing factors that were considered include their individual and household sociodemographic characteristics, travel behavior and needs, and residential location accessibility to and by transit, as well as their attitudes towards travel mode choices, increasing car usage, usage frequency of travel modes other than car mode, and perceived policy effectiveness, acceptability, and fairness.

(5) The personal and societal impacts of the motorcycle full-ban policy on the home-to-work morning commute of motorcyclists were analyzed using self-reported travel behavioral data and stated travel mode shift response under such policy collected in Foshan City, China. The policy aims to force all motorcyclists in the city to shift to walk, bike, bus, or car mode by 2020. The complex impacts of the policy on travel mode shifts are studied across population sub-groups defined by gender and residential status (migrants and residents). For model estimation, random parameters multinomial logit models with heterogeneity in parameter means and variances were estimated to better track unobserved heterogeneity compared to their counterpart models with fixed means and variances. In addition, out-of-pocket cost, opportunity cost of travel time, emissions, and energy consumption before and after the motorcyclists' travel mode shifts and safety-related impacts were quantified and compared across the population sub-groups.

1.4 Dissertation Structure

This dissertation consists of seven chapters. Figure 1.1 provides an overview of the research framework. As illustrated in Figure 1.1, this dissertation centered around two key components: information technologies and related policies. Dark blue colored items represent information technologies introduced in this dissertation with light blues as their components, and red items represent the policies studied. The green items represent observations captured by various methods.

Chapters 2 and 3 center around a LAR app framework proposed in this dissertation to influence travel behavior and the potential policies can be developed to facilitate the implementation of such LAR apps. Chapter 2 proposes a framework for behavioral intervention strategies through LAR apps and uses Pokémon GO to evaluate the potential of such apps with the proposed framework on various aspects of short- and long-term travel decisions using self-reported survey data. Understanding these impacts can provide insights into how futures apps for influencing travel behavior can be improved and what features to include. However, using such apps can potentially have safety and health implications which are addressed in Chapter 3.

Chapter 3 selects Pokémon GO as a case study to understand driving- and cycling-related safety implications and physical and mental health implications of using LAR apps through analyzing self-reported behavioral data from an online survey. Understanding these safety implications can help facilitate the design of app mechanisms to increase LAR app attractiveness and promoting physical activity increase without compromising user safety. The resulting insights can also aid legislators and law enforcement to formulate, tighten, or enforce laws related to LAR app usage. Both Chapters 2 and 3 aims to leverage information technologies and related-policies to influence short-term travel behaviors and promote long-term lifestyle changes towards sustainable travel behavior. The next chapter helps to capture the potential of influencing short-term travel behavior through influence long-term decisions.

To provide a better understanding of how long-term decisions can influence short-term decisions, Chapter 4 proposes a design of personalized neighborhood accessibility information (IOAMA) for intervention strategies to influence the residential location decision-making process and foster formation of more sustainable travel behavior after relocation. The effectiveness of the proposed strategy was evaluated by comparing the after relocation behavior of experimental group participants who received information with after relocation behavior of control group participants who did not have access to such information. Statistical analysis was carried out to determine whether there are statistically significant differences between the experimental and control group participants in terms of their perceived importance of the different factors affecting their residential location choice, the chosen residential neighborhood's accessibility for different trip purposes, and their travel behavior such as weekly "drive alone" trips made and mode share. Simultaneous equation models are used to analyze the impact of having personalized neighborhood accessibility information along with household sociodemographic, personal preferences, and other neighborhood characteristics on participants' residential location choice and car usage. The following two chapters focus on understanding how various types of regional and political characteristics affect the effectiveness of different transportation-related policies.

Chapters 5 and 6 are used to capture the impacts of unique regional and political characteristics on travel behavior under economic policies and legal policies, and identify potential behavioral differences among subgroups of population. Chapter 5 aims to understand the differences and similarities in the factors that affect the morning commute mode shift responses of migrant and resident millennial car travelers under a three-tier congestion pricing policy and a three-tier reward policy in China. A web-based stated preference survey for Beijing's inner districts in China was designed and distributed in 2017. A multimodal online information mapping tool (MOIM) is designed to provide mode options to participants. Separate random parameters bivariate ordered probit models were estimated for migrants and residents to simultaneously examine each person's mode shift responses under the congestion pricing and reward policies.

Chapter 6 investigates the personal and societal impacts of the motorcycle full-ban policy on motorcyclists' home-to-work morning commute travel mode shift across gender and residential status categories in China. Random parameters models with heterogeneity in means and variances were estimated for each population sub-group to provide a better understanding of the impacts of a number of factors on travel mode shifts, and to ascertain whether these factors contribute similarly or differently to travel mode shifts of these population sub-groups. In addition, the changes in the out-of-pocket cost, the opportunity cost of travel time, emissions, energy consumption, and safety before and after the travel mode shifts were also estimated for each of these population sub-groups.

The last chapter (Chapter 7) summarizes insights and findings of the dissertation. The contributions, limitations, and future work are also discussed.

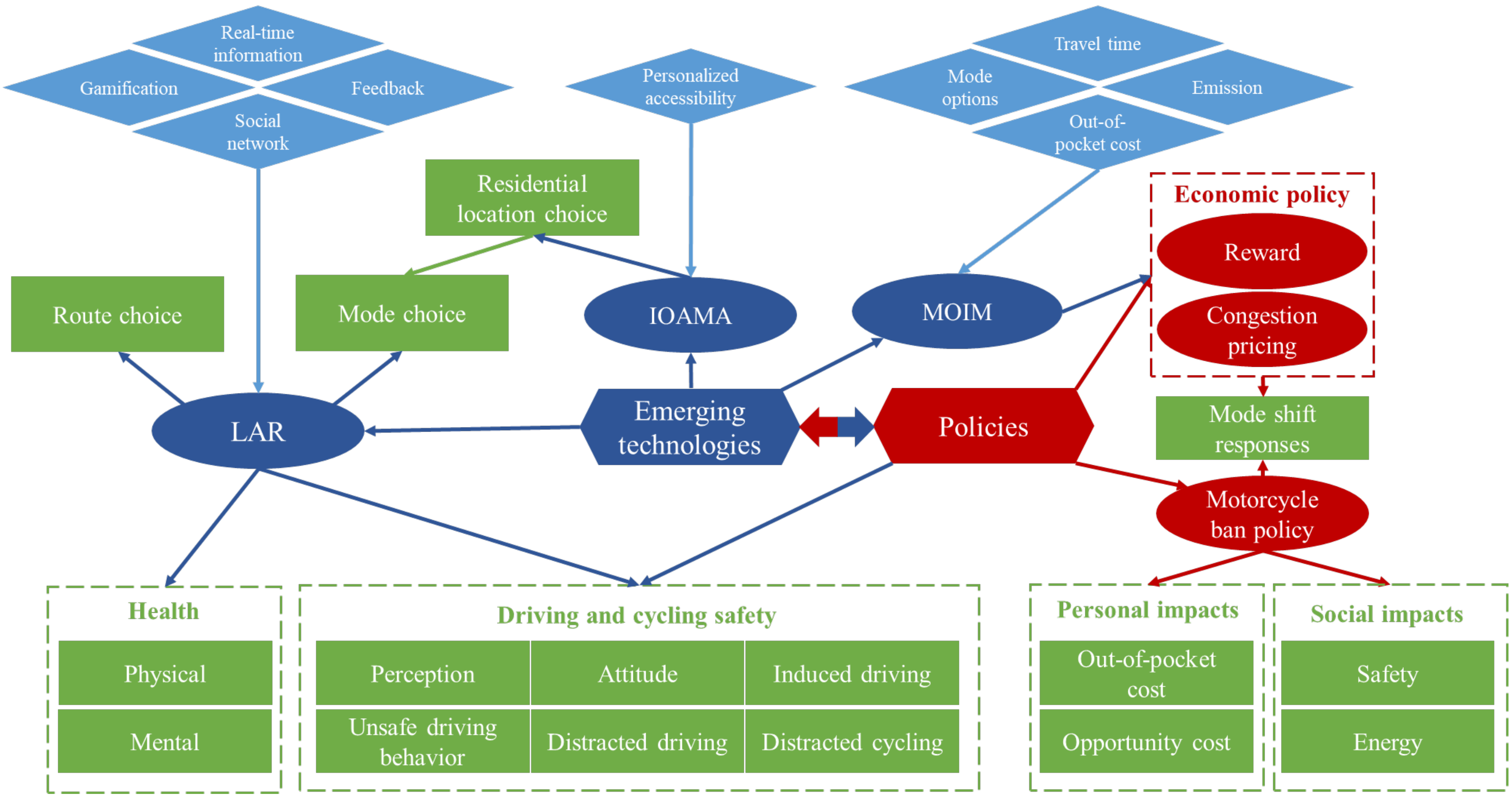


Figure 1.1 Organization of the Dissertation

CHAPTER 2. EXPLORING THE POTENTIAL FOR LAR APPS TO INFLUENCE TRAVEL DECISIONS: UNDERSTANDING THE IMPACTS OF POKÉMON GO ON ROUTE AND MODE CHOICE DECISIONS

2.1 Introduction

Recent advances in mobile technologies and the proliferation of smartphones have led to several efforts in academia and industry to design mobile apps to influence users' short- and long-term travel decisions. Table 2.1 summarizes some related studies. These apps leverage the large market penetration rate of smartphones (over 65% of the U.S. population uses smartphones) as a ready-to-use platform to deliver travel-related information and information-based feedback to users. Tracking mechanisms in these apps use mobile phone sensors such as accelerometer and global position system (GPS) to collect information on individual users' time profiles of location, physical activities, and route and mode choice decisions. Based on the collected information, these apps provide travel-related information on route and mode options for a trip, and information-based feedback on their travel decisions in terms of economic (e.g., travel time and monetary costs), health (e.g., amount of physical activity) and environmental (e.g., carbon emissions) feedback on their route and mode choice decisions. By providing such information and feedback, these apps help users to make informed route and mode choice decisions, improve awareness of travel-related environmental impacts, and foster green attitudes for making long-term mode shifts from driving alone to alternative modes. In addition, some of the apps introduce gamification, achievement feedback and social elements by introducing achievable mobility challenges (e.g., using bus instead of driving for a trip), virtual badges, points system, and leaderboard (i.e., a ranking system based on points scored among all users and/or among all online friends connected through apps) that can potentially improve app attractiveness and foster long-term sustainable mode shifts.

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions

App/study	Main functionality	Design purpose	System-level management	Gamification	Social component	Deployment and commercialization
Ubigreen (Froehlich et al., 2009)	• Semi-automatic mode detection through mobile sensing • Information-based feedback • Achievement feedback	• Improves awareness of travel-related environmental impact • Promotes sustainable mode shift	N/A	• Virtual badges • Points system (e.g., collecting points for using bus and non-motorized modes which can be redeemed for rewards)	• Social comparison (e.g., comparing badges collected or points collected) • Social competition (e.g., competing with other users for most points collected) • Social sharing (e.g., sharing personal achievements on social networks)	• 3-week field study (*N*=13) • Google play: N/A • Apple store: N/A
PEIR (Mun et al., 2009)	• Semi-automatic mode detection through mobile sensing • Carbon emissions estimation • Environmental feedback	• Improves awareness of travel-related environmental impacts	N/A	N/A	• Social comparison	• 2-month field study (*N*=20-30) • Google play: N/A • Apple store: N/A
i-Tour (Magliocchetti et al., 2011)	• Multi-modal travel-related information and navigation • Automatic mode detection through mobile sensing • Information-based feedback	• Promotes sustainable mode shift	N/A	N/A	• Information sharing (e.g., rating cleanliness of buses on certain routes)	• No field studies • Google play: N/A • Apple store: N/A

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions (continued)

App/study	Main functionality	Design purpose	System-level management	Gamification	Social component	Deployment and commercialization
Tripzoom (Broll et al., 2012)	• Automatic mobility profile creation through mobile sensing • Information-based feedback • Achievement feedback • Monetary incentives for sustainable mode shift	• Improves awareness of travel-related environmental impacts • Promotes sustainable mode shift	• System performance evaluation • Incentive program management • Mobility policy assessment	• Mobility challenges (e.g., taking bike to work instead of the bus) • Points system • Virtual badges	• Social comparison • Social competition • Social sharing	• No field studies • Google play: 100+ installs • Apple store: N/A
SUPERHUB (Carreras et al., 2012; Wells, et al., 2013)	• Automatic mobility profile creation through mobile sensing • Multi-modal travel-related information • Information-based feedback • Monetary incentives for sustainable mode shift	• Improves awareness of travel-related environmental impacts • Promotes sustainable mode shifts	• System performance evaluation • Mobility policy assessment	N/A	• Social comparison • Social sharing	• No field studies • Google play: N/A • Apple store: N/A
MatkaHupi (Jylhä et al., 2013)	• Automatic mobility profile creation through mobile sensing • Transit journey planner • Information-based feedback • Achievement feedback	• Promotes sustainable mode shifts	N/A	• Mobility challenges	N/A	• 4-week field study (*N*=12) • Google play: N/A • Apple store: N/A

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions (continued)

App/study	Main functionality	Design purpose	System-level management	Gamification	Social component	Deployment and commercialization
Peacox (Schrammel et al., 2013)	• Multi-modal travel-related information and navigation • Information-based feedback • Personalized sustainable mode shift plan •	• Improves awareness of travel-related environmental impacts • Promotes sustainable mode shifts	N/A	• N/A	• N/A	• No field studies • Google play: N/A • Apple store: N/A
IPET (Meloni et al., 2014; Meloni and di Teulada, 2015; Piras et al., 2018)	• Automatic mobility profile creation through mobile sensing • Information-based feedback • Achievement feedback • Personalized sustainable mode shift plan • Monetary incentives for sustainable mode shifts	• Promotes sustainable mode shifts	N/A	• Mobility challenges • Persuasive message in text and cartoon • Points system • Virtual badges	• N/A	• 6-day pilot test (*N*=10) • 2-week field study (*N*=28) • Google play: N/A • Apple store: N/A
ViaggiaTrento & Viaggia Rovereto Play & Go (Bordin et al., 2014; Kazhamiakin et al., 2015)	• Multi-modal travel-related information and navigation • Highlight low carbon alternatives	• Improves awareness of travel-related environmental impacts • Promotes sustainable mode shifts	N/A	• Points system • Points leaderboard and ranking • Virtual badges	• Social comparison • Social competition	• 5-week field study (*N*=36) • Google play: 1,000+ installs • Apple store: insufficient ratings

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions (continued)

App/study	Main functionality	Design purpose	System-level management	Gamification	Social component	Deployment and commercialization
Quantified Traveler (Jariyasunant et al., 2015)	• Automatic mobility profile creation through mobile sensing • Information-based feedback	• Promotes sustainable mode shifts	N/A	N/A	• Social comparison	• 3-week field study (*N*=78) • Google play: N/A • Apple store: N/A
Metropia (Hu et al., 2015)	• Driving-related information • Personalized departure time and route recommendations • Monetary incentives for following app recommendations •	• Makes informed route choice and departure time decisions • Improves system performance	• System performance evaluation Incentive program management	• Points system	• N/A	• 10-week field study (*N*=36) • Google play: 10,000+ installs • Apple store: 22 ratings
trafficO_2 (Di Dio et al., 2015)	• Multi-modal travel-related information • Information-based feedback • Achievement feedback • Monetary incentives for sustainable mode shifts	• Promotes sustainable mode shifts	N/A	• Mobility challenges for individual users and teams • Challenging other users • Points system • Virtual badges	• Social comparison • Social competition	• 4-week field study (*N*=77) • 4-week field study (*N*=245) • Google play: N/A • Apple store: N/A

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions (continued)

App/study	Main functionality	Design purpose	System-level management	Gamification	Social component	Deployment and commercialization
Waze and Waze carpool (Vasserman et al., 2015)	• Driving-related information and navigation • Information-based feedback • Achievement feedback	• Assists in making informed route choices • Vehicle sharing and ridesharing platform	N/A	• Points system • Points leaderboard and ranking • Virtual badges • Virtual avatar	• Social comparison • Social competition • Information sharing	• Google play: 100 million+ installs • Apple store: 1.6 million ratings
Google Maps / Apple Maps (Khoo and Asitha, 2016)	• Multi-modal travel-related information and navigation • Information-based feedback • Achievement feedback	• Assists in making informed travel decisions	N/A	• Virtual badges	• Information sharing	• Google play: 5 billion+ installs • Apple store: 2 million ratings
Interactive Accessibility Map (Guo and Peeta, 2017)	• Personalized neighborhood accessibility information for different travel modes	• Assists in making informed residential location choices • Promotes sustainable mode shifts	N/A	N/A	N/A	• Before-and-after field study (*N*=282) • Google play: N/A • Apple store: N/A

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions (continued)

App/study	Main functionality	Design purpose	System-level management	Gamification	Social component	Deployment and commercialization
MM (Nakashima et al., 2017)	• Automatic mobility profile creation through mobile sensing • Information-based feedback • Achievement feedback	• Improves physical health • Promotes sustainable mode shifts	N/A	• Evaluation (various images and comments) based on number of steps walked • Points system • Points leaderboard and ranking	• Social comparison • Social competition	• 2-week field study (*N*=34) • Google play: N/A • Apple store: N/A
Tripod (Azevedo et al., 2018)	• Multi-modal travel-related information • Information-based feedback • Monetary incentives for improving system wide energy performance	• Optimizes system wide energy performance	• System-level energy performance management	• Points system	N/A	• No field studies • Google play: N/A • Apple store: N/A

Table 2.1 Recent Studies on the Influence of Apps on Travel Decisions (continued)

App/study	• **Main functionality**	• **Design purpose**	**System-level management**	• **Gamification**	• **Social component**	• **Deployment and commercialization**
Apps for Lyft, Uber and DIDI Chuxing (Jin et al., 2018; Tang et al., 2019)	• Driving-related information and navigation • Information-based feedback	• Shared mobility platforms that include vehicle (car, motorcycle, scooter and bike) sharing and ridesharing	Fleet management	• Points system	• Vehicle sharing and ridesharing • Information sharing	• Google play: about 10 million+ installs • Apple store: about 4 million ratings
MUV (Di Dio et al., 2019)	• Information-based feedback • Achievement feedback • Monetary incentives for sustainable mode shifts	• Promotes sustainable mode shifts	N/A	• Mobility challenges for individual users and teams • Points system • Points leaderboard and ranking • Virtual badges • Virtual avatar • Training (e.g., providing tasks and materials to improve user understanding of the app	• Social comparison • Social competition • Social collaboration (e.g., moving with other users together by using bus and non-motorized modes for extra points) • Information sharing	• No field studies • Google play: 1,000+ installs • Apple store: insufficient reviews
Porotype app without official name (Roider et al., 2019)	• Multi-modal travel-related information • Information-based feedback • Achievement feedback • Monetary incentives for using non-motorized modes	• Improves awareness of travel-related environmental impacts • Promotes non-motorized travel	N/A	• Collecting points by using sustainable travel modes	N/A	• 2-week field study (*N*=57) • Google play: N/A • Apple store: N/A

The insights from implementing the aforementioned strategies illustrate that they influence within-day and day-to-day route choice decisions and/or reduce automobile usage (e.g., travel distance and time) during the initial implementation period, such as one month. However, they also show that these apps have limited ability to influence long-term travel decisions, such as inducing mode shifts from driving alone to alternative modes, for three key reasons. First, these apps provide personalized travel-related information in terms of route and mode suggestions when users input the origin and destination, and information-based feedback based on their subsequent travel decisions. However, most of these apps are designed from an individual user perspective. They do not allow the system operator to leverage past travel decisions of users to provide them real-time personalized incentives to dynamically influence their short- and long-term travel decisions to achieve system-level goals which can potentially benefit both users and non-users.

Second, while these apps seek to provide tangible benefits such as travel time and cost savings to users, they rarely emphasize intangible benefits such as user's sense of involvement, satisfaction and achievement. Some of these apps include gamification elements such as offering mobility challenges/tasks (e.g., "walk 3km, cycle 3km and tram 3km" in MatkaHupi or "go for a walk during your lunch break" in Tripzoom), and providing points or virtual badges for completing them, which can be used to compare scores within the app community or redeem rewards in the real world (e.g., free coffee). However, these mobility challenges/tasks can sometimes be viewed as repetitive as they always involve using one mode over the other which can reduce the app's attractiveness, and diminish user engagement over the long-term.

Third, most of these apps have information sharing, social comparison and social competition within the community (e.g., competing points scored within the community), but lack social components that provide opportunities for social interactions, cooperation, support and reinforcement among users, which can induce users to make long-term sustainable mode shifts (Abou-Zeid and Ben-Akiva, 2011; Hamari and Koivisto, 2013). In the literature (Lehto and Kukkonen, 2010; Ploderer et al., 2014), some health-related apps have already integrated such social components, and shown promising results (e.g., improving app effectiveness in promoting physical actively level increase).

Lastly, the commercialization level of some of the apps, particularly those designed to promote sustainable travel behavior, and their accessibility are relatively low based on their availability, numbers of reviews and installs provided by Google Play and App Store, the official app store for Android and iOS operating systems, respectively. Most apps have only been field-tested within a restricted pool of participants (e.g., students) and several participants have dropped out from studies even with monetary incentives for completion. This suggests that the attractiveness of most apps designed to promote sustainable travel behavior can be limited among the general population.

Pokémon GO, a LAR gaming app developed by Niantic, Inc, became the most popular mobile gaming app in U.S. history in terms of its massive daily active users (50 million at its peak in early August) after its release on July 6, 2016 in the U.S. (Allan, 2016). Though the app was created for gaming, it can potentially have profound impacts on the travel behavior of millions of users around the globe, partly due to its three features, namely location-based AR, gamification and social component.

Pokémon GO leverages augmented reality (AR) to overlay incentivizing fixed- and dynamic-location virtual objects on the map that have the potential to influence route and mode choices. It uses the smartphone's GPS to display Pokémon through AR within around 200-meter radius from the user's location. These Pokémon are dynamic-location virtual creatures (objects) that users can collect and use to interact with other such creatures in the app. They randomly spawn on the map and disappear after a few minutes. PokéStops and Gyms are fixed-location virtual objects overlaid in the real-world using AR for users to interact (within their 40-meter radius action range circle) and collect in-app benefits instantaneously. Users can accrue in-app benefits such as PokéBalls from PokéStops and Gyms. These incentivizing objects encourage users to interact with them for in-app benefits, which can synergistically lead users to change routes and modes for more in-app benefits. Gyms can also be captured by battling rival teams (three teams in total) and controlling them can provide in-game currency over time. These competitions among teams, catching Pokémon, earning virtual badges based on in-app progress, and other gaming experience and mechanisms leverage people's natural desires for mastery, achievement, status and competition in games (Hamari et al., 2014) that can provide users with intangible benefits, such as sense of involvement, satisfaction and achievement. Capturing a Gym takes relatively longer time (a few minutes) compared to interacting with a PokéStop (a few seconds), but this duration can be reduced through collaboration with users of the same team. This has the potential to encourage users to not only collaborate on app-related activities, but also on their travel plans (e.g., carpooling to a Gym and capturing it). In addition, these social interactions, along with the integration of gamification and achievement feedback, can provide intangible benefits to users for increasing the apps' attractiveness and maintaining user engagement over the long-term to reduce their dropout rate (O'Brien and Toms, 2008; Gerlich et al., 2015). Some of the PokéStops and Gyms are not reachable by car or transit, but are easy to access by walking or cycling. In addition, for safety reasons, most in-game features (such as interacting with PokéStops) are disabled if users are moving faster than approximately 20 kilometers per hour based on the authors' experience. These mechanisms encourage users to walk and ride a bike more for obtaining in-app benefits faster, leading to substantial success in terms of promoting users' physical activity (Gaziano et al., 2007; Tate et al., 2015). Despite the potential of Pokémon GO to influence route and mode choice behaviors, most existing studies focus on understanding its safety and health impacts (e.g., Wagner-Greene et al., 2017).

2.2 Survey Design, Implementation, and Descriptive Sociodemographic Statistics

This study draws on an anonymous online questionnaire-based survey the authors conducted in the U.S. between September 7, 2016 and December 12, 2016. The survey has one common section that captures participants' sociodemographic and behavioral characteristics, and two conditional sections for Pokémon GO users that capture participants' level of familiarity with and involvement in Pokémon GO, and Pokémon GO-related behaviors, respectively.

Participants were recruited based on the criteria that they are at least 18 years old and live in the U.S. at the time of completing the survey. Flyers with an online questionnaire link were placed in several businesses and educational institutions in Indiana, Kentucky, Tennessee and California, and posted on social networking services (e.g., Facebook) and online forums (e.g., Reddit). In addition, participants were also recruited by contacting employers and educational institutions in the U.S. to distribute recruitment emails. Cash incentives were offered to increase response rate. Two winners among participants who completed the survey were selected using random draws and each received 50 dollars. Participation in the survey is voluntary, and participants can end the survey at any time. The recruitment and data collection protocol were examined and approved by the Institutional Review Board at Purdue University. 1036 participants completed the survey, and 19 of them were excluded because of mismatching self-reported residence location and IP-based geolocation collected by the survey. Of the remaining 1,017 participants, 493 participants were still using Pokémon GO and 524 participants were not, based on their self-reported information.

Participants are from 41 different states in the U.S., with the top three in terms of number of participants being from Indiana (N=114), California (N=65), and Texas (N=32). Table 2.2 presents the participants' sociodemographic characteristics.

Table 2.2 Sociodemographic Characteristics of Participants

	Users	**Non-Users**
Number of participants	493	524
Gender (percentage)		
Male	54.7	54.5
Female	45.3	45.5
Age (percentage)		
25 or younger	45.9	42.7
26 ~ 35	38.0	40.2
Older than 35	16.1	17.1
Average	28.6	29.2
Marital status (percentage)		
Married	32.0	32.3
Single	64.5	61.8
Other	3.5	5.9
Education (percentage)		
Without college degree	24.7	18.5
College degree	38.4	34.6
Post graduate degree	36.9	46.8
Employment status (percentage)		
Employed full- or half-time	50.0	42.9
Student	41.2	53.2
Others	8.8	3.9
Income (percentage)		
Under $25,000	39.2	29.1
$25,000 ~ $50,000	20.0	31.5
Over $50,000	40.8	39.4
Hours of exercise per week (percentage)		
Under 2 hours	15.7	14.2
2 ~ 7 hours	61.6	63.5
Over 7 hours	22.7	22.3
Average (hours)	5.1	5.0
Residential location's levels of urbanization (percentage)		
Urban	34.7	36.8
Suburban	53.9	51.0
Rural	11.4	12.2
Licensed drivers (having a valid U.S. driver licenses) (percentage)	78.4	79.9
Have a valid U.S. driver license for 5 years or more among drivers	70.3	60.1
Drive 15,000 miles or more annually among drivers	15.3	10.6

Table 2.2 Sociodemographic Characteristics of Participants (counited)

	Users	Non-Users
Self-identified bus riders (answered "yes" to "do you ride a bus") (percentage)	33.3	25.3
Self-identified bike riders (answered "yes" to "do you ride a bike") (percentage)	34.1	52.8
Wear or carry a device that tracks steps (percentage)	43.6	45.9
Average number of steps per day before playing Pokémon GO among those with tracking device	6,727	N/A
Current average number of steps per day (after playing Pokémon GO) among those with tracking device	9,487	7,606
Average number operative automobiles per household	2.91	2.72
Average number of persons per household	2.63	2.51

Two key observations can be identified in Table 2.2. First, most participants are either single, Millennials (between 20 and 35 of age at the time of survey), highly educated (college degree or above), or work as full-time employees, and nearly half of them are Pokémon GO users. This is likely because of the voluntary nature of the survey and online survey distribution methods, and our participants represent subpopulations who have better access to Internet, have higher interest in apps, are more likely to play Pokémon GO, and/or are more likely to know someone who plays Pokémon GO, making them more likely to access and complete the survey. Second, self-identified Pokémon GO users are slightly younger, have higher percentage with marital status as single, and reported more number of steps walked everyday compared to non-users. However, as survey participants are not representative of the general population, these descriptive sociodemographic characteristics of Pokémon GO users do not reflect the differences between Pokémon GO users and non-users.

2.3 Methodology

To understand the impacts of various contributing factors (including sociodemographic and behavioral characteristics, familiarity and involvement with Pokémon GO, and app usage behavior) on seven travel decisions of interest, and to capture heterogeneity among users, seven random parameters ordered probit models (Mannering et al., 2016) are used to analyze self-reported travel decisions of users who have a valid U.S. driver's license (drivers). Table 2.3 presents aggregated statistics of these travel decisions (i.e., dependent variables) and all of them are ordered data on a 5-point Likert scale.

Table 2.3 Travel Decisions of Interest for Users who Drive, in Percentage (N = 400)

	Never	**Rarely**	**Sometimes**	**Most of the time**	**Almost always**
How frequently do you use Pokémon GO while driving? (MARKET)	25.7	28.4	27.8	9.3	8.8
How frequently do you change route for work trips to interact with PokéStops and Gyms (i.e., fixed-location virtual objects)? (WORK)	31.8	26.9	30.5	6.3	4.5
How frequently do you change route for non-work trips to interact with PokéStops and Gyms? (NON-WORK)	17.0	20.5	45.9	11.8	4.9
How frequently do you change route for catching Pokémon (i.e., dynamic-location virtual objects)? (DYNAMIC)	27.8	28.8	30.8	9.5	3.0
	Extremely unlikely	**Unlikely**	**Neutral**	**Likely**	**Extremely likely**
How likely are you to ride a bus more if Pokémon GO can provide additional in-app benefits compared to driving alone? (BUS)	27.2	28.7	17.3	20.3	6.5
How likely are you to use non-motorized modes more if Pokémon GO can provide additional in-app benefits compared to driving alone? (NON-MOTORIZED)	13.2	18.8	21.5	29.0	17.5
How likely are you to carpool more instead of drive alone for in-app collaboration (e.g., Gym battle and Pokémon hunting)? (CARPOOL)	41.7	15.5	25.0	12.3	5.5

Note: The abbreviations for these dependent variables are shown in parentheses.

The generalized ordered probit models can be formulated as follows (Washington et al., 2010):

$$y_n^* = \beta X_n + \varepsilon_n \tag{1}$$

where y_n^* is a latent variable determining the discrete ordered outcomes for each observation, n (n = 1,…, N, where $N=400$ is the total number of observations included in the model), X_n is the vector of independent variables considered affecting the dependent variable, β is the vector of estimable coefficients, and ε_n is a random error term assumed to follow a standard normal distribution.

The value of the dependent variable for observation is defined as:

$$\begin{aligned} &y_n = 1 \ \ if\ y_n^* \leq \mu_0 \\ &y_n = 2 \ \ if\ \mu_0 < y_n^* \leq \mu_1 \\ &y_n = 3 \ \ if\ \mu_1 < y_n^* \leq \mu_2 \\ &y = \cdots \\ &y_n = I \ \ if\ y_n^* > \mu_{I-1} \end{aligned} \tag{2}$$

where μ are estimable parameters or thresholds that define y_n as integer ordering converted from ordered responses, and I is the highest integer ordered response. For example, in this study, the responses to "how frequently do you use Pokémon GO while driving?" were converted to integers (e.g., never = 1, rarely = 2, sometimes = 3, and almost always or most of the time = 4).

μ and β were estimated jointly by determining the probability of I specific ordered responses for each observation n. Hence, the ordered probit model results can be presented in the form of ordered selection probabilities as follows,

$$\begin{aligned} &P_n(y_n = 1) = \Phi(-\beta X_n) \\ &P_n(y_n = 2) = \Phi(\mu_1 - \beta X_n) - \Phi(-\beta X_n) \\ &P_n(y_n = 3) = \Phi(\mu_2 - \beta X_n) - \Phi(\mu_1 - \beta X_n) \\ &\ldots \\ &P_n(y_n = I) = 1 - \Phi(\mu_{I-1} - \beta X_n) \end{aligned} \tag{3}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function.

Previous studies in the transportation domain (e.g., Christoforou et al., 2010; Zhang et al., 2014; Guo and Peeta, 2015; Guo et al., 2016a; Guo et al., 2016b) have utilized random parameters models to capture the unobserved heterogeneity present in the data. Fixing the parameters to be constant when in reality, they vary across observations, can lead to inconsistent, inefficient, and biased parameter estimates (Washington et al., 2010). By adding an error term that correlates with the unobserved factors in ε, individual heterogeneity can be translated into parameter heterogeneity as follows (Greene, 2000):

$$\beta_n = \beta + \varphi_n \tag{4}$$

where φ_n is a randomly distributed term. 200 Halton draws are used in simulated maximum likelihood estimation for random parameters ordered probit models (Washington et al., 2010).

In addition to the random parameters ordered probit models, two other types of econometric modeling approaches were considered, including those that can capture potential correlations among dependent variables and the others that are designed for a single dependent variable. Modeling approaches belonging to the former type include bivariate ordered probit (Yamamoto and Shankar, 2004), multivariate ordered probit (Hasegawa, 2010), random parameters bivariate ordered probit (Anastasopoulos et al., 2012; Russo et al., 2017) models, and modeling approaches belonging to the latter type include random parameters ordered probit with random thresholds (Fountas and Anastasopoulos, 2017), and correlated random parameters ordered probit (Fountas et al., 2018) models. Some recently developed methods such as mixed generalized ordered models (Bhowmik et al., 2019), latent class ordered probit (Fountas et al., 2018), and zero-inflated ordered probit models (Fountas and Anastasopoulos, 2018) were not considered in the study but are worth exploring in future studies.

To assess the statistical performance of two competing modeling approaches or models, likelihood ratio tests were conducted (Washington et al., 2011):

$$X^2 = -2[LL(\beta_{lc1}) - LL(\beta_{lc2})] \tag{5}$$

where $LL(\beta_{lc1})$ and $LL(\beta_{lc2})$ are the log-likelihood functions at convergence of two models. The statistical test follows a chi-squared distribution, and is defined by degrees of freedom equal to the difference in the number of estimable parameters between the competing models.

Three types of goodness-of-fit measures are also computed, including the McFadden pseudo-R^2, the Akaike Information Criterion (AIC), and the corrected Akaike Information Criterion (AICc). Models with higher values of McFadden pseudo-R^2, and lower values of AIC and AICc are considered to have better statistical fit. Table 2.4 presents the final seven models using random parameters ordered probit models based on statistical performance comparison and goodness-of-fit measures. Table 2.5 presents the *t*-statistic of independent variables in Table 2.4. Several alternative distributions for the random parameters were explored, including normal, uniform, triangular, Weibull, and lognormal. The normal distribution was found to provide the best statistical fit, which is consistent with several previous studies (Anastasopoulos, 2016; Guo et al., 2018).

Table 2.6 presents descriptive statistics of independent variables that were found to have statistically significant correlation ($t \geq 1.96$ or statistically significant at 0.95 level of confidence) in the final models. As shown in Table 2.4, based on participants' self-reported monitoring before and after using Pokémon GO, some users have already changed their primary mode of transportation for work and non-work trips because of using the app. Among those who have already switched modes, the most common mode switch is from driving alone to walking, possibly due to its added in-app benefits compared to driving alone. In addition, about 27% and 46% of users are "likely" or "extremely likely", respectively, to switch from driving alone to using bus and non-motorized modes if in-app benefits are provided for using these modes (Table 2.4). However, the app can potentially induce additional automobile usage for some users in terms of increased weekly driving distance and frequency since they may intentionally make redundant trips to play Pokémon GO to obtain in-app benefits (e.g., driving around to collect Pokéballs and Pokémon). Apart from the variables included in Table 2.4, other potential independent variables were also considered (Table 2.7).

Table 2.4 Model Estimation Results for Seven Travel Decisions of Interest (N=400)

Variable	**MARKET**	**WORK**	**NON-WORK**	**DYNAMIC**	**CARPOOL**	**BUS**	**NON-MOTORIZED**
Constant	0.040	0.145	0.219	1.181	-0.545	0.690	0.596
Familiarity and involvement with Pokémon GO							
Extremely familiar indicator (1, if user is “extremely familiar” with Pokémon GO; 0, otherwise)	0.453	0.278	0.615	--	--	0.248	--
Extremely likely to use indicator (1, if user is “extremely likely” to use Pokémon GO for the next three months; 0, otherwise)	0.176 (1.117)	0.332	--	0.264	--	-0.054 (0.527)	0.233
Pay indicator (1, if user spends “at least $10” on Pokémon GO; 0, otherwise)	--	0.082 (0.541)	0.148 (1.012)	--	0.103 (0.756)	-0.386	0.085 (0.435)
Pokémon GO usage behavior							
Pokémon GO passenger indicator (1, if user’s passenger(s) “almost always” or “most of the time” use Pokémon GO while driving; 0, otherwise)	0.437	--	--	--	--	--	--
Carpool indicator (1, if user “almost always” or “most of time” carpools to collaborate in Pokémon GO; 0, otherwise)	--	0.038 (0.054)	0.657 (1.055)	--	--	--	--

Table 2.4 Model estimation results for seven travel decisions of interest (N=400) (continued)

Pokémon GO usage behavior (continued)							
Not safe indicator (1, if user considers using Pokémon GO while driving is “definitely” or “probably” dangerous; 0, otherwise)	-1.274	-0.515	--	--	--	--	--
Should not be forbidden indicator (1, if user considers using Pokémon GO while driving should “definitely” or “probably” not be forbidden; 0, otherwise)	0.646	--	-0.203 (0.449)	0.114 (1.243)	0.147 (0.779)	--	-0.078 (1.264)
Induced driving indicator (1, if user drives around because of Pokémon GO “at least twice a week”; 0, otherwise)	0.659	0.439	0.743	0.292	--	--	--
Slow indicator (1, if user “almost always” or “most of the time” intentionally drives slower because of using Pokémon GO; 0, otherwise)	--	0.850	1.204	0.489 (1.185)	--	--	--
Walk and use indicator (1, if user “almost always” or “most of the time” uses Pokémon GO while walking; 0, otherwise)	0.751	--	--	-0.042 (0.520)	--	--	--

Table 2.4 Model estimation results for seven travel decisions of interest (N=400) (continued)

Variable	**MARKET**	**WORK**	**NON-WORK**	**DYNAMIC**	**CARPOOL**	**BUS**	**NON-MOTORIZED**
Pokémon GO usage behavior (continued)							
Driving increase indicator (1, if user considers using Pokémon GO "definitely" or "probably" increases weekly driving distance; 0, otherwise)	0.900	--	--	0.455	0.903	0.056 (1.741)	0.651 (0.757)
Walk and use is not dangerous indicator (1, if user considers walking and using Pokémon GO is "definitely" or "probably" not dangerous; 0, otherwise)	--	--	--	--	-0.350	-0.348 (0.645)	--
Walk more indicator (1, if user considers using Pokémon GO "definitely" or "probably" makes them walk more; 0, otherwise)	--	0.387	--	0.489	0.362	--	--
Healthy indicator (1, if user considers using Pokémon GO "definitely" or "probably" makes them healthier; 0, otherwise)	--	--	0.454	--	0.421	0.555	0.643
Sociodemographic and behavioral characteristics							
Male indicator (1, if user is male; 0, otherwise)	0.292	--	--	--	--	0.244 (0.917)	-0.129 (0.437)
Young indicator (1, if user is 25 or younger; 0, otherwise)	--	--	0.333	0.074 (0.715)	--	--	--
Single indicator (1, if user is single; 0, otherwise)	--	--	--	--	0.337		0.176

Table 2.4 Model estimation results for seven travel decisions of interest (N=400) (continued)

Experienced driver indicator (1, if user has a valid U.S. driver license for "5 years or more"; 0, otherwise)	0.485	--	--	--	--	--	--
Short driving time indicator (1, if user's driving distance to work is 20 minutes or less; 0, otherwise)	--	0.083 (0.077)	--	--	--	--	--
Long distance driver indicator (1, if user drives 9,000 miles or more a year; 0, otherwise)	--	--	--	--	0.153 (0.657)	--	--
Self-identified bus rider indicator (1, if user answered "yes" to "do you ride a bus"; 0, otherwise)	--	--	--	--	--	1.150	--
Self-identified cyclist indicator (1, if user answered "yes" to "do you ride a bike"; 0, otherwise)	--	--	--	--	--	--	0.461
Active indicator (1, if user exercises at least five hours a week; 0, otherwise)	0.204	--	--	--	--	--	--
Suburb indicator (1, if user lives in suburb; 0, otherwise)	0.134 (0.248)	--	--	--	--	--	--
ρ^2	0.187	0.104	0.126	0.071	0.090	0.071	0.061

Table 2.5 Random Parameters Ordered Probit Models (t-Statistics)

Variable	**MARKET**	**WORK**	**NONWORK**	**DYNAMIC**	**CARPOOL**	**BUS**	**NON-MOTORIZED**
Familiarity and involvement with Pokémon GO							
Extremely familiar indicator	3.350**	2.098*	4.530**	--	--	2.025*	--
Extremely likely to use indicator	1.353 (10.316**)	2.682**	--	2.129*	--	-0.407 (5.522**)	1.977*
Pay indicator	--	0.641 (5.337**)	1.017 (4.215**)	--	0.578 (5.308**)	-2.724**	0.605 (3.915**)
Pokémon GO usage behavior							
Pokémon GO passenger indicator	3.268**	--	--	--	--	--	--
Carpool indicator	--	0.270 (2.483*)	4.053** (7.198**)	--	--	--	--
Not safe indicator	-4.450**	-2.493*	--	--	--	--	--
Should not be forbidden indicator	3.416**	--	-1.021 (2.590**)	0.618 (6.459**)	1.152 (5.438**)	--	-0.380 (5.724**)
Frequent drive and use indicator	3.988**	2.898**	4.135**	2.793**	--	--	--
Slow indicator	--	4.300**	5.224**	2.270* (5.787**)	--	--	--
Walk and use indicator	2.908**	--	--	-0.292 (7.003**)	--	--	--

Table 2.5 Random Parameters Ordered Probit Models (t-Statistics) (continued)

Variable	MARKET	WORK	NONWORK	DYNAMIC	CARPOOL	BUS	NON-MOTORIZED
Pokémon GO usage behavior (continued)							
Driving increase indicator	5.267**	--	--	2.530*	6.191**	0.351 (9.317**)	3.886** (5.296**)
Walk and use is not dangerous indicator	--	--	--	--	-2.605**	-2.565* (8.202**)	--
Walk more indicator	--	2.350*	--	2.786**	2.023*	--	--
Healthy indicator	--	--	3.411**	--	3.005**	4.186**	5.033**
Sociodemographic and behavioral characteristics							
Male indicator	2.339*	--	--	--	--	1.968* (9.514**)	-1.064 (5.228**)
Young indicator	--	--	-2.585**	0.551 (7.138**)	--	--	--
Single indicator	--	--	--	--	2.633**		2.405*
Experienced driver indicator	3.580**	--	--	--	--	--	--
Short driving time indicator	--	0.670 (2.108*)	--	--	--	--	--
Long distance driver indicator	--	--	--	--	1.209 (6.520**)	--	--
Bus rider indicator	--	--	--	--	--	7.780**	--
Cyclist indicator	--	--	--	--	--	--	3.516**
Active indicator	2.681**	--	--	--	--	--	--
Suburb indicator	1.083 (3.423**)	--	--	--	--	--	--

Note: For a random parameter, the number shown in parentheses denotes the *t*-statistic of its standard deviation.
* Denotes the parameter is significant at 0.05 level.
** Denotes the parameter is significant at 0.01 level.

Table 2.6 Descriptive Statistics of Independent Variables (N = 400)

	Never	**Rarely**	**Sometimes**	**Most of the time**	**Almost always**
How frequently do your passenger(s) use Pokémon GO while you are driving?	10.8	10.5	47.9	14.3	16.5
How frequently do you intentionally drive slower than the traffic because of using Pokémon GO?	35.8	23.9	28.5	6.8	5.0
How frequently do you carpool to play Pokémon GO?	63.5	13.7	13.5	5.9	3.4
How frequently do you use Pokémon GO while walking?	1.0	5.5	25.7	28.2	39.6
	Extremely unlikely	**Unlikely**	**Neutral**	**Likely**	**Extremely likely**
How likely are you to continue using Pokémon GO for the next three months?	4.7	8.8	9.2	31.6	45.7
Please indicate if you agree with the following statements. Using Pokémon GO…	**Strongly disagree**	**Somewhat disagree**	**Neutral**	**Somewhat agree**	**Strongly agree**
while driving is dangerous	0.0	2.1	4.1	21.8	72.0
while driving should be forbidden	4.9	7.6	14.7	26.5	46.3
increases my weekly driving distance	46.3	19.8	6.5	18.0	9.4
while walking is dangerous	31.0	39.8	17.2	10.6	1.4
can make me walk more	2.7	9.8	7.3	30.8	49.4
can make me healthier	3.3	12.9	25.1	34.8	23.9

Table 2.6 Descriptive Statistics of Independent Variables (N = 400) (continued)

	Not familiar at all	**Not very familiar**	**Moderately familiar**	**Very familiar**	**Extremely familiar**
What is your level of familiarity with Pokémon GO?	0.0	1.8	8.0	28.4	61.8
In-game purchase					
Have not spent money	54.1				
Spent less than $10	13.1				
Spent between $10 and $100	25.9				
Spent more than $100	6.9				
Average number of days of playing Pokémon GO (standard deviation)	54.1 (10.7)				
Answered “yes” to question “have you changed your primary mode of transportation for work trips because of Pokémon GO?”	9.8				
Answered “yes” to question “have you changed your primary mode of transportation for non-work trips because of Pokémon GO?”	19.6				
Answered “yes” to question “do you drive around because of Pokémon GO at least twice a week?”	26.7				

Table 2.7 Some Other Factors that were Considered but not Found to be Statistically Significantly Correlated with Travel Decisions of Interest

Familiarity and involvement with Pokémon GO
Number of days played at the time of survey
Player level at the time of survey
Date of starting to play Pokémon GO
Pokémon GO related behavior
Motivations to play Pokémon GO
Sources of information or tips related to Pokémon GO
Smartphone operating system used for Pokémon GO
Frequency of playing Pokémon GO with people they know and strangers
Experience of playing Pokémon GO with people they know and strangers
Sociodemographic and behavioral characteristics
Self-reported location lived in at the time of survey
Average monthly temperature of the city that individual lived in at the time of survey
Educational level
Employment status
Race/ethnicity
Number of vehicles available
Annual household income
Work/school flexibility
Number of household members

2.4 Model Estimation Results

2.4.1 Impacts of Familiarity and Involvement with Pokémon GO

The model results show that "extremely familiar" users are more likely to report higher frequency of app usage while driving. Their extreme familiarity with the app in terms of app mechanics and locations of virtual objects allows them to frequently change routes based on fixed-location virtual objects for both work and non-work trips (e.g., amount of in-app benefits on each route), along with other route characteristics (e.g., travel time). In addition, such users are more likely to be willing to ride a bus if it provides additional in-app benefits. This suggests that users with higher familiarity with the app may be more susceptible to its influence in making travel behavior changes. Niantic, the developer of Pokémon GO, and online and offline communities of Pokémon GO provide numerous supplementary materials for the app such as usage tutorials and official and nonofficial moderated online forums for app information sharing and discussions that allow Pokémon GO users to improve their familiarity with the app. Such materials and online forums are often lacking in some of the apps developed for influencing travel decisions in the literature (Table 2.1) which may limit the effectiveness of such apps.

Users who reported higher willingness to engage with Pokémon GO for a relatively longer term ("extremely likely" to use for the next three months) are more likely to be influenced by potential additional in-app incentives to change their route and mode choice decisions. It suggests that retaining users by maintaining or increasing their engagement with Pokémon GO plays an important role in affecting the impacts of the app on travel decisions. This is achieved by improving game design through regular app updates to improve user experience (e.g., new Pokémon and Pokéstop), and promoting social interactions among users to improve long-term user engagement (e.g., Pokémon exchange and new Gym battle mechanisms).

The model results also suggest that users who spent "at least $10" in the app are more likely to frequently change their route choice and are more willing to use non-motorized modes if provided additional in-app benefits to enhance their app usage experience. Also, they collect more in-app benefits as they may feel more invested or engaged with the app. As shown in YouGov (2016), over 70% of Pokémon GO users do not spend any money in the app, and only around 10% of them spend over $20. However, some of these users may spend money to accelerate or bypass app mechanisms for improving their app experience rather than adjusting their travel decisions based on app mechanisms. This result is often observable in gaming apps where some users choose to improve their skill or spend time on the apps to make progress, while others choose to accomplish that by spending money (Hsiao and Chen, 2016). This illustrates the limitations of gamification; that is, some gamification features may motivate certain users to spend money and can be profitable to developers, but their influence on travel decisions of such users may be limited.

2.4.2 Pokémon GO Usage Behavior

The model results show that most users who consider that using Pokémon GO while driving should "definitely" or "probably" not be forbidden, drive around because of Pokémon GO "at least twice a week", have a valid U.S. driver license for 5 years or more, and drive 9,000 miles or more a year are more likely to frequently change their route choice decisions as they may be more comfortable with and/or are more experienced in using the app while driving. Most of these users are also more likely to be willing to carpool more instead of driving alone for in-app collaboration. In addition, users are more likely to report a higher frequency of using Pokémon GO while driving if their passengers "almost always" or "most of the time" use Pokémon GO. This illustrates that these passengers may help users play the game so that they can gather in-app benefits without compromising driving safety. For example, some users reported that they often carpool with their friends or coworkers who are also Pokémon GO players and let them play on their behalf. However, some of these users only want to use Pokémon GO while driving, and are less willing to shift to riding a bus or using non-motorized modes. Using mobile apps while driving can lead to distracted driving and potentially compromise safety. Therefore, many states in the U.S. have already forbidden cellphone usage or using apps such as Pokémon GO (Wagner-Greene et al., 2017). Therefore, it is important to ensure that the app design does not compromise safety while maintaining its attractiveness.

Users who perceive that playing Pokémon GO "definitely" or "probably" increases weekly driving distance, are more likely to report a higher frequency of change in their routes for collecting dynamic-location incentives. They are also likely to carpool to mitigate increased driving. In addition, model estimation results show heterogeneous behavior among such users in their willingness to ride a bus or non-motorized modes if provided with additional in-app benefits. It suggests that the current mechanisms used in Pokémon GO do not curb the potential induced driving demand caused by users who are hunting for incentives.

Most users who consider that using Pokémon GO while walking is "definitely" or "probably" not dangerous are more likely to be willing to shift to riding a bus if it provides additional in-app benefits compared to driving alone. Similarly, most users who "almost always" or "most of the time" play Pokémon GO while walking, are more willing to shift to bus and using non-motorized modes if additional in-app benefits can be accrued. Some of these users are not willing to change their mode even if additional in-app benefits are provided as these two independent variables have random parameters. This suggests that such users may use the app only to pass time while walking. In addition, users are more likely to be willing to change their route choice and are also likely to carpool instead of driving alone if they believe that using Pokémon GO "definitely" or "probably" makes them walk more or healthier. These results illustrate that although Pokémon GO does not directly provide health feedback, it may foster the perception of increased physical health among its users, making them more susceptible to the influence of the app in changing their route and mode choice decisions.

2.4.3 Sociodemographic and Behavioral Characteristics

The results suggest that most male users are more likely to report a higher frequency of using the app while driving and are more likely to be willing to shift to bus and using non-motorized modes if provided with additional in-app benefits compared to driving alone. This is consistent with previous studies (e.g. Lee et al., 2014) which showed that, on average, males embrace new technologies more easily, hold more positive attitudes towards them and are more attached to them; thee make males more susceptible to the influence of these technologies.

Younger adults (under 26 years of age) are more likely to report a higher frequency of route changes when responding to dynamic app features (i.e., Pokémon). Younger adults, who are millennials or post-millennials (expected to be the largest demographic group in the U.S. in 2019), are more interested in and comfortable with mobile apps compared to older generations (Hopkins and Stephenson, 2014; Owens et al., 2015). In addition, as millennials and post-millennials start aging, they will likely continue to use apps to make travel decisions, thereby impacting the travel behavior of future older generations.

Users who are single are more likely to be willing to carpool more instead of driving alone for increasing social interactions (such as spending time and socializing with friends) through in-app collaboration. They are more likely to use non-motorized modes if these modes provide additional in-app benefits compared to driving alone. This could be because users who are single are more independent and flexible in terms of making mode choice decisions.

Users living in suburbs are more likely to report higher frequency of using Pokémon GO while driving. This may be because the density of virtual objects in Pokémon GO is sparse and public transit routes are limited in suburbs, which makes using the app while walking, cycling or riding a bus less favorable compared to using it while driving. Another possible reason is that it is relatively easier to drive and use Pokémon GO at the same time in suburban areas compared to in urban areas. In addition, users whose driving distance to work is relatively short (i.e., 20 minutes or less) are more likely to report higher frequency of changing routes to work, possibly because the perceived travel time increase for changing routes for a shorter trip is relatively small. Model results also show that providing additional incentives can reinforce the benefits of riding a bus and using non-motorized modes for current bus riders and cyclists and motivates them to further reduce automobile usage. Users who are relatively active (exercise at least 5 hours a week) are more likely to use Pokémon GO while driving as they may consider that using the app while driving can be an effective way for them to enjoy the app without spending too much time on it.

2.5 Moving forward beyond Pokémon GO: Some Concluding Comments

This chapter illustrates how Pokémon GO can impact users' route and mode choice decisions by leveraging AR, gamification and social component for interactions. While the popularity of mobile apps such as Pokémon GO is based partly on their entertainment quotient, such apps also have the potential to provide a platform for leveraging the increasing ubiquity of mobile devices, the level of comfort that Millennials and generations thereafter have with technology and interactions thereof, the advances in AR and virtual reality technologies, and the emerging trend of virtual socialization to develop a new generation of incentivizing strategies to influence travel decisions that address multiple user- and system-level goals. Using the findings from model estimation results, a conceptual framework (Figure 2.1) is proposed to integrate AR, gamification and social interactions through mobile apps (hereafter referred to as "integrated apps") for influencing individual users' route and mode choice decisions, and address goals from the perspectives of both the system operator and individual users.

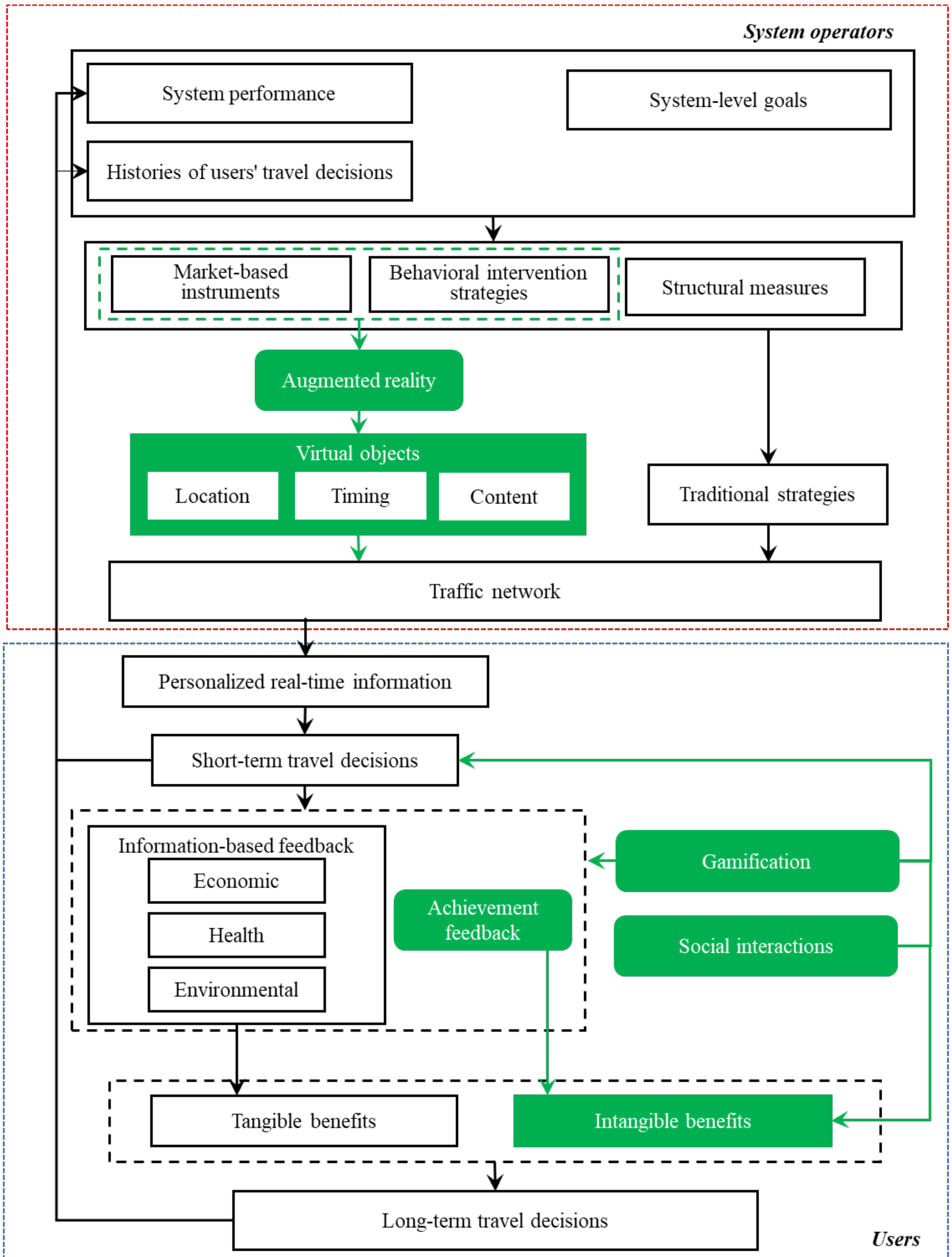


Figure 2.1 Conceptual Framework for Integrated Apps

In terms of route choice decisions, this study shows that providing in-app benefits through fixed- and dynamic-location virtual objects using AR can influence users' work and non-work route choice decisions. However, in Pokémon GO, fixed-location virtual objects are predetermined by Ingress, another app developed by Niantic, and dynamic-location virtual objects are randomly spawned around users. In the proposed integrated app framework, a system operator can leverage AR to develop low-cost app-based solutions to manage traffic in real-time, particularly during peak hours, by adjusting location, content and timing of virtual objects in the traffic network. From a practical standpoint, these capabilities of such integrated apps would be particularly attractive to transportation planning and operational agencies. Rather than relying solely on high-cost or labor-intensive physical infrastructure (for example, toll facilities or dedicated lanes), the emerging convergence of smartphone-based apps, AR-based technologies, and social platforms can provide opportunities for innovative, incentive-based solutions that are flexible, convenient and low-cost, and that further incorporate users' behaviors revealed through the app. Also, at the system level, proposing solutions that are more consistent with user behavior can potentially enhance their effectiveness in achieving networkwide goals such as enhanced traffic network performance, and reduced emissions and/or energy usage (Gärling et al., 2002). Furthermore, the use of AR is synergistic with the emerging connected and automated vehicular technologies that can seamlessly obtain information from integrated apps and perform actions based on user preferences, thereby reducing their distraction arising from interactions with the app.

Model estimation results related to mode choice decisions suggest that certain subpopulations of Pokémon GO users have carpooled frequently and are willing to carpool more instead of driving alone for in-app collaboration, and are more willing to shift from driving alone to transit and non-motorized modes if provided with additional in-app benefits. Several Pokémon GO users have already shifted from driving alone to walk for work and non-work related trips, and increased the levels of their physical activity (Table 2.4). In addition, incorporating social interactions that encourage carpooling can potentially mitigate safety concerns by distributing the driving burden and fostering collaborations in the app. This illustrates the importance of integrating gamification and social component in the proposed framework. The integrated gamification can encourage individual users to set up personal economic, health and environmental goals, monitor their progress, and acknowledge and reward their achievements upon completion of goals. For example, the app can create periodic achievement tasks for users to collect energy saving points by using transit instead of driving. In addition, gamification can enable the system operator to generate economic, health and environmental challenges for individual users that can contribute to achieving system-level goals, and encourage users to complete these goals and feel a sense of ownership in achieving them. These intangible benefits can improve the effectiveness of the app in influencing users' travel decisions. However, it may be beneficial to ensure that gamification related experiences are constantly evolving to avoid potential repetitive nature of tasks/challenges that can diminish user interest, particularly if the putative benefits to users cannot be monetized.

The social component of the proposed framework provides individual users opportunities for social interaction through their social components that include opportunities for competition (e.g., competing to reduce vehicular emissions among peers), collaboration (e.g., carpooling with peers instead of driving alone to achieve emission reduction goals), companionship (e.g., building friendship with peers who share similar emission reduction goals), and social reinforcement (e.g., obtaining support on social media by sharing achievements). Social interactions, along with the integration of gamification and achievement feedback, can provide intangible benefits to users for increasing the apps' attractiveness and maintaining user engagement over the long-term to reduce their dropout rate (O'Brien and Toms, 2008; Gerlich et al., 2015). Furthermore, social interactions foster the formation of communities that provide social support to app users to make long-term travel decisions towards usage of sustainable modes, help to spread such attitudes, and establish corresponding social norms. These tangible and intangible benefits through integrated apps provide users learning experiences to adjust their behavior and form long-term travel attitudes towards using sustainable modes that lead to achieving system-level goals.

The use of such integrated apps can also create emergent challenges such as redundant trips made by users to engage in app-related activity (induced demand) and unsafe driving maneuvers (e.g., intentionally slowing down to interact with virtual objects) which are observed among Pokémon GO users. Thus, it will be critical to address these issues through proper human-machine interface designs and in-app mechanisms, and optimal spatiotemporal distribution of incentives for making such apps safe and effective while maintaining their attractiveness.

Finally, this study has its limitations. First, with regard to the survey data collection process, the voluntary nature of and the topic of the online survey can potentially limit the types of participants as they are more likely to be either Pokémon GO users, or people who show interest in Pokémon GO or apps in general. Second, with regard to the data collected, self-reported behavioral data used in this study has its limitations which have been well-documented in the literature (e.g., Hessing et al., 1988; Langenbucher and Merrill, 2011). Without detailed sociodemographic or behavioral information from Niantic (who are not likely to release them) or in the absence of any other studies related to understanding the impact of Pokémon GO on travel behavior (to the best of the my knowledge), I cannot validate the representativeness of the sample compared to Pokémon GO users in general. Third, only data from self-identified Pokémon GO users was used to analyze the impacts of Pokémon GO on route and mode choice decisions. It is not clear if similar observations/attitudes can be found among people who do not use or are not interested in using apps such as Pokémon GO but are asked to use it. Fourth, although this study was conducted when the initial Pokémon GO excitement had passed (two months after its launch date), only the self-reported intentions can be used to evaluate potential long-term travel behavior changes because of playing Pokémon GO instead of observing such changes.

This study can be extended in several directions. First, additional studies are needed to understand the impacts of Pokémon GO on driving, walking and cycling safety, and physical and mental health. Second, to address the limitations of self-reported data, future studies can include tracking mechanisms to collect Pokémon GO users' travel decisions which can help to provide a better understanding in terms of the impacts of Pokémon GO on travel behavior. Third, a prototype integrated app can be developed to evaluate its effectiveness in influencing short- and long-term travel decisions. Fourth, the impacts of integrated apps and the apps' market penetration on network performance in a real-world context can be studied using an integrated app prototype.

CHAPTER 3. SAFETY AND HEALTH IMPLICATIONS OF LOCATION-BASED AUGMENTED REALITY MOBILE APPS

3.1 Introduction

Advancements in information and communication technologies have led to exponential growth in smartphone ownership and usage over the last decade. By the end of 2016, 77% of the United States (U.S.) adults and about 90% of Millennials (i.e., people who were born between 1981 and 1996 (Pew Research Center, 2019)) had smartphones (Pew Research Center, 2017). Smartphones have gradually become an integral part of everyday life and have profound impacts on users' decisions (e.g., what to buy and where to go) (Wang et al., 2016; Li et al., 2019). It is expected that people, particularly future generations, will spend more time on smartphones and its related technologies (e.g., smartphone apps), and will become more comfortable with them, and more susceptible to their influence (Owens et al., 2015; Comscore, 2017).

Smartphone proliferation provides great opportunities to policymakers for using smartphones as a low-cost ready-to-use platform to promote apps that can influence user travel behavior such as departure time (Guo and Peeta, 2017; Sunio and Schmöcker, 2017; Li et al., 2019). Location-based augmented reality apps (hereafter referred to as "LAR apps") have recently gained widespread attention. Such apps use augmented reality technologies to overlay interactive virtual objects with digital content (e.g., in-app benefits such as in-app items and contents) on top of real-world locations, and encourage people to interact with these virtual objects for tangible (e.g., information) and intangible benefits (e.g., enhanced user experience) based on their locations tracked via Global Positioning System (GPS), digital compass, accelerometers and other tracking mechanisms (Dirin and Laine, 2018). A recent effort by Guo et al. (2019) proposed a framework for using LAR apps that allows system operators (e.g., traffic control centers) to overlay incentivizing virtual objects in the real-world traffic network based on users' locations for influencing their route and mode choice decisions in both short- and long-term. Such apps can provide a low-cost solution to improve transportation system performance (e.g., reduced total system travel time) by reducing the need to invest in physical infrastructure.

Despite the popularity and potential benefits of LAR apps, little or no research has been carried out to investigate some key safety- and health-related issues of using such apps. First, similar to engaging in phone-related activities such as making phone calls and texting, using LAR apps to locate and interact with virtual objects while driving and cycling can increase users' safety risk exposure due to app-related distracted driving and cycling (Stutts et al., 2001; Simons-Morton et al., 2005; Stavrinos et al., 2011; Guo et al., 2017; Lin and Huang, 2017; NHTSA, 2017; Stavrinos et al., 2018). A recent study has shown that drivers that tend to be distracted by visual-manual-cognitive tasks (e.g., using apps) are 4.5 times more likely to experience crashes compared to other drivers (Higgins et al., 2017). Second, LAR apps will most likely bring new safety hazards such as app-induced driving that do not exist in other types of phone-related activities. Such apps, particularly when integrated with gamification or social components, often encourage users to drive more frequently, longer, and to different locations for gaining in-app incentives through their interaction with virtual objects (Guo et al., 2019). This app-induced driving can not only aggravate traffic congestion but also make users more susceptible to road accidents. As shown in literature, as people drive longer, the likelihood of them having accidents increases (e.g., McEvoy et al., 2006; Zhou et al., 2009; Sween et al., 2017). In addition, users may end up driving in unfamiliar areas while trying to locate virtual objects which can further heighten the risk of accidents (Dingus et al., 2016). Third, a common practice used by app developers (e.g., Niantic) to improve driving safety is to limit or disable certain app features if the detected speed is over a certain threshold. This might be counterproductive as some users may perform unsafe driving maneuvers (e.g., abrupt braking) or intentionally drive slower than the traffic to interact with LAR apps which can be more hazardous to both app users and other road users. Fourth, few studies have focused on understanding users' safety perceptions of using LAR apps while driving and cycling and opinion of prohibiting its usage while driving and cycling, if these perceptions are correlated, and what sociodemographic (e.g., gender) and behavioral (e.g., if they drive or not) factors affect them. Such perceptions can be different from the perceptions of doing other types of phone-related activities while driving and cycling which have been addressed in previous studies. Furthermore, these perceptions impact the ability to attract new users, retain current users, and user compliance with legislative regulations to limit unsafe app usage. As shown in literature (Wogalter and Mayhorn, 2005; Nelson et al., 2009), several failed legislative efforts to limit cellphone usage while driving can be partly explained by low public support due to drivers' low perceived safety risk cellphone use while driving. Thus, without addressing the aforementioned safety-related issues, using LAR apps can potentially jeopardize the safety of all road users. Last but not the least, the integration of gamification and social component with LAR apps that reward walking, cycling, and user collaboration can potentially promote physical activities and social interactions. There is ample evidence that doing these can promote physical and mental health benefits including greater longevity and reduced of chronic diseases (e.g., Type 2 diabetes) and mental illness (e.g., depression) (Krittanawong et al., 2017; Miles, 2007). However, few studies have focused on identifying factors associated with perceived increase in physical health and social interaction due to the use of LAR apps.

3.2 Methodology

Pokémon GO, the LAR gaming app chosen for the proposed case study, leverages AR to put fixed- (e.g., PokéStops) and dynamic-location (e.g., Pokémon) virtual objects overlaying in the real-world and rewards users for interacting with them (e.g., in-app items). Based on detected user moving speed (via GPS and accelerometers), the app can promote walking and cycling by rewarding users with additional in-app benefits, and discourage induced driving by disabling certain features. It has attracted massive number of users since its launch in 2016 and ranks top 10 grossing app on both Google Play and App Store (Kogan et al., 2017).

Most of the existing studies related to Pokémon GO (Kogan et al., 2017; Nigg et al., 2017; Vella et al., 2017) have been focused on understanding its potential to promote physical activity, decrease sedentary behavior, and provide opportunities for social interactions using self-reported survey data. Some studies have addressed a few safety impacts of the app usage. For example, after analyzing Tweeter postings between July 10 and 19, 2016, Ayer et al. (2016) suggested that many drivers and pedestrians were distracted by Pokémon GO. LaMagna (2016), Serino et al. (2016), and Chong et al. (2018) advised caution on using Pokémon GO while walking and driving. Barbieri et al. (2017) and Sawano et al. (2017) conducted app-related accident case studies to illustrate the increased risk of using Pokémon GO while walking and driving. Pourmand et al. (2017) reviewed 44 peer-reviewed publications related to videogame-related illness and injury alone with 17 news reports related to Pokémon GO-related injuries, and predicted the immersive experience brought by the app can potentially lead to both physical trauma as well as psychological and behavioral disorders.

3.2.1 Survey Design and Implementation

An 80-item anonymous online questionnaire was designed for this study. The survey consists of three unconditional sections for all participants and four conditional sections for some participants. The survey flow is presented in Figure 3.1.

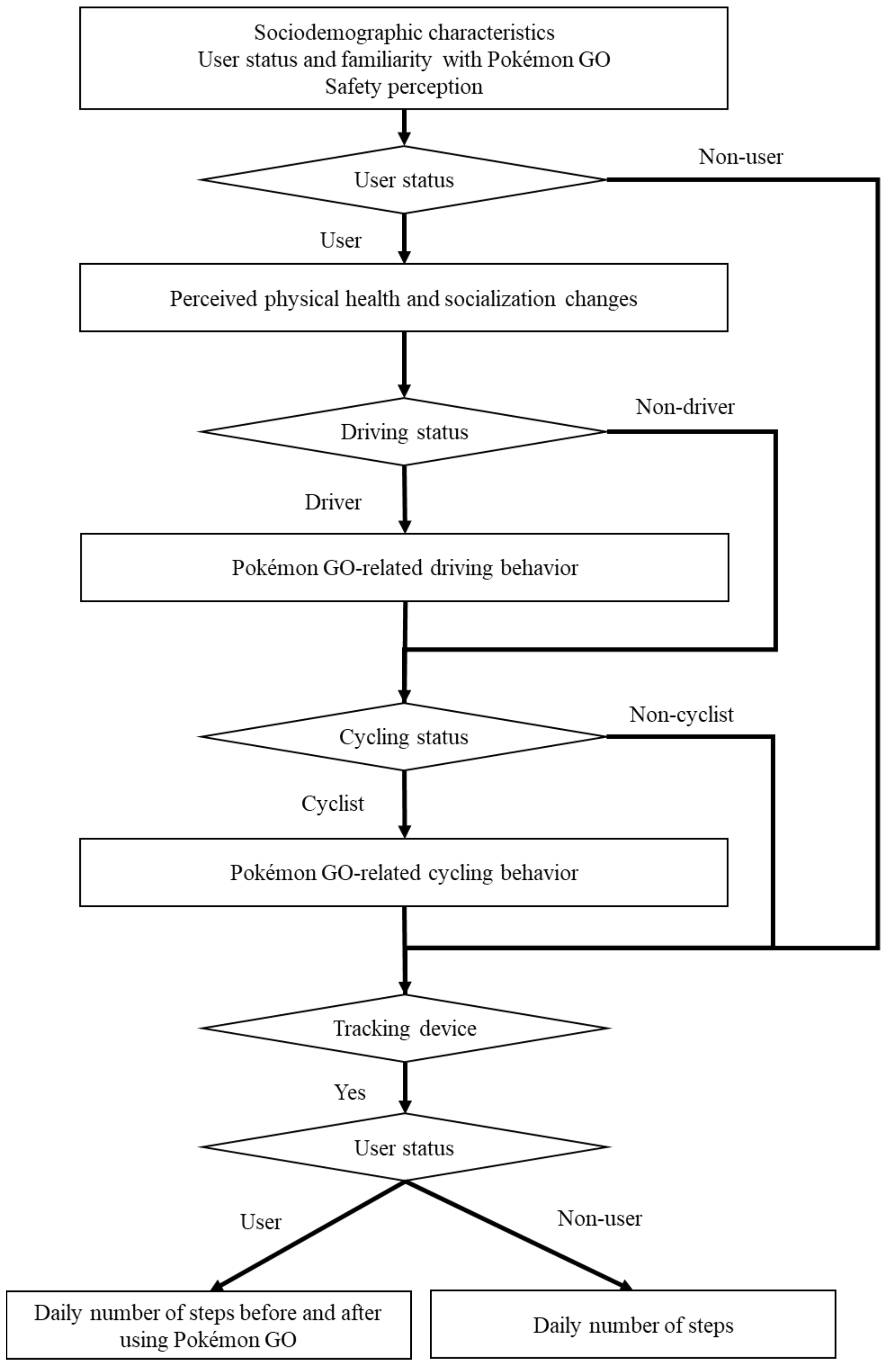


Figure 3.1 Flow of the Questionnaire Survey

The first unconditional section was composed of questions related to the participants' sociodemographic characteristics such as gender, age, marital status, residential location, household structure, driving and cycling experience, and car ownership. The second unconditional section was designed to capture participants' user status (i.e., user or non-user) and familiarity with Pokémon GO. The third unconditional section asked participants to provide their response to four safety perception-related questions including perceived risk of using Pokémon GO while driving and cycling, and their opinions on whether using it while driving and cycling should be prohibited.

Conditional sections were designed for users: users who are drivers (i.e., have a valid U.S. driver license, and hereafter referred to as "user-drivers"), users who are cyclists (i.e., reported that they ride a bike, and hereafter referred to as "user-cyclists"), or participants who wear or carry a device that tracks daily walk/run steps and willing to share the information (hereafter referred to as "participants with an activity tracker"), respectively. Users were asked questions related to how frequently they discuss Pokémon GO with friends/family and strangers, and how frequently they used the app with them, and if they agree that using Pokémon GO can make them physically healthier and socialize more in the first conditional section. In the second conditional section, user-drivers were asked to provide their app-related driving behavior such as frequency of using the app while driving, if their weekly driving distance increased because of using the app, and frequency of intentionally driving slower than the traffic to interact with virtual objects in the app. In the third conditional section, user-cyclists were asked to provide their app-related cycling behavior such as frequency of using the app while cycling.

All the questions in third unconditional section and first three conditional sections were measured on a 5-point Likert scale where 1 is "never", "definitely not risky", "definitely should not be prohibited", or "definitely no", and 5 is "almost always", "definitely risky", "definitely should be prohibited" or "definitely yes". The last conditional section was designed for participants with an activity tracker. These participants were asked to check the data from their activity tracker when they answered this section of survey. Non-users only needed to report their average daily walk/run steps for the week prior to the time of survey, while users needed to report their average daily walk/run steps for the week prior to using Pokémon GO and for the week prior to the time of survey which can be considered after using Pokémon GO. If such users used Pokémon GO for less than a week, they were asked to provide average daily walk/run steps two days prior to the survey. Apart from these relatively restricted questions, users were also given an opportunity to share their experiences related to Pokémon GO in an open-ended question which can potentially be used to explain some of the self-reported behavior and perceptions.

Participants were recruited through social networking services (e.g., Twitter) and online forums (e.g., Reddit) postings, flyer distributions, and email recruitment distributed by contacting employers and institutions. The data collection protocol was examined and approved by the Institutional Review Board at Purdue University. Participants could quit the survey at any time, and two attention check questions were included (e.g., please select the third answer for this question). Only completed surveys with correct attention check question answer were used in data analysis. 1166 completed surveys from participants (18 years old or older and living in the U.S.) from 41 states in the U.S. (Figure 3.2) were recruited between September 2016 and January 2017. Based on participants' Pokémon GO user status, they are classified into two groups, including 566 users and 600 non-users. Table 3.1 summarizes their sociodemographic and behavioral characteristics.

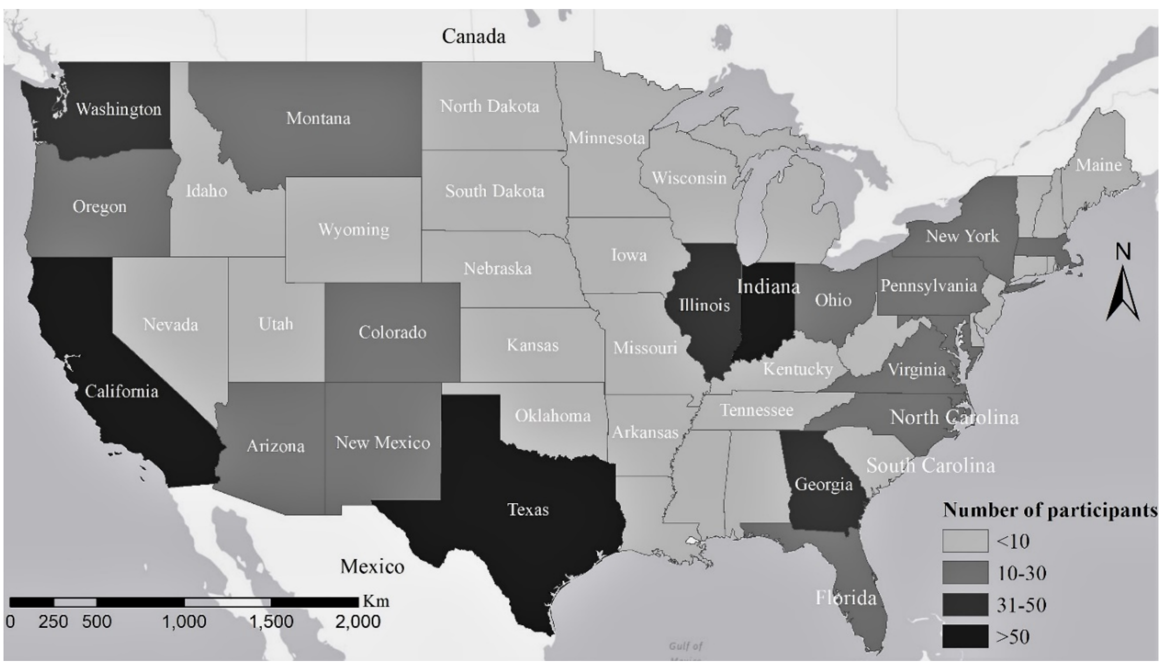


Figure 3.2 Participants' Location Distribution based on where They Took the Survey

Table 3.1 Sociodemographic and Behavioral Characteristics of Participants

	Users	Non-users
Number of participants	566	600
Gender (percentage)		
Male	54.2	51.8
Female	45.8	48.2
Age		
Post-Millennials (born after 1996)	19.1	17.1
Millennials (born between 1981 and 1996)	65.0	66.2
Generations older than Millennials (born before 1981)	15.9	18.7
Average age (standard deviation)	28.5 (9.5)	29.0 (9.6)
Marital status (percentage)		
Married	31.4	31.8
Single	65.0	62.5
Other	3.6	5.67
Education (percentage)		
Without college degree	26.1	20.2
College degree	37.8	35.5
Post graduate degree	36.1	44.3
Employment status (percentage)		
Employed full or half time	49.3	42.1
Student	41.5	54.0
Others	9.2	3.9
Household income (percentage)		
Under $25,000	38.5	41.0
$25,000 ~ $50,000	20.3	21.7
Over $50,000	41.2	37.3
Residential location's level of urbanization (percentage)		
Urban	34.3	36.3
Suburban	54.2	51.5
Rural	12.5	12.2
Drivers (percentage)	78.8	80.5
Driving experience (among drivers)		
Novice drivers (2 years or less)	13.0	15.3
2 to 5 years	17.9	24.2
More than 5 years	69.1	60.5
Annual mileage (among drivers)		
Less than 9,000 miles	57.6	65.7
9,000 to 14,999 miles	27.2	24.4
15,000 miles or more	15.2	9.9
Cyclists (percentage)	33.9	50.7
Average number of automobiles per household	2.96	2.76
Average number of persons per household	2.69	2.55
Familiarity with Pokémon GO (percentage)		
Extremely familiar	61.7	6.8
Very familiar	28.5	18.3
Moderately familiar	8.1	38.3
Not very familiar	1.7	24.9
Not familiar at all	0	11.7

3.2.2 Data Analysis

To understand factors that affect safety perception (i.e., perceived app-related driving and cycling risk and opinion of prohibiting app usage while driving and cycling), multivariate binary probit models were estimated. Such models can account for correlations in the error terms among participants' safety perceptions rather than modeling each perception separately (Greene, 2012). These models were estimated using Monte Carlo integration methods. The model details can be found in Chib and Greenberg (1998). Six separate random parameters ordered probit models were estimated using the simulated maximum likelihood method with 300 Halton draws to understand factors affecting (i) increased app-related distracted driving and cycling among user-drivers and user-cyclists (i.e., self-reported frequency of using the app while driving and cycling), (ii) self-reported increase in app-induced driving and potentially unsafe driving behavior among user-drivers, and (iii) perceived physical health and social interactions changes because of using Pokémon GO among users. These models can capture heterogeneity among subgroups of app users and the ordered discrete nature of the dependent variables. The model details can be found in Greene (2000). Multivariate binary probit models and random parameters bivariate ordered probit models were also considered for these six dependent variables. All model estimations were performed using NLOGIT 6. The selection of the final model is based on likelihood ratio tests (Washington et al., 2010) and goodness-of-fit measures (McFadden pseudo-R2, Akaike Information Criterion (AIC), and corrected Akaike Information Criterion (AICc)). In terms of average daily steps before and after using the app, subpopulation analyses were conducted to illustrate if some subpopulation groups have a larger changes because of Pokémon GO compared to other subgroups based on gender, age, marital status, driving status (i.e., driver or non-driver), automobile ownership, physical activity level before playing Pokémon GO and their involvement in Pokémon.

3.3 Safety Implications

3.3.1 Safety Perceptions related to Using the App while Driving and Cycling

Descriptive statistics of participants' perceived app-related driving and cycling risk and opinions of prohibiting its usage while driving and cycling are presented in Figure 3.3. It shows that most participants perceived app-related cycling risk to be lower compared to app-related driving risk, and more of them considered using the app while cycling should not be prohibited unlike their opinion of using it while driving. Multivariate binary probit models were estimated for these four safety perceptions to understand factors that affect these perceptions while capturing the possible correlations among them. If a participant rated his or her perceived risk as “somewhat risky” or “definitely risky”, or his or her opinion was “somewhat should be prohibited” or “definitely should be prohibited”, the corresponding dependent variables were set to one in the dataset used for model estimations; otherwise, these variables were set to zero.

Table 3.2 presents the model estimation results and a few key observations can be made. First, users perceived app-related driving and cycling risk to be lower compared to non-users, and their opinions of using the app while driving and cycling are more likely to lean towards not prohibiting its usage while driving and cycling. The differences in perception/opinion may be attributed to two underlying factors: (i) their experience with the app may provide a more informed perception/opinion, or (ii) users may be overconfidence in their ability to interact the app while driving and cycling that can lead to bias in their perception/opinion. Such differences can also be partly explained by the cognitive dissonance theory (Harmon-Jones and Mills, 1999) that people tend to seek consistency between their perception and behavior. One of them must change when there is an inconsistency to eliminate the dissonance, and in most cases, perception will change to accommodate the behavior. In our case, if a user uses the app while driving or cycling, he or she may then try to justify their action by stating or considering such behavior as less risky. Similar observations were also found in Nelson et al. (2009) and Atchley et al. (2011) in which many drivers would engage in texting and tried to justify their texting behavior by suggesting such behavior as less risky. Second, females are more likely to support prohibiting app usage while driving and cycling compared to males. This is consistent with previous findings that females are more likely to support legislations that prohibit distractions (reading and sending texts/emails) while driving or cycling, compared to males (Struckman-Johnson et al., 2015; Rudisill and Zhu, 2017; Pope et al., 2019) due to personality factors (Costa et al., 2001) or gender-based socialization (Schwebel and Barton, 2005). Third, post-millennials are more likely to perceive app-related cycling risk is lower compared to relatively older generations, and less likely to support for prohibiting app usage while cycling. Such results are consistent with previous studies (Ichikawa and Nakahara, 2008; Chataway et al., 2014; Useche et al., 2018) that younger generations perceived using cellphone while cycling are less risky. This may be partially attributable to their underestimation of the risk of serious consequences while cycling, overestimation of their cycling skills and limited ability to recognize cycling-related safety hazards. Fourth, the statistically significant positive correlation coefficients between four dependent variables suggest that all four app-related safety perceptions are positively correlated. In addition, participants' perceived safety of using the app in a specific mode (driving or cycling) has a higher correlation with their opinion of prohibiting app usage for the corresponding travel mode compared to their opinion of prohibiting app usage for the other mode, and vice versa.

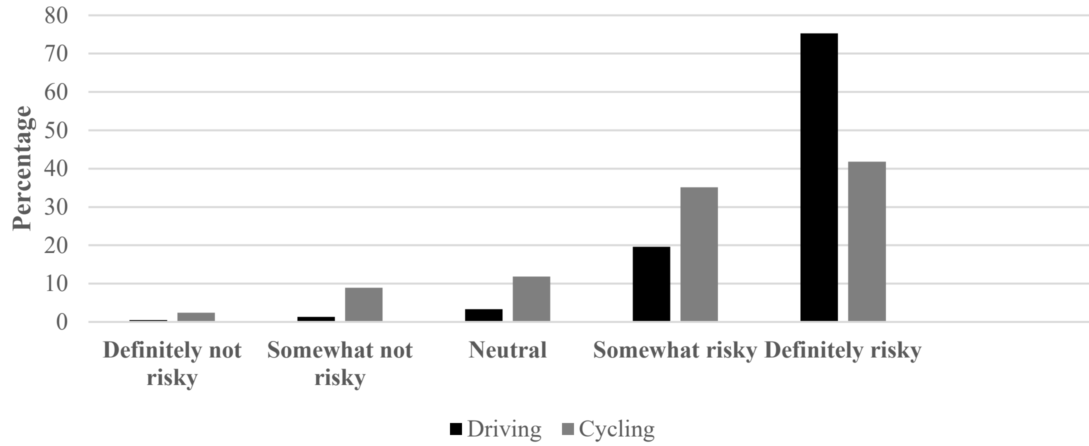


Figure 3.3a

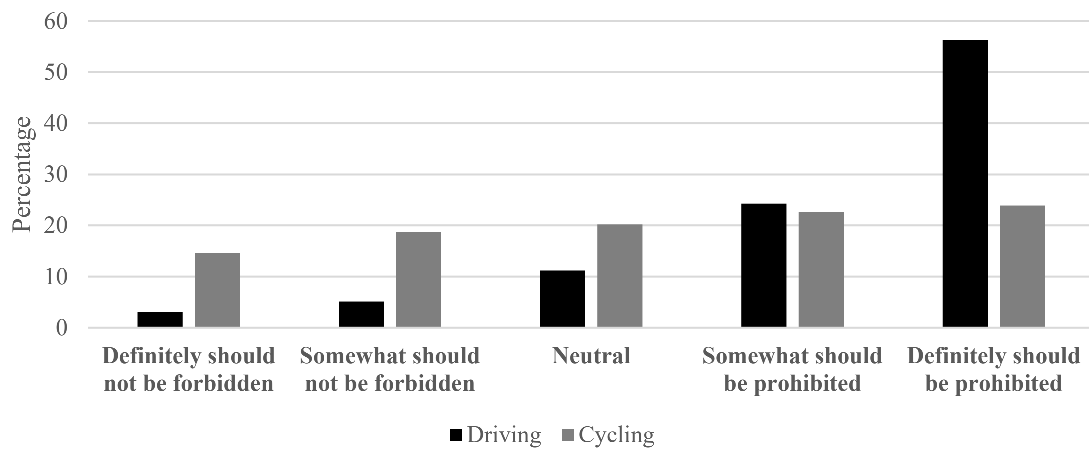


Figure 3.3b

Figure 3.3**.** Risk Perception (a) of Using the App while Driving and Cycling and Opinion of Prohibiting the App Usage while Driving and Cycling (b).

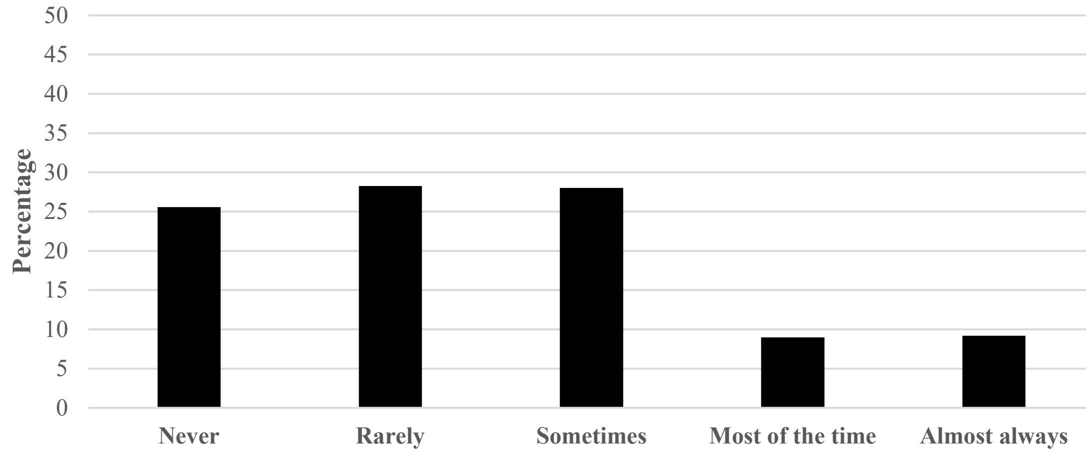
Table 3.2 Multivariate Binary Probit Model Estimation Results of Safety Perception of Using the App while Driving and Cycling (N=1166)

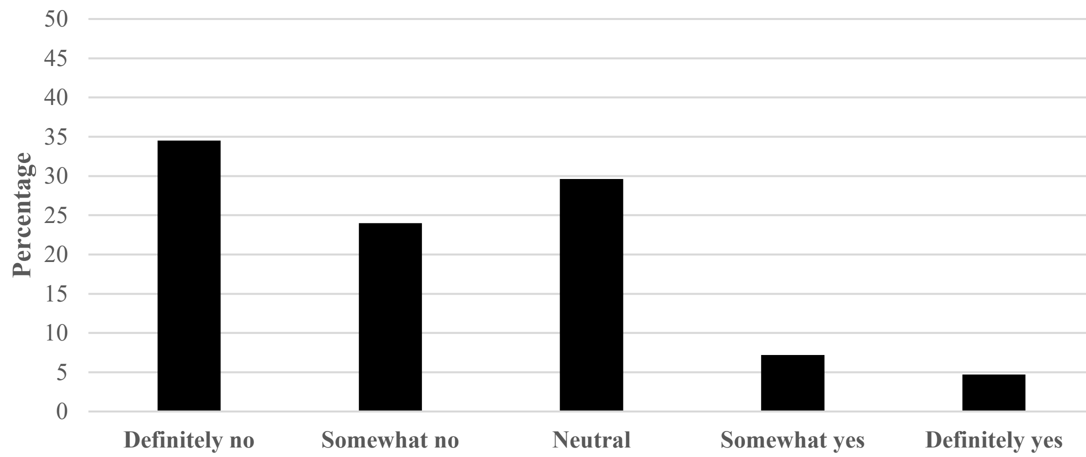
	Coefficient	*t*-statistic
RD: Risk driving		
Constant	1.64*	25.02
FD: Prohibited driving		
Constant	1.23*	14.93
User indicator (1, if participant is a user; 0, otherwise)	-0.46*	-5.52
Female indicator (1, if participant is a female; 0, otherwise)	0.21*	2.61
RC: Risk cycling		
Constant	1.40*	16.01
User indicator	-0.88*	-9.74
Post-millennials indicator (1, if participant is a post-millennial; 0, otherwise)	-0.23*	-2.27
Cyclist indicator (1, if participant is a cyclist; 0, otherwise)	-0.31*	-3.63
FC: Prohibited cycling		
Constant	0.53*	7.18
User indicator	-0.73*	-9.44
Female indicator	0.17*	2.45
Post-millennials indicator	-0.27*	-2.74
Cyclist indicator	-0.38*	-5.06
Correlation coefficient		
Rho (RD -- FD)	0.73	15.30
Rho (RD -- RC)	0.49	7.63
Rho (RD -- FC)	0.26	3.51
Rho (FD -- RC)	0.45	9.66
Rho (FD -- FC)	0.67	18.07
Rho (RC -- FC)	0.85	25.75

Note: Risk and Prohibited denote risk perception and whether it should be prohibited, respectively. Driving and Cycling denote using the app while driving and cycling, respectively.
Likelihood Ratio Test: Rho (RD -- FD) = Rho (RD -- RC) = Rho (RD -- FC) = Rho (FD -- RC) = Rho (FD -- FC) = Rho (RC -- FC) = 0: chi-square(6) = 293.55; Prob>chi2=0.0000.
* Denotes the parameter is significant at 0.05 level.

3.3.2 Self-reported App Usage Frequency while Driving, App-induced Driving and Unsafe Driving Behavior

To understand factors that affect self-reported increase in app-related distracted driving (i.e., app usage frequency while driving), self-reported increase in app-induced driving and potentially unsafe driving behavior (i.e., intentionally driving slower than the traffic) for using the app, random parameters ordered probit models were estimated for user-drivers (N=466). The descriptive statistics of three dependent variables are presented in Figure 3.4. Independent variables that are statistically significantly correlated with either of the three dependent variables ($p<0.05$) are presented in Table 3.3. Tables 3.4-3.6 present the model estimation results. Normal, uniform, triangular, Weibull, and lognormal distributions for random parameters were explored. The normal distribution was found to provide the best statistical fit, which is consistent with several previous studies for different data sets (Anastasopoulos, 2009; Guo et al., 2018). All random parameters were found to be normally distributed. As all independent variables are indicators variables, their marginal effects illustrate the estimated probability changes for each ordered outcome when it changes from zero to one while other variables are set to their estimated means (Washington et al., 2010).





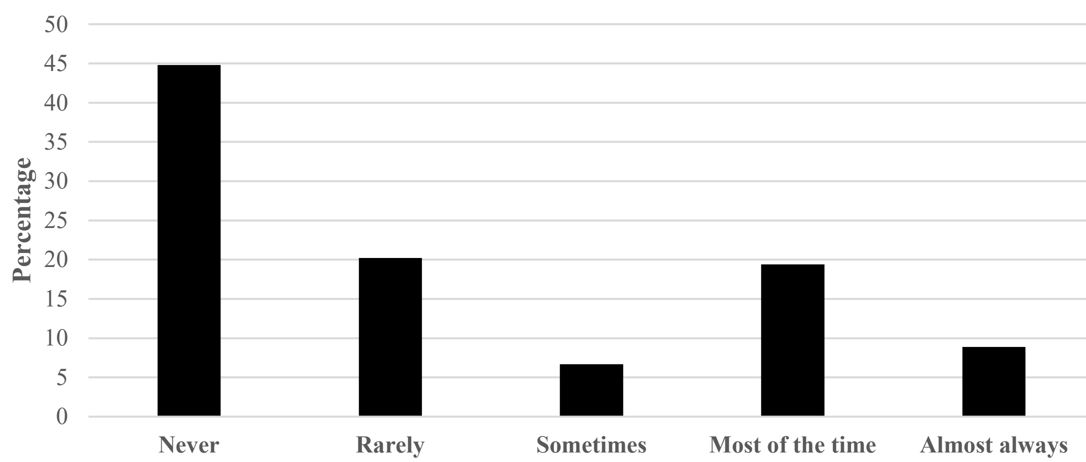


Figure 3.4c

Figure 3.4 Self-reported App Usage Frequency while Driving, Increase in Distracted Driving and Frequency of Intentionally Driving Slower than the Traffic.

Table 3.3 Descriptive Statistics of Independent Variables that are Statistically Significantly Correlated with Increase in Driving-related Risk Exposure (*N*=466)

	Percentage
App perception and usage	
App familiarity	
“Somewhat familiar”, “not very familiar” or “not familiar at all”	40.6
“Extremely familiar” or “very familiar”	59.4
Likelihood of continuing using the app for the next three months	
“Neutral”, “unlikely” or “very unlikely”	24.5
“Extremely likely” or “likely”	75.5
In-app spending	
$10 or less	70.8
More than $10	29.2
Passenger app usage frequency while driving	
“Sometimes”, “rarely” or “never”	71.2
“Almost always” or “most of the time”	28.8
Risk perception of using the app while driving	
“Somewhat risky”, “neutral”, “somewhat not risky”, or “definitely not risky”	33.5
“Definitely risky”	66.5
Sociodemographic characteristics	
Age	
Post-millennials	19.3
Millennials or older generations	80.7
Annual driving distance	
Less than 9,000 miles	59.5
9,000 miles or more	40.5

As shown in Tables 3.4-3.6, user-drivers who consider that using the app while driving is “definitely” risky are less likely to report frequent app-related distracted driving and frequent intentionally drive slower, and most of them are less likely to agree that their app-induced driving increases. However, a small portion of such user-drivers were more likely to report app-induced driving increase (about 7%) despite acknowledging its risk as this indicator variable has random parameters (Table 3.5). Such conflicting behavior suggest that despite methods focusing on improving user-driver risk awareness by providing warning messages such as “do not play Pokémon GO while driving” in the app can reduce the likelihood of increased distracted driving and potential dangerous driving behavior, it may not prevent the app-induced driving which is unique to LAR apps. This suggests that certain app mechanisms and other types of strategies should be in place to further discourage app-induced driving.

User-drivers who have high app familiarity ("very familiar" or "extremely familiar" with the app) are more likely to report higher frequency of app-related distracted driving and engaging unsafe driving behavior, and most of them are more likely to report increased app-induced driving. Their high familiarity with the app may suggest that they have better knowledge of app mechanisms (e.g., know where they can interact with virtual objects and at what speed they should drive to enable most app features) and try to leverage their knowledge to gain more in-app benefits. Some of these user-drivers (36%) are less likely to report increased app-induced driving despite of their high app familiarity. It is possible that these user-drivers may choose to ride a bike or walking more to these virtual object locations instead of driving as they may perceive riding a bike or walking can provide additional in-app benefits.

The model estimation results show that user-drivers whose passenger(s) "almost always" or "most of the time" use the app while driving are also more likely to report high frequency of app-related distracted driving, increase in app-induced driving, and high frequency of engaging unsafe driving behavior (Tables 3.4-3.6). These findings can be partly attributed to the impacts of social influence. For example, these user-drivers may observe passengers using the app to collect in-app benefits while they are driving and perceive that using the app in the car is a good way to collect in-app benefits or pass time. Such results are similar to others studies which show subjective norms (e.g., "others think I should talk on the mobile phone or texting while driving"), injunctive norm (e.g., "talking on the mobile phone or texting while driving is acceptable behavior"), observing peers or parents talking on the mobile phone or texting while driving, and other types of social influence play an important role in influencing people's intention to making phone calls or texting while driving (Riquelme et al., 2010; Carter et al., 2014). Considering that passengers and drivers may also engage in app-related conversations while both of them are using the app, this could constitute another form of distraction that could further increase the risk of user-drivers and their passengers.

User-drivers who have high likelihood of continuing app usage in near future ("extremely likely" or "likely" to use the app for the next three month), and most user-drivers who spend more money than average user (spends "more than $10" with 3-month after using the app as most of the users spend less than $10 at the time of the survey (YouGov, 2016)) are more likely to report high frequency of app-related distracted driving, increase in app-induced driving, and high frequency of engaging in potentially unsafe driving behavior. These two variables can be considered as metrics to identify likely retained users and active users, respectively. 90-day user retention rate (percentage of users returning to the app at least once within 90 days) is often used to measure the success of an app by comparing it to market average in practice (Birnbaum et al., 2015). Activities related to in-app purchases (e.g., total money spent and number of transactions compared to user average) have been used as one of several indicators to identify active users in prior studies (Hadiji et al., 2014; Runge et al., 2014; Lee and Shin, 2016). Such model estimation results suggest that likely retained user-drivers and most active user-drivers are more likely to actively seeking ways to enhance their app usage experience and collect more in-app benefits as they may feel more invested or engaged in the app. At the same time, such high app engagement may have safety implications such as high frequency of app-related distracted driving, increase in app-induced driving, and high frequency of engaging in potentially unsafe driving behavior. However, some of user-drivers who spend more money than their peers are more likely to report lower frequency of app-related distracted driving (19%), no increase in app-induced driving (32%) and lower frequency of engaging potentially unsafe driving behavior (16%). These findings may be attributed to heterogeneities in user-driver motivations of in-app spending. It is possible that some of these user-drivers may not be active users but spend money to accelerate app progress or bypass app mechanisms for improving their app experience rather than using the app more frequency or spending more efforts. It is important to note that in-app purchase is only one of several indictors (e.g., time spent and frequency of logging in) used to identify active users.

Table 3.4 Random Parameters Ordered Probit Models for App Usage Frequency while Driving (1 Being "Never" and 5 Being "Almost Always") (N=446)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	0.58	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.44*	—	—	-0.13	-0.05	0.09	0.05	0.04
Likely continue user indicator (1, if user is "extremely likely" or "likely" to use it for the next three months; 0, otherwise)	0.37*	—	—	-0.11	-0.03	0.08	0.04	0.03
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.42*(0.46*)	81.9	18.1	-0.11	-0.06	0.08	0.05	0.04
Passenger indicator (1, if user's passenger(s) "almost always" or "most of the time" use the app while driving; 0, otherwise)	0.80*	—	—	-0.26	-0.03	0.18	0.07	0.05
Risk perception of using the app while driving								
Driving-related app usage risky indicator (1, if user considers using the app while driving is "definitely risky"; 0, otherwise)	-1.01*	—	—	0.23	0.16	-0.14	-0.11	-0.13
Sociodemographic characteristics								
Student indicator (1, if user-driver is an undergraduate or graduate student; 0, otherwise)	-0.31*	—	—	0.09	0.03	-0.07	-0.03	-0.02
Short driving distance indicator (1, if user-driver drives less than 9,000 miles; 0, otherwise)	0.36*	—	—	-0.09	-0.03	0.07	0.03	0.02
Threshold 1	1.01							
Threshold 2	2.08							
Threshold 3	2.62							
ρ^2	0.27							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

Table 3.5 Random Parameters Ordered Probit Models for Self-reported Increase in App-induced Driving (1 Being “Definitely no”, and 5 being “Definitely yes”) (N=446)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	-0.24	—	—					
App perception and usage								
Familiar indicator (1, if user is “extremely familiar” or “very familiar” with Pokémon GO; 0, otherwise)	0.27* (0.71*)	64.8	35.2	-0.10	0.01	0.02	0.06	0.01
Likely continue user indicator (1, if user is “extremely likely” or “likely” to use it for the next three months; 0, otherwise)	0.51*	—	—	-0.20	0.04	0.03	0.11	0.02
App spending indicator (1, if user spends “more than $10” on the app within 3-month after using the app; 0, otherwise)	0.40* (0.86*)	67.8	32.2	-0.15	0.01	0.02	0.10	0.03
Passenger indicator (1, if user’s passenger(s) “almost always” or “most of the time” use the app while driving; 0, otherwise)	0.63*	—	—	-0.25	0.05	0.04	0.13	0.03
Risk perception of using the app while driving								
Driving-related app usage risky indicator (1, if user considers using the app while driving is “definitely risky”; 0, otherwise)	-0.50* (0.13*)	6.5	93.5	0.19	-0.01	-0.03	-0.13	-0.04
Sociodemographic characteristics								
Student indicator (1, if user-driver is an undergraduate or graduate student; 0, otherwise)	-0.27*	—	—	0.11	-0.02	-0.02	-0.06	-0.01
Short driving distance indicator (1, if user drives less than 9,000 miles; 0, otherwise)	0.45*	—	—	-0.17	-0.01	0.02	0.12	0.04
Threshold 1	0.71							
Threshold 2	1.02							
Threshold 3	2.16							
ρ^2	0.29							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

Table 3.6 Random Parameters Ordered Probit Models for Self-reported Frequency of Potentially Unsafe Driving Behavior (1 Being "Never", and 5 Being "Almost Always") (N=446)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	0.07	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.43*	—	—	-0.15	-0.01	0.11	0.03	0.02
Likely continue user indicator (1, if user is "extremely likely" or "likely" to use it for the next three months; 0, otherwise)	0.33*	—	—	-0.12	-0.01	0.09	0.02	0.01
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.48* (0.48*)	84.1	15.9	-0.16	-0.03	0.12	0.04	0.02
Passenger indicator (1, if user's passenger(s) "almost always" or "most of the time" use the app while driving; 0, otherwise)	0.75*	—	—	-0.28	0.02	0.19	0.05	0.02
Risk perception of using the app while driving								
Driving-related app usage risky indicator (1, if user considers using the app while driving is "definitely risky"; 0, otherwise)	-0.65*	—	—	0.21	0.05	-0.16	-0.06	-0.03
Sociodemographic characteristics								
Short driving distance indicator (1, if user drives less than 9,000 miles; 0, otherwise)	0.45*	—	—	-0.14	-0.04	0.11	0.04	0.02
Threshold 1	0.74							
Threshold 2	1.02							
Threshold 3	2.23							
ρ^2	0.27							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

Among variables related to users' sociodemographic characteristics, the results show that user-drivers who are graduate or undergraduate students are less likely to report high app usage frequency while driving or increased app-induced driving. This is possibly attribute to the imbalanced distribution of virtual objects as many universities often have clusters of virtual objects such as Pokémon and PokéStops. Such users do not need to drive long distance to interact with virtual objects as most of these objects can be easily access in their everyday life. User-drivers who drive relatively less (less than 9,000 miles per year) are also more likely to report high frequency of app-related distracted driving, increase in app-induced driving, and higher frequency of engaging potentially unsafe driving behavior. A possible explanation is that these user-drivers do not need to drive long distances and/or drive frequently to meet their daily travel needs before using the app (e.g., live closer to work and non-work locations), but incentives provided by the app lead them to drive to new or unfamiliar locations which may require them drive longer. It is also possible that these user-drivers are not exhausted from long-distance day-to-day travel and have more time and/or energy to drive after work/school. These results suggest the potential safety implications of LAR apps as these user-drivers driving in an unfamiliar driving environment while using the app at the same time which may lead to a higher probability of experiencing app-related accidents. As shown in previous studies, people driving in an unfamiliar environment are more likely to involve in accidents compared to driving in a familiar environment (Wilks et al., 1999; Ansari et al., 2000; Wu, 2015).

3.3.3 Self-reported App Usage Frequency while Cycling

To understand factors that affect self-reported increase in distracted cycling (i.e., app usage frequency while cycling), random parameters ordered probit models were estimated for user-cyclists (N=192). Descriptive statistics of app usage frequency while cycling among user-cyclists are presented in Figure 3.5. Over a quarter of cyclists reported that "most of the time" or "almost always", they use the app while cycling which can potentially lead to safety hazards as these users may be more likely to have demonstrated unsafe behavior (e.g., not slowing down to look both ways before crossing) and be involved in a bicycle crash compared to those who does not use the app while cycling (Goldenbeld et al., 2012; Terzano, 2013). Table 3.7 presents the independent variables that have statistically significantly correlation with app usage frequency while cycling ($p<0.05$). Table 3.8 presents the model estimation results.

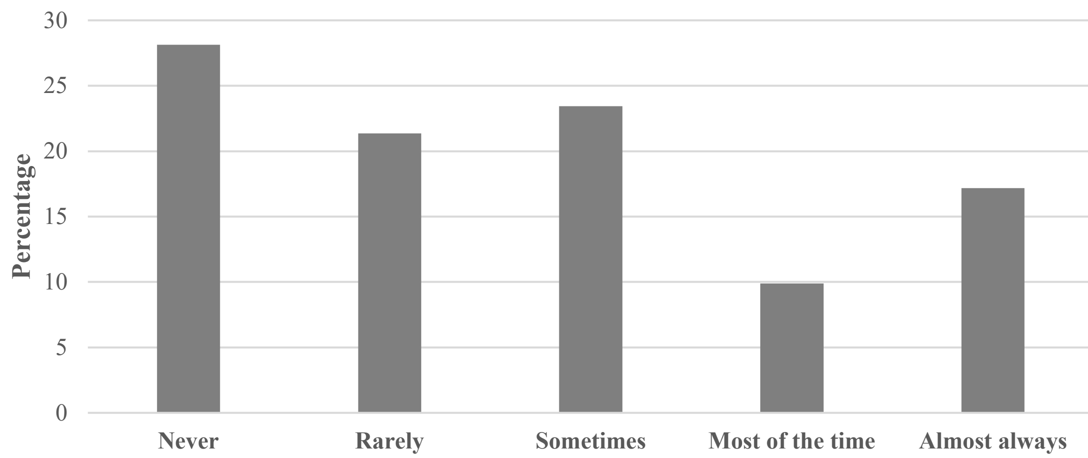


Figure 3.5 Self-reported App Usage Frequency while Driving

Table 3.7 Descriptive Statistics of Independent Variables that have Statistically Significantly Correlation with Self-reported App Usage Frequency while Cycling (N=192)

	Percentage
App perception and usage	
App familiarity	
"Somewhat familiar", "not very familiar" or "not familiar at all"	10.9
"Extremely familiar" or "very familiar"	89.1
Risk perception of using the app while cycling	
"Somewhat risky", "neutral", "somewhat not risky", or "definitely not risky"	70.2
"Definitely risky"	20.8
Sociodemographic characteristics	
Gender	
Male	62.5
Female	37.5
Living area	
Urban	32.3
Suburban or rural	67.7

Table 3.8 Random Parameters Ordered Probit Models for App Usage Frequency while Cycling (1 Being "Never" and 5 Being "Almost Always") (N=192)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	-0.71	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.71*	—	—	-0.27	-0.01	0.11	0.08	0.08
Risk perception of using the app while driving								
Cycling-related app usage not risky indicator (1, if user considers using the app while cycling is "definitely not risky" or "somewhat not risky"; 0, otherwise)	1.04*	—	—	-0.34	-0.05	0.08	0.12	0.20
Sociodemographic characteristics								
Male indicator (1, if user is male; 0, otherwise)	0.56* (0.43*)	0.90	0.10	-0.21	-0.01	0.09	0.06	0.07
Urban indicator (1, if user lives in urban area; 0, otherwise)	-0.12* (0.69*)	0.43	0.57	0.04	0.01	-0.02	-0.01	-0.02
Threshold 1	0.36							
Threshold 2	1.30							
Threshold 3	1.82							
ρ^2	0.28							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

The model estimation results show that user-cyclists who consider using the app while cycling is less risky ("definitely not risky" or "somewhat not risky") are more likely to report high frequency of app-related distracted cycling (Table 3.8). This is similar to user-drivers reporting higher frequency of app usage while driving if such users perceive it as low risk (Table 3.4). These results illustrate the importance of increasing risk awareness of using the app while cycling to reduce app-related distracted cycling. User-cyclists who have high app familiarity, like user-drivers with the same characteristics, are also more likely to report higher frequency of app-related distracted cycling.

Both male and urban indicators are random parameters which capture unobserved heterogeneity among male user-cyclists and user-cyclists who live in urban area in terms of their frequency of app-related distracted cycling. Majority of male cyclists (about 90%) are likely to report higher frequency of app-related distracted cycling compared to female cyclists. This is consistent with previous studies related to cellphone usage while cycling (Chataway et al., 2014; Ethan et al., 2016; Truong et al., 2016). Truong et al. (2016) suggested a possible explanation for such gender differences is that female cyclists who often keep their cellphones in a handbag cannot easily access their cellphones while cycling compared to male cyclists who often keep their cellphones in the pocket. Over half of cyclists (around 60%) who live in urban area are less likely to report higher frequency of app-related distracted cycling. This may be attributed to that most users-cyclists consider using the app while cycling in a more complex urban cycling environment (e.g., higher traffic on shared roads) difficult which make them less frequently to use the app while cycling. However, around 40% of such user-cyclists are more likely to use the app while cycling. This is possibly due to relatively high virtual objects density in urban areas that encourage user-cyclists to use the app more frequently while cycling despite the potential complex cycling environment.

3.4 Health Implications

3.4.1 Perceived Physical Health and the Amount of Social Interactions Changes

To understand factors that affect users' perceived physical health benefits (i.e., "do you agree that playing Pokémon GO can increase your physical health") and the amount of social interaction (i.e., "do you agree that using Pokémon GO can increase your social interactions") changes because of using Pokémon GO, random parameters ordered probit models were estimated. Table 3.9 presents descriptive statistics of both dependent and independent variables, and Tables 3.10 and 3.11 present the model estimation results.

In terms of perceived physical health changes because of using Pokémon GO, the model estimation results show that users who are more familiar or engaged with the app are more likely to perceive that using the app can promote improvement in their physical health (Table 10). It shows that familiar and engaged users (i.e., spend more in-app purchase than average users) are more likely to report more favorable perception of the app in terms of app's benefits to physical health. Users who frequently walk around just to use the app (more than six times a week on average) are more likely to agree that using the app can improve their physical health likely due to their increased walking frequency which they consider as physical health improvement. Heterogeneities exist among physically active users (exercised at least six hours a week) as majority of them (78.8%) considered using the app can improve physical health, while the rest did not. This may suggest that some of such users consider Pokémon GO-related physical activities as light exercise (Nigg et al., 2017), which may not contribute much to their overall physical health as they have already exercised a lot (averaging more than one hour per day).

Model estimation results show that users who frequently use Pokémon GO with family members, friends or strangers, or frequently carpool with other users to collaborate in the app are more likely to consider it can promote their increased social interactions (Table 3.11). These results suggest that social component in Pokémon GO for encouraging and rewarding collaborations can offer social interactions opportunities for its users to connect with family members and friends, and meet new people. The results also show that users who frequently discuss Pokémon GO with family members and friends when they are not using the app are more likely to consider it increased their social interactions. As shown in some of the stories shared by participants in the open-ended question, Pokémon GO has become a convenient conversion starter with family members and friends regardless of if they are users or not, and some participants said that the app help them to spend more time with their children and they became more open to share non-Pokémon GO stories with each other giving them a good bonding experience.

Slightly over half of users who are single stated that using the app can increase their social interactions while the rest did not. This is possible due to the heterogeneity existed among these users in terms of how they used the app. Additional studies are needed to address how social component in LAR apps affect users who are single.

Table 3.9 Descriptive Statistics of Health-related Dependent Variables and Independent Variables that Statistically Significantly Correlated with Them (N=566)

	Percentage
Dependent variables	
Do you think using Pokémon GO can make you healthier physically	
Definitely no	3.4
Somewhat no	12.0
Neutral	25.3
Somewhat yes	34.8
Definitely yes	24.5
Do you think using Pokémon GO can increase your social interactions	
Definitely no	13.6
Somewhat no	19.8
Neutral	30.7
Somewhat yes	28.6
Definitely yes	7.3
Independent variables	
How frequently do you walk around just to use Pokémon GO in a week on average	
"0-1", "2-3", or "4-5"	83.6
"6-7" or "more than 7"	16.4
How many hours do you exercise in a week on average	
Under six hours a week	63.3
Seven hours or more a week	36.7
How often do you use Pokémon GO with friends and/or family members	
"Sometime", "rarely" or "never"	69.8
"Almost always" or "most of the time"	30.2
How often do you discussion Pokémon GO-related topics with friends and/or family members when not using Pokémon GO	
"Sometime", "rarely" or "never"	76.7
"Almost always" or "most of the time"	23.3
How often do you carpool with other people to use Pokémon GO	
"Rarely" or "never"	76.9
"Almost always", "most of the time", or "sometimes"	23.1
How often do you use Pokémon GO with strangers	
"Rarely" or "never"	84.6
"Almost always", "most of the time" or "sometimes"	15.4

3.4.2 Self-reported Changes in Daily Steps

Among 1,166 participants, 496 participants with an activity tracker (240 users and 256 non-users) were included to study the impacts of Pokémon GO on users' daily steps. Non-users reported an average of 7,825 daily walk/run steps (standard deviation 5096), while users reported an average of 6,788 daily walk/run steps (standard deviation 3419) for the week prior to they started date for using Pokémon GO (hereafter referred to as "before using Pokémon GO") and 9634 daily walk/run steps (standard deviation 3961) for the week prior to the time of survey (hereafter referred to as "after using Pokémon GO") representing an over 40% increase on average. Figure 3.6 illustrates daily walk/run steps change among users before and after using Pokémon GO. Over 70% of users reported increase in number of daily steps on average after using Pokémon GO, but six participants (2.8%) reported the opposite. These six participants were given the options to share the reasons of their reduced physical activities.

A commonly cited reason is the proximity of PokéStops to their home or work location which incentive them to use the app at home or work during free time and reduced their desire to do other outdoor activities. Considering that nearly 75% of users are very likely to use Pokémon GO for the next three months, Pokémon GO could potentially have a measurable impact on these users' increase in life expectancy due to well-established health benefits of increased physical activity on reducing heart disease, stroke, Type 2 diabetes, depression, and some cancers, etc. (e.g. Sparling et al., 2000) if these users can maintain the same activity level. Based on several government agency recommendations and some studies (Tudor-Locke and Bassett, 2004; CDC, 2014; ODPHP, 2016), 8,000 steps per day is considered as the activity guideline for staying healthy, but only 21% of the U.S. adults meet this guideline (Althoff et al., 2016).

About 70% users reached the activity guideline after using Pokémon GO, compared to about 43% of them reached it before using Pokémon GO and 50.0% non-users reached it. It is also important to note that a larger percentage of participants reached physical activity guideline compared to the national average regardless of their Pokémon GO user status. This is likely because participants with an activity tracker are more health conscious and enthusiastic on average (Dennison et al., 2013), and Pokémon GO provides them a channel to have light-exercise while enjoying it at the same time. These factors may also contribute to user perceived overall physical activity increases after using Pokémon GO.

Table 3.10 Random Parameters Ordered Probit Models for Physical Health Improvement (1 Being "Definitely No" and 5 Being "Definitely Yes") (N=566)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	1.52	—	—					
App perception and usage								
Familiar indicator (1, if user is "extremely familiar" or "very familiar" with Pokémon GO; 0, otherwise)	0.29*	—	—	-0.02	-0.05	-0.05	0.03	0.08
App spending indicator (1, if user spends "more than $10" on the app within 3-month after using the app; 0, otherwise)	0.33*	—	—	-0.02	-0.05	-0.06	0.02	0.10
Walk around and play indicator (1, if user walks around just to use Pokémon GO at least 6 times a week on average; 0, otherwise)	0.57*	—	—	-0.02	-0.07	-0.10	0.01	0.19
Sociodemographic characteristics								
Active indicator (1, if user exercise at least seven hours per week; 0, otherwise)	0.24* (0.30*)	78.8	21.2	-0.01	-0.04	-0.04	0.02	0.08
Threshold 1	0.85							
Threshold 2	1.69							
Threshold 3	2.69							
ρ^2	0.26							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.

* Denotes the parameter is significant at 0.05 level.

Table 3.11 Random Parameters Ordered Probit Models for Social Interaction Increase (1 Being "Definitely No" and 5 Being "Definitely Yes") (N=566)

	Parameter estimates	Random parameters percentage of distribution		Marginal Effects				
		Above zero	Below zero	1	2	3	4	5
Constant	0.82	—	—					
App perception and usage								
High frequency of using the app with friends and family (1, if user "almost always" or "most of the time" using Pokémon GO with friends/family); 0 otherwise)	0.21*	—	—	-0.03	-0.04	-0.01	0.06	0.02
High frequency of using the app with strangers (1, if user "almost always", "most of the time" or "sometime" using Pokémon GO with strangers); 0 otherwise)	1.02*	—	—	-0.11	-0.16	-0.12	0.24	0.15
High frequency of discussing the app with friends and family (1, if user "almost always", "most of the time" or "sometimes" using Pokémon GO with friends/family); 0 otherwise)	0.41*	—	—	-0.06	-0.07	-0.02	0.12	0.04
Carpool indicator (1, if user "almost always", "most of the time" or "sometimes" carpool to collaborate in Pokémon GO; 0, otherwise)	0.68*	—	—	-0.09	-0.11	-0.05	0.18	0.07
Sociodemographic characteristics								
Single indicator (1, if user is single; 0, otherwise)	0.01 (0.18*)	52.2	47.8	-0.01	-0.01	-0.01	0.01	0.01
Threshold 1	0.75							
Threshold 2	1.69							
Threshold 3	3.10							
ρ^2	0.31							

Note: For a random parameter, the number shown in parentheses for a parameter estimate denotes its standard deviation.
* Denotes the parameter is significant at 0.05 level

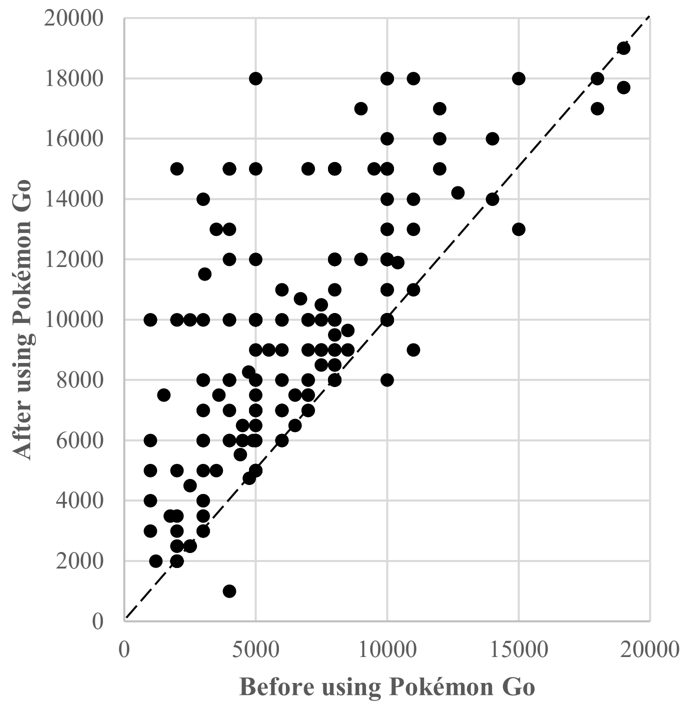


Figure 3.6 Self-reported Steps/day before and after Using Pokémon GO

Additional tests were performed to examine whether certain subpopulations among users experienced a larger increase in daily steps compared to other subpopulations. Gender, age, marital status, driver or non-driver, automobile ownership, physical activity level before playing Pokémon GO and involvement in Pokémon GO were the criteria used to specify different subgroups. The main observation identified is that users, who are female (46.4% increase), millennials or younger (44.3% increase), single (44.0% increase), drivers (45.4% increase), have more than two cars (46.9% increase), have higher engagement level (spending at least $10 on in-game purchase) (51.2% increase), or had physical activity level below the activity guideline (75.8% increase), experienced a larger increase in daily steps after using Pokémon GO compared to their counterparts. It is important to note that such subgroup comparison does not suggest the independency among these groups, and additional studies are needed to provide a better understanding in terms of factors contributing to physical activity increase associated with Pokémon GO usage.

3.5 Discussions and Conclusions

As smartphones and apps are more and more integrated into people's daily lives, several efforts have been made recently to use location-based AR-driven apps for changing travel behavior, gaming, education, tourism, etc. These apps can provide digital content to users by overlaying interactive virtual objects with information on users' real-world locations through smartphones based on their locations. Users are often encouraged to frequently interact with virtual objects for in-app benefits by changing their real-world locations. These unique features differentiate LAR apps from other apps and have the potential to change users' behavior. However, using such apps can have safety implications when users are using the app to locate and interact with virtual objects while driving or cycling as they are physically and cognitively distracted from their primary task (driving or cycling). In addition, some users may increase their driving distance to collect more in-app benefits and/or engage in unsafe driving maneuvers such as intentionally driving slower than the traffic to bypass speed-limitation based regulatory app mechanisms. These potential safety hazards are relatively unique to LAR apps and may not exist in many other cellphone/smartphone-related activities such as making phone call and texting which are the primary focuses of most previous studies. Furthermore, gamification and social component that often exist in LAR apps also can potential have health implications such as improving physical health and increasing social interactions. To provide a better understanding of LAR apps' safety and health implications, this study uses Pokémon GO, a LAR gaming app, as a case study to understand the safety perception and self-report app usage behavior of LAR apps while driving and cycling, including frequency of app-related distracted driving and cycling, self-reported increase in app-induced driving and potentially unsafe driving behavior, perceived physical health and social interactions changes, and factors that attribute to these behavior and perception.

The results show that most people understand the risk of using LAR apps while driving and agree such app usage should be prohibited while driving. However, many users reported increase in app-induced driving despite acknowledging its risk based on model estimation results. It is also important to note that many user-drivers still reported app-related distracted driving and dangerous driving maneuvers despite acknowledging its risk. These results show that improving user risk awareness of using the app while driving can reduce likelihood of app-related distracted driving and dangerous driving maneuvers, but additional app mechanisms are still needed to further reduce increased app-induced driving. Possible app mechanisms can include (i) using the concept of diminishing returns (Thornton and Francia, 2014) by reducing the in-app benefits received as the total number interactions with virtual objects increase within a given period to reduce the attractive of making redundant trips and increasing driving distance by making such trips less rewarding; (ii) utilizing multiple communication systems (e.g., identifying if the smartphone is connected with vehicle's Bluetooth) to detect whether users are driving rather than relying only on moving speed to detect it. This can potentially make actions such as intentionally driving slower than the traffic for interacting with virtual objects less feasible; and (iii) promoting the usage of LAR apps in a relatively safer environment such as using it on a bus or ridesharing services by providing additional in-app incentives for using these modes instead of limiting or prohibiting most of app features if the detected moving speed is over a threshold. These mechanisms can potentially reduce app-related distractions and likelihood of making unsafe maneuvers without compromising the apps' attractiveness. Additional studies are needed to further evaluate the effectiveness of the proposed mechanisms.

Most people stated that using Pokémon GO are less risky while cycling and reported higher frequency of app-related distracted cycling compared to frequency of app-related distracted driving. These results may raise concerns related to potential high exposure to app-related cycling risk. As many recent studies (Byington and Schwebel, 2013; Ethan et al., 2015; Tate et al. 2015) have shown, distracted cycling can lead to reduced attention to traffic, increased injury risk and likelihood of performing risky behavior. To address the potential app-related distracted cycling, efforts can be made to (i) promote safety awareness of using the app while cycling such as pushing in-app safety awareness messages and launch public awareness programs; (ii) provide technology-based and app mechanism-based solutions such as promoting the usage of bicycle electronic device holders (Mwakalonge et al., 2014) or cellphone armbands and offering hand-free options to collect in-app benefits automatically while cycling; and (iii) introduce legislation to prohibit or limit using hand-held devices while cycling. As several states have prohibit using hand-held devices while driving, the safety awareness related to using hand-held devices while cycling is low and relevant legislations are relatively sparse.

In terms of potential health impacts of using LAR apps, the results illustrate their mechanism for rewarding physical movement and integrated social component for collaboration can potentially motivate users to go outside and exercise or walk more, especially for users who are under the recommended daily physical active level, and foster interactions with friends, family members, and other users whom they may not have opportunities to interact with.

Finally, this study is not without its limitations. First, the voluntary nature of and the topic of the survey, and its online delivery method can potentially limit the types of participants to people who have internet access and may already have interest in LAR apps or Pokémon GO. Second, the analysis was conducted using self-reported behavioral data which has its limitations such as social desirability bias (i.e., answer questions in a manner that will be viewed favorably or positively by others) (Langenbucher and Merrill, 2011). Third, the study sights were drawn from one LAR app, Pokémon GO. Future study can potentially include other LAR apps designed for non-gaming purpose to provide additional insights on the safety and health implications of LAR apps.

The study findings and insights can aid transportation planners and app designs to design LAR app-related policy and app mechanisms while factoring the potential safety- and health-related implications associated with using such apps. An extension of this study can be to compare user-driver performance (e.g., response time) while they are engaging LAR apps to their performance while doing other phone-related activities in a realistic or simulated driving environment. This can potentially address the limitations of stated preference survey and self-reported behavioral data used in this study. This study can also be extended to other LAR apps to validate the findings of this study. Another research direction can be studying the long-term impacts of LAR apps on users' physical activity level and social interactions by observing a group of LAR app users.

CHAPTER 4. IMPACTS OF PERSONALIZED ACCESSIBILITY INFORMATION ON RESIDENTIAL LOCATION CHOICE AND TRAVEL BEHAVIOR

4.1 Introduction

Due to the challenges associated with ever-increasing road congestion, automobile dependency, urban sprawl, and pollution, there is a critical need to develop effective strategies for changing people's short- and long-term travel decisions that can foster more sustainable travel behavior by reducing automobile usage and increase the usage of sustainable travel modes such as walking, riding a bicycle, and using public transit (hereafter referred to as "walk, bike, and transit modes"). Travel-related decisions are often made across a broad spectrum of time, from the short term to the long term. With regard to the short term, people make decisions on parking options (e.g., free street parking or reserved parking structure) and non-work destinations (e.g., grocery shopping and restaurants). Choice of travel mode may be a day-to-day decision, while route choice can be spontaneous. One the other hand, in the long-term, individuals decide on their residential location, vehicle ownership, whether to make life-style changes, and employment. Despite the broad range of time frames, current information intervention strategies, which use transportation information to influence travel decisions, focus on the short-term end of the spectrum (Peeta and Mahmassani 1995; Paz and Peeta 2009). For example, real-time information on current roadway congestion and transit service schedules (Emmerink et al. 1995; Lam and Chan 2001; Kenyon and Lyons 2003; Ben-Elia and Shiftan 2010) can be relevant to the day-to-day mode and route choices but will rarely affect decisions made over longer time frames.

Information intervention strategies have been identified by researchers and policy-makers as an effective solution to address aforementioned car-related challenges by providing information to travelers and making them more informed on short- and long-term travel decisions (Kenyon and Lyons 2003; Rodriguez and Rogers 2014). An information intervention strategy designed to improve the sustainability of travel behavior would ideally work along the full time-scale range, particularly since longer-term choices frequently constrain the shorter-term options. For example, if an individual chooses a residence with relatively low transit accessibility, he/she is less likely to use transit mode and more likely to use a private vehicle to travel (hereafter referred to as "car mode"). Yet not enough is known about designing such information, the impact of such information on decisions at varying time scales, or the impact of longer-term decisions on those made over the shorter term. Strategies based on up-to-the-minute transportation information, while desirable for multiple reasons, have demonstrated limited ability to significantly alter travel behavior, especially for habitual travel behavior (e.g., mode choice), towards a more sustainable direction (Chorus et al. 2006; Guo 2011; Zhou 2012; Andersson et al. 2018).

The objective of this study is to design personalized neighborhood accessibility information for intervention strategies to influence the residential location decision-making process and foster formation of more sustainable travel behavior after relocation. Relocators (people who change their residence from one city to another) are used to evaluate the effectiveness of the personalized neighborhood accessibility information because they make more long- and short-term travel decisions that can be observed compared to the general population. As shown in the literature (Matthies et al. 2002), while travel decisions, in principle, can vary on a day-to-day basis (e.g., driving to work versus using transit), they are more often habitual and are rarely meaningfully reconsidered (e.g., most people know which mode they want to use for work without reconsidering each time they leave home for work). When people relocate, however, they are more likely to form a new set of habits (Rodriguez and Rogers 2014) which makes relocation the ideal time for providing such information to potentially foster more sustainable travel behavior. We develop an Interactive Online Accessibility Mapping Application (IOAMA 2015) to provide personalized accessibility information. Neighborhood accessibility quantifies the ability to access different services and opportunities from a neighborhood using the available transportation modes (Guo et al. 2016b). Potential users are prompted to input their work locations and assign weights to six different trip purposes, including work, healthcare, social or recreational, restaurants, education, and retail or grocery shopping. Based on the work location and the assigned weights for each trip purpose, the IOAMA provides personalized neighborhood accessibility information for four transportation modes (walk, bike, transit, and car). This information manifests itself in the participants' ability to visualize five personalized accessibility levels for each mode ranging from 1 (very low accessibility) to 100 (highest accessibility). To evaluate the effectiveness of the designed information, an experiment was designed and administered to a sample of participants selected from people relocating to Tippecanoe County in Indiana U.S. in 2014. These participants were randomly allocated to an experimental group or a control group. The experimental group participants were provided access to IOAMA to assist in their residential location and travel-related decision-making process, while those in the control group did not have access. Statistical analysis was carried out to determine whether there are statistically significant differences between the experimental and control group participants in terms of their perceived importance of different factors affecting their residential location choice, the chosen residential neighborhood's accessibility for different trip purposes, and their travel behavior such as weekly "drive alone" trips made and mode share. Simultaneous equation models were used to analyze the impact of having personalized neighborhood accessibility information along with household sociodemographic, personal preferences, and other neighborhood characteristics (such as school district, tax rate, and crime rate) (Prashker et al. 2008; Lee and Waddell 2010; Pinjari et al. 2011; Guo et al. 2017; Guo et al. 2018; Searcy et al. 2018) on participants' residential location choice in terms of neighborhood accessibility, and car usage in terms of weekly driving time (minutes/week).

The remainder of this chapter is organized as follows. Section 2 reviews previous studies on understanding the impacts of information on residential location choice and travel behavior. Section 3 discusses the proposed experimental design and implementation, and the methodological underpinnings of IOAMA. Section 4 discusses the statistical analysis and model estimation results of the experiment and the impacts of the accessibility information on the relocators' residential location choice and travel behavior. Section 5 provides some concluding comments.

4.2 Literature Review

4.2.1 Information and Residential Location Decision-making Process

Traditionally, the residential location decision-making process has been studied under the assumption that individuals have complete information about the available choices in their residential location selection process and have ability to process such information (e.g., Muth 1969; Hechter and Kanazawa 1997). Individuals choose their residence by comparing available options and performing trade-offs among different factors that contribute to their residential location decision-making process. Four key categories of contributing factors that influence the residential location decision-making process have been identified in previous studies (e.g., Prashker et al. 2008; Lee and Waddell 2010; Kortum et al. 2012), including a property's physical characteristics, neighborhood environment, transportation accessibility, and decision-maker sociodemographic and preference. Previous studies have shown that transportation accessibility-related factors, including work commute time, distance (e.g., Molin et al. 1999; Zondag and Pieters 2005; Bayoh et al. 2006), and costs (e.g., Anas 1985), are important factors that affect the residential location choice. However, several recent studies (Palm and Danis 2001; Schwanen and Mokhtarian 2004; Chorus et al. 2006; Simonsohn 2006; Rodriguez and Rogers 2014) suggest that people may not have complete accessibility-related information (e.g., commuting times) and/or the ability to process it, particularly for relocators from other cities. For example, it can be difficult for people to quantify the level of access for each neighborhood despite knowing the locations of their potential destinations through information sources, such as Google Maps. Hence, relocators tend to experience longer average commute times and higher automobile dependency after relocation compared to long-time residents. In addition, some relocators often have to move a second time within the city partly due to the mismatch between their preferred and actual commute times from their initial residence as they become more familiar with the city, which may be a heavy social and financial burdens on relocators (Simonsohn 2006).

4.2.2 Residential Location and Travel Behavior

Many studies have shown that there is a strong correlation between residential location and travel behavior. Handy et al. (2005) found that relocators' changes in their neighborhood built environment (e.g., accessibility and land use mix) before and after relocation were significantly correlated with their driving behavior changes in the same time span. Bhat and Guo (2007) developed a methodological framework and showed that the neighborhood built environment is an important factor affecting both residential location choice and car ownership decisions. Choocharukul et al. (2008) analyzed a sample of 176 relocators in Thailand and concluded that those with frequent car use were less likely to choose a neighborhood with convenient public transportation. Ewing and Cervero (2010) performed a meta-analysis of the residents' residential neighborhood built environment and their travel behavior, and determined that accessibility and street network design had a strong correlation with vehicle miles traveled. They also identified the residents' residential land use diversity, intersection density, and the number of destinations within walking distance as having a strong correlation with their number of steps walked per week. Cao et al. (2010) identified transit access and neighborhood safety as having a strong impact on vehicle-miles driven. Majid et al. (2014) analyzed the correlation between housing development designs and vehicle-miles traveled in Iskanda, Malaysia, and concluded that housing density, accessibility, and diversity had a strong influence on vehicle-miles traveled. Macfarlane et al. (2015) explored the relationship between relocators' historical exposure to the built environment and their vehicle ownership after relocation and found that those who have previously lived in a high-density area or had been exposed to non-motorized modes (walk and bike) were more likely to have low vehicle ownership rates. They also suggested that planners should consider policies or strategies that can increase land use density and provide non-motorized alternatives (e.g., bike sharing programs). Rodriguez and Rogers (2014), using a group of undergraduate and graduate students in their experiment, studied the potential for providing rental properties' generalized accessibility information such as distance to campuses, shopping malls, and bus stops to influence their rental property choices. The results showed that students with accessibility information choose to rent an apartment closer to campus and travel less using cars compared to those without information. However, the types and amount of accessibility information provided were limited and not personalized. Also, results using a student population may not be transferable to the general population due to their sociodemographic and travel needs differences, and the decision-making process of renting can be very different from that of buying a residence.

To address these limitations, this study provides designed personalized accessibility information to relocators and investigates its potential to influence their residential location choices and travel behaviors in an experiment that includes the following: (i) accessibility information provided to users is personalized accessibility information based on their travel needs and mode choice through the IOAMA developed by the authors, and (ii) the experiment is implemented for the general population, and participants could choose to rent or buy from various residential types. The next section describes the experimental design and implementation, the methods used to create the IOAMA, and the modeling methods used to study the impacts of the interactive accessibility information intervention strategy on residential location choice and travel behavior.

4.3 Methodology

4.3.1 Experimental Design Framework

Figure 4.1 illustrates the experimental design, which had two phases: Phase I (before the participants made their residential location choice) and Phase II (three months after the participants relocated). In Phase I, a pilot test with ten participants was conducted for improving user experience of IOAMA and maximizing the study attractiveness to potential participants. A group of participants were recruited from individuals relocating to Tippecanoe County (referred to as “relocators” hereafter). Tippecanoe County is in the northwest quadrant of Indiana, with about 170,000 people in 2010 (U.S. Census Bureau 2010). It consists of 13 townships and two cities (Lafayette and West Lafayette). Over 60% of its population is in Lafayette (38.9%) and West Lafayette (24.2%).

Participants were recruited by contacting employers in the Tippecanoe County area to distribute recruitment emails in Spring 2014 to their newly hired employees who would start work in Fall 2014, which ensured an adequate sample of relocators and a higher chance that the personalized accessibility information was given to participants before they made their residential location choice. Participation in the study was voluntary and participants were able to quit at any time. Participants were randomly assigned to a control or an experimental group. The experimental group participants were given password-protected access to the IOAMA designed to assist their residential location decision-making processes while control group participants did not receive this information.

In Phase I, a pre-relocation survey (Pre-relocation survey for control group 2014; Pre-relocation survey for experimental group 2014) was conducted in Spring 2014 for each group to obtain information related to the participants’ self-reported current residence, residential location choice preference and travel behavior before relocation, and other sociodemographic characteristics. The IOAMA information was only available in the survey given to the experimental group participants which was the only difference in the pre-relocation surveys received by both groups.

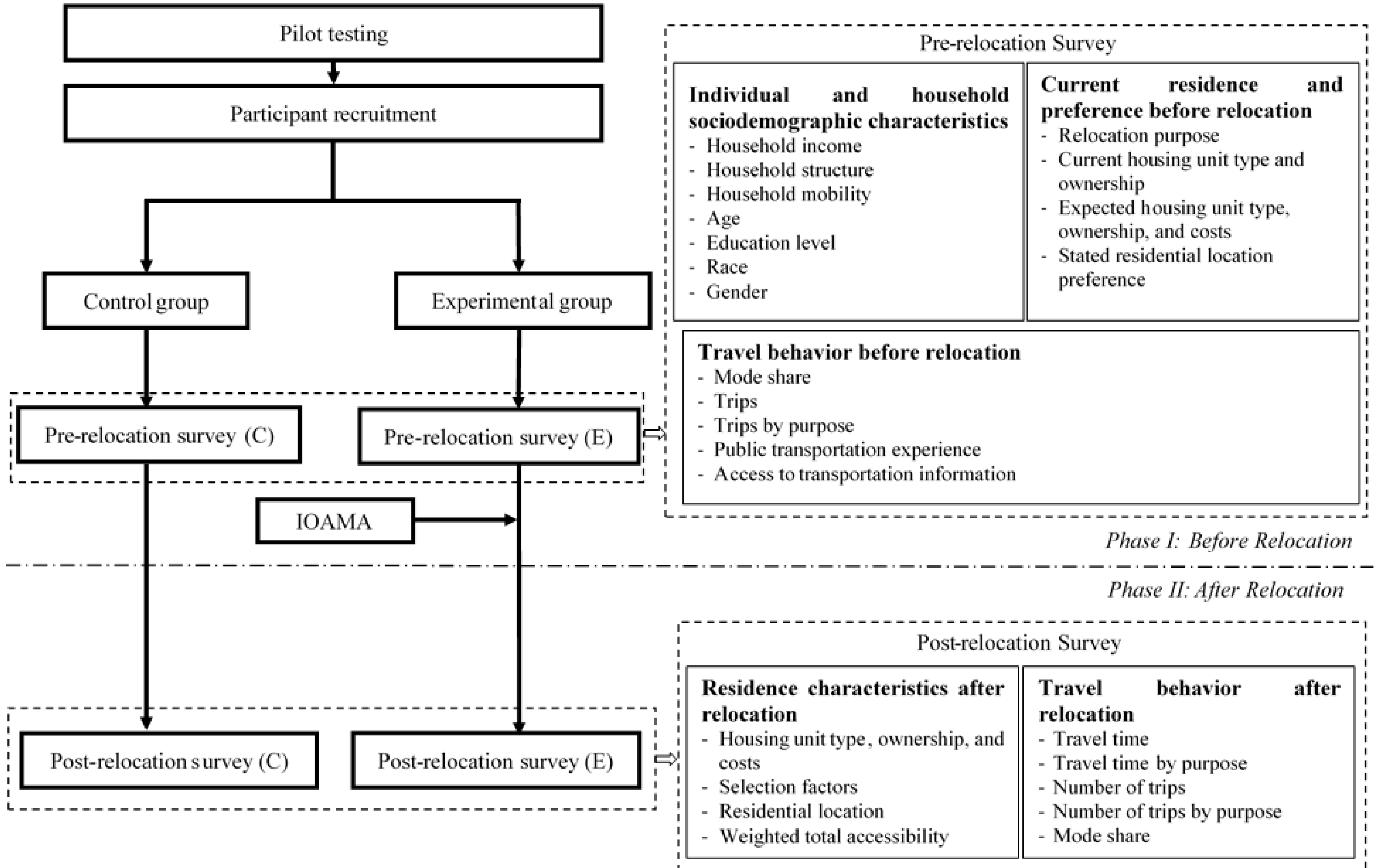


Figure 4.1 The Conceptual Framework of Experimental Design for Evaluating Proposed Behavioral Intervention Strategy

In Phase II, a post-relocation survey (Post-relocation survey for control group 2014; Post-relocation survey for experimental group 2014), was conducted from August 2014 to October 2014 as a follow-up survey to participants who had completed surveys in Phase I. This was done three months after the participant's confirmed relocation so that they were more likely to have established a stable travel behavior. The survey included information related to the participants' self-reported residential characteristics and travel behavior after relocation, and the residential location choice. Only the experimental group participants received questions related to the perceived usefulness of IOAMA, which was the only difference in the post-relocation surveys received by both groups. The complete survey can be found in Appendixes B and C of this dissertation.

To quantify the impacts of having personalized accessibility information on the participants' residential location choice and travel behavior, four sets of outcomes (two residence-related outcomes and two travel-related outcomes) were selected to analyze the differences between the control and experimental groups. The first set consisted of the participants' perceived importance of 11 factors affecting their residential location decision-making process before and after relocation on a scale of 1-5, where 1 indicates "not at all important" and 5 indicates "extremely important." The second set consisted of six types of neighborhood accessibility values (work, healthcare, social or recreational, restaurant, education, and retail or grocery accessibility) using four modes (walk, bike, transit, and car). The third and fourth sets were self-reported average driving time of "drive alone" trips made after relocation and mode share for different purposes after relocation, respectively.

4.3.2 Interactive Accessibility Information Design

The IOAMA provides users with personalized accessibility information for each neighborhood of interest based on their travel needs associated with each transportation mode. Each neighborhood represented a census block group (The U.S. Census Bureau 2010), and Tippecanoe County had 102 neighborhoods. The weighted accessibility of neighborhood *i* using mode *c* for participant *n*, A_{nic} , was calculated as:

$$A_{nic} = w_n^O A_{nic}^O + w_n^H A_{nic}^H + w_n^S A_{nic}^S + w_n^R A_{nic}^R + w_n^E A_{nic}^E + w_n^G A_{nic}^G \quad (1)$$

and, $w_n^O + w_n^H + w_n^S + w_n^R + w_n^E + w_n^G = 100\%$ (2)

where w_n^O, w_n^H, w_n^S, w_n^R, w_n^E, and w_n^G are the weights assigned by participant *n* to work, healthcare, social or recreational, restaurant, education, and retail or grocery shopping accessibility, respectively, and A_{nic}^O, A_{nic}^H, A_{nic}^S, A_{nic}^R, A_{nic}^E, and A_{nic}^G are the corresponding accessibilities using mode *c* for participant *n.* It is important to note that a neighborhood's personalized accessibility was very different among participants due to their diverse work locations and the weights assigned based on their travel needs.

To quantify accessibilities, the Hansen-gravity measure and floating catchment methods (FCMs) were considered. Although the Hansen-gravity accessibility measure is considered more conceptually complete than the FCMs, many studies (Joseph and Phillips 1984; Luo and Qi 2009; Guo et al. 2016b; Guo et al. 2017) found that it is not intuitive to interpret, particularly for practitioners and the general public. FCMs represent a specific type of Hansen-gravity measures and are more intuitive to interpret compared to Hansen-gravity measures (Luo and Qi 2009; Guo et al. 2017). To ensure that participants can easily process the provided personalized accessibility information, FCMs were used. It is important to note that the method used to calculate work accessibility is different from other types of accessibility metrics because each participant needs access to only one job location; in principle, they can access multiple locations for other trips purposes within a travel time threshold.

Work accessibility (A_{nic}^O) was determined using a floating catchment method (FCM) (Luo 2004). The work accessibility of neighborhood *i* is calculated as follows:

Given a neighborhood *j*, identified by participant *n* as his/her work location, search any neighborhood *i* within a threshold travel time (t_{0c}) using mode *c*. Then,

$$A_{nic}^O = f\left(t_{ijc}, t_{0c}\right) \tag{3}$$

where t_{ijc} is the travel time between *i* and *j* using mode *c* with a threshold value of the travel time (t_{0c}) under mode *c*, and $f\left(t_{ijc}, t_{0c}\right)$ is the travel time decay function. t_{ijc}, collected using Google Maps, is the travel time between the centroid point of neighborhood i to neighborhood j using mode *c*. The travel time decay function captures the inverse relationship between travel time and accessibility, and a kernel function is often used to reflect such relationship (Dai and Wang 2011; Guo et al. 2017). The Epanechnikov function is selected (Dai and Wang 2011; Guo et al. 2017; Guo et al. 2016b) to capture the travel time decay. The distance decay function can be written as:

$$\begin{cases} f(t_{ijc}, t_{0c}) = \frac{3}{4}\left[1 - \left(\frac{t_{ijc}}{t_{0c}}\right)^2\right], if\ t_{ijc} \leq t_{0c} \\ \quad f(t_{ijc}, t_{0c}) = 0\ if\ t_{ijc} > t_{0c} \end{cases} \tag{4}$$

The threshold travel time implies that only destinations within a threshold value for travel time are considered accessible from a neighborhood, and those outside are not. The threshold travel time to work location for all four modes was set as 60 minutes. The main reason for this threshold travel time is that, based on Google Maps, the longest driving time between two neighborhoods in Tippecanoe County is about 57 minutes during morning peak hours and the longest bus travel time between any two bus stops (without waiting time) is one hour and nine minutes. Based on this, we assumed the threshold travel time to work location was 60 minutes. Then, the work accessibility values calculated using Eq. (3) were normalized to the indexed accessibility score ranging from 0 to 100 for each mode. The normalization scales the values of accessibility with different orders or magnitudes to a value between 0 and 100 (Luo and Qi 2009; Guo et al. 2016b; Guo et al. 2017). These values were used to quantify the work accessibility of a neighborhood.

There are two key reasons for using a travel time-based accessibility quantification method rather than a travel distance-based one in a multimodal context. On one hand, a travel distance-based method cannot capture the amount of travel from a neighborhood to a potential destination using transit mode, whereas a door-to-door transit trip includes walking from a neighborhood to the transit stop, time spent in transit, and walking from the transit stop to the destination (Guo et al. 2016b). For example, for identical travel distances from two neighborhoods to a retail location, the travel time for a neighborhood with bad transit access (e.g., fewer bus stops or routes) may be significantly higher than that for the one with good transit access. On the other hand, previous studies (e.g., Guo et al. 2016b) suggest that travel distance-based methods do not adequately capture the impact of congestion on accessibility.

A neighborhood's non-work related accessibilities were calculated using a modified FCM method proposed by Guo et al. (2017). Given a neighborhood *i*, search the intended destinations *k* for participant *n* was searched within a threshold value of the travel time (t_{0c}) under mode *c*. Then,

$$A_{nic}^{D} = \sum_{k \in (t_{ikc} \leq t_{0c})} M_k f(t_{ikc}, t_{0c}) \tag{5}$$

where t_{ikc} is the travel time between the centroid point of neighborhood *i* and intended healthcare related destination k using mode *c*, $D \in \{H, S, R, E, G\}$ and M_k is the weight of destination *k*. In this study, the weights of the intended destinations were assumed proportional to their physical areas. For example, for the same amount of travel time, a larger healthcare facility (such as a general hospital) was assumed to provide higher healthcare accessibility compared to a smaller healthcare facility (such as a clinic). $f(t_{ikc}, t_{0c})$ represents the travel time decay function, and can be written similar to Eq. (4),

$$\begin{cases} f(t_{ikc}, t_{0c}) = \frac{3}{4}\left[1 - \left(\frac{t_{ikc}}{t_{0c}}\right)^2\right], if\ t_{ikc} \leq t_{0c} \\ f(t_{ikc}, t_{0c}) = 0\ if\ t_{ikc} > t_{0c} \end{cases} \quad (6)$$

The threshold travel time for all four modes to all destinations other than the work location was set as 30 minutes. There were three reasons to select 30 minutes as the threshold travel time for non-work destinations. First, many studies (e.g., Krizek 2003; Guo et al. 2016c) have found that people often travel a shorter distance or time for services and shopping compared to travel to work. Second, the longest vehicular travel time between a neighborhood and a major non-work location (such as a supermarket for retail or grocery shopping) was within 30 minutes in Tippecanoe County during off-peak hours (assuming these types of travels were made mostly during off-peak hours). Third, several recent studies in a related domain (e.g., Dai and Wang 2011) identified 30 minutes as an appropriate threshold travel time for non-work destinations in the U.S. Then, the accessibility values calculated using Eq. (6) were normalized to the indexed accessibility score ranging from 0 to 100 for each combination of accessibility type and mode. These values were used to quantify the healthcare, social or recreational, restaurant, education, and retail or grocery shopping accessibilities of a neighborhood. The information for these destinations (including their locations and sizes) was collected using Reference USA (Reference USA 2014). Reference USA is a U.S. business database which contains millions of verified business information. When IOAMA was provided to the experimental group participants, a detailed description was provided along with it related to how to use it and how such accessibility information was calculated.

4.3.3 Simultaneous Equation Model Formulation

To understand the factors that affect the residents' neighborhood average weighted accessibility (average of accessibility using each mode of transportation) and weekly driving time (minutes/week) of the participants, econometric models were used. If separate ordinary least squares (OLS) regression models are used, the estimation results would not address the potential correlation between neighborhood accessibility and vehicle usage (e.g., Ewing and Cervero 2010; Cao et al. 2010); these two models are interrelated whereby the dependent variable (residential location's neighborhood average weighted accessibility) in one equation can be the independent variable in the other. This limits the use of OLS regression, as a potential estimation problem exists due to the violation of a key OLS assumption in that a correlation exists between regressors and disturbances, and common unobserved factors may exist affecting both dependent variables (Washington et al. 2010). Ignoring such endogeneity can lead to erroneous conclusions (Shankar and Mannering 1998; Tielemans et al. 1998). To address this limitation of OLS regression for estimating the two models separately, a simultaneous equation system was used:

$$ln(A) = \beta_A Z_A + \varepsilon_A \tag{7}$$

$$ln\,(V) = \beta_V Z_V + \lambda_V \ln(A) + \varepsilon_V \tag{8}$$

where A is the average weighted accessibility of the neighborhood to which an individual relocated, V is the weekly driving time (minutes/week), Z is the vector of exogenous variables (other contributing factors related to participants' sociodemographic characteristics) influencing A and V, β are the vectors of the estimable parameters, λ is the estimable scalar, and ε is the disturbance term. Given that the dependent variables are always positive, semi-logarithmic transformations are used. Two types of estimation methods can be used to estimate the simultaneous equation system, including single-equation methods (e.g., two-stage least squares) and system estimation methods (e.g., three-stage least squares (3SLS)). 3SLS was used in this study as it produces more efficient parameter estimates (Washington et al. 2010).

4.4 Results

4.4.1 Descriptive Statistics

Only individuals who completed both the pre-relocation and the post-relocation surveys were included in the analysis. A total of 282 completed responses were collected, including 147 in the experimental group and 135 in the control group. As shown in Figure 4.1, the pre-relocation survey questions were organized into three parts: (1) individual and household sociodemographic characteristics, (2) travel behavior before relocation, (3) residence-related characteristics before relocation. Tables 4.1-4.3 illustrate some of the descriptive statistics.

Table 4.1 illustrates the aggregated individual and household sociodemographic characteristics. Most of the participants in both the control and experimental groups are Caucasians between the ages of 25 and 54, had a more than high school diploma or had more than two private vehicles in the household. Most participants fit in the general sociodemographic in Tippecanoe County (U.S. Census Bureau 2010).

The participants in both groups had similar travel behavior and residence characteristics before relocation (Tables 4.2 and 4.3). Table 4.2 shows that car mode ("drive alone" and "drive with passenger(s)") had the largest mode share for both work (round trip from home to work and comes back as one trip) and non-work (round trip from home to places other than work and comes back as one trip) trips for participants in both groups before relocation. The reason for separating participants' usage of "drive alone" mode and "drive with passenger(s)" mode for car mode was to investigate if a participant would choose a residence that can meet the travel needs of multiple household members. If so, participants are likely to drive more with other household members ("drive with passenger(s)") to save time and money by combining multiple purposes in one trip. All the participants had used transit before, but only a few were still using it at the time of the pre-relocation survey. "Transit service is not frequent enough" and "riding transit is not comfortable" were the two most important factors that discouraged participants from using transit. Most participants checked transportation-related information regularly (more than three times a week) and radio was the most commonly used source of such information. Table 4.3 illustrates the participants' residence type and ownership before relocation, residence type of interest after relocation, and expected residence ownership and costs after relocation. Most participants owned a single-family detached home and expected to purchase a single-family detached home with a mortgage in Tippecanoe County at the time of the pre-relocation survey.

The post-relocation surveys consisted of two parts: (1) self-reported residence type, ownership, and residence's neighborhood after relocation, and (2) importance of different factors when choosing residence. Table 4.4 shows the self-reported residence type and ownership after relocation. Most of the experimental group participants (over 95%) reported that they relocated to a residence consistent with their preference at the time of the pre-relocation survey in terms of the residence type and ownership compared to control group participants (about 70%) (Table 4.3). More than 10% of the control group participants reported that they choose to rent a residence instead of buying one. In addition, the experimental group participants planned to stay longer in their current property compared to the control group participants, suggesting greater satisfaction with their residential location choice. The results show that participants who had accessibility information were more likely to find residences that satisfied their needs, and they purchased the residence. In contrast, some participants without accessibility information did not find an initial residential location that satisfied their needs and were therefore more likely to rent a residence for a short period with a higher likelihood of moving later to a residence meeting their needs within the region.

Table 4.1 Sociodemographic Characteristics of Participants

	Control Group (N = 135)	**Experimental Group (N = 147)**
Gender		
Male	50.4%	52.4%
Female	49.6%	47.6%
Race/Ethnicity		
African American	14.8%	21.1%
Asian	23.7%	13.6%
Hispanic/Non-white	8.9%	6.8%
Hispanic/White	5.2%	4.1%
Caucasian	47.4%	54.4%
Other	0%	0%
Marital Status		
Married	44.4%	47.8%
Single	45.2%	45.4%
Separated	3.7%	1.4%
Divorced	6.7%	5.4%
Education level		
Some high school	5.2%	7.5%
High school diploma	13.3%	11.6%
Technical college degree	25.2%	27.9%
College degree	29.6%	30.6%
Post graduate degree	26.7%	22.4%
Annual household income		
Under $14,999	5.9%	5.4%
$15,000 – $24,999	11.9%	13.6%
$25,000 – $34,999	15.6%	12.9%
$35,000 – $49,999	18.5%	17.0%
$50,000 – $74,999	16.3%	18.4%
$75,000 – $99,999	14.8%	13.6%
$100,000 or more	17.0%	19.0%
Age		
Under 25	16.3%	15.6%
25 – 34	29.6%	36.7%
35 – 44	31.1%	25.9%
45 – 54	13.3%	12.9%
Over 54	9.6%	8.8%
Average number of people living in a household	1.9	2.1
Participants with children under 6	11.9%	15.0%
Participants with children between 6 and 17	14.8%	10.2%
Average number of licensed and operable motor vehicles in a household	2.2	2.1

Table 4.2 Travel Behavior before Relocation

	Control Group (N = 135)	**Experimental Group (N = 147)**
Average number of single work trips per week		
Drive-alone	7.84 (74.6%)	7.52 (71.5%)
Drive with passenger(s)	0.44 (4.2%)	0.88 (8.4%)
Transit	1.70 (16.2%)	1.50 (14.2%)
Bike	0.37 (3.5%)	0.41 (3.9%)
Walk	0.15 (1.4%)	0.20 (2.0%)
Average number of single non-work trips per week		
Drive-alone	5.04 (33.0%)	6.20 (38.9%)
Drive with passenger(s)	4.77 (31.2%)	4.57 (28.7%)
Transit	1.35 (8.8%)	0.82 (5.1%)
Bike	1.41 (9.2%)	1.69 (10.6%)
Walk	2.71 (17.7%)	2.65 (16.7%)
Expected work-related parking behavior after relocation		
Monthly parking pass	20.0%	25.2%
Paid daily parking	3.7%	2.7%
Free parking provided by employer	18.5%	17.7%
Free street parking	38.5%	37.4%
Not driving to work	19.3%	17.0%
Transit usage (percent)		
Still using	29.6%	25.2%
Not using, but has experience	70.4%	74.8%
No experience	0.0%	0.0%
Most relevant factor that discourages transit usage		
Transit service is not frequent enough	27.4%	29.9%
Riding transit is not comfortable	22.2%	20.4%
Transit service is not reliable	20.0%	19.0%
Wait time at transit stops is too long	16.3%	15.0%
Do not have access to transit related information	7.4%	6.8%
Riding and waiting for transit feels unsafe	6.7%	8.8%
Frequency of accessing travel-related information per week		
Never	12.6%	12.9%
Once or twice	19.3%	21.8%
3 – 5 times	30.4%	29.9%
Once a day	26.7%	24.5%
More than once a day	11.1%	10.9%
Most frequently used source of travel-related information		
Radio	46 (39.0%)	42 (32.8%)
Television	28 (23.7%)	32 (25.0%)
Internet	26 (22.0%)	24 (18.8%)
Applications on cell phone	18 (15.3%)	30 (23.4%)
Others	0 (0.0%)	0 (0.0%)

Table 4.3 Residence Characteristics and Preference before Relocation

	Control Group (N = 135)	**Experimental Group (N = 147)**
Current residence unit type		
Single-family detached home	48.9%	42.2%
Row house/townhouse	23.0%	32.0%
Apartment	28.1%	25.9%
Mobile home	0.0%	0.0%
Other	0.0%	0.0%
Ownership of current residence unit		
Owning without mortgage	8.9%	10.2%
Owning with mortgage	56.3%	65.3%
Renting	34.8%	24.5%
Relocation purpose		
Going to work	93.3%	94.5%
Attending school	6.7%	5.5%
Residence type of interest (multiple choice)		
Single-family detached home	65.2%	63.3%
Row house/townhouse	33.3%	38.1%
Apartment	36.3%	31.3%
Mobile home	0.0%	0.0%
Other	0.0%	0.0%
Expected ownership after relocation		
Owning without mortgage	15.6%	14.3%
Owning with mortgage	57.0%	53.1%
Renting	27.4%	32.7%
Expected total costs if decided to own a house without mortgage after relocation		
Under $150,000	8 (38.1%)	11 (44.0%)
$150,000 – $199,999	11 (52.4%)	12 (48.0%)
$200,000 – $299,999	2 (9.5%)	2 (8.0%)
$300,000 – $499,999	0 (0%)	0 (0%)
$500,000 or more	0 (0%)	0 (0%)
Expected monthly mortgage if decided to own a house with mortgage after relocation		
Under $1,000	29 (57.1%)	33 (42.3%)
$1,000 – $1,499	47 (61.0%)	44 (56.4%)
$1,500 – $1,999	1 (1.3%)	1 (1.3%)
$2,000 or more	0 (0.0%)	0 (0.0%)
Expected rent if decided to rent		
Under $500	23 (62.2%)	30 (63.8%)
$500 – $749	11 (29.7%)	13 (27.7%)
$750 – $999	3 (8.1%)	4 (8.5%)
$1,000 – $1,499	0 (0.0%)	0 (0.0%)
$1,500 or more	0 (0.0%)	0 (0.0%)

Figures 4.2 and 4.3 show the aggregated self-reported residential locations in Tippecanoe County for the control and experimental group participants, respectively. The experimental group participants' residences were located closer to downtown areas (downtown Lafayette and West Lafayette) and their work locations, on average, compared to the control group participants' residences. The average estimated distance from the residence's neighborhood to downtown Lafayette (the shortest network distance from the centroid point of the neighborhood to downtown)

was about 20% shorter, and to downtown West Lafayette was over 30% shorter compared to those of the control group participants. In addition, the average estimated distance for the experimental group participants from their neighborhood to their work locations was about 25% shorter compared to the control group participants.

4.4.2 Perceived Importance of Various Factors of Residential Location Choice

Participants were requested to rate their perceived importance of various factors that affected their residential location decision-making process on a scale of 1-5, where 1 indicates "not important at all" and 5 indicates "extremely important." Eleven factors in three categories were considered: (1) physical characteristics of residence (cost, number of bedrooms/bathrooms, and parking); (2) neighborhood environment (aesthetic value and safety); and (3) transportation accessibility to education, work, park/recreational/public facilities, restaurants, retail/grocery, and healthcare. Table 4.5 illustrates the average ratings of these factors.

Before relocation, the cost of renting or buying, safety of neighborhood, accessibility to work, and number of bedroom/bathrooms were considered as the four most important factors by participants from both groups in their residential location decision-making process. A Mann-Whitney U test comparison of the factor means revealed that none of them were statistically significantly different (at the 0.05 level) across the two groups. In addition, Spearman's rank correlation coefficients (Guo and Peeta 2015; Guo et al. 2016a) were used to analyze the statistical dependence for the within-group ranking (based on the average rating) differences between the ratings given by the participants from both groups for these factors. The rankings for the two groups on these factors were found to be statistically significantly correlated. Both tests suggested a high degree of similarity existed among the participants of the control and experimental groups in terms of their perceived importance of the factors in their residential location decision-making process before relocation.

The Mann-Whitney U test and Spearman's rank correlation coefficients were used to compare the participants' perceived importance of the factors in the residential location decision-making process before and after relocation. The Mann-Whitney U test indicated that none of the factors were statistically significantly different (at the 0.05 level) for the control group before and after relocation, while four out of the eleven factors for the experimental group participants were. Among these four factors, three (accessibility to education, parks/recreational/public facilities, and retail/grocery/other destinations) were related to transportation accessibility, and the average ratings of the participants after relocation were higher than before relocation. The control group participants ranked “parking availability” four positions higher and “accessibility to parks, recreational, or public facilities” four positions lower compared to the experimental group participants after relocation. The results illustrate that there was a high degree of dissimilarity in the ratings of the experimental group participants before and after relocation, on the factors that affect their residential location choices after receiving the personalized accessibility information. In contrast, the control group participants that did not receive the information reported similar ratings on these factors before and after relocation. These results were possibly because relocators with personalized accessibility information were more informed on transportation accessibility and placed higher importance on accessibility-related factors in their residential location decision-making process.

4.4.3 Neighborhood Accessibility to Different Trip Purposes

In the post-relocation surveys, participants were asked to identify the neighborhood where their residence was located rather than their address for privacy reasons. Table 4.6 shows that the averages of the neighborhood accessibility for the six trip purposes using the four modes for the experimental group participants were higher than those of the control group, particularly for neighborhood accessibility using non-automobile modes. These results show that personalized accessibility information can assist relocators in selecting neighborhoods with better access to their potential destinations using different modes of transportation, particularly regarding non-automobile modes (which, typically, are is not easily accessible to relocators).

Table 4.4 Residence Characteristics after Relocation

	Control Group (N = 135)	**Experimental Group (N = 147)**
Current residence type		
Single-family detached home	40.0%	46.2%
Row house/townhouse	25.9%	32.0%
Apartment	34.1%	21.9%
Mobile home	0.0%	0.0%
Other	0.0%	0.0%
Ownership of current residence		
Owning without mortgage	10.4%	14.9%
Owning with mortgage	54.0%	59.9%
Renting	35.6%	25.2%
Total costs of current residence if the ownership is owning without mortgage		
Under $150,000	2 (14.3%)	4 (18.2%)
$150,000 – $199,999	7 (50.0%)	10 (45.5%)
$200,000 – $299,999	5 (35.7%)	8 (36.4%)
$300,000 – $499,999	0 (0.0%)	0 (0.0%)
$500,000 or more	0 (0.0%)	0 (0.0%)
Monthly mortgage of current residence if the ownership is owning with mortgage		
Under $1,000	17 (23.3%)	32 (36.4%)
$1,000 – $1,499	44 (60.3%)	45 (51.1%)
$1,500 – $1,999	12 (16.4%)	11 (12.5%)
$2,000 or more	0 (0.0%)	0 (0.0%)
Rent of current residence if the ownership is renting		
Under $500	17 (35.4%)	11 (29.7%)
$500 – $749	14 (29.2%)	16 (43.2%)
$750 – $999	16 (33.3%)	10 (27.0%)
$1,000 – $1,499	1 (2.1%)	0 (0.0%)
$1,500 or more	0 (0.0%)	0 (0.0%)
Expected number of years of staying at the current residence		
Less than 1 year	25.2%	17.7%
1 – 5 years	15.6%	10.9%
5 – 10 years	57.0%	68.0%
More than 10 years	2.2%	3.4%

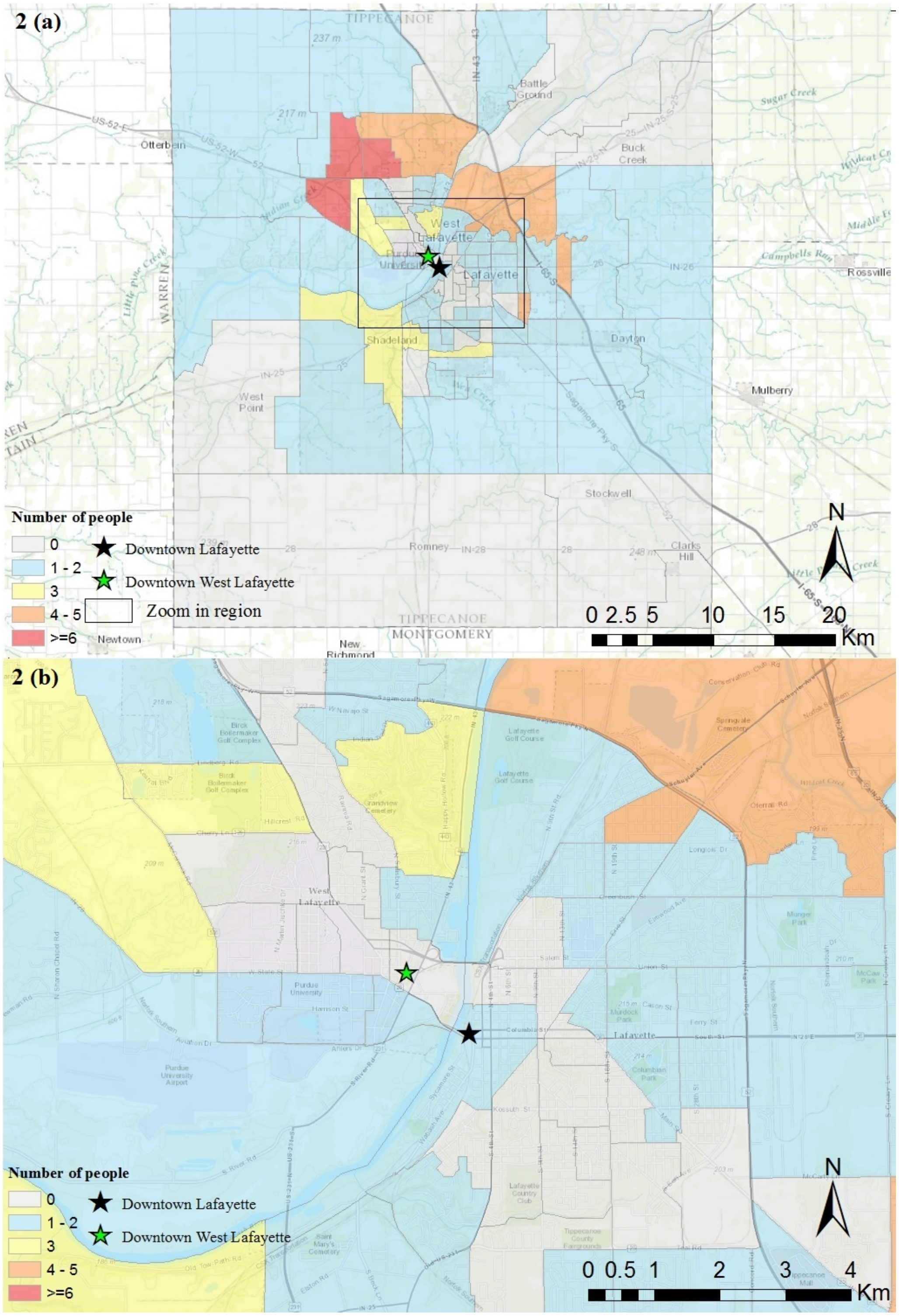


Figure 4.2 Self-reported Residential Locations of Control Group Participants in (a) Tippecanoe County, and (b) Downtown Regions of Tippecanoe County

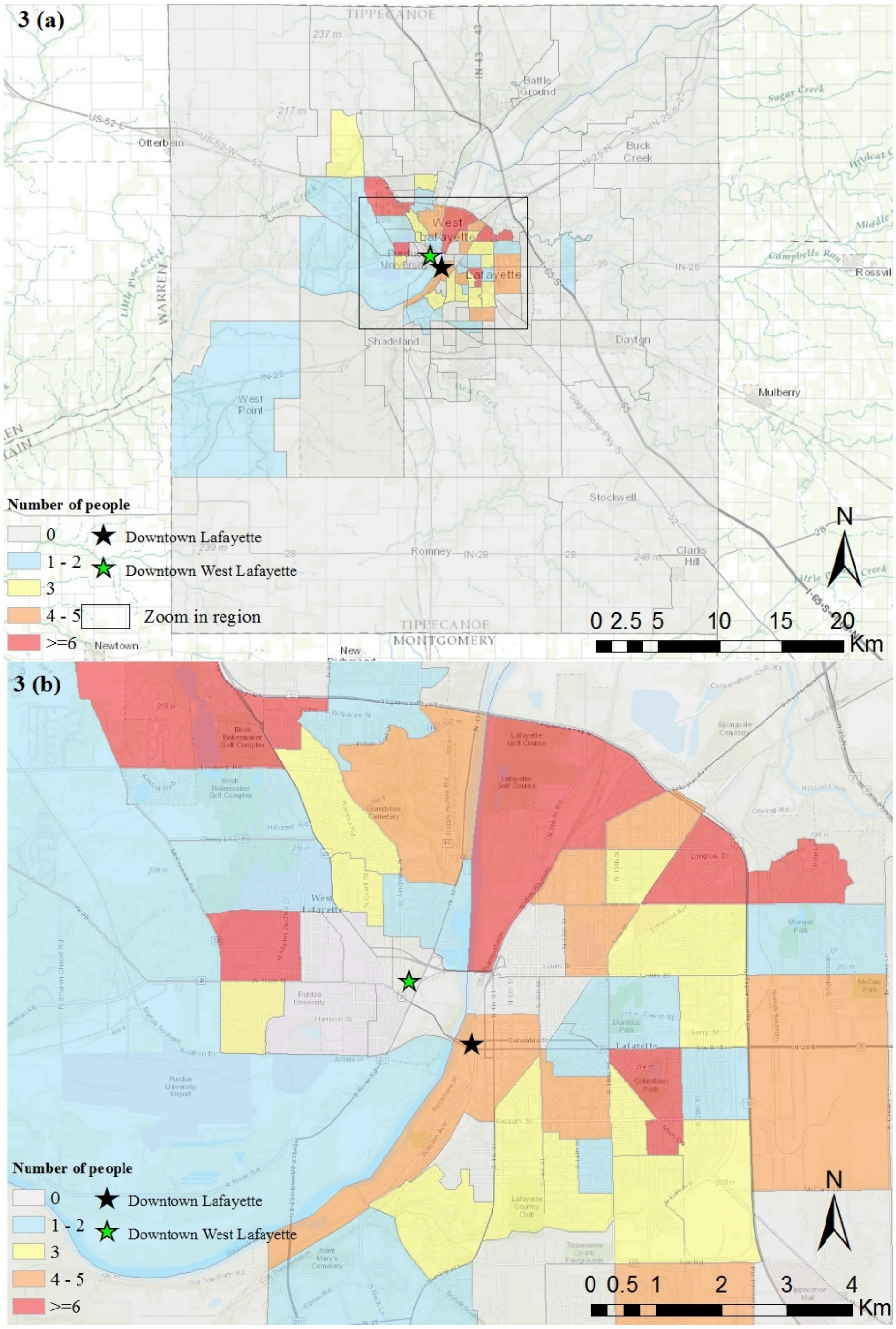


Figure 4.3 Self-reported Residential Locations of Experimental Group Participants in (a) Tippecanoe County, and (b) Downtown Regions of Tippecanoe County

Table 4.5 Importance of Different Factors Affecting Participants' Residential Location Decision-making Process

	Before relocation			**After relocation**			
	Control Group	Experimental Group	p-value	Control Group	p-value	Experimental Group	p-value
Physical characteristics of the residence after relocation							
Cost of renting or buying	3.90	3.95	0.72	3.96	0.68	3.79	0.42
Number of bedrooms/bathrooms	2.97	3.01	0.74	3.02	0.73	2.95	0.86
Parking availability	2.55	2.51	0.79	2.74	0.20	2.22	0.02*
Neighborhood environment							
Safety of neighborhood	3.21	2.99	0.15	3.31	0.55	3.14	0.64
Aesthetic value	2.91	2.86	0.74	3.03	0.46	2.97	0.70
Transportation accessibility							
Accessibility to work	3.03	2.99	0.79	3.06	0.86	2.88	0.31
Accessibility to restaurants	2.58	2.48	0.39	2.67	0.45	2.74	0.16
Accessibility to retail, grocery or other destinations	2.44	2.49	0.69	2.56	0.35	2.82	0.00*
Accessibility to parks, recreational, or public facilities	2.39	2.37	0.91	2.45	0.66	2.85	0.00*
Accessibility to education	2.36	2.44	0.65	2.27	0.56	2.82	0.00*
Accessibility to healthcare	1.44	1.36	0.47	1.33	0.28	1.62	0.15

* denotes significance at a 95% level of confidence

4.4.4 Weekly "Drive Alone" Trips and Mode Share for Various Trip Purposes

Table 4.7 illustrates the aggregated travel behavior of participants in the control and experimental groups. After relocation, the experimental group participants used the walk mode more often than the control group (17.8% versus 10.7%) as well as transit mode (13.1% versus 10.6%). In contrast, the control group used "drive alone" mode more often than the experimental group (38.2% versus 47.7%). In addition, although car mode ("drive alone" and "drive with passenger(s)") was still the most common mode of transportation, the experimental group participants used "drive with passenger(s)" mode more often compared to the control group participants. This suggests that the residential location chosen by the experimental group participants may better addressed the needs of multiple household members, making the possibility of joint trips within the household much easier.

For all trip purposes, the experimental group participants experienced shorter average driving times using "drive alone" mode compared to the control group participants, and these differences were statistically significant for work, social/recreational, restaurants, and retail/grocery shopping trips. In addition, the shares of trips using non-automobile modes (transit, bike, and walk) were higher for the experimental group participants compared to the control group participants, especially for walk mode in social/recreational, restaurants, and retail/grocery shopping trips.

Additional analyses were carried out to examine whether certain subgroups among the experimental group participants experienced a larger impact from the personalized accessibility information using t-test. The criteria used to specify the different subgroups are gender, age, household income, marital status, automobile ownership, whether using transit before relocation, and the frequency of accessing transportation-related information per week. No difference in impact was found based on gender, age, household income, automobile ownership, and whether using transit before relocation. However, the married participants indicated that they used "drive with passenger(s)" mode more often compared to unmarried participants. These results indicate that married participants may have used the IOAMA to determine a residence location that met the needs of multiple family members. Hence, they can make more coordinated travel plans and use "drive with passenger(s)" mode more often instead of "drive alone" mode after relocation. The experimental group participants who accessed transportation-related information more often (more than three times a week) chose residences in neighborhoods with higher accessibility. This suggests that participants who accessed transportation-related information more often may have used the IOAMA more effectively or were more receptive to the information from IOAMA in their residential location decision-making process.

4.4.5 Simultaneous Equation Estimation Results

Table 4.8 shows the simultaneous equation model estimation results. For comparison, the two models were also run as separate ordinary least squares regression models. The comparison results illustrated that the two separate ordinary least squares regression models showed noticeably higher standard errors resulting in lower t-statistics compared to the simultaneous equation models. Similar observations were also found in previous studies (e.g., Shankar and Mannering 1998).

As shown in Table 4.8, six variables were found to have a statistically significant correlation ($t \geq 1.96$) with the average weighted accessibility of the neighborhood that an individual selected after relocation (hereafter labeled as the neighborhood average weighted accessibility), including three variables related to individual and household sociodemographic characteristics, two variables related to travel behavior before relocation, and one variable related to whether an individual was in the experimental group or otherwise.

Four variables were found to have a statistically significant correlation ($t \geq 1.96$) with weekly driving time (minutes/week) after relocation, including one variable related to individual and household sociodemographic characteristics, one variable related to travel behavior before relocation, one variable related to whether an individual was in the experimental group or not, and the neighborhood average weighted accessibility.

Table 4.6 Average Neighborhood Accessibility Values for Different Trip Purposes

	Control Group (N = 135)	**Experimental Group (N = 147)**	***p*-value**
Accessibility to work:			
Car	72.75	89.63	0.67
Transit	62.83	84.52	0.03*
Bike	65.11	86.93	0.07*
Walk	61.34	77.84	0.05*
Accessibility to healthcare:			
Car	50.24	57.21	0.62
Transit	52.42	55.72	0.80
Bike	56.48	58.67	0.72
Walk	55.90	59.72	0.52
Accessibility to social and recreational activities			
Car	67.75	85.22	0.04*
Transit	61.04	86.27	0.00*
Bike	62.69	82.64	0.05*
Walk	63.10	87.62	0.03*
Average accessibility to restaurants			
Car	70.25	82.56	0.40
Transit	69.02	84.55	0.32
Bike	65.42	86.21	0.08*
Walk	67.53	87.00	0.09*
Accessibility to educational activities			
Car	72.42	74.62	0.75
Transit	70.20	73.45	0.80
Bike	71.25	75.69	0.69
Walk	72.21	76.01	0.65
Accessibility to retail/grocery activities			
Car	64.38	88.34	0.04*
Transit	66.71	87.63	0.06*
Bike	65.17	89.21	0.02*
Walk	66.08	90.26	0.01*
Weighted accessibility			
Car	67.74	80.60	0.00*
Transit	64.43	81.23	0.00*
Bike	65.42	84.54	0.00*
Walk	67.22	82.10	0.00*

Table 4.7 Comparison of Travel-related Outcomes after Relocation

	Control Group (N = 135)	**Experimental Group (N = 147)**	***p*-value**
Work trips			
Average driving time of using “drive alone” mode (minutes)	9.38	8.25	0.00*
Average weekly driving time using “drive alone” mode (minutes)	93.47	81.85	0.00*
Percentage of “drive with passenger(s)” mode share	7.41	11.60	0.23
Percentage of transit mode share	13.19	19.51	0.15
Percentage of bike mode share	3.26	3.68	0.84
Percentage of walk mode share	5.93	9.28	0.27
Healthcare-related trips			
Average driving time of using “drive alone” mode (minutes)	11.33	9.44	0.60
Average weekly driving time using “drive alone” mode (minutes)	24.25	21.50	0.68
Percentage of “drive with passenger(s)” mode share	29.41	31.25	0.91
Percentage of transit mode share	5.88	0.00	0.32
Percentage of bike mode share	0.00	0.00	--
Percentage of walk mode share	0.00	6.25	0.32
Social/recreational trips			
Average driving time of using “drive alone” mode (minutes)	8.21	7.66	0.08*
Average weekly driving time using “drive alone” mode (minutes)	32.65	27.60	0.04*
Percentage of “drive with passenger(s)” mode share	36.29	36.34	0.64
Percentage of transit mode share	7.87	4.76	0.13
Percentage of bike mode share	15.23	13.53	0.44
Percentage of walk mode share	19.04	28.82	0.07*
Restaurant-related trips			
Average driving time of using “drive alone” mode (minutes)	8.65	7.71	0.00*
Average weekly driving time using “drive alone” mode (minutes)	36.15	30.32	0.00*
Percentage of “drive with passenger(s)” mode share	40.70	37.41	0.23
Percentage of transit mode share	4.91	6.47	0.70
Percentage of bike mode share	1.75	1.80	0.74
Percentage of walk mode share	7.02	22.30	0.08*
Education-related trips			
Average driving time of using “drive alone” mode (minutes)	8.93	8.11	0.72
Average weekly driving time using “drive alone” mode (minutes)	52.29	45.47	0.84
Percentage of “drive with passenger(s)” mode share	32.69	28.68	0.92
Percentage of transit mode share	15.38	14.73	0.87
Percentage of bike mode share	5.77	3.88	0.74
Percentage of walk mode share	12.50	12.40	0.84
Retail/grocery shopping trips			
Average driving time of using “drive alone” mode (minutes)	9.13	8.05	0.01*
Average weekly driving time using “drive alone” mode (minutes)	19.29	16.19	0.00*
Percentage of “drive with passenger(s)” mode share	39.89	36.84	0.77
Percentage of transit mode share	13.30	15.31	0.60
Percentage of bike mode share	0.00	0.96	0.16
Percentage of walk mode share	15.43	24.88	0.04*

The estimation results indicate that the experimental group participants who received personalized accessibility information were more likely to choose a neighborhood with higher average weighted accessibility and traveled less by private vehicle. This is consistent with the results of the t-test comparison of the average neighborhood accessibility and travel-related outcomes after relocation between the control and experimental group participants (Tables 4.6 and 4.7), which suggest that the designed personalized accessibility information can assist participants in selecting neighborhoods with a better average weighted accessibility and thereby reduce their car usage.

Table 4.8 Simultaneous Equation Estimation Results

Variables	**Estimates**	***t*-Statistics**	**Standard error estimates**
Dependent variable: Neighborhood average weighted accessibility			
Constant	3.17	10.11	0.31
Experimental group indicator: 1, if individual was in experimental group; 0, otherwise	1.03	7.21	0.14
High income indicator: 1, if individual's annual household income is over $49,999; 0, otherwise	0.33	2.08	0.16
Married indicator: 1, if individual is married; 0, otherwise	0.14	2.43	0.06
Average number of licensed and operable motor vehicles in individual's household	-0.46	-2.77	0.17
Automobile-habit indicator: 1, if at least 60% of individual's trips were made using "drive alone" mode before relocation; 0, otherwise	-0.96	-7.30	0.13
Dependent variable: Neighborhood average weighted accessibility (continued)			
Frequent transportation information access indicator: 1, if individual's frequency of accessing transportation-related information per week is three times or more; 0, otherwise	1.01	3.65	0.28
Dependent variable: Weekly driving time after relocation (minutes/week)			
Constant	4.13	14.19	0.29
Average weighted accessibility	-0.97	-7.47	0.13
Experimental group indicator: 1, if individual was in experimental group; 0, otherwise	-0.83	-5.53	0.15
Average number of licensed and operable motor vehicles in individual's household	0.37	3.41	0.12
Automobile-habit indicator: 1, if at least 60% of individual's trips were made using "drive alone" mode before relocation; 0, otherwise	-0.74	3.27	0.23
Number of observations		282	
R-squared—Average weighted accessibility		0.41	
R-squared—Automobile travel per week		0.47	
3SLS system R-squared		0.46	

The neighborhood average weighted accessibility was found to have a statistically significant negative correlation with weekly driving time after relocation. Similar results were also found in previous studies (e.g., Cao et al. 2010); that is, individuals who lived in neighborhoods with higher accessibility traveled less using car mode compared to those who lived in neighborhoods with lower accessibility. This outcome indicates that the proposed strategy can foster sustainable long-term travel behavior, in terms of reducing car usage by assisting participants' with information that will assist their selection of a neighborhood that offers better access to their potential destinations.

The average number of licensed and operable vehicles in a household was found to have a statistically significant negative correlation with the neighborhood average weighted accessibility, but was found to have a statistically significant positive correlation with weekly driving time after relocation. A possible explanation for this is that households with more mobility resources may value neighborhood accessibility less, but value other factors (such as costs of renting or buying) more in their residential location decision-making process due to their high household mobility.

The residential property price was not found to have a statistically significant correlation with a neighborhood's average weighted accessibility. This may seem to contradict to several previous studies (e.g., Guo et al. 2016b) that found that a property's neighborhood accessibility is positively correlated with its property price. However, such correlation may not exist between neighborhood average weighted accessibility and property price, because of the significant difference between neighborhood average weighted accessibility and neighborhood accessibility. A property's neighborhood average weighted accessibility depends not only on its various types of non-work-related neighborhood accessibilities but also on an individual's work location and travel needs. An individual's work location determines the neighborhood work accessibility, and his/her travel needs dictate the importance he/she attaches to each type of accessibility. This indicates that, for the same property, different people can have different assessments in terms a property's weighted accessibility. For example, among the participants, some individuals who work in rural areas weighed work accessibility much more than other types of accessibility. They may be more likely to select a property located near their work location, and the property's price may also be lower in a rural region. In this case, a residential property's price may be negatively correlated with the neighborhood average weighted accessibility among these participants.

Individuals with similar sociodemographic characteristics whose jobs are located downtown and weighed non-work-related accessibilities much higher than work accessibility, may select a property location that offers better access to non-work-related activities. Also, the property's price may be higher than the one located in a rural region. In this case, a residential property's price is positively correlated with the neighborhood average weighted accessibility. Hence, as people have different work locations and diverse travel needs, it is reasonable that the estimation results show that there is no statistically significant correlation between a residential property's price and its neighborhood average weighted accessibility. However, it does not imply that the residential property price is not considered in the residential location decision-making process.

Two variables related to individual and household sociodemographic characteristics, household income and marital status, were found to be statistically significantly correlated with the neighborhood average weighted accessibility but not with weekly driving time after relocation. If an individual's annual household income is over $49,999, they are more likely to select a neighborhood with higher average weighted accessibility. In 2014, the median annual household income in Tippecanoe County was $44,474 (the U.S. Census Bureau 2015). An individual with a higher annual household income may be less sensitive to costs of renting or buying, and other factors such as accessibility may be more important in their residential location decision-making process. Hence, they are more likely to relocate to neighborhoods with higher average weighted accessibility. The results also show that if an individual is married, he or she is more likely to select a neighborhood with higher average weighted accessibility after relocation because married individuals are more likely to have diverse travel needs and travel behavior in their household when making residential location choice, while unmarried or separated/divorced individuals may only have to factor their own needs. Hence, married individuals are more likely to select a neighborhood with high accessibility for different trip purposes using different modes of transportation, which is consistent with the subgroup study results. If an individual made at least 60% of his/her trips using "drive alone" mode before relocation, he/she was more likely to choose a neighborhood with lower average weighted accessibility and have a higher weekly driving time after relocation. This is similar to findings in previous studies (e.g., Choocharukul et al. 2008), in that individuals with a frequent car usage habit was less likely to relocate to a neighborhood with convenient public transportation. This indicates that an individual's travel behavior before relocation has a strong impact on his/her residential location decision-making process and travel behavior after relocation.

The results also illustrate that individuals who access transportation-related information more frequently (three times or more per week) were more likely to select neighborhoods with higher average weighted accessibility after relocation because such individuals often may be more amenable to using accessibility-related information and value a higher level of accessibility more when choosing their residential location, which also consistent with the insights in this paper.

4.5 Concluding Comments

This study proposes a design of personalized accessibility information and evaluates its potential to foster sustainable travel behavior by providing it to relocators' to influence their long-term residential location choices so that they reduce car usage and increase the usage of sustainable travel modes. Previous studies in this domain were limited in terms of the types and amount of accessibility information provided, the study population's sociodemographics, and the residential location preferences (residence type, location and ownership). To address these limitations, this study developed an IOAMA that provided personalized neighborhood accessibility information which factors an individual's work location, travel needs, and mode choice. Although other neighborhood-related characteristics, such as school district, crime rate, etc., also can influence the long-term residential location decision-making process, this study focused on analyzing the impacts of personalized accessibility information on residential location decision-making process and travel behavior. A key motivation for this focus is that advances in information and communication technologies can potentially be leveraged to enable relocators to be more informed in their decision-making process through the provision of intuitive visual information.

The descriptive statistics and model estimation results show that the designed personalized accessibility information can influence relocators' residential location decision-making process. The experimental group participants who received personalized accessibility information were more likely to place more importance on the accessibility-related factors of potential residence locations in their residential location decision-making process and choose a residence in a neighborhood that had better overall accessibility using different modes of transportation, and was more suitable to their specific household travel needs. It is also important to note that the designed information may inspire experimental group participants to check more transportation-related information for the neighborhood which can further help them to make more informed residential location decision. They are also less likely to consider changing their residence again after relocation compared to the control group participants. Since the experimental group participants' travel needs were better addressed in their residence after relocation, they tended to drive alone less, drove with other household members more, and walked, rode a bicycle, and used transit more.

By influencing the long-term residential location choice, the long-term travel behavior of individuals also can be altered and a new travel behavior formed after relocation in terms of reducing car usage and increasing their mode share of walk, bike and transit. These insights have three important implications for planners and policy-makers in the context of designing information for intervention strategies to improve the sustainability of travel behavior.

The descriptive statistics and model estimation results also show that marital status, frequency of accessing transportation-related information, and car usage before relocation, can have a significant impact on the residential location decision-making process and long-term travel behavior. Married individuals are more likely to select neighborhoods that can address the diverse travel needs of several household members. A potential policy implication is that the design of information for intervention strategies should consider the travel needs and travel behavior of individuals as well as their household members. Individuals who more frequently access transportation-related information are more likely to be amenable to the influence of accessibility information for intervention strategies. From a policy perspective, this implies that this information should be delivered through channels to which people are more accustomed to, and the application should be easy to access and use. The effectiveness of the proposed strategy may have a relatively lower impact on individuals with a strong automobile use habit. A potential policy implication is that long-term information for intervention strategies can be bundled with other long- and short-term strategies (such as real-time information about transit operations) to improve their ability to influence individuals with strong automobile use habit. Furthermore, the IOAMA is built on generally available data and can be easily replicated for deployment in other metropolitan regions. In addition, the designed application also can be used to assist relocators in selecting a residential location choice that suits their travel needs.

This study has several potential limitations. First, the voluntary nature of the online survey without compensation, and the use of IOAMA which is an online application, may limit the types of participants in the study in terms of their sociodemographic characteristics (e.g., they need to have internet access) and may not be fully representative of relocators to Tippecanoe County. Second, education accessibility provided was measured based only on travel time to different schools which may not reflect the actual access to educational services (e.g., school zone boundaries and school quality). Third, the threshold travel time in this study was predetermined from the literature instead of personalized threshold travel time. In the pilot test, with the personalized threshold travel time option, most pilot test participants suggest that the map loading time can be too long which may make them want to quit the study. A tradeoff was made to reduce some interactive features and improve study participation. Fourth, the data analysis relies on self-reported survey data which has its limitations in terms of data accuracy that can be difficult to verify. Fifth, the use of census blocks as neighborhood boundaries may not be ideal because, in many cases, a census block does not represent a neighborhood (Coulton et al. 2001).

Future study directions can include the following: (i) implement the proposed intervention strategy in a larger metropolitan area with a larger sample size and develop separate econometric models for the participants in the control and experimental groups to evaluate the proposed strategy's effectiveness; (ii) use the designed personalized accessibility information as a foundation to develop a more comprehensive livability index from a transportation perspective with bundled information related to accessibility and the neighborhood built environment (such as school district quality); and (iii) include additional interactive features (e.g., adjustable threshold of travel time, restaurant preference, etc.) to IOAMA and link it with real estate websites (e.g., Zillow, Trulia, etc.) to provide easier access to both residential location choices and personalized accessibility information which can better assist relocators to make more informed residential location choices.

CHAPTER 5. CHINA'S MILLENNIAL CAR TRAVELERS' MODE SHIFT RESPONSES UNDER CONGESTION PRICING AND REWARD POLICIES: A CASE STUDY IN BEIJING

5.1 Introduction

Rapid economic growth has led to drastic increases in car ownership in China over the past decades, from less than a quarter-of-a-million in 1990 to approximately 150 million in 2016 (MEP, 2016). In 2018, over 35% of the travelers in Beijing used car mode (driving a private car, using a traditional taxi, or using a ride-sharing service) as their primary mode of transportation (hereafter referred to as "car travelers") for their morning commute compared to less than 15% in 2008 and less than 5% in 1996 (Li, 2004; Beijing Transport Institute, 2019). China contributed to nearly 30% of the global car sales in 2016 (Baan et al., 2019); and Didi, the largest ride sharing company in China, claimed to have provided 30 million rides per day in 2018, which was higher than Uber (15 million), Grab (4 million), and Lyft (1 million) combined (Iqbal, 2019). Although the growth in car ownership and usage offer travelers a fast and convenient travel choice, that growth, along with other factors, also has created many challenges in metropolitan areas of China, such as increasing traffic congestion and pollution.

To address these challenges, various types of travel demand management measures (TDM) have been considered and implemented in China. TDM can be broadly classified into four categories: physical infrastructure measures, legal policies, behavioral intervention measures, and economic policies (Steg, 2003). The first three measures have been implemented and have experienced success in China (Wang et al., 2013; Xie et al., 2017). Physical infrastructure measures, such as the introduction and expansion of subway networks in metropolitan areas, promote many car and electric bike travelers to shift to using the subway (Wang et al., 2013). The vehicle registration lottery system, road space rationing system (i.e., about one-fifth of the vehicles are not allowed onto the road in a workday based on the last digit of their license plate number), the license plate auction system, and other legal policies, have sharply curtailed new vehicle registration in metropolitan cities such as Beijing and Shanghai (Yang et al., 2014; Xie et al., 2017). Behavioral intervention measures such as public information campaigns have improved public awareness of the environmental impacts of increased car usage (Jiang et al., 2017). However, economic policies such as congestion pricing and reward policies have yet to be implemented in China due to equity and public acceptance concerns (Link, 2015).

Congestion pricing policies have been studied extensively and have been implemented in many cities around the world since their introduction in the 1960s (Hårsman and Quigley, 2010). Such policies focus on disincentivizing car usage by imposing link (road segment) or time-dependent charges; and the revenues generated from those policies then are invested in sustainable travel modes (transit, bike, and walk) to improve the efficiency of the existing infrastructure and to promote the desired mode shift from the car mode to sustainable travel modes (Eliasson and Mattsson, 2006). However, implementing such policies often faces issues of public acceptance, equality (how costs and benefits are distributed across socioeconomic groups), and fairness (Oberholzer-Gee and Weck-Hannemann, 2002). To address such issues, more recent efforts have been made to use reward policies to promote mode shift by incentivizing the use of sustainable travel modes (e.g., employee-sponsored transit passes and cycling reward program) (Lachapelle and Frank, 2009; de Kruijf et al., 2018). These policies have been found to be more effective in promoting mode shifts compared to congestion pricing policies over the long-term; but despite these potential advantages, limited studies have been done to evaluate its potential in China. One of the most recent effort by Li et al. (2019) attempted to address the impacts of congestion pricing and reward policies on car travelers' mode shift responses (i.e., will they shift from using the car mode to using sustainable travel modes) using a stage-based model framework. However, the authors did not consider the potential correlation between a traveler's mode shift response under congestion pricing and their response under reward policies nor the impacts of factors others than psychological factors on mode shift responses. Such other factors can include the sociodemographic characteristics of travelers, accessibility to transit (i.e., ease of access to transit stations), accessibility by transit (i.e., ease of access to destinations using transit), and their travel behavior and needs. These factors have been identified in previous studies as key factors that affect mode share and transit usage (Moniruzzaman and Páez, 2012; Owen and Levinson, 2015).

Furthermore, the impacts of congestion pricing and reward policies on migrants and residents can vary greatly due to the current massive internal migration and the unique household registration system in China. Due to the unbalanced economic development between regions, many people have migrated from rural to urban areas and from underdeveloped inland provinces to developed coastal provinces in the past two decades for better wages and more opportunities. In

2018, there were over 280 million migrant workers in China, which account for almost 40% of the total workforce (NBS, 2019). These migrant workers sent approximately one-third of their income to support their family members who still reside in their province of origin (Shen, 2013) and thus may have less financial resources to support their travel needs compared to residents with similar incomes (Guo et al., 2018). In addition, the household registration system in China can serve as an institutional barrier for migrants to access some basic benefits (e.g., sending children to local public schools) as these benefits depend on one's household registration location, instead of the place of residence or work, and most migrants do not have local household registration. Some recent studies have shown that the travel-related behavior of migrants can be very different from residents (Zhao and Howden-Chapman, 2010; Lau, 2013; Guo et al., 2016b; Guo et al., 2018). These results suggest that the responses of migrants and residents to congestion pricing and reward policies can be different. However, none of the previous studies have considered such differences.

To understand the potential impacts of congestion pricing and reward policies on the responses of migrants and residents, it is important to understand the responses of Chinese millennials (born between 1979 and 2000) who are the driving force behind the drastic increase in private car purchases and ride-sharing service usage (Sima and Pugsley, 2010; Liu et al., 2012). Unlike older generations in China who grew up when private car usage was a rarity (Li, et al., 2010) or some of their millennial peers in the U.S. who have shown trend of decreasing automobile ownership, usage, and interest in getting a driver's license (Klein and Smart, 2017; Newbold and Scott, 2017), China's millennials are more likely to buy a car and use car mode as their primary and/or preferred mode choice (Ivan and Penev, 2011; Belgiawan et al., 2014; Guo et al., 2018). In 2014, individuals in the 18-29 age group surpassed other age groups as the age group with the highest percentage of car ownership in China (Credit Suisse Emerging Consumer Survey, 2015). This can be partly attributed to their unique attitudes and values that set them apart from their older generations or western peers. These attitudes and values are shaped by several major events through the memories shared with their generation. Such events include the Chinese economic reforms in 1978 which led to decades of economic growth; relaxation of the household registration system in 1978 which, along with economic development in urban and coastal regions, have promoted massive internal migration; implementation of the one-child policy in 1979 which resulted in a generation of single-child urban families; and the nine-year compulsory education policy in 1982 which boosted education for the masses. These events and shared memories collectively shaped millennials in China and made most of them more affluent, more likely to grow up in an only-child family, more likely to value individuality, more self-centered, more educated, more technology-savvy, more exposed to the outside world, more entrepreneurial and capitalistic, and more likely to live in different cities from where they grew up compared to their parents, who experienced famine and instability within a large family (average of three children per family in the 1960s) and were likely to have a "collective interest" mentality, watched and read state-controlled media with limited outside communication, and were confined to living in one region (Sun and Wang, 2010; Kong et al., 2015). Over half of the migrants in China are millennials, who represent a new generation of migrants who are more socially connected, more inspired to settle in the cities to which they migrate, and who yearn for equal access to welfare and government services as residents compared to the older generation of migrants (Yue et al., 2010; Cheng et al., 2014).

5.2 Methodology

To simultaneously model the morning commute mode shift responses of millennial car travelers under the congestion pricing and reward policies, a bivariate ordered probit was developed in which the dependent variables were the participants' responses under the congestion pricing policies and their responses under the reward policies. A bivariate model can account for potential correlation between two dependent variables' error terms as most of the sociodemographic and behavioral factors may correlate with both dependent variables.

First, the observed ordinal data y for each observation i; two outcomes were defined as (Greene and Hensher, 2009):

$$\begin{aligned} y_{i,1} &= \beta_1^{'} X_{i,1} + \varepsilon_{i,1}, \quad y_{i,1} = j \ \ if. \mu_{j-1} < y_{i,1} < \mu_j, \ j = 0, \ldots J_1, \\ y_{i,2} &= \beta_2^{'} X_{i,2} + \varepsilon_{i,2}, \quad y_{i,2} = j \ \ if. \theta_{j-2} < y_{i,2} < \theta_j, \ j = 0, \ldots J_2, \end{aligned} \tag{1}$$

where y_1 and y_2 correspond to the ordered mode shift responses to the congestion pricing policies (i.e., "I will switch to sustainable travel modes if congestion fee is 5-yuan," "I will switch to sustainable travel modes if congestion fee is 15-yuan," "I will switch to sustainable travel modes if congestion fee is 25-yuan," and "I will continue using car mode even if congestion fee is 25-yuan") and the reward policies (i.e., "I will switch to sustainable travel modes if using sustainable travel modes rewards me 1-yuan", "I will switch to sustainable travel modes if using sustainable travel modes rewards me 1.5-yuan," "I will switch to sustainable travel modes if using sustainable travel modes rewards me 2-yuan," and "I will continue using car mode even if using sustainable travel modes rewards me 2-yuan"). X are the vectors of the explanatory variables that determine the sociodemographic and behavioral characteristics, β are the vectors of the estimable parameters, μ and θ are the estimable thresholds which were estimated jointly with β, j is the integer ordered choice (J_1 and J_2 =3), and ε is the random error which is assumed to be normally distributed with the mean and variance equal to zero and one, respectively.

The cross-equation correlated error terms can be written as

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{2}$$

The bivariate ordered probit model with ordered selection joint probability P for $y_{i,1}=j$ and $y_{i,2}=k$ was then defined as (Equation 3):

$$P(y_{i,1}=j, y_{i,2}=k \mid X_{i,1}, X_{i,2}) = \begin{pmatrix} \Phi_2[(\mu_j - \beta_1' X_{i,1}), (\theta_k - \beta_2' X_{i,2}), \rho] \\ -\Phi_2[(\mu_{j-1} - \beta_1' X_{i,1}), (\theta_k - \beta_2' X_{i,2}), \rho] \end{pmatrix} - \begin{pmatrix} \Phi_2[(\mu_j - \beta_1' X_{i,1}), (\theta_{k-1} - \beta_2' X_{i,2}), \rho] \\ -\Phi_2[(\mu_{j-1} - \beta_1' X_{i,1}), (\theta_{k-1} - \beta_2' X_{i,2}), \rho] \end{pmatrix} \tag{3}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function.

To interpret the model estimation results, the marginal effects were calculated at the sample mean of each ordered category as follows (Equation 4):

$$\frac{P(y=j)}{\partial X} = [\phi(\omega_{j-1} - \beta X) - \phi(\omega_j - \beta X)]\beta \tag{4}$$

where $P(y=j)$ is the probability of ordered response j, and ω is the thresholds.

Random parameters were estimated to factor the potential unobserved heterogeneity by allowing parameters to vary across observations. Such variability was incorporated as follows (Equation 5):

$$\beta_i = \beta + \varphi_i \tag{5}$$

where β_i was the vector of the observation-specific parameters, and φ_i was the randomly distributed term. Several distributions for the random parameters were explored, including normal, uniform, triangular, Weibull, and lognormal. The normal distribution was found to provide the best statistical fit, which is consistent with several previous studies (Guo and Peeta, 2015;

Anastasopoulos, 2016; Guo et al., 2016a; Seraneeprakarn et al., 2017; Hou et al., 2018; Chen et al., 2019; Guo et al., 2019). 200 Halton draws are used in simulated maximum likelihood estimation for random parameters bivariate ordered probit models (Washington et al., 2010).

5.3 Survey Design and Data

The survey contained four main sections: (i) individual and household sociodemographic factors, such as gender, age, and residential status; (ii) travel behaviors, such as number of commutes per week, number of pickups and drop offs per week, most and second most common mode choice for their morning commute, and other modes of transportation used; (iii) attitudinal factors, such as their perceptions of the effectiveness, fairness, and acceptability of different pricing policies, their levels of environmental and personal health concerns, and attitudes towards sustainable travel modes; and (iv) the participants' stated-preference mode shift responses under the designed three-tier congestion pricing and reward policies. To assist the participants in making more informed mode shift responses, the participants were asked to enter their most common commute origin and destination in an interactive AutoNavi-based map developed for this study through which they were provided with travel information for eight travel modes, including car mode (using a private vehicle, a taxi, or a ridesharing service) and sustainable travel modes (bus, subway, electric bike, manual bike, shared manual bike, and walk). Such information included the estimated trip costs, in-vehicle travel time (time spent in a car, bus, or subway), and the walking distance between stations and their origin/destination for the bus and subway mode options. Providing this map to participants helped them to have a better understanding of the travel mode choices available to them and also collected information related to their accessibility to buses and subways as well as the accessibility of their destinations by bus and subway, which were found to affect mode choice in the literature (Moniruzzaman and Páez, 2012; Papa and Bertolini, 2015).

The three-tier congestion pricing policies were designed based on some of the congestion policies implemented in the real-world: 1) the pricing of Congestion Charge used in London (flat daily fee of \$15.21 per vehicle per day), 2) the congestion tax scheme used in Stockholm (up to \$8.23 per vehicle per day), and 3) the electronic road pricing scheme in Singapore (up to \$4.00 during peak-hours). These charges roughly were equal to between 20% and 80% of the average hourly salary of full-time employed residents. The designed congestion pricing fee was equal to approximately 10%, 25%, and 40% of the average hourly salary in Beijing in 2017 (approximately

62-yuan an hour or 9,942-yuan per month (China Daily, 2017)). One yuan was equal to $0.145 (USD) based on world bank annual average middle exchange rate in 2017. The three-tiers of reward policies were designed to make most of the sustainable travel modes for morning commute cost-free. The walk and manual bike modes were considered zero cost modes, shared bikes costs less than 2-yuan an hour, bus tickets 1-yuan with a bus pass (only a 20-yuan deposit is needed to obtain) or 2-yuan without one for a trip within 10 kilometers, and the average estimated subway ticket cost per traveler per trip was 4.3-yuan (roughly 12 kilometers). Both the congestion pricing policies and the reward policies were designed as a flat rate one-time daily charge/payment. It means that the car travelers make a one-time daily payment to use the car mode during peak hours under congestion pricing policies, or they could get a one-time daily reward if they do not use the car mode during the peak hours for their morning commute.

Approximately 6,000 surveys were distributed between June 10 and August 25, 2017, and another 2,000 surveys were distributed between September 1 and September 30, 2017 by Sojum Survey Company among a survey participant pool that fit our selection criteria. A total of 2,138 completed surveys were collected (987 migrants and 1,151 residents). Each participant was paid approximately $1.00 for completing the survey. Figure 5.1 illustrates the origins and destinations of the migrant (Figure 5.1a) and resident (Figure 5.1b) car travelers, and Tables 5.1 and 5.2 show the selected sociodemographic and behavior characteristics of the migrants and residents, respectively.

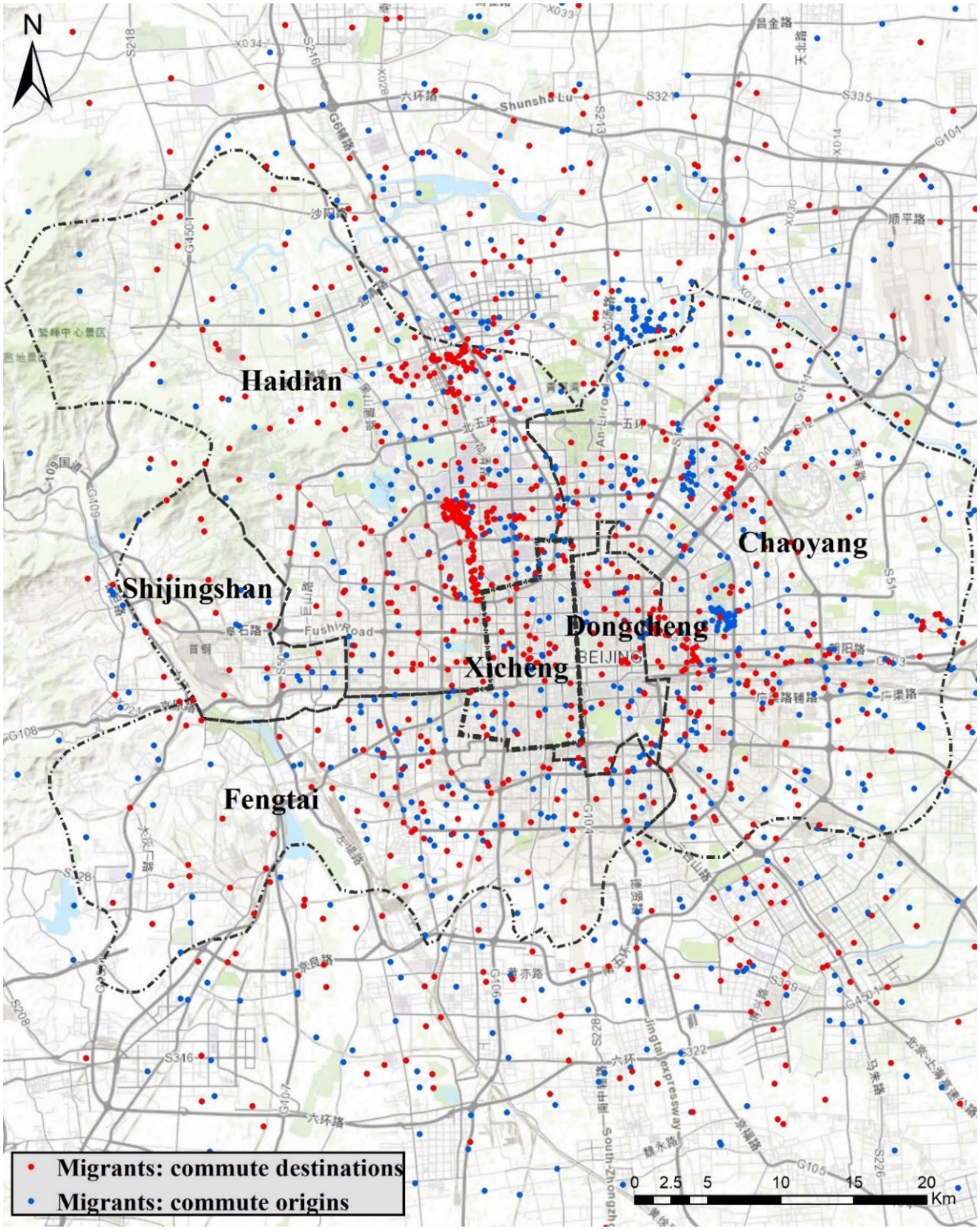


Figure 5.1 Commute Origins and Destinations of Migrant Car Travelers in a Normal Work Day (Each Dot Represents a Traveler's Trip Origin or Destination)

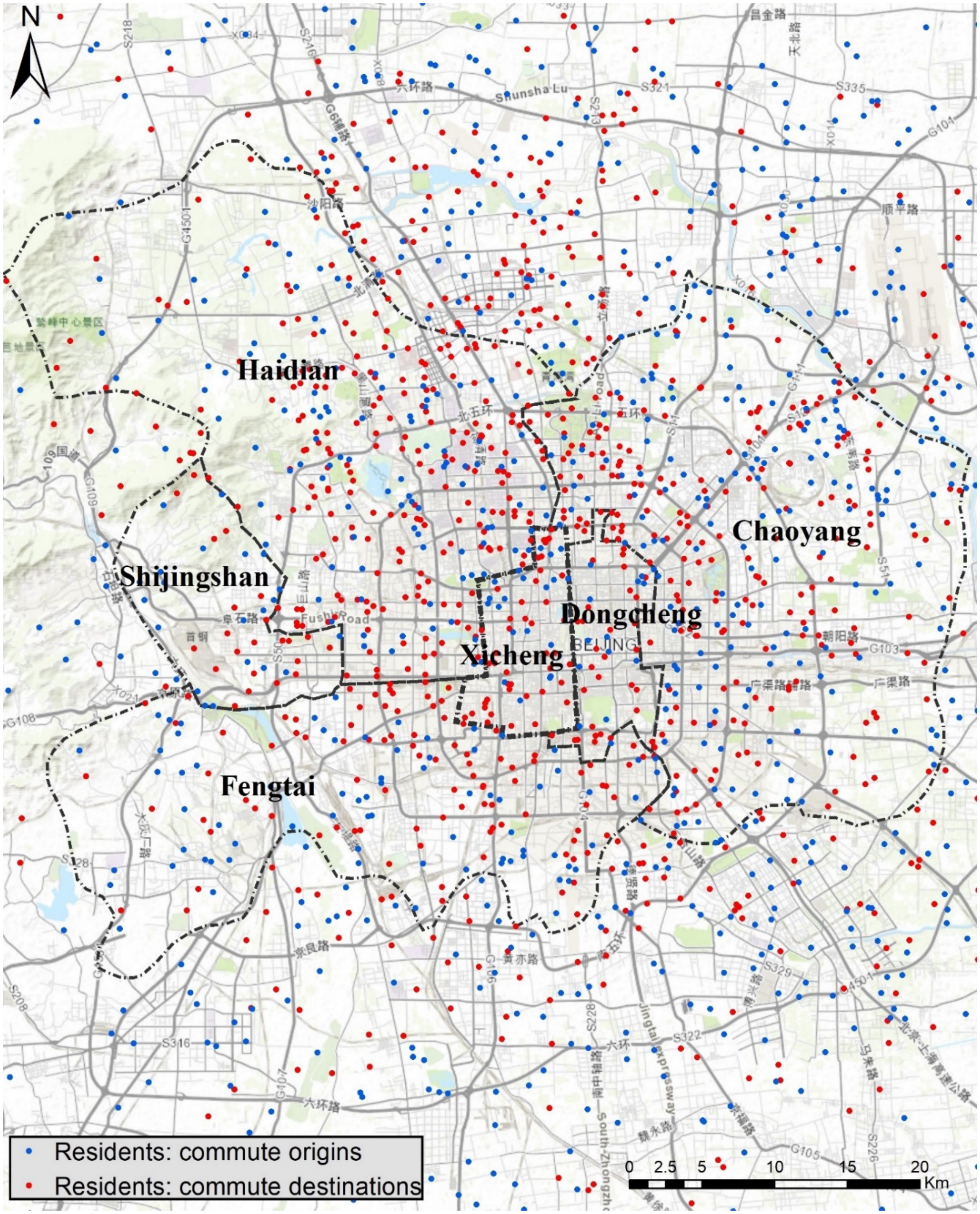


Figure 5.2 Commute Origins and Destinations of Resident Car Travelers in a Normal Work Day (Each Dot Represents a Traveler's Trip Origin or Destination)

Table 5.1 Descriptive Statistics of Sociodemographic and Behavior Characteristics

	Migrants (N=987)	Residents (N=1151)
Gender: Male (percentage)	55.4	51.4
Gender: Female (percentage)	44.6	48.6
Age: 18-25 (percentage)	18.7	12.9
Age: 26-34 (percentage)	63.2	57.4
Age: 35-38 (percentage)	18.1	29.7
Monthly income: Under 10,000-yuan (percentage)	62.2	66.1
Monthly income: 10,000-yuan or higher (percentage)	37.8	33.9
Work/school flexibility: Very inflexible (percentage)	55.1	54.5
Work/school flexibility: Somewhat flexible or very flexible (percentage)	44.9	45.5
Number of cars in the household: 0 or 1 (percentage)	92.7	84.9
Number of cars in the household: 2 or more (percentage)	7.3	15.1
Frequency of using bike sharing services: once a week or less (percentage)	65.3	56.8
Frequency of using bike sharing services: at least twice a week (percentage)	34.7	43.2
Residential property ownership: Rent (percentage)	72.3	32.8
Residential property ownership: Owned (percentage)	27.7	67.2
Second most common mode of transportation for commute trips: Using "car" modes (percentage)	26.4	38.5
Second most common mode of transportation for commute trips: Using sustainable travel modes (percentage)	73.6	61.5
Frequency of using bike sharing services:		
The most important factor affecting travel mode choice: Travel time (percentage)	56.1	55.2
The most important factor affecting travel mode choice: Travel cost (percentage)	16.5	17.5
The most important factor affecting travel mode choice: Others (reliability, safety, physical health, comfort, sustainability) (percentage)	27.4	27.3
Weekly commute trip frequency (i.e., from home-to-work and back): 5 times or under (percentage)	56.9	49.9
Weekly commute trip frequency: Over 5 times (percentage)	43.1	50.1
Average travel time by "car" mode (standard deviation) (minutes)	34.4 (18.0)	29.9 (17.7)
Average travel time by "bus" mode (standard deviation) (minutes)+	79.9 (62.8)	70.9 (59.6)
Average travel time by "subway" mode (standard deviation) (minutes) *+	89.8 (68.2)	67.7 (47.8)
Average walking distance from the commute origin to the departing bus stop plus the distance from the arriving bus stop to destination (meters)	2430.8 (1028.7)	2526.8 (1050.0)
Average walking distance the commute origin to the departing subway station plus the distance from the arriving subway station to destination * (meters)	3128.0 (1233.7)	2968.75 (1073.7)

* Note that if the distance between a subway station which provides the shortest commute travel time and a participant's commute origin or destination is over 3-kilometer, "subway" mode is considered inaccessible (Dang et al., 2014). Therefore, only those who have access to "subway" mode were considered in the estimation. It means 638 migrant and 738 resident travelers have subway access.

\+ Travel time by "bus" and "subway" mode includes walking time from home to departure stations and from arrival station to work location.

Table 5.2 Attitude towards and Mode Shift Responses under Congestion Pricing and Reward Policies

	Migrants (N=987)	Residents (N=1151)
Response to congestion pricing policies (percentage)		
I will switch to sustainable travel modes if congestion fee is 5-yuan	39.8	33.7
I will switch to sustainable travel modes if congestion fee is 15-yuan	31.5	29.6
I will switch to sustainable travel modes if congestion fee is 25-yuan	11.8	16.8
I will continue using a car even if congestion fee is 25-yuan	16.9	19.9
Perceived effectiveness of congestion pricing policies (percentage)		
"Very ineffective", "somewhat ineffective", or "neither effective nor ineffective"	53.3	39.9
"Somewhat effective" or "very effective"	46.7	60.1
Perceived fairness of congestion pricing policies (percentage)		
"Very unfair", "somewhat unfair", or "neither fair nor unfair"	63.6	63.1
"Somewhat fair" or "very fair"	36.4	36.9
Perceived acceptance of congestion pricing policies (percentage)		
"Very unacceptable", "somewhat unacceptable", or "neither acceptable nor unacceptable"	63.9	78.5
"Somewhat acceptable" or "very acceptable"	36.1	21.5
Response to reward policies (percentage)		
I will switch to sustainable travel modes if using sustainable travel modes rewards 1-yuan	41.6	44.5
I will switch to sustainable travel modes if using sustainable travel modes rewards 1.5-yuan	25.8	21.6
I will switch to sustainable travel modes if using sustainable travel modes rewards 2-yuan	9.3	8.9
I will continue using a car even if using sustainable travel modes rewards 2-yuan	23.2	24.9
Perceived effectiveness of reward policies (percentage)		
"Very ineffective", "somewhat ineffective", or "neither effective nor ineffective"	62.6	62.7
"Somewhat effective" or "very effective"	37.4	37.3
Perceived fairness of reward policies (percentage)		
"Very unfair", "somewhat unfair", or "neither fair nor unfair"	53.6	59.0
"Somewhat fair" or "very fair"	46.4	41.0
Perceived acceptance of reward policies (percentage)		
"Very unacceptable", "somewhat unacceptable", or "neither acceptable nor unacceptable"	36.6	59.1
"Somewhat acceptable" or "very acceptable"	63.4	40.9
Perceived environmental concerns caused by increasing car usage (average rating on a 1-5 Likert scale with 1 as "not at all concerned" and 5 as "very concerned")	3.51	3.35
Perceived personal health concerns related to physical inactive caused by increasing car usage (average rating on a 1-5 Likert scale with 1 as "not at all concerned" and 5 as "very concerned")	3.37	3.13
Attitude towards sustainable travel modes (average rating on a 1-5 Likert scale with 1 as "very negative" and 5 as "very positive")	3.69	3.71

\

It is important to note that a few origin and destination clusters existed among the migrant car travelers compared to the resident car travelers (Figure 5.1). The destination cluster located near the boundary of the Xicheng and Haidian Districts is called Zhongguancun, which is a technology hub also referred to as “China’s Silicon Valley,” likely because Zhongguancun is a fast-developing area in Beijing with many new job opportunities that is attracting an influx of migrants. One origin cluster located in the western part of the Chaoyang District is the Liulitun neighborhood and its surrounding neighborhoods, which has four transfer subway stations for subway lines 1, 2, 6, and 10. These differences may be partly attributed to the residential location decision-making process and residence ownership. As shown in Table 5.1, most migrants do not own residential property in Beijing while most residents do. The average unit price of residential property in Beijing’s inner districts ranged from approximately 40,000-yuan per m2 to 65,000-yuan per m2 in 2016 (National Bureau of Statistics, 2017) which has increased approximately 2-3 times in the past ten years. It means the costs of one-squared meter residents roughly is equal to four to six months of the average salary of a full-time employee in Beijing (9,942-yuan per month). The property price can be a little lower in the surrounding districts of the inner districts where the average residential property price ranges approximately 20,000-yuan per m2 to 49,000-yuan per m2. Considering that most residents have lived in Beijing longer, they likely own a property they purchased when the price was more manageable, while it is less likely for migrants to own a property considering the amount of investment required. Hence, migrants are more likely to rent a residence and live farther away from the inner districts, which is reflected in their longer average travel time using the car, bus, or subway modes compared to residents. Similar observations also were found in other cities in China (Zhao and Howden-Chapman, 2010; Guo et al., 2018). It is also important to note that car ownership is relatively low and many car travelers are not driving a personal car, but rather using taxi or ridesharing services, especially for migrant car travelers. This can be largely attributed to Beijing’s bi-monthly license plate lottery system where the odds of getting a license is 1 in 2,000 (6,333 licenses in the lottery with 2.8 million applicants in May 2018).

In terms of their attitudes and mode shift responses towards congestion pricing and reward policies, some key differences and similarities were found between migrant and resident car travelers (Table 5.2). First, migrant car travelers were more likely to shift to sustainable travel modes compared to resident car travelers when the congestion fee is 5-yuan, while resident car travelers were more likely to shift compared to migrant car travelers when the award is 1-yuan.

Second, the resident travelers considered congestion pricing policies more effective and less acceptable compared to the migrant travelers, while the migrant travelers considered the reward policies fairer and more acceptable compared to residents. Third, most of the migrants and residents were concerned about environmental issues and the physical inactivity caused by increased car usage and had a more positive attitude towards sustainable travel modes, as shown by their average scores on these subjects of three and higher.

5.4 Model Estimation Result and Discussion

Tables 5.3 and 5.4 present the model estimation results as well as the marginal effects for the random parameters bivariate ordered probit models for migrant and resident millennial car travelers' mode shift responses under the congestion pricing and reward policies, respectively. Table 5.5 summarizes the findings by subpopulations and illustrates the effects of the independent variables on their mode shift responses under the congestion pricing and reward policies. The independent variables were classified into six categories: 1) individual sociodemographic characteristics and household mobility, 2) travel behavior and travel needs, 3) transit accessibility, 4) most important factors affecting mode choice, 5) attitudes towards increasing car usage and sustainable travel modes, and 6) perceptions of the congestion pricing and reward policies. The cross-equation correlation coefficient (ρ) of the mode shift responses under the congestion pricing and the response under the reward policies were statistically significant at 99.9% level of confidence for both the migrant and resident car travelers and indicated a positive association between the mode shift responses under the congestion pricing policies and the responses under the reward policies. It means that car travelers who were more likely to shift from using the car mode to using sustainable travel modes as their primary morning commute mode choice (hereafter referred to as "make a mode shift to sustainable travel modes") at a lower congestion fee amount also were more likely to make a mode shift to sustainable travel modes at a lower reward amount, and vice versa. The hypothesis that the parameters are transferable across migrant and resident car travelers was tested using a combination of likelihood ratio tests, and the results show that estimating the separate models for migrants and residents was superior to estimating them together.

The car traveler's income played an important role in the mode shift response outcome probabilities under the congestion pricing policies but not under the reward policies. Travelers with a lower than average monthly salary in Beijing (under 10,000-yuan a month) were more likely to make a mode shift to sustainable travel modes at a lower congestion fee. These findings may be attributed to the possibility that low-income travelers were more concerned about the potential penalty and financial burden brought by the congestion pricing policies and hence were more likely to make a mode shift. Travelers were more likely to make a mode shift to sustainable travel modes at a lower congestion fee if their households had more than one vehicle, which may suggest that they have multiple family members who are car travelers and their financial burden would increase drastically if they had more vehicles under the congestion pricing policies.

With regard to the factors related to travel behavior and travel needs, migrant and resident car travelers who needed to commute more than five times a week were more likely to make a mode shift to sustainable travel modes at a lower congestion fee. This finding may be attributed to the increased travel cost as these car travelers must commute more often under the congestion pricing policies. Most migrant and resident car travelers who used sustainable travel modes as their second most common travel mode choice for their morning commute were more likely to make a mode shift to sustainable travel modes at a lower reward amount, which suggests that travelers who do not have a strong car travel habit (i.e., use sustainable travel modes regularly) may be more agreeable to reward policies, which has been shown in a recent study (Li et al., 2019). The model estimation results also show that how much millennial car travelers use bike sharing services played an important role in the mode shift response outcome probabilities under the congestion pricing and reward policies for both migrants and residents. Most of the car travelers were more likely to make a mode shift to sustainable travel modes at a lower congestion fee and reward amount if they already used bike sharing services at least twice a week. As shown in the literature (Chang and Lai, 2015; Guo et al., 2018), one of the unique characteristics of the travel mode choices in China is the predominance of bicycles and motorcycles. Since motorcycle usage has been banned in Beijing since 1987, bike sharing services have provided a familiar alternative that promotes migrant and resident car travelers making mode shift to sustainable travel modes since their launch in 2014. Some of such migrant car travelers were more likely to continue using the car mode under congestion pricing policies, which may be attributed to their relatively long commute distance and they can be potentially captive car mode travelers.

Both types of transit accessibility, including accessibility to and by transit, played a key role in the mode shift responses under the congestion pricing and reward policies, especially for migrant car travelers. Specifically, car travelers with low accessibility to bus/subway lines are more likely to continue using car mode under the congestion pricing policies. Whereas, car travelers with high accessibility to and by bus/subway lines are more likely to make a mode shift to sustainable travel modes at a lower congestion fee and reward amount. These findings are consistent with previous studies that transit accessibility and other types of built environment factors influence traveler mode choice decisions (Handy et al., 2005; Rodriguez and Rogers, 2014; Guo and Peeta, 2019). These results also illustrate the importance of improving transit accessibility in promoting mode shift to sustainable travel modes under both the congestion pricing and reward policies.

The variables representing the travelers' perceptions toward the most important factor affecting the travel mode choice also were found to play an important role in the mode shift response outcome probabilities for both migrants and residents. Car travelers who considered travel cost as the most important factor affecting their travel mode choice were more likely to not make a mode shift to sustainable travel modes at lower congestion fee amounts and more likely to continue using the car mode. Among car travelers who considered travel time as the most important factor affecting their travel mode choice, migrant car travelers and most resident car travelers were more likely to make a mode shift to sustainable travel modes at lower congestion fee amounts. Only resident car travelers who considered factors others than travel time and travel cost as the most important factor affecting their travel mode choice were more likely to not make a mode shift to sustainable travel modes at lower congestion fee amounts or were more likely to continue using the car mode. These findings may be attributable to their travel cost perception, residence familiarity, and income-specific heterogeneity.

The factors related to travelers' attitudes towards increasing car usage and sustainable travel modes were found to influence the mode shift responses of both the migrant and resident car travelers under the congestion pricing and reward policies. Car travelers who were "somewhat not concerned" or "not at all concerned" about the physical inactivity associated with increasing car usage were less likely to make a mode shift to sustainable travel modes at a lower congestion pricing amount and were more likely to continue using the car mode. Whereas, car travelers who were "somewhat concerned" or "very concerned" about the negative environmental impact brought by increasing car usage were more likely to make a mode shift to sustainable travel modes at a lower reward amount. Most car travelers who had "somewhat negative" or "very negative" attitude towards sustainability were less likely to make a mode shift to sustainable travel modes at a lower congestion pricing and reward amount and were more likely to continue using the car mode. However, some such travelers were more likely to make a mode shift to sustainable travel modes at a lower reward amount, which may be attributable to the heterogeneity among such car travelers in terms of how they value the potential penalty for continuing to use the car mode, the potential reward for using sustainable travel modes, and their negative attitude towards sustainable travel modes.

Table 5.3 Random Parameters Bivariate Ordered Probit Model Estimation Results for Migrants (N=987)

Variable	Parameter estimate	*t*-Statistic	Random parameters percent of distribution		Average marginal effects (random parameters model)			
			Above zero	Below zero	y=0	y=1	y=2	y=3
Mode choice towards congestion pricing policy								
Constant	1.09	8.22	—	—				
Low-income indicator (1 if traveler's monthly income is under 10,000-yuan, 0 otherwise)	-0.73	-7.73**	—	—	0.24	-0.06	-0.08	-0.11
Car indicator (1 if traveler has more than one car, 0 otherwise)	-0.45	-3.52	—	—	0.13	-0.04	-0.04	-0.04
Bike indicator (1 if traveler uses bike sharing services twice a week or more, 0 otherwise)	-0.37 (0.45)	-4.24** (6.20**)	20.6	79.4	0.11	-0.03	-0.04	-0.07
Travel time indicator (1 if travel time is identified as the most important factor affecting mode choice, 0 otherwise)	0.40	5.66**	—	—	-0.07	0.02	0.02	0.03
Low health concern indicator (1 if traveler is "somewhat not concerned" or "not at all concerned" about physical inactivity associated with increasing car usage, 0 otherwise)	0.42	4.37**	—	—	-0.17	0.04	0.05	0.07
High commute frequency indicator (1 if traveler commute more than five times a week, 0 otherwise)	-0.40	-3.56**	—	—	0.22	-0.08	-0.06	-0.07
High perceived effectiveness indicator (1 if traveler consider congestion pricing policy is "somewhat effective" or "very effective" in promoting mode shift from car to sustainable travel modes, 0 otherwise)	-0.85	-12.62**	—	—	0.43	0.09	-0.13	-0.22
Low accessibility to bus/subway indicator (1 if walking distance from the commute origin to the departing bus/subway station plus the distance from the arriving bus/subway station to destination is over four kilometers, 0 otherwise)	0.52	4.63**	—	—	-0.15	0.02	0.05	0.08

Table 5.3 Random Parameters Bivariate Ordered Probit Model Estimation Results for Migrants (N=987) (continued)

	Parameter estimate	*t*-Statistic	Random parameters percent of distribution		Average marginal effects (random parameters model)			
			Above zero	Below zero	y=0	y=1	y=2	y=3
High accessibility by bus/subway indicator (1 if travel time using bus or subway is less than two times of travel time using car, 0 otherwise)	-0.41	-4.98**	—	—	0.15	0.03	0.07	0.11
Negative attitude towards sustainable travel modes indicator (1 if traveler's attitude towards sustainable travel modes is "somewhat negative" or "very negative")	-0.23 (0.32)	-3.19** (3.62**)	23.6	76.4	-0.23	0.02	0.06	0.16
μ_1	1.12	15.91						
μ_2	1.62	22.24						
Mode choice towards reward policy								
Constant	0.44	3.02**						
Bike indicator (1 if traveler uses bike sharing services twice a week or more, 0 otherwise)	-0.40	-4.19**	—	—	0.19	-0.04	-0.06	-0.09
Travel cost indicator (1 if travel cost is identified as the most important factor affecting mode choice, 0 otherwise)	-0.27	-2.22*	—	—	0.04	-0.01	-0.01	-0.03
High environmental concern indicator (1 if traveler is "somewhat concerned" or "very concerned" about environmental problems associated with increasing car usage, 0 otherwise)	-0.61	-4.41**	—	—	0.16	-0.06	-0.05	-0.05
Sustainable travel mode alternative indicator (1 if traveler's second most common mode of transportation is one of the sustainable travel modes, 0 otherwise)	-0.64 (0.55)	-6.23** (4.19**)	12.2	87.8	0.10	-0.02	-0.03	-0.05
High perceived acceptableness indicator (1 if traveler consider reward policy is "somewhat acceptable" or "very acceptable" in promoting mode shift from car to sustainable travel modes, 0 otherwise)	-0.65	-7.14**	—	—	0.26	-0.03	-0.07	-0.17

Table 5.3 Random Parameters Bivariate Ordered Probit Model Estimation Results for Migrants (N=987) (continued)

	Parameter estimate	*t*-Statistic	Random parameters percent of distribution		Average marginal effects (random parameters model)			
			Above zero	Below zero	y=0	y=1	y=2	y=3
High perceived fairness indicator (1 if traveler consider reward policy is "somewhat fair" or "very fair" in promoting mode shift from car to sustainable travel modes, 0 otherwise)	-0.87	-7.54**	—	—	0.25	0.03	-0.05	-0.23
High accessibility to bus/subway indicator (1 if walking distance from the commute origin to the departing bus/subway station plus the distance from the arriving bus/subway station to destination is less than two kilometers, 0 otherwise)	-0.24	-2.82**	—	—	0.07	-0.01	-0.01	-0.05
High accessibility by bus/subway indicator (1 if travel time using bus or subway is less than two times of travel time using car, 0 otherwise)	-0.66	-8.05**	—	—	0.38	-0.04	-0.01	-0.03
μ_1	0.74	12.65						
μ_2	1.19	15.59						
ρ	0.95							
LL(0)	-2044.69							
LL(β)	-1621.94							

* Denotes the parameter is significant at 0.05 level.

** Denotes the parameter is significant at 0.01 level.

Table 5.4 Random Parameters Bivariate Ordered Probit Model Estimation Results for Residents (N=1151)

Variable	Parameter estimate	*t*-Statistic	Random parameters percent of distribution		Average marginal effects (random parameters model)			
			Above zero	Below zero	y=0	y=1	y=2	y=3
Mode choice towards congestion pricing policy								
Constant	0.95	6.32**						
Low-income indicator (1 if traveler's monthly income is under 10,000-yuan, 0 otherwise)	-0.67	-8.66**	—	—	0.21	0.02	-0.09	-0.13
Car indicator (1 if traveler has more than one car, 0 otherwise)	-0.57	-6.47**	—	—	0.16	0.04	-0.07	-0.13
Bike indicator (1 if traveler uses bike sharing services twice a week or more, 0 otherwise)	-0.29	-3.46**	—	—				
Travel time indicator (1 if travel time is identified as the most important factor affecting mode choice, 0 otherwise)	0.28	3.86**	—	—	-0.09	-0.01	0.04	0.06
Other factor indicator (1 if factor (reliability, safety, physical health, comfort, sustainability) is identified as the most important factor affecting mode choice, 0 otherwise other)	0.31	4.24**	—	—	-0.08	-0.01	0.04	0.05
Low health concern indicator (1 if traveler is "somewhat not concerned" or "not at all concerned" about physical inactivity associated with increasing car usage, 0 otherwise)	0.43	5.48**	—	—	-0.12	-0.01	0.05	0.08
High commute frequency (1 if traveler commute more than five times a week, 0 otherwise)	-0.39	-4.05**	—	—	0.12	0.01	-0.05	-0.08
High perceived effectiveness indicator (1 if traveler consider congestion pricing policy is "somewhat effective" or "very effective" in promoting mode shift from car to sustainable travel modes, 0 otherwise)	-0.88	-12.02**	—	—	0.34	0.01	-0.14	-0.21

Table 5.4 Random Parameters Bivariate Ordered Probit Model Estimation Results for Residents (N=1151) (continued)

	Parameter estimate	*t*-Statistic	Random parameters percent of distribution		Average marginal effects (random parameters model)			
			Above zero	Below zero	y=0	y=1	y=2	y=3
High perceived fairness indicator (1 if traveler consider congestion pricing policy is "somewhat fair" or "very fair" in promoting mode shift from car to sustainable travel modes, 0 otherwise)	-0.47	-2.73**	—	—	0.12	0.03	-0.06	-0.10
Low accessibility to bus/subway indicator (1 if walking distance from the commute origin to the departing bus/subway station plus the distance from the arriving bus/subway station to destination is over four kilometers, 0 otherwise)	0.28 (0.30)	1.98* (2.57**)	82.5	17.5	-0.07	-0.05	-0.01	0.05
μ_1	1.12	15.91						
μ_2	1.62	22.24						
Mode choice towards reward policy								
Constant	0.57	4.35**						
Bike indicator (1 if traveler uses bike sharing services twice a week or more, 0 otherwise)	-0.18	-2.14*	—	—	0.06	-0.01	-0.01	-0.04
Travel cost indicator (1 if travel cost is identified as the most important factor affecting mode choice, 0 otherwise)	-0.37 (0.26)	-4.06** (3.12**)	7.7	92.3	0.19	-0.00	-0.03	-0.17
High environmental concern indicator (1 if traveler is "somewhat concerned" or "very concerned" about environmental problems associated with increasing car usage, 0 otherwise)	-0.45	-5.35**	—	—	0.16	-0.01	-0.03	-0.12
Sustainable travel mode alternative indicator (1 if traveler's second most common mode of transportation is one of the sustainable travel modes, 0 otherwise)	-0.48	-5.15**	—	—	0.22	-0.04	-0.04	-0.13

Table 5.4 Random Parameters Bivariate Ordered Probit Model Estimation Results for Residents (N=1151) (continued)

	Parameter estimate	*t*-Statistic	Random parameters percent of distribution		Average marginal effects (random parameters model)			
			Above zero	Below zero	y=0	y=1	y=2	y=3
High perceived acceptableness indicator (1 if traveler consider reward policy is "somewhat acceptable" or "very acceptable" in promoting mode shift from car to sustainable travel modes, 0 otherwise)	-0.27	-3.24**	—	—	0.12	-0.01	-0.02	-0.10
High accessibility by bus/subway indicator (1 if travel time using bus or subway is less than two times of travel time using car, 0 otherwise)	-0.53	-3.58**	—	—	0.18	-0.01	-0.03	-0.17
Negative attitude towards sustainable travel modes indicator (1 if traveler's attitude towards sustainable travel modes is "somewhat negative" or "very negative")	-0.41	-5.00**	—	—	0.16	-0.02	0.05	0.19
μ_1								
μ_2								
ρ	0.67	27.99						
LL(0)	-2542.65							
LL(β)	-2075.73							

* Denotes the parameter is significant at 0.05 level.

** Denotes the parameter is significant at 0.01 level.

Table 5.5 Summary of Findings: Effects of Independent Variables on Traveler Response to Congestion Pricing and Reward Policies

	Migrants		Residences	
	Congestion pricing	Reward	Congestion pricing	Reward
Individual Sociodemographic and household mobility				
Low-income indicator	↓	—	↓	—
Car indicator	↓	—	↓	—
Travel behavior and travel needs				
Bike indicator	Mixed effect (primarily ↓)	↓	↓	↓
High commute frequency indicator	↓	—	↓	—
Sustainable travel mode alternative indicator	—	Mixed effect (primarily ↓)	—	↓
Transit accessibility				
Low accessibility to bus/subway indicator	↑	—	Mixed effect (primarily ↑)	—
High accessibility to bus/subway indicator	—	↓	—	—
High accessibility by bus/subway indicator	↓	↓	—	↓
Most important factor affecting travel mode choice				
Travel time indicator	↑	—	↑	—
Travel cost indicator	—	↓	—	Mixed effect (primarily ↓)
Other factor indicator	—	—	↓	—
Attitude towards increasing car usage and attitude towards sustainable travel modes				
Low health concern indicator	↑	—	↑	—
High environmental concern indicator	—	↓	—	↓
Negative attitude towards sustainable travel modes indicator	Mixed effect (primarily ↓)	—	—	↓
Perception of policy in promoting mode shift from car to sustainable travel modes				
High perceived effectiveness indicator	↓	—	↓	
High perceived acceptableness indicator	—	↓	—	↓
High perceived fairness indicator	—	↓	↓	—

The car travelers' perceptions about the effectiveness, acceptability, and fairness of the congestion pricing and reward policies also were found to play an important role in their mode shift responses to corresponding policies. Both the migrant and resident car travelers were more likely to make the mode shift to sustainable travel modes at a lower congestion pricing amount if they perceived the policy as "somewhat effective" or "very effective." They were more likely to make a mode shift to sustainable travel modes at a lower reward amount if they perceived the policy as "somewhat effective" or "very effective." Migrant car travelers who perceived the reward policy as “somewhat unfair” or “very unfair” were less likely to make a mode shift to sustainable travel modes at a lower reward amount and were more likely to continue using car mode. Whereas, resident car travelers who perceived the congestion pricing policy as “somewhat unfair” or “very unfair” were less likely to make a mode shift to sustainable travel modes at a lower congestion pricing amount and were more likely to continue using car mode.

5.5 Concluding Comments

This chapter of the dissertation presented the results of the investigation of migrant and resident car traveler mode shift responses under congestion pricing and reward policies. Random parameters bivariate ordered probit models were estimated by residential status (migrants and residents) to account for unobserved heterogeneity and for possible correlations between mode shift responses under the congestion pricing and reward policies and to identify the specific factors affecting the mode shift responses of migrant and resident car travelers.

The model estimation results show that introducing complementary intervention modules such as educational programs that promote attitudinal change in car travelers’ perceptions of congestion pricing and reward policies and raise awareness of the environmental and personal health benefits associated with using sustainable travel modes can potentially promote the effectiveness of both policies. The model estimation results also show that the factors affecting mode shift responses under congestion pricing and under reward policies are different, which indicates that it is important to invest in different complementary intervention modules under a budget constraint as the effectiveness of the same complementary intervention module can be different under various congestion pricing and reward policies.

The model estimation results further demonstrate that migrant and resident millennial car travelers have different mode shift responses under both congestion pricing and reward policies under the same or similar circumstances, which partly may be attributable to a combination of the unique regional characteristics and policies that contribute to some of the key challenges faced by migrant car travelers in Beijing. First, several relatively recent policies aimed at reducing car usage have greatly affected the capability of relatively newer potential car owners who are more likely to be migrants (as were most of the migrants to Beijing in recent years) to buy a vehicle. The license plate lottery system, which has been in effect since 2011 requires potential car owners to enter a bimonthly drawing system in which about 1 in 2,000 applicants is rewarded with a Beijing conventional gasoline-powered vehicle license plate (there is a slightly higher chance to get an electric vehicle license plate). It is somewhat easier to get a non-Beijing vehicle license plate, but those vehicles are not allowed to enter the Beijing Inner City area during the morning and evening peak hours without special permits during workdays (maximum of 12 permits per year and each permit is valid for seven workdays) due to the road space rationing system. Furthermore, the road space rationing system requires each locally licensed gasoline-powered vehicle to be idle one day a week. These policies have led to relatively low car ownership among migrant car travelers, forcing them to use taxi or ridesharing services for their commute. It is already a large financial burden for migrants as the travel costs of taxis or ridesharing services are higher than driving a personal vehicle per trip. The potential introduction of a congestion pricing policy may add further burdens on migrant car travelers. Second, the increasing residential property prices in Beijing have resulted in newer homeowners and apartment renters, among whom most are migrants, spending a significant portion of their income for mortgages and rent. For example, the average unit price for buying a second-hand apartment in Beijing was 60,074-yuan/m2 in June 2019 which is about 3% higher than in June 2018 and over 400% higher than in June 2009 (Anjuke, 2019). It means that a 50-m2 second-hand two-bedroom apartment is equal to the 25-year salary of an average full-time employed worker in Beijing. It would cost approximately 6,000-yuan to rent a similar apartment, which is equal to 60 percent of the monthly salary of an average full-time employed worker in Beijing; and the rent can potentially be even higher if it is close to subway stations. Furthermore, it is common practice for migrants to remit a significant portion of their income to their inflow regions (one-third on average) to support family members in their inflow regions (Cai, 2003; Akay et al., 2014). Such practice may further limit the disposable income a migrant can allocate for travel compared to a resident with a similar income.

Finally, this study has its limitations. First, the usage of self-reported behavioral information and stated preferences online survey data has its limitations (Langenbucher and Merrill, 2011). Second, the findings of the case study in Beijing needs to be compared with potential future studies in megacities such as Shanghai and Guangzhou as they have different vehicle registration systems and public transit systems. Third, a car traveler's accessibility to and by bus or subway were measured using only the bus or subway route that provided the shortest commute travel time. Such measurement has its limitations as a person has multiple route options for using a bus or subway so their accessibility to and by bus or subway should ideally increase too. Fourth, the congestion pricing charges and rewards were predetermined, and more flexible options can be offered in the future.

In conclusion, this study can be viewed as a first step in empirically understanding the impacts of congestion pricing and reward policies on the mode shift responses of migrant and resident millennial car travelers in China. Additional studies are needed to understand the potential generational gaps between millennial car travelers and older generations in terms of their mode shift responses to congestion pricing and reward policies. The study method potentially can be used to understand traveler responses to other types of transportation policies while factoring the potential differences among resident, migrant, and immigrant travelers so that various complementary measures can be designed to address the potential unintended consequences towards inequality among the subpopulations of travelers. Future work can include the pilot testing of congestion pricing and reward policies among a group of migrant and resident car travelers to reveal and examine the short- and long-term impacts of such policies on their mode choice behaviors.

CHAPTER 6. PERSONAL AND SOCIETAL IMPACTS OF MOTORCYCLE FULL-BAN POLICY ON MOTORCYCLISTS' HOME-TO-WORK MORNING COMMUTE IN CHINA

6.1 Introduction

Motorcycles (i.e., gasoline-powered scooters and mopeds) play a vital role in daily commute patterns in China, and ownership of them has increased rapidly over the last three decades. Over 100 million motorcycles were operating in 2014 compared to 200,000 in 1981 (NBSC, 2015). The motorcycle is considered as a faster and cheaper transportation mode compared to cars, and a more convenient and dependable mode for door-to-door travel compared to transit, especially for those who have low-to-medium income or live in neighborhoods with inconvenient, insufficient or inefficient public transportation systems (Weinert et al., 2007; Frank et al., 2008; Ye and Wang, 2011; Paulssen et al., 2014; Xu, 2014; Liu et al., 2016; Guo et al., 2016c; Guo et al., 2018).

Despite these benefits, the sharp rise in motorcycle ownership and usage also has contributed to several unique motorcycle-related transportation challenges in many Asian countries, including China, which are different from those in developed countries where car usage is predominant (Pucher et al., 2007; Weinert et al., 2007). These challenges include: high frequency of motorcycle-related accidents and fatalities; increasing motorcycle-related pollution and congestion; and motorcycle snatch theft and robbery (Pucher et al., 2007; Xu, 2010; Ye and Wang, 2011; Xu, 2014). These challenges are further intensified in China by its distinctive regional and political characteristics, including extensive internal migration, the national family planning policy (a state policy to restrict number of children most families can have), and household registration (hukou) system (a state institution that tie eligibility for most public benefits and welfare to one's hukou location, instead of the place of residence or work), especially in cities with a large percentage of migrants (Du et al., 2005; Chan, 2007; Chang et al., 2011; Shen, 2013; Xu, 2014;).

To address these challenges, policy-makers in China have started introducing policies that restrict motorcycle usage, hereafter referred to as "motorcycle ban policies". Such policies include stopping new motorcycle license issuance, banning motorcycles from main streets, banning motorcycles from the central business district (CBD), banning non-local licensed motorcycles, a motorcycle full-ban, etc. The motorcycle full-ban policy which prohibits motorcycle usage within the city limits except for police was first introduced in Beijing in 1985. Since then, more than 160 cities in China, including all five first tier cities (Beijing, Shanghai, Guangzhou, Shenzhen and Tianjin), over 30% of 363 prefecture-level cities, and about 1.5% of 2861 county level cities have implemented at least one type of motorcycle ban policy by 2009 (Zuo, 2009). Many policy-makers in China claim there are two main benefits of motorcycle ban policies: (i) "cutting the legs" of motorcycle related accidents and motorcycle snatch theft by reducing motorcycle usage in the city, and (ii) limiting motorcycle accessibility, thereby making other more environmentally-friendly modes of transportation (e.g., public transit, walk, and bike modes) more appealing and encouraging motorcyclists (for whom motorcycle is their primary mode of transportation) to shift to more environmentally-friendly modes (Xu, 2014). Song and Zhong (2015) further argue that the implementation of motorcycle ban policies may put more pressure on government officials to improve public transit systems as it would be expected that a significant portion of motorcyclists would shift to public transit and government would have no choice but to improve the transit system.

Despite the potential benefits claimed by some studies, many recent studies (Deng, et al., 2009; Ye and Wang, 2011; Xu, 2011; Xiong and Wei, 2013; Xu, 2014) have shown that motorcycle ban policies can significantly increase the out-of-pocket cost for motorcyclists, particularly for migrant motorcyclists. In addition, these policies potentially can add new dimensions to the social exclusion and ability to survive of migrant motorcyclists (Xu, 2014). As shown in Xu (2010 and 2014), motorcycles play a more significant role in migrants' lives compared to residents as far as improving mobility, combating poverty, and in some cases, allowing them to work as a full or part-time motorcycle taxi drivers for extra income. Furthermore, some studies (He et al., 2013; Liu et al., 2016) have shown that the implementation of motorcycle ban policies may make motorcyclists more likely to shift to the car mode as their incomes increase, making cars more affordable, and transit systems are insufficient. While these findings are interesting, they do not allow for understanding the factors that determine motorcyclists' travel mode shifts, or provide quantified analysis of the personal and societal impacts of motorcycle ban policies on travel mode shifts in China. Furthermore, none of previous studies have attempted to analyze the potential similarities and differences of travel mode shifts and impacts caused by motorcycle ban policies that may exist across population sub-groups defined by gender and residential status (migrants and residents) in China. As shown in many recent studies, travel-related choices can be very different across these population sub-groups (Simma and Axhausen, 2001; Matthies et al., 2002; Scheiner and Holz-Rau, 2007; Shen, 2013; Yang et al., 2013; Guo et al., 2016a; Guo and Peeta, 2019).

This part of the dissertation investigates the personal and societal impacts of the motorcycle full-ban policy on motorcyclists' home-to-work morning commute travel mode shift across gender and residential status categories in China. Random parameters models with heterogeneity in means and variances were estimated for each population sub-group to provide a better understanding of the impacts of a number of factors on travel mode shifts, and if these factors contribute similarly or differently to travel mode shifts of these population sub-groups. These factors include motorcyclists' individual and household sociodemographic characteristics (income, household structure and mobility resources); behavioral characteristics (perspectives on the factors that have the most impact on their travel mode choice and the most important improvement needed in transit and transportation systems); and trip-specific characteristics. In addition, the changes in the out-of-pocket cost, the opportunity cost of travel time, emissions, energy consumption, and safety before and after the travel mode shifts were also estimated by these population sub-groups.

For the analysis, self-reported travel mode choice and stated travel mode shift response (i.e., which mode they would use to replace motorcycle for their morning commute) survey data are used. The data were collected by the local government through paper surveys in October 2010 in Foshan, Guangdong province, China. Guangdong province has received the largest number of migrants over the past 20 years in China. For model estimation, four transportation modes (walk, bike, bus and car) were considered as the potential modes to shift for motorcyclists' home-to-work morning commute, hereafter referred to as "morning commute". To access the performance of the proposed approach, both random parameters logit models with fixed means and variances with heterogeneity in means and variances were estimated and evaluated in terms of their statistical fit and explanatory power.

6.2 Methodology

6.2.1 Random Parameters Approach with Heterogeneity in Means and Variances

Travel-related behavior, such as travel mode shift, has been traditionally modeled within a discrete choice framework using multinomial logit models and their derivatives, such as mixed logit and latent class models (Bhat, 2000; Green and Hensher, 2003; Bhat and Sardesai, 2006; McMillan, 2007; Dissanayake and Morikawa, 2010; Anastasopoulos et al., 2012; Kang and Fricker, 2013; Kamargianni et al., 2015; Guo et al., 2016b). After the motorcycle full-ban policy is implemented, the motorcyclists must shift to car, bus, bike, or walk mode for their morning commute.

To begin with, the linear function form of the multinomial logit model for travel mode shift, MS_{mn}, that determines discrete outcome *m* for observation *n* such that (Equation 1):

$$MS_{mn} = \beta_n X_{mn} + \varepsilon_{mn} \tag{6}$$

where X_{mn} is a vector of the observable variables that determine discrete outcomes for observation, m, β_n is a vector of the estimable parameters for outcome *n*, and ε_{mn} is an error term (McFadden, 1973). It is assumed that ε_{mn} is extreme value Type I (Gumbel) distributed (Washington et al., 2011).

To account for the unobserved heterogeneity in the means and variances of the random parameters in Eq. 1, β_{mn} is introduced as follows (Seraneeprakarn et al., 2017),

$$\beta_{mn} = \beta + \Theta_{mn} Z_{mn} + \sigma_{mn} EXP(\omega_{mn} W_{mn}) v_{mn} \tag{7}$$

where β is the mean parameter estimate across all observations, $\mathbf{Z}_{mn}$ is a vector of the observable variables which captures the heterogeneity in the mean that determines a discrete outcome, Θ_{mn} is a corresponding vector of the estimable parameters, $\boldsymbol{W}_{mn}$ is a vector of the explanatory variables which captures the heterogeneity in the standard deviation σ_{mn} with corresponding parameter vector ω_{mn}, and v_{mn} is a disturbance term. Relaxing these assumptions provides a better opportunity to track any unobserved heterogeneity in the data as shown in several recent empirical studies (Behnood and Mannering, 2017; Seraneeprakarn et al., 2017).

Using a specification that helps accommodate observation-specific unobserved heterogeneity, the outcome probability of travel mode shift is introduced as follows (Train, 2009) (Equation 3),

$$P_n(m) = \int \frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})} f(\beta|\varphi) d\beta \tag{8}$$

where $P_n(m)$ is the probability of a motorcyclist *n* shifting to mode *m* conditional on $f(\beta|\varphi)$, φ represents a vector of the density function, and all other terms are as previously defined previously. The model is estimated using the simulated maximum likelihood approach with 300 Halton draws to provide sufficient accuracy in parameter estimation as suggested by previous studies (Anastasopoulos and Mannering, 2009; Train, 2009; Guo and Peeta, 2015). Normal, lognormal, triangular and uniform distributions were considered as potential distributions for random parameters. The results showed that the normal distribution for the parameter density functions provided the best statistical fit for the estimated models, which is in line with prior research (Anastasopoulos and Mannering, 2009; Anastasopoulos and Mannering, 2011; Behnood and Mannering, 2017; Seraneeprakarn et al., 2017).

Direct and cross marginal effects are used to illustrate the effects of each contributing factor on the probability of shifting to one of the four modes. Marginal effects are used to illustrate the effect that a one-unit increase in an observable variable has on the travel mode shift probability (Washington et al., 2011).

The direct marginal effect is defined as follows (Seraneeprakarn et al., 2017),

$$\eta_{x_{mn}}^{P_n(m)} = \frac{dP_n(m)}{dx_{mn}} = \frac{d}{dx_{mn}} \int \frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})} f(\beta|\varphi) d\beta \tag{9}$$

Using Leibniz rule, two integral components are generated as

$$\int \beta \frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})} f(\beta|\varphi) d\beta - \int \beta \left[\frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})} \right]^2 f(\beta|\varphi) d\beta \tag{10}$$

This results in,

$$\int \beta L_n(m)(1 - L_n(m)) f(\beta|\varphi) d\beta \tag{11}$$

where $L_n(m) = \frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})}$

The cross marginal effect is defined as follows (Seraneeprakarn et al., 2017),

$$\eta_{x_{qn}}^{P_n(m)} = \frac{dP_n(m)}{dx_{qn}} = \frac{d}{dx_{qn}} \int \frac{EXP(\beta_q X_{qn})}{\sum_{\forall M} EXP(\beta_q X_{qn})} f(\beta|\varphi) d\beta \forall q \neq m \tag{12}$$

Using Leibniz rule, two integral components are generated as

$$-\int \beta \left[\frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})} \right] \left[\frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})} \right] f(\beta|\varphi) d\beta \tag{13}$$

This gives the expression,

$$-\int \beta L_n(m) L_n(k) f(\beta|\varphi) d\beta \tag{14}$$

where $L_n(m) = \frac{EXP(\beta_m X_{mn})}{\sum_{\forall M} EXP(\beta_m X_{mn})}$ and $L_n(k) = \frac{EXP(\beta_k X_{kn})}{\sum_{\forall M} EXP(\beta_k X_{kn})} \forall k \neq m$

6.2.2 Estimating the Personal and Societal Impacts of Motorcycle Full-ban Policy

To quantify the personal and societal impacts of the motorcycle full-ban on motorcyclists, the opportunity cost of travel time, out-of-pocket costs, fuel consumption, emissions changes, and the safety-related impacts before and after the travel mode shift were estimated as follows.

The opportunity cost of travel time change (O_n) for motorcyclist n is estimated as follows,

$$O_n = SR_n \left(t_{nijm} - t_{nijb} \right) \tag{15}$$

where SR_n is the salary (¥/minute) of motorcyclist n, t_{nijb} is the travel time between his or her home neighborhood i and work neighborhood j using a motorcycle in minutes, and t_{nijm} is the estimated travel time in minutes between these neighborhoods using the mode m to which he or she is likely to shift. t_{nijb} is acquired from the survey data, while t_{nijm} is calculated as follows:

$$t_{nijm} = \frac{\sum_{k=1}^{K_{ijm}} t_{kijm}}{K_{ijm}} \tag{16}$$

where t_{kijm} is the travel time between neighborhood i and j using mode m by traveler k, and K_{ijm} is the total number of people traveling between neighborhood i and j using mode m.

The out-of-pocket costs change (TC_n) for motorcyclist n who shifts to car (a) is estimated as follows,

$$TC_n = (FE_{na} - FE_{nb}) \times g \tag{17}$$

where FE_{na} and FE_{nb} are the fuel consumption using a car and a motorcycle, respectively, and g is the gasoline price at the time of the survey. For motorcyclists who shifted to bike or walk mode, the out-of-pocket costs change can be estimated as follows:

$$TC_n = -FE_{nb} \times g \tag{18}$$

For motorcyclists who shifted to bus, out-of-pocket costs change can be estimated as follows:

$$TC_n = p - FE_{nb} \times g \tag{19}$$

where p is the bus ticket price in 2010.

Fuel consumption changes (FE_n) of motorcyclist n are estimated by,

$$FE_n = \frac{F_m \times t_{nijm} \times v_m}{L_m} - \frac{F_b \times t_{nijb} \times v_b}{L_b} \tag{20}$$

where F_b is the fuel consumption rate of the motorcycle, F_m is the fuel consumption rate of mode m to which motorcyclist n is likely to shift, L_b is the average passenger load of the motorcycle and L_m is the average passenger load of mode m, and v_b and v_m are the average speed of the motorcycle and mode m, respectively.

Five types of emissions are considered: carbon monoxide (CO), volatile organic compounds (VOC), oxides of nitrogen (NO_X), particulate matter (PM), and carbon dioxide (CO_2). For emission type x, the emission changes of motorcyclist n (E_{np}) are estimated by,

$$E_{nx} = \frac{CI_m \times t_{nijm} \times v_m}{L_m} - \frac{CI_b \times t_{nijb} \times v_b}{L_b} \tag{21}$$

where CI_m and CI_b are the vehicle emission factors of mode m and motorcycle, respectively.

Four types of safety impacts are considered: changes in the number of accidents, deaths, injuries and direct property loss. The safety impact h, SF_{nh},

$$SF_{nh} = O_{mh} - O_{bh} \tag{22}$$

where $O_{mh}$and O_{bh} are the estimated safety factors of mode m and motorcycle mode, respectively. The values used in this subsection are summarized in Table 6.1. The safety data related to walk and bike modes per trip per person were not available.

Table 6.1 Values Used to Estimate the Personal and Societal Impacts of the Motorcycle Full-Ban Policy

	Motorcycle	Walk	Bike	Bus	Car
Gasoline price, *g* (RMB/L) (National Development and Reform Commission, 2010)	6.31	N/A	N/A	N/A	6.31
Bus ticket price for migrants (RMB) (Foshan Public Security Bureau, 2016)	N/A	N/A	N/A	1.5	N/A
Bus ticket price for residents with monthly bus ticket (RMB) (Foshan Public Security Bureau, 2010)	N/A	N/A	N/A	0.64	N/A
Fuel consumption rate, *F* (L/km) (Volvo, 2006; Cherry et al., 2009)	33.3 (gasoline)	0	0	2.5 (diesel)	11.03 (gasoline)
Average passenger load, *L* (passenger/vehicle) (Loo and Li, 2012; He et al., 2013)	1.1	1	1	39	1.4
Average speed, *v* (km/h) (Wang et al., 2008)	30 km/h	6 km/h	12 km/h	30 km/h	40 km/h
Vehicle emission factors, *CI* (g/km) (Wang et al., 2008)					
CO	13.86	0	0	37.15	13.34
VOC	5.36	0	0	3.71	1.19
NOx	0.31	0	0	16.19	1.58
PM	0.15	0	0	0.22	0.01
CO2	64.69	0	0	965.43	445.98
Safety (per vehicle per person) (Traffic Management Bureau of the Public Security Ministry, 2011)					
Number of related accidents	$46.54*10^{-5}$	N/A	N/A	$4.11*10^{-5}$	$10.23*10^{-5}$
Number of related deaths	$11.24*10^{-5}$	N/A	N/A	$1.03*10^{-5}$	$5.18*10^{-5}$
Number of related injuries	$60.27*10^{-5}$	N/A	N/A	$4.88*10^{-5}$	$11.13*10^{-5}$
Related direct property loss (¥)	0.623	N/A	N/A	0.192	1.239

6.3 Empirical Setting

Travel survey data for 4,529 motorcyclists from 3,578 households were collected in October 2010 by the government of Foshan City, Guangdong province, China (as shown in Figure 6.1) to identify their current travel patterns and potential mode shift responses to the motorcycle full-ban policy. Foshan City planned to implement the policy in 2011 in city CBD and eventually ban all motorcycle usage by 2020. Guangdong province had over 25 million inflow migrants between 1990 and 2005 in China compared to the second place Zhejiang province with 8 million (Shen, 2013). In manufacturing centers such as Shenzhen and Dongguan, Guangdong, migrants accounted for over 70% of the labor force (Chan, 2007). Despite the benefits of internal migrations, recent studies (Chan, 2007; Wong and Song, 2008) voiced their concerns regarding the everyday travel, the quality of life and social status of migrants because of the hukou system. Foshan City is a prefecture-level city in Guangdong province of China with over 7.5 million people (3.7 million residents and 3.8 million migrants) living under this city's jurisdiction in 2010 (National Bureau of Statistics of China, 2015). At the time of survey, there was no subway service in the city. In 2010, the average individual annual income was 27,245 RMB (about $4,300) and the average individual annual income of the top 10% was 57,130 RMB (about $9,100) in Foshan City (NBSC, 2015). In 2010, the mode share of motorcycle among migrant travelers is around 31% while the mode share of motorcycle among resident travelers is around 42%.

Figure 6.1 Foshan City and Some of its Neighboring Cities

The survey contained three sections: (i) individual and household sociodemographic characteristics (gender, residential status, age, occupancy, income, household structure, household mobility resources and car purchase plan); (ii) workday travel diary (trip purpose, origin and destination, travel time, and mode choices); and (iii) motorcyclists' perspectives towards the most important factors affecting their travel mode choice, the most important improvement needed in transit and transportation systems, and the stated travel mode shift response after the implementation of motorcycle full-ban policy. Some of the aggregated survey results are shown in Tables 6.2 and 6.3. The key findings are discussed below.

Table 6.2 shows that the percentage of high-income (over 49,999 RMB ($8,000) annually) female migrants was higher than the other population sub-groups. Most motorcyclists are relatively young (under 35), and migrant motorcyclists are younger than their resident counterparts. Migrant motorcyclists stated that they were more likely to shift from using a motorcycle to riding a bus or cycling for their morning commute, while resident motorcyclists stated that they were more likely to shift to riding a bus or using a car, possibly capturing stated travel mode shift response heterogeneity across the two sub-population groups. On average, motorcyclists were expected to experience travel time increases after implementation of the motorcycle full-ban policy, with those shifting to the bus mode experiencing the largest travel time increase. Table 6.3 shows that most of the motorcyclists' households had more than one motorcycle, low car ownership, and no plan to purchase a car. Four sub-populations shared similar perspectives towards the most important improvement needed in the transit and transportation systems.

As shown in the literature (Matthies et al., 2002; Guo et al., 2017), different factors are likely to affect travel-related behaviors within different gender and residential status groups; thus, the factors that affect mode shift may also vary across groups. To test the hypothesis, likelihood ratio tests were conducted. Using the two combined likelihood ratio tests proposed by Washington et al. (2011), the first set of tests is formulated as follows:

$$X^2 = -2\left[LL(\beta_T) - \sum_{s=1}^{S} LL(\beta_s)\right] \tag{23}$$

where $LL(\beta_T)$ is the log-likelihood of the model at convergence estimated using all data, $LL(\beta_s)$ is the log-likelihood at convergence of the model estimated with sub-population s (gender or residential status), and S is the total number of sub-populations. The second set of tests is as follows:

$$X^2 = -2\left[LL(\beta_{s_2 s_1}) - LL(\beta_{s_1})\right] \tag{24}$$

where $LL(\beta_{s_2 s_1})$ is the log-likelihood of the model using the converged parameters from sub-population data s_1 sub-population data s_2, and $LL(\beta_{s_1})$ is the log-likelihood at convergence using sub-population data s_1. Both test statistics are Chi-squared distributed, with the degrees of freedom equal to the summation of the number of parameters in the overall model (Equation 18), or to the number of parameters in $\beta_{s_2 s_1}$ (Equation 19).

Table 6.2 Motorcyclists' Socio-economic Characteristics, Mode Shift and Travel Time before and after Travel Mode Shift (the Numbers in Parentheses are Travel Time Changes after the Mode Shift and a Positive Number Indicates Travel Time Increases)

	Female		**Male**	
	Migrant	**Residents**	**Migrant**	**Residents**
Number of motorcyclists	876	1225	909	1519
Age in percentage				
<25	10.94	13.10	10.67	11.72
25-30	34.38	27.53	23.32	23.51
31-35	21.09	16.68	20.16	13.70
36-40	17.97	18.83	26.09	13.86
41-45	11.72	11.67	10.28	10.15
>45	3.91	12.18	9.48	27.06
Occupation in percentage				
Manufacturing worker	31.25	22.62	51.78	25.33
Administrative employee	18.75	21.60	10.08	17.33
Service industry worker	15.63	14.12	15.42	10.89
Civil servant	12.50	18.94	3.95	18.07
Individual business operator	11.72	8.80	11.46	11.88
Agricultural worker	0.00	0.61	0.00	1.73
Other	10.15	13.31	7.31	14.77
Annual individual income in percentage (in RMB)				
Less than 20,000	10.94	11.57	10.28	9.41
20,000 ~ 29,999	35.16	34.80	39.53	31.68
30,000 ~ 49,999	29.69	37.15	34.39	38.61
50,000 ~ 79,999	16.41	12.18	12.65	15.43
More than 80,000	7.80	4.30	3.15	4.87
Stated travel mode shift response in percentage				
Shift to walk	8.22	6.97	4.95	6.93
Shift to bike	24.66	15.00	24.42	16.57
Shift to bus	37.67	39.92	45.87	43.43
Shift to car	29.45	38.11	24.75	33.07
Average travel time if a motorcyclist shifts to walk (in minutes)	14.64 (+3.81)	13.82 (+1.10)	21.46 (+9.79)	14.6 (+4.35)
Average travel time if a motorcyclist shifts to bike (in minutes)	16.59 (+1.62)	18.99 (+6.53)	18.06 (+2.97)	15.86 (+2.58)
Average travel time if a motorcyclist shifts to bus (in minutes)	41.72 (+23.36)	33.48 (+18.17)	30.01 (+16.53)	30.47 (+12.62)
Average travel time if a motorcyclist shifts to car (in minutes)	17.05 (+2.55)	17.22 (+4.15)	18.50 (+4.48)	19.11 (+5.93)

Table 6.3 Motorcyclists' Household Characteristics and Perspectives towards Mode Selection and Improvement needed in Transportation and Transit Systems

	Female		Male	
	Migrant	**Resident**	**Migrant**	**Resident**
Number of households	753	924	810	1091
Average family members in the household	3.10	3.53	2.92	3.53
Households with more than one motorcyclist having morning commute in percentage	16.80	28.79	24.89	33.55
Average number of children in the household	0.23	0.23	0.23	0.24
Household mobility				
Number of bicycles	0.62	0.83	0.81	0.85
Number of motorcycles	1.25	1.67	1.13	1.67
Number of cars	0.14	0.15	0.08	0.09
Household car purchase plan in percentage				
Within 3 years	9.38	15.35	5.53	14.69
Between 3 years and 5 years	6.25	14.74	2.77	12.79
After 5 years	17.19	16.17	17.00	17.74
No plan	67.18	53.74	74.70	54.78
The most important factor affecting travel mode choices in percentage				
Travel time	44.53	48.41	38.34	47.94
Comfort	20.31	14.43	11.46	11.14
Out-of-pocket cost	17.19	19.34	30.04	19.80
Lack of other mode choices	11.72	10.44	12.65	14.19
Safety	6.25	7.38	7.51	6.93
The most important improvement needed in transportation systems in percentage (up to three choices)				
Improve bus transit system	56.25	57.73	62.06	57.51
Improve rail transit system	45.31	49.13	47.04	46.04
Improve vehicle parking	41.41	44.42	30.83	38.20
Improve road condition	32.81	19.55	31.62	21.37
Increase no truck zones	14.84	16.79	11.07	14.93

Table 6.3 Motorcyclists' Household Characteristics and Perspectives towards Mode Selection and Improvement needed in Transportation and Transit Systems (continued)

	Female		**Male**	
	Migrant	**Resident**	**Migrant**	**Resident**
The most important improvement needed in transit system in percentage (up to three choices)				
Increase bus transit routes	65.63	75.74	66.01	69.55
Increase number of buses	60.16	67.45	57.31	65.02
Improve waiting environment	40.63	30.81	37.15	33.83
Improve the quality of bus service	36.72	41.97	43.87	39.93
Improve walking environment near transit stops	34.38	24.77	28.85	21.37
Increase pedestrian crossing facilities (e.g. tunnels)	30.47	27.84	24.51	24.92
Improve street crossing facilities (e.g. elevators)	20.31	12.69	16.21	11.96

6.4 Results and Discussion

Four mode shift models for motorcyclists (female migrants, female residents, male migrants and male residents) were estimated. The results for both tests suggested that the parameters were not transferable at a 99.99% confidence level. These results validate the estimation of separate models by gender and residential status. The performances of a random parameters logit approach with heterogeneity in means and variances and a mixed logit approach were evaluated. Based on log-likelihood at convergence, a random parameters logit approach with heterogeneity in means and variances outperformed a mixed logit approach in all the sub-populations. These findings are consistent with the earlier findings of Seraneeprakarn et al. (2017) and Behnood and Mannering (2017). Only the results of the random parameters logit approach with heterogeneity in means and variances are presented in Tables 6.4 through 6.7. The models were estimated by including only the statistically significant parameters at the 0.95 level of confidence or greater, and the results revealed that the different factors indeed affected travel mode shift responses for the different sub-populations.

6.4.1 Motorcyclists' Individual and Household Sociodemographics

A number of individual and household sociodemographic characteristics were found to affect the stated travel mode shift response of motorcyclists. For example, Tables 6.4 through 6.7 show that the motorcyclists' income played a key role in the travel mode shift probabilities for all the models. Higher-income motorcyclists (with more than 49,999 RMB ($8,000) annual income of around the top 20% income in the city) were more likely to shift from using a motorcycle to using a car for their morning commute. These findings may be attributable to the possibility that higher-income motorcyclists may be less sensitive to the out-of-pocket cost increase, but they may be more sensitive to the opportunity cost of a travel time increase. Lower-income migrant motorcyclists (less than 30,000 RMB ($4,800) annual income, which is less than the Foshan average) are more likely to shift to walk, while low-income resident motorcyclists are more likely to shift to riding a bus. These findings likely capture the effect of the pricing policy of the Foshan bus system in that a Foshan monthly bus pass ($9/month with unlimited bus rides) is available for purchase only to residents with proper identification while migrants can only buy regular ride bus tickets ($0.25/ride) and need to carry the exact change (most buses in Foshan are self-service ticketing and no change will be provided), which subsequently discourages them from using the bus. These findings are consistent with previous studies (Guo et al., 2016c, Guo et al., 2018) as to why lower income migrants prefer walk over bus mode.

The age of the motorcyclist is another sociodemographic characteristic that is found to affect travel mode shift outcome probabilities for the migrant sub-populations (see Tables 6.4 and 6.6). Most of the older motorcyclists (over 35 years old) were less likely to shift to bike mode, which may be attributed to the possibility that riding a bicycle may demand more physical strength compared to walking, riding a bus, or driving a car, and it may discourage older motorcyclists from biking. Only a small portion of older male resident motorcyclists were more likely to shift to bike mode as it is a random parameter in the estimation (Table 6.8).

Table 6.4 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Female Migrants' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Constant [B]	1.824**	2.475				
Constant [T]	1.723**	2.139				
Constant [A]	1.086**	2.098				
Individual and household characteristics						
Low-income indicator (1 if motorcyclists' household annual income is less than ¥30,000, 0 otherwise) [W]	0.591**	2.193	0.0925	-0.0109	-0.0244	-0.0102
High-income indicator (1 if motorcyclists' household annual income is more than ¥49,999, 0 otherwise) [A]	2.135**	3.775	-0.1136	-0.0743	-0.0448	0.0473
Older indicator (1 if a motorcyclist is older than 35, 0 otherwise) [B]	-3.358**	-3.530	0.0899	-0.4619	0.0092	0.0899
Multiple traveler indicator (1 if the household has more than two travelers, 0 otherwise) [W]	2.304**	3.804	1.2512	-0.0120	-0.0780	-0.2637
Live longer indicator (1 if migrated to Foshan for more than 1 year, 0 otherwise) [A]	2.336**	4.103	-0.9964	-0.4445	-0.3152	0.8916
Bicycle indicator (1 if the household has more than one bicycle, 0 otherwise) [B]	2.625**	5.322	-0.5483	0.3315	-0.1493	-0.5483
Motorcycle indicator (1 if the household has more than one motorcycle, 0 otherwise) [W]	1.189**	2.596	0.3308	-0.0414	-0.0313	-0.0928
Car indicator (1 if the household has at least one car, 0 otherwise) [A]	1.230**	3.464	-0.2255	-0.1010	-0.0783	0.1198
No car indicator (1 if the household does not have a car or car purchase plan; 0 otherwise) [W]	1.440**	3.109	0.3209	-0.0539	-0.0289	-0.0738
Travel-related behaviors						
Travel time indicator (1 if travel time is identified as the most important factor affecting mode choice, 0 otherwise) [W]	1.235**	3.054	0.2301	-0.1129	-0.0991	-0.0869
Comfort and safety indicator (1 if comfort or safety is identified as the most important factor affecting mode choice, 0 otherwise) [A]	1.452**	3.198	-0.1220	-0.0955	-0.0749	0.2410
Rail indicator (1 if rail system is identified as the most important improvement needed in transportation system, 0 otherwise) [W]	1.563**	3.626	0.5887	-0.0781	-0.0363	-0.1285
Bus indicator (1 if bus system is identified as the most important improvement needed in transportation system, 0 otherwise) [T]	1.437**	3.103	-0.0638	-0.0771	0.1083	-0.0581
Residential location-related factors						
Close to transit indicator (1 if distance to the nearest transit station is less than 5 minutes, 0 otherwise) [T]	6.483**	2.328	-0.1407	-0.0317	0.8188	-0.1407
CBD indicator (1 if live in CBD, 0 otherwise) [T]	6.244**	2.322	-0.0564	-0.0123	0.0510	-0.564
Random parameters (normally distributed)						
Bicycle improvement indicator (1 if bicycle related infrastructure or policy is identified as the most important improvement needed in transportation system, 0 otherwise) [B]	-2.577**	-2.326	-0.0770	0.3416	-0.0017	-0.077
Standard deviation of "bicycle improvement"	4.825**	3.204				
Bus route indicator (1 if adding more bus routes is identified as the most important improvement needed in transit system, 0 otherwise) [T]	0.740	0.52	-0.0438	-0.0087	0.0810	-0.0438
Standard deviation of "bus route indicator"	16.462**	2.264				

Table 6.4 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Female Migrants' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car) (continued)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Heterogeneity in the mean of the random parameters						
Bicycle improvement indicator: bicycle indicator	3.148**	3.635				
Bus route indicator: bicycle indicator	-8.912**	-2.118				
Heterogeneity in the variance of the random parameters						
Bus route indicator: bicycle improvements indicator	16.447**	2.266				
Model statistics						
Number of observations	876					
McFadden ρ^2	0.266					

Table 6.5 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Male Migrants' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Constant [B]	-3.091**	-3.693				
Constant [T]	4.830**	5.322				
Constant [A]	2.158**	2.125				
Individual and household characteristics						
Low-income indicator (1 if motorcyclists' household annual income is less than ¥30,000, 0 otherwise) [W]	2.034**	3.620	0.1435	-0.0233	-0.0143	-0.0378
High-income indicator (1 if motorcyclists' household annual income is more than ¥49,999, 0 otherwise) [A]	1.077**	2.470	-0.0378	-0.0269	-0.0114	0.0943
Older indicator (1 if a motorcyclist is older than 35, 0 otherwise) [B]	-1.255**	-2.565	0.0176	-0.1387	0.0345	0.0267
Multiple traveler indicator (1 if the household has more than two travelers, 0 otherwise) [W]	2.707**	3.363	1.4844	-0.1543	-0.0698	-0.2402
Live longer indicator (1 if migrated to Foshan for more than 1 year, 0 otherwise) [A]	1.811**	3.511	-0.7826	-0.4310	-0.2147	0.6217
Bicycle indicator (1 if the household has more than one bicycle, 0 otherwise) [B]	4.535**	6.382	-1.1013	1.2267	-0.3830	-1.1013
Motorcycle indicator (1 if the household has more than one motorcycle, 0 otherwise) [T]	1.258**	3.294	-0.1065	-0.0460	0.0573	-0.1065
Car indicator (1 if the household has at least one car, 0 otherwise) [A]	0.566**	3.338	-0.0416	-0.0294	-0.0124	0.0200
No car indicator (1 if the household does not have a car or car purchase plan; 0 otherwise) [W]	3.151**	4.884	0.8364	-0.5040	-0.1786	-0.5040
Travel-related behaviors						
Travel time indicator (1 if travel time is identified as the most important factor affecting mode choice, 0 otherwise) [W]	-3.272**	-4.237	-1.0943	0.0124	0.0027	0.0179
Comfort and safety indicator (1 if comfort or safety is identified as the most important factor affecting mode choice, 0 otherwise) [A]	0.926**	3.026	-0.1634	-0.0961	-0.575	0.1512
Rail indicator (1 if rail system is identified as the most important improvement needed in transportation system, 0 otherwise) [W]	0.872**	2.707	0.1852	-0.1601	-0.0485	-0.2638
Bus route indicator (1 if adding more bus routes is identified as the most important improvement needed in transit system, 0 otherwise) [T]	1.0776**	2.187	-0.0871	-0.0932	0.1561	-0.0567
Residential location-related factors						
Close to transit indicator (1 if distance to the nearest transit station is less than 5 minutes, 0 otherwise) [T]	2.101**	5.809	-0.1347	-0.0608	0.2600	-0.1347
CBD indicator (1 if live in CBD, 0 otherwise) [T]	1.189**	2.543	-0.0263	-0.0167	0.1782	-0.0254
Random parameters (normally distributed)						
Bicycle improvements indicator (1 if bicycle related infrastructure or policy is identified as the most important improvement needed in transportation system, 0 otherwise) [B]	3.949**	3.353	-0.1314	0.8394	-0.0812	-0.1314
Standard deviation of "pedestrian/bicycle improvements"	3.577**	3.549				
Bus indicator (1 if bus system is identified as the most important improvement needed in transportation system, 0 otherwise) [T]	0.2182	0.232	0.0053	-0.0198	0.0299	0.0053
Standard deviation of "bus route indicator"	10.687**	2.751				
Heterogeneity in the mean of the random parameters						
Bicycle improvement indicator: bicycle indicator	2.654**	3.478				
Bus indicator: bicycle indicator	-1.652*	-2.069				

Table 6.5 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Male Migrants' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car) (continued)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Heterogeneity in the mean of the random parameters						
Bicycle improvement indicator: bicycle indicator	2.654**	3.478				
Bus indicator: bicycle indicator	-1.652*	-2.069				
Heterogeneity in the variance of the random parameters						
Bus indicator: bicycle improvements indicator	2.644**	2.902				
Model statistics						
Number of observations	909					
McFadden ρ^2	0.282					

Table 6.6 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Female Residents' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Constant [B]	1.990**	2.655				
Constant [T]	3.242**	5.557				
Constant [A]	3.585**	6.211				
Individual and household characteristics						
Lower-income indicator (1 if motorcyclists' household annual income is less than 30,000 RMB, 0 otherwise) [T]	0.705**	2.068	-0.0107	-0.0107	0.1329	-0.0107
Higher-income indicator (1 if motorcyclists' household annual income is more than 49,999 RMB, 0 otherwise) [A]	0.445**	2.432	-0.0294	-0.0333	-0.0387	0.0344
Older indicator (1 if a motorcyclist is older than 35, 0 otherwise) [B]	-1.483**	-4.224	0.0572	-0.1684	0.0780	0.0780
Multiple traveler indicator (1 if the household has more than two travelers, 0 otherwise) [W]	0.834**	3.229	0.9337	-0.0607	-0.0950	-0.0950
Bicycle indicator (1 if the household has more than one bicycle, 0 otherwise) [B]	0.439**	3.290	-0.0385	0.2615	-0.0624	-0.0624
Car indicator (1 if the household has at least one car, 0 otherwise) [A]	0.682**	4.211	-0.1185	-0.1370	-0.1512	0.1081
No car indicator (1 if the household does not have a car or car purchase plan; 0 otherwise) [T]	0.442**	3.168	-0.0848	-0.0864	0.1096	-0.1024
Travel-related behaviors						
Travel time indicator (1 if travel time is identified as the most important factor affecting mode choice, 0 otherwise) [W]	-0.165**	-2.594	0.0576	-0.0722	-0.0811	-0.0645
Out-of-pocket cost indicator (1 if out-of-pocket cost is identified as the most important factor affecting mode choice, 0 otherwise) [T]	1.008**	2.713	-0.0190	-0.0126	0.1407	-0.0190
Comfort and safety indicator (1 if comfort or safety is identified as the most important factor affecting mode choice, 0 otherwise) [A]	0.878**	4.695	-0.0679	-0.0779	-0.0859	0.0496
Bicycle improvements indicator (1 if bicycle related infrastructure or policy is identified as the most important improvement needed in transportation system, 0 otherwise) [B]	0.373**	2.613	-0.0163	0.1206	-0.0261	-0.0261
Bus indicator (1 if bus is identified as the most important improvement needed in transportation system, 0 otherwise) [T]	0.582**	4.111	-0.1454	-0.1447	0.1838	-0.1729
Number of bus improvement indicator (1 if number of bus is identified as the most important improvement needed in transit system, 0 otherwise) [T]	0.615**	3.987	-0.1697	-0.1731	0.2312	-0.2077
Residential location-related factors						
Close to work indicator (1 if considers distance to work is close, 0 otherwise) [W]	3.583**	4.578	0.0383	-0.0213	-0.0261	-0.0261
Random parameters (normally distributed)						
Motorcycle indicator (1 if the household has more than one motorcycle, 0 otherwise) [W]	-0.031	-0.05	0.4188	-0.0101	-0.0557	-0.0557
Standard deviation of "motorcycle improvements"	0.700*	2.713				
Rail indicator (1 if rail is identified as the most important improvement needed in transportation system, 0 otherwise) [B]	-2.759	-1.594	-0.0011	0.3354	-0.0112	-0.0112
Standard deviation of "rail indicator"	2.602**	2.401				
CBD indicator (1 if live in CBD, 0 otherwise) [T]	-0.463	-0.269	-0.0234	-0.0062	0.2181	-0.0234
Standard deviation of "CBD indicator"	2.126*	2.413				

Table 6.6 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Female Residents' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car) (continued)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Heterogeneity in the mean of the random parameters						
CBD indicator: bicycle indicator	0.264**	2.506				
Motorcycle indicator: bicycle indicator	-0.061*	-2.402				
Rail indicator: bicycle indicator	0.163**	2.345				
Heterogeneity in the variance of the random parameters						
Motorcycle indicator: CBD indicator	-0.489*	-2.434				
Rail indicator: CBD indicator	0.580*	2.420				
Rail indicator: motorcycle indicator	1.777**	2.452				
Model statistics						
Number of observations	1224					
McFadden ρ^2	0.233					

Table 6.7 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Male Residents' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Constant [B]	-0.775**	-2.007				
Constant [T]	2.087**	11.447				
Constant [A]	1.294**	7.379				
Individual and household characteristics						
Low-income indicator (1 if motorcyclists' household annual income is less than ¥30,000, 0 otherwise) [T]	0.683**	3.003	-0.0871	-0.0541	0.1390	-0.0901
High-income indicator (1 if motorcyclists' household annual income is more than ¥49,999, 0 otherwise) [A]	1.144**	5.458	-0.0738	-0.0671	-0.0738	0.0727
Multiple traveler indicator (1 if the household has more than two travelers, 0 otherwise) [W]	0.456**	2.534	0.0739	-0.0125	-0.0144	-0.0201
Bicycle indicator (1 if the household has more than one bicycle, 0 otherwise) [B]	0.202**	1.986	-0.0259	0.0951	-0.0259	-0.0207
Motorcycle indicator (1 if the household has more than one motorcycle, 0 otherwise) [T]	0.436**	2.840	-0.0993	-0.0993	0.4457	-0.0765
Car indicator (1 if the household has at least one car, 0 otherwise) [A]	0.849**	4.570	-0.0647	-0.0469	-0.0647	0.0649
Travel-related behaviors						
Travel time indicator (1 if travel time is the most important factor that affects mode choice, 0 otherwise) [W]	-0.543**	=2.654	-0.1028	0.0845	0.0721	0.0624
Out-of-pocket cost indicator (1 if out-of-pocket cost is the most important factor that affects mode choice, 0 otherwise) [T]	1.689**	5.120	-0.0862	-0.0862	0.1697	-0.0745
Comfort and safety indicator (1 if comfort or safety is the most important factor that affects mode choice, 0 otherwise) [A]	0.792**	3.445	-0.0363	-0.0257	-0.0363	0.0422
Bicycle improvements indicator (1 if bicycle related infrastructure or policy is identified as the most important improvement needed in transportation system, 0 otherwise) [B]	0.482**	2.186	-0.0102	0.1145	-0.0151	-0.0105
Bus indicator (1 if bus system is identified as the most important improvement needed in transportation system, 0 otherwise) [T]	0.398**	2.861	-0.1412	-0.0906	0.1089	-0.1075
Number of bus improvement indicator (1 if number of bus is identified as the most important improvement needed in transit system, 0 otherwise) [T]	1.414**	4.009	-0.0144	-0.0092	0.0442	-0.0119
Residential location-related factors						
Close to transit indicator (1 if distance to the nearest transit station is less than 5 minutes, 0 otherwise) [T]	0.352**	2.680	-0.0742	-0.0485	0.0732	-0.0507
CBD indicator (1 if live in CBD, 0 otherwise) [W]	0.570**	2.409	0.0860	-0.0093	-0.0142	-0.0100
Random parameters (normally distributed)						
Rail indicator (1 if rail system is identified as the most important improvement needed in transportation system, 0 otherwise) [W]	-0.132	0.529	0.0881	-0.0471	-0.0314	-0.0314
Standard deviation of "rail indicator"	2.251**	2.715				
No car indicator (1 if the household does not have a car or car purchase plan; 0 otherwise) [T]	-1.695*	-2.1465	-0.0371	-0.0371	0.2598	-0.0397
Standard deviation of "no car indicator"	3.368**	2.786				
Older indicator (1 if motorcyclist is older than 35, 0 otherwise) [B]	-0.583	0.439	0.0530	-0.2315	0.0530	0.0417
Standard deviation of "older indicator"	1.292*	2.517				

Table 6.7 Random Parameters Logit Model with Heterogeneity in Means and Variances Estimation Results of Male Residents' Stated Travel Mode Shift Response (Parameters Defined for: [W] Walk; [B] Bike; [T] Bus; [A] Car) (continued)

Variable	Parameter estimate	*t*-statistics	Averaged marginal effects			
			Walk	Bike	Bus	Car
Heterogeneity in the mean of the random parameters						
Rail indicator: bicycle indicator	-0.319**	-2.589				
No car indicator: bicycle indicator	0.253**	2.720				
Older indicator: bicycle indicator	0.273**	2.963				
Heterogeneity in the variance of the random parameters						
No car indicator: rail indicator	0.119**	2.085				
Older indicator: rail indicator	-0.091**	2.139				
Older indicator: no car indicator	0.466**	2.809				
Model statistics						
Number of observations	1518					
McFadden ρ^2	0.183					

The variable representing motorcyclists who had been migrating to Foshan over a year also was found to affect migrant motorcyclists' travel mode shift outcome probabilities for migrant sub-populations (see Tables 6.4 and 6.6). Migrant motorcyclists who had lived in Foshan City for more than a year were more likely to shift to using a car for their morning commute. These findings may be attributed to the possibility that migrants living in Foshan City longer are in better or more stable financial situations compared to who just arrived.

The number of travelers (individuals six years old or older) in the household was found to affect the travel mode shift outcome probabilities for all sub-populations. As the number of travelers in the household increased, the more likely motorcyclists were to switch to walk mode for the morning commute. This finding may be attributed to the possibility that large families are more likely to select their residential location close to their family members' place of employment to minimize travel time, distance and cost of travel.

The mobility sources available in the household played a key role as well in the travel mode shift outcome probabilities for the sub-populations. Tables 6.4 through 6.7 show that motorcyclists with more than one bicycle in the household were more likely to consider bike mode as the preferred travel mode shift choice for their morning commute. Likewise, car mode is likely to be the preferred mode shift choice for motorcyclists with at least one car in the household. These findings may suggest that the motorcycle full-ban policy may reduce motorcycle-related traffic congestion, pollution and safety issues but may generates more automobile-related issues at the same time. As shown in Table 6.3, over 30% of the motorcyclists' households indicated having plans to purchase a car in a few years, illustrating a high interest in using cars in the future.

Tables 6.4 through 6.7 also show that female motorcyclists with more than one motorcycle were more likely to shift to walk mode for the morning commute, whereas male motorcyclists with more than one motorcycle were more likely to shift to riding a bus. This finding may likely capture the gender and income inequality specific heterogeneity when the mobility resources in the household are limited. Migrant motorcyclists without a car or car purchase plan were more likely to shift to walk mode whereas resident motorcyclists were more likely to shift to riding a bus for the morning commute. This finding may be attributed to the pricing policy of the Foshan bus system and is consistent with the finding that lower-income migrant motorcyclists were more likely to shift to walk mode, while low-income resident motorcyclists were more likely to shift to riding a bus.

6.4.2 Effects of Residential Location-related Factors

The results in Tables 6.4 through 6.7 show that transit accessibility plays a role in the stated travel mode shift response. For example, migrant motorcyclists whose residence was within a five-minute walk away from the nearest bus stop or in the CBD were more likely to shift to riding a bus for their morning commute. This choice likely captures the possibility of household location specific heterogeneity within areas having high quality bus transit service, such as the CBD. These results, in combination with the motorcyclists' perceptions of the top two most important improvements needed for Foshan being improvement of the bus and rail transit systems (Table 4), offer policy insights to promote the travel mode shift to transit mode through transit network improvements instead of car mode.

6.4.3 Motorcyclists' Travel-related Behavior

Eight behavioral characteristics were found to affect the stated travel mode shift response. For example, Tables 6.4 to 6.7 show that the motorcyclists' perspectives about the most important factor affecting travel mode choice played a key role in the travel mode shift outcome probabilities for all the models. Motorcyclists who considered travel time as the most important factor affecting their travel mode choice were less likely to shift to walk mode for the morning commute, whereas those who considered comfort or safety as the most important factor affecting their travel mode choice were more likely to shift to using a car for the morning commute. Resident motorcyclists who considered their out-of-pocket cost as the most important factor affecting their travel mode choice were more likely to shift to riding a bus for the morning commute. These three findings likely reflect homogeneity in terms of the motorcyclists' perceptions of the travel speed, cost, safety, and comfort related to each mode.

The motorcyclists' perceptions about the important improvements needed in transportation and transit systems also were found to play a key role in travel mode shift outcome probabilities for all the models. Among motorcyclists who considered rail transit as needing the most important improvement in the transportation system, migrant and male resident motorcyclists were more likely to shift to walk mode for their morning commute, whereas female motorcyclists were more likely to shift to riding a bus for the morning commute. Motorcyclists who considered bus transit as needing the most improvement in the transportation system were more likely to shift to riding a bus for their morning commute. Motorcyclists who considered bike-related infrastructure or policy as needing the most improvement in the transportation system were more likely to shift to cycling. Among motorcyclists who considered adding more bus routes as the most needed improvement in the transit system, migrant motorcyclists were more likely to shift to riding a bus for the morning commute. Among the motorcyclists who considered adding more buses as one of the most needed improvements in the transit system, resident motorcyclists were more likely to shift to riding a bus for the morning commute.

6.4.4 Heterogeneity in Means and Variances

Eight variables were found to produce random parameters with heterogeneity in the means and variances. For example, in both the female and male migrant motorcyclists models, the bicycle improvement indicator (identified bicycle-related infrastructure or policy as the most important aspect to improve in the transportation system) for motorcyclists who had more than one bicycle in their household increased the mean, making the shift to bike mode more likely (relative to those who had one or no bicycle in their households). Similarly, in the female migrant motorcyclists model, for the bus route indicator (identified adding more bus routes as the most important aspect to improve in the transit system), and in the male migrant motorcyclists model for the bus transit indicator (identified bus transit as the most important aspect to improve in the transportation system), motorcyclists who had more than one bicycle in their households increased the mean, making the shift to bike mode more likely (relative to those who had one or no bicycle in their households).

In the female resident motorcyclists model, for the rail transit indicator (identified rail transit as the most important aspect to improve in the transportation system), motorcyclists who had more than one bicycle in their households had an increase in their mean, making the shift to bike mode more likely. For the CBD indicator (reflecting motorcyclists who lived in the CBD), motorcyclists who had more than one bicycle in their households had an increase in their mean, making the shift to transit more likely. For motorcyclists who had more than one motorcycle, those who had more than one bicycle in their household had a decrease in their mean, making the shift to walk mode less likely.

For male resident motorcyclists who considered rail transit as the most important aspect to improve in the transportation system, those who had more than one bicycle in their households had a decrease in their mean, making the shift to walk mode less likely. For male resident motorcyclists who had neither a car nor a plan to purchase one, who had more than one bicycle in their household, had an increase in their mean, making their shift to transit more likely. For male resident motorcyclists who were older than 35, those who had more than one bicycle in their households had an increase in their mean, making the shift to riding a bike less likely.

These results illustrate the importance of bike mode on the morning commute in both the migrant and resident motorcyclists' mode shift choices after implementation of the motorcycle full-ban policy.

6.4.5 Personal and Societal Impacts of Motorcycle Full-Ban Policy

Table 6.8 presents the quantifiable personal (i.e., out-of-pocket cost and opportunity cost of travel time) and societal (i.e., emissions, energy consumption, and safety) impacts of the motorcycle full-ban on the travel mode shift choice by different sub-populations. The results show that the motorcycle full-ban would increase motorcyclists' personal cost, on average, across the sub-populations but would have mixed societal impacts.

Table 6.8 shows three key findings related to the personal impacts of the motorcycle full-ban on the travel mode shift choice by the four sub-populations. First, the male migrant motorcyclists experienced the largest personal cost percentage increase (54.66%) on average after the travel mode shift. Second, migrant motorcyclists who shifted to walk or bike mode for their morning commute experienced an out-of-pocket cost reduction, but these benefits were offset by a larger increase in the opportunity cost of travel time. Third, motorcyclists who shifted to riding a bus experienced the largest percentage increase in opportunity cost of travel time, especially migrant motorcyclists. These results illustrate that the motorcycle full-ban would increase motorcyclists' out-of-pocket cost and opportunity cost of travel time on average, especially migrant motorcyclists. Considering that migrant motorcyclists and their family members have already been excluded from many basic welfare and services (Xu, 2010, 2014) and need to send some of their income to their home regions, the travel-related cost increase would create additional economic burdens for them. In addition, migrant motorcyclists' accessibility to jobs and opportunities also would be limited. Hence, the motorcycle full-ban could lead to further societal inequity and exclusion for migrants.

Table 6.8 also shows three key observations in terms of societal impacts of the motorcycle full-ban across the four sub-populations. First, over 25% of the motorcyclists indicated a shift to using a car for their morning commute. On average, motorcyclists' fuel consumption per trip per person therefore would increase because a car consumes more fuel compared to a motorcycle. Second, NO_X and CO_2 emissions will increase while CO, VOC, and PM emissions will decrease across all the sub-populations. This finding has policy implications in that the increase in NO_x emission may worsen the already severe photochemical smog and haze pollution in the Pearl River Delta region as NO_x is one of the main contributors to the pollution in this region (He et al., 2002; Wang et al., 2006; Ma et al., 2012). Third, in terms of transportation safety, the number of accidents, injuries, and deaths would decrease while the direct property loss would increase. In summary, these results show that the motorcycle full-ban would have mixed societal impacts in that while it has the potential to improve safety and reduce the emission of some toxic gases and particles, it also potentially could increase fuel consumption and emission of greenhouse gases.

Table 6.8 Personal and Societal Impacts of Motorcycle Full-Ban Policy (a Positive Number Indicates an Increase after Policy Implementation, while a Negative Number Indicates a Decrease after Policy Implementation)

	Female		**Male**	
	Migrant	**Resident**	**Migrant**	**Resident**
Personal costs: Out-of-pocket costs (in RMB)				
Motorcyclists shifting to walk (per trip per person)	-1.03	-1.21	-1.11	-0.97
Motorcyclists shifting to bike (per trip per person)	-1.42	-1.18	-1.43	-1.26
Motorcyclists shifting to bus (per trip per person)	-0.34	-0.81	0.12	-1.05
Motorcyclists shifting to car (per trip per person)	5.13	5.33	5.73	6.04
Personal costs: Opportunity cost of travel time (in RMB)				
Motorcyclists shifting to walk (per trip per person)	1.77	0.88	0.87	1.05
Motorcyclists shifting to bike (per trip per person)	1.15	0.95	1.59	0.60
Motorcyclists shifting to bus (per trip per person)	3.57	1.48	2.53	1.60
Motorcyclists shifting to car (per trip per person)	1.03	1.39	1.75	1.16
Personal costs increase (in percentage)	39.86	37.35	54.66	33.86
Fuel consumption changes (in liter per trip per person)				
Gasoline	0.07	0.19	0.07	0.16
Diesel	0.08	0.07	0.07	0.07
Emission changes per trip per person (in percentage)				
CO	-56.48	-35.18	-59.41	-46.49
CO_2	198.55	350.53	183.70	271.64
VOC	-89.73	-84.81	-90.52	-87.46
NO_x	267.11	385.68	187.99	303.97
PM	-93.05	-91.41	-95.08	-92.82
Safety (in percentage)*				
Accidents	-83.20	-82.23	-84.98	-82.45
Death	-69.51	-67.08	-74.01	-68.29
Injury	-85.53	-84.75	-86.98	-84.89
Direct property loss	29.24	40.29	8.81	34.31

* Excluding motorcyclists shifting to walk or bike mode

The findings from Table 6.8 suggest that the societal impacts of the motorcycle full-ban policy in Foshan City, China and other types of motorcycle ban policies will vary in different cities because of the differences in the motorcyclists' mode shift preferences, the quality of the public transit service, and the population composition. If a significant portion of motorcyclists shift to using a car for their morning commute, motorcycle ban policies can have negative personal and societal impacts. The findings show the importance of investigating motorcyclists' travel mode shifts and analyzing the impacts before implementing motorcycle ban policies. They also illustrate the importance of implementing policies that can limit car usage along with implementing motorcycle ban policies to address the motorcycle-related challenges in China.

6.5 Concluding Comments

This paper investigated the personal and societal impacts of the motorcycle full-ban policy on motorcyclists' home-to-work morning commute travel mode shift in Foshan City, China. Random parameter logit models with heterogeneity in the parameter means and variances were estimated by the gender and the residential status of migrants and residents to account for possible heterogeneity in the means and variances of the random parameters. This approach improved the overall model fit and allowed the identification of population sub-group specific factors that can affect travel mode shift. A combination of likelihood ratio tests was used to test the hypothesis that the parameters were transferable across the population sub-groups (female migrants, male migrants, female residents, and male residents), and the results confirmed the benefits of estimating separate travel mode shift models for each sub-group. In addition, five types of personal (out-of-pocket cost and opportunity cost of travel time) and societal (emissions, energy consumption, and safety) costs of a motorcycle full-ban policy on travel mode shift were quantified by gender and residential status. The quantification results revealed an increase in the motorcyclists' personal costs on average across the sub-populations and the mixed societal costs of travel mode shift. It was also revealed that different parameters can affect the stated travel mode shift response and the different personal and societal impacts of the motorcycle full-ban policy on those responses.

The model estimation results showed that migrant and resident motorcyclists exhibited different travel mode shift preferences under the same or similar circumstances (i.e., motorcyclists with similar income levels, motorcyclists with similar perceptions towards the most important improvement needed in transit system, or motorcyclists that do not own or plan to own a car). In addition, the cost quantification results showed that migrant motorcyclists would experience a larger out-of-pocket cost and opportunity cost of travel time increase on average compared to resident motorcyclists after a travel mode shift, especially for male migrant motorcyclists, who could experience a more than 50% increase in personal costs. The policy implications of these differences are that the motorcycle full-ban policy may cause two main challenges for migrants in Foshan City that can potentially reduce their overall quality of life. First, the increased out-of-pocket cost and opportunity cost of travel time due to the travel mode shift would add to the financial burden of migrant motorcyclists due their common practice of sending a significant portion of their income to their inflow regions. Second, the public transit system is costly and inconvenient for migrant motorcyclists compared to residents due to the institutional barriers, such as the hukou system, and their mode shift choices for the morning commute may be limited as over one-third of them stated that they would shift to the bus transit system after the implementation of the motorcycle full-ban. These challenges may add a new dimension to the social inequality and exclusion of migrant motorcyclists along with the existing household registration policy. In some extreme cases, motorcyclists may even attempt to continue using motorcycles after the implementation of the motorcycle full-ban policy, which may result in conflict and even violence between motorcyclists and law enforcement (Xu, 2014). Considering the significant contributions made by migrants to the development of both their inflow and outflow regions, it is important for planners and policymakers to accommodate the travel needs of both migrants and residents after the implementation of the motorcycle full-ban policy.

The model estimation results also revealed that the factors affecting the travel mode shifts of male and female motorcyclists are different. The results showed that among motorcycle-dependent households (with two or more motorcycles), female motorcyclists were more likely to shift to lower cost modes compared to male motorcyclists due to possible gender and income inequality. In addition, the model estimation results illustrated a potential increase in car demand and usage after a travel mode shift, particularly among motorcyclists who already have a car or plan to buy one soon. The quantification of the motorcycle full-ban policy's societal impacts also indicated a significant increase in CO_2 and NO_x emissions after travel mode shifts, among which NO_x emission was the main source of the photochemical smog and haze pollution in the Pearl River Delta region.

In conclusion, this part of the dissertation was the first to analyze the contributing factors that affect the travel mode shift preferences of motorcyclists caused by the motorcycle full-ban policy as well as to quantify the personal and societal impacts of such travel mode shifts across the gender and residential status of motorcyclists. To capture the unobserved heterogeneity in travel mode shift analysis, the use of random parameters multinomial logit models with heterogeneity in the parameter means and variances allowed for a more general structure for capturing unobserved heterogeneity compared to traditional multinomial logit models.

CHAPTER 7. SUMMARY AND CONCLUSIONS

7.1 Summary and Conclusions

This dissertation systematically addressed the potential of leveraging information technologies and related policies to influencing short- and long-term travel behavior by: (1) developing a framework for apps that integrate augmented reality, gamification, and social component to influence travel decisions that address multiple user- and system-level goals, (2) understanding the safety and health impacts of these apps, (3) developing strategies to influence residential location decision-making to foster sustainable post-relocation travel behavior, (4) investigating the impacts of economic and legal policies on travel decisions by considering distinctive regional and political characteristics.

Chapter 2 proposed a conceptual framework to integrate AR, gamification and social interactions through mobile apps for influencing individual users' route and mode choice decisions, and address goals from the perspectives of both the system operator and individual users by studying the impacts of Pokémon GO on users' route and mode choice decisions. A system operator can leverage AR to manage traffic in real-time by dynamically adjusting location, content and timing of virtual objects in the traffic network. This provides transportation planning and operational agencies a flexibility flexible, convenient and low-cost solution to influence short- and long-term travel behavior without relying solely on high-cost or labor-intensive physical infrastructure. The gamification of the app encourages individual users to set up personal goals, complete generate goals set up by the system operator, monitor their progress, and acknowledge and reward their achievements upon completion of goals. The social component provides individual users with opportunities for social interaction and facilitates the formation of communities that provide social support to app users to make long-term travel decisions towards usage of sustainable modes, help to spread such attitudes, and establish corresponding social norms. The combination of gamification and social component can provide intangible benefits to users for increasing and/or maintaining the apps' attractiveness and user engagement over the long-term.

Chapter 3 showed that several LAR users reported increase in app-induced driving, app-related distracted driving, app-related distracted cycling, and dangerous driving maneuvers despite acknowledging their risk. Possible app mechanisms such as using concept of diminishing returns are proposed to reduce app-related distractions and likelihood of making unsafe maneuvers without compromising the apps' attractiveness. It also shows that LAR apps can promote users to go outside and exercise or walk more, and foster interactions with friends, family members, and opportunities to interact with other users.

In Chapter 4, a design of personalized accessibility information (IOAMA) was proposed and its effectiveness to foster sustainable travel behavior was evaluated using a group of relocators. The results showed that the experimental group participants who received personalized accessibility information were more likely to place more importance on the accessibility-related factors of potential residence locations in their residential location decision-making process and choose a residence in a neighborhood that had better overall accessibility using different modes of transportation, and was more suitable to their specific household travel needs. In addition, they tended to drive alone less, drove with other household members more, and walked, rode a bicycle, and used transit more. These results showed that, first, the design of information needs to consider the impacts of long-term decisions such as residential location choice on short-term travel decisions, such as route choice. Second, strategies can be more effective if they are implemented before the targeted individuals form habitual transportation-related behavior. Third, personalized information delivery and visualization potentially can be more useful for people as an easier way to process information, thus improving the information's attractiveness and effectiveness compared to strategies that provide generalized information based on a "one-size-fits-all" approach.

Chapter 5 presents the results of this dissertation's investigation of migrant and resident car traveler mode shift responses under congestion pricing and reward policies. It showed that complementary intervention modules (e.g., increasing awareness of the personal health benefits associated with using sustainable travel modes) can potentially promote the effectiveness of both policies. It also shows that migrant and resident millennial car travelers have different mode shift responses under both congestion pricing and reward policies under the same or similar circumstances. Such differences can be attributed to a combination of the unique regional characteristics and policies: (1) existing policies such as license plate lottery system and road space rationing system limit potential new car users to own a car or use a personal car and may need to rely on more expensive ridesharing services; (2) the rising costs of buying or renting a property in Beijing and the practice of supporting other family members limit resources available for migrants to spend on their travel needs. These potential challenges, which are only intensified under congestion pricing policies may further contribute to the widening income and social inequality between migrants and residents caused by long-term social and institutional barriers such as the household registration system. Therefore, planners and policymakers should consider addressing the needs of both migrants and residents when implementing congestion pricing and reward policies.

In Chapter 6, the personal and societal impacts of the motorcycle full-ban policy on motorcyclists' home-to-work morning commute travel mode shift in Foshan City, China were investigated. The results showed that migrant and resident motorcyclists exhibited different travel mode shift preferences under the same or similar circumstances. In addition, the cost quantification results showed that migrant motorcyclists would experience a larger out-of-pocket cost and opportunity cost of travel time increase on average compared to resident motorcyclists after a travel mode shift, particularly for male migrant motorcyclists. These results are consistent with the findings in Chapter 5 and illustrate the importance of factoring unique regional and institutional differences. Furthermore, the mixed societal impacts of the motorcycle full-ban policy show that the motorcycle full-ban policy alone may not solve the urban transportation challenges faced by many cities in China. There is a need to manage the impacts of the motorcycle full-ban policy by increasing the attractiveness of transit (optimized route service, planning subway service, and equitable pricing fare policies) and cycling (bicycle-sharing, bicycle lane planning, and bicycle promotion initiatives). Without these policies, the motorcycle full-ban policy may not achieve its purpose but instead can create additional economic and social issues, particularly for migrant motorcyclists.

Apart from the unique insights provided by each chapter, some of the shared observations and insights can be used to assist the designs of information-technologies and related-policies for influencing short- and long-term travel decisions. First, it is important improve user familiarity with different information technologies to increase their effectiveness in influencing travel decisions. This can be achieved by providing supplementary tutorials and opening moderated online forums for integrated apps. Second, it is critical to factor travelers' long-term decisions on short-term ones as the short-term decisions are often restricted by long-term ones. It is important to provide personalized accessibility and livability information to relocators so that they can identify a residence that suits their travel needs, have multiple route and mode options available, and reduce the likelihood of relocation which can cause social and financial burdens to them. Third, it is important to not only ensure the policies can improve the overall travel condition and quality of life for most residences but also address the needs of potential vulnerable population subgroups and factor unique regional and political characteristics instead of a one-size-fits-all approach. Last but not the least, it is important to address the safety-related issues associated with information technology usage, design related-policies to facilitate its usage, and improve personal health awareness of the benefits associated with using sustainable modes of transportation to ensure the safe and effective implementation of information technologies and related-policies.

Despite the potential benefits and potential of information technologies, there are many challenges faced by system operators and policymakers around the globe. First, information security (e.g., information storage and sharing) can be a critical issue to ensure the implementation of information technologies. Second, it is important to address the privacy concerns of individual users to help me understand what information they shared, how such information is used, who has access to such information, how secure such information is, etc. Third, considering the amount of information transmitted between system operators and individual users and the amount of information that needs to be processed, communication stability and computational power of the transportation control centers need to be improved to ensure successful information communication and delivery of reliable real-time travel information. Fourth, although it is encouraging to see many millennials are good at understanding information technologies and can use them effectiveness, it is equally important to develop innovative measures to address the needs of elders, travelers with disabilities, minors, and other potentially vulnerable population subgroups.

7.2 Summary of Contributions

This dissertation makes several important contributions to the field about serval aspects of using information technologies and related policies to influence short- and long-term travel behavior.

(1) Pokémon GO, a popular LAR gaming app, leverages AR to introduce incentivizing virtual objects at fixed (i.e., PokéStops and Gyms) and dynamic (i.e., Pokémon) locations that translate through the app interface to incentives in the real world that have the potential to influence route and mode choices. However, existing Pokémon GO-related studies focused on the app's health and safety implications. This dissertation represents the first effort to understand its impacts on route and mode choices.

(2) Extensive efforts have been spent on developing mobile apps to influence users' short- and long-term travel decisions. However, these apps often cannot address the needs of both individual users and system operators, rarely emphasize the importance of providing intangible benefits to their users to improve app attractiveness and maintain long-term user engagement, or contain effective social components that provide opportunities for social interactions, cooperation, support and reinforcement among users. This dissertation proposed a conceptual framework to integrate AR, gamification and social interactions through mobile apps for influencing individual users' route and mode choice decisions, and address goals from the perspectives of both the system operator and individual users.

(3) This dissertation represents one of the early efforts to comprehensive address the perception and attitude towards LAR apps' safety and health implications. New LAR app-related safety hazards (e.g., app-induced driving and app-related unsafe driving maneuvers) that do not exist in other types of phone-related activities were identified and studies. Potential policies and app mechanisms were proposed to address the safety concerns of using such apps, and provide physical and mental health benefits to its users.

(4) In this dissertation, a designed of personalized accessibility information (IOAMA) was proposed and implemented for general population to investigate its potential to influence possible relocators' residential location choice and travel behaviors after relocation. It represents one of few successfully implemented efforts to promote sustainable travel behavior through influencing travelers' long-term decisions (e.g., residential location).

(5) This dissertation represents the first effort to study China's millennial car travelers' mode shift responses under congestion pricing and reward policies, and identify the potential mode shift response differences between the migrant and resident millennial car travelers. It not only provided insights for the design of future congestion pricing and reward policies and complementary measures but also illustrated the potential challenges to migrant car travelers associated with the implementation of such policies.

(6) In this dissertation, one of the first effort to analyze the personal and societal impacts of motorcycle full-ban policies on motorcyclists' mode shift response across population sub-groups defined by gender and residential status (migrants and residents) was presented.

7.3 Limitations and Future Work

This dissertation has several limitations, which can be addressed in future studies, as listed below.

(1) In terms of the survey data collection process and data collected, the voluntary nature of the online survey and self-reported behavioral data used in this dissertation can be improved in serval future studies. The current scope of dissertation focuses on building the theoretical foundation of a series of research topics. Extensive efforts were made to collect offline observations to validate the results of stated preference and self-reported survey data. However, these efforts did not yield concrete results due to privacy concerns, potential high participants drop-offs, and funding available. First, tracking mechanisms can be installed LAR app users to better monitor their app-related activities which can help to provide a better understanding in terms of the impacts of Pokémon GO on travel behavior. Second, a prototype integrated app can be developed to evaluate its effectiveness in influencing short- and long-term travel decisions, and its impacts on network performance in a real-world context. Third, a realistic or simulated driving/cycling environment can be developed to evaluate user performance (e.g., response time) while they are engaging LAR apps to their performance while doing other phone-related activities.

(2) The findings of the case study in Beijing and Foshan can be compared with potential future studies in megacities such as Shanghai and Guangzhou as they have different vehicle registration systems and public transit systems.

(3) The implementation of the proposed intervention strategy (Chapter 4) in a larger metropolitan area with a larger sample size and develop separate econometric models for the participants in the control and experimental groups to evaluate the proposed strategy's effectiveness.

(4) Interactive Online Accessibility Mapping Application can be used as a prototype to develop a more comprehensive livability index from a transportation perspective with bundled information related to accessibility and the neighborhood built environment (such as school district quality). In addition, it can also include additional interactive features (e.g., adjustable threshold of travel time, restaurant preference, etc.) and link it with real estate websites (e.g., Zillow, Trulia, etc.) to provide easier access to both residential location choices and personalized accessibility information which can better assist relocators to make more informed residential location choices.

(5) The multimodal online information mapping application which was used to show millennial car travelers’ mode options showed only the bus or subway route that provided the shortest commute travel time. This design can be improved to show multiple bus or subway routes.

REFERENCES

Abou-Zeid, M., & Ben-Akiva, M. (2011). The effect of social comparisons on commute well-being. *Transportation Research Part A: Policy and Practice*, *45*(4), 345-361.

Akay, A., Giulietti, C., Robalino, J. D., & Zimmermann, K. F. (2014). Remittances and well-being among rural-to-urban migrants in China. *Review of Economics of the Household*, *12*(3), 517-546.

Allan, R. (2016). Pokémon GO usage statistics say it's the most popular mobile game in US history. Retrieved from *https://www. surveymonkey. com/business/intelligence/pokemon-go-usage-statistics*.

Althoff, T., White, R. W., & Horvitz, E. (2016). Influence of Pokémon Go on physical activity: study and implications. *Journal of Medical Internet Research*, *18*(12), e315.

American Academy of Pediatrics, 2012. Dangers of texting while driving. Retrieved from http://www.news-medical.net/news/20120430/Dangers-of-texting-whiledriving.aspx. Accessed August 7, 2016.

Anas, A. (1985). The combined equilibrium of travel networks and residential location markets. *Regional Science and Urban Economics*, *15*(1), 1-21.

Anastasopoulos, P. C. (2016). Random parameters multivariate tobit and zero-inflated count data models: addressing unobserved and zero-state heterogeneity in accident injury-severity rate and frequency analysis. *Analytic Methods in Accident Research*, *11*, 17-32.

Anastasopoulos, P. C., Karlaftis, M. G., Haddock, J. E., & Mannering, F. L. (2012). Household automobile and motorcycle ownership analyzed with random parameters bivariate ordered probit model. *Transportation Research Record*, *2279*(1), 12-20.

Anastasopoulos, P. C., & Mannering, F. L. (2009). A note on modeling vehicle accident frequencies with random-parameters count models. *Accident Analysis & Prevention*, *41*(1), 153-159.

Anastasopoulos, P. C., & Mannering, F. L. (2011). An empirical assessment of fixed and random parameter logit models using crash-and non-crash-specific injury data. *Accident Analysis & Prevention*, *43*(3), 1140-1147.

Andersson, A., Hiselius, L. W., & Adell, E. (2018). Promoting sustainable travel behaviour through the use of smartphone applications: A review and development of a conceptual model. *Travel Behaviour and Society*, *11*, 52-61.

Anjuke (2019). Average housing pricing in Beijing for the past twelve months. Retrieved from https://beijing.anjuke.com/market/

Ansari, S., Akhdar, F., Mandoorah, M., & Moutaery, K. (2000). Causes and effects of road traffic accidents in Saudi Arabia. *Public Health*, *114*(1), 37-39.

Atchley, P., Atwood, S., & Boulton, A. (2011). The choice to text and drive in younger drivers: Behavior may shape attitude. *Accident Analysis & Prevention*, *43*(1), 134-142.

Ayers, J., Leas, E., Dredze, M., Allem, J., Grabowski, J., Hill, L. (2016). Pokémon GO—a new distraction for drivers and pedestrians. *JAMA Internal Medicine*, *176*(12), 1865-1866.

Azevedo, C. L., Seshadri, R., Gao, S., Atasoy, B., Akkinepally, A. P., Christofa, E., ... & Ben-Akiva, M. (2018). Tripod: sustainable travel incentives with prediction, optimization, and personalization. In *Transportation Research Board 97th Annual Meeting*.

Baan, W., Gao, P., & Zipser, D. Savvy and sophisticated: Meet China's evolving car buyers. McKinsey & Company. Retrieved from https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/savvy-and-sophisticated-meet-chinas-evolving-car-buyers

Bamberg, S., Fujii, S., Friman, M., & Gärling, T. (2011). Behaviour theory and soft transport policy measures. *Transport Policy*, *18*(1), 228-235.

Barbieri, S., Vettore, G., Pietrantonio, V., Snenghi, R., Tredese, A., Bergamini, M., ... & Feltracco, P. (2017). Pedestrian inattention blindness while playing Pokémon Go as an emerging health-risk behavior: a case report. *Journal of Medical Internet Research*, *19*(4), e86.

Bayoh, I., Irwin, E. G., & Haab, T. (2006). Determinants of residential location choice: How important are local public goods in attracting homeowners to central city locations?. *Journal of Regional Science*, *46*(1), 97-120.

Belgiawan, P. F., Schmöcker, J. D., Abou-Zeid, M., Walker, J., Lee, T. C., Ettema, D. F., & Fujii, S. (2014). Car ownership motivations among undergraduate students in China, Indonesia, Japan, Lebanon, Netherlands, Taiwan, and USA. *Transportation*, *41*(6), 1227-1244.

Behnood, A., & Mannering, F. (2017). Determinants of bicyclist injury severities in bicycle-vehicle crashes: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research*, *16*, 35-47.

Ben-Elia, E., & Shiftan, Y. (2010). Which road do I take? A learning-based model of route-choice behavior with real-time information. *Transportation Research Part A: Policy and Practice*, *44*(4), 249-264.

Bhat, C. R. (2000). Incorporating observed and unobserved heterogeneity in urban work travel mode choice modeling. *Transportation Science*, *34*(2), 228-238.

Bhat, C. R., & Guo, J. Y. (2007). A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. *Transportation Research Part B: Methodological*, *41*(5), 506-526.

Bhat, C. R., & Sardesai, R. (2006). The impact of stop-making and travel time reliability on commute mode choice. *Transportation Research Part B: Methodological*, *40*(9), 709-730.

Birnbaum, F., Lewis, D. M., Rosen, R., & Ranney, M. L. (2015). Patient engagement and the design of digital health. *Academic Emergency Medicine: Official Journal of the Society for Academic Emergency Medicine*, *22*(6), 754.

Bordin, S., Menéndez, M., & De Angeli, A. (2014). ViaggiaTrento: an application for collaborative sustainable mobility. *ICST Trans. Ambient Systems*, *1*(4), e5.

Broll, G., Cao, H., Ebben, P., Holleis, P., Jacobs, K., Koolwaaij, J., ... & Souville, B. (2012, December). Tripzoom: an app to improve your mobility behavior. In *Proceedings of the 11th international conference on mobile and ubiquitous multimedia* (p. 57). ACM.

Byington, K. W., & Schwebel, D. C. (2013). Effects of mobile Internet use on college student pedestrian injury risk. *Accident Analysis & Prevention*, *51*, 78-83.

Cai, Q. (2003). Migrant remittances and family ties: a case study in China. *International Journal of Population Geography*, *9*(6), 471-483.

Cao, X. J., Xu, Z., & Fan, Y. (2010). Exploring the connections among residential location, self-selection, and driving: Propensity score matching with multiple treatments. *Transportation Research Part A: Policy and Practice*, *44*(10), 797-805.

Carter, P. M., Bingham, C. R., Zakrajsek, J. S., Shope, J. T., & Sayer, T. B. (2014). Social norms and risk perception: Predictors of distracted driving behavior among novice adolescent drivers. *Journal of Adolescent Health*, *54*(5), S32-S41.

Carreras, I., Gabrielli, S., Miorandi, D., Tamilin, A., Cartolano, F., Jakob, M., & Marzorati, S. (2012, June). SUPERHUB: a user-centric perspective on sustainable urban mobility. In *Proceedings of the 6th ACM workshop on Next generation mobile computing for dynamic personalised travel planning* (pp. 9-10). ACM.

Centers for Disease Control and Preventions (CDC). Facts about physical activity. Retrieved from https://www.cdc.gov/physicalactivity/data/facts.htm

Chan, K. W. (2007). Misconceptions and complexities in the study of China's cities: Definitions, statistics, and implications. *Eurasian Geography and Economics*, *48*(4), 383-412.

Chan, K. W. (2013). China: internal migration. *The Encyclopedia of Global Human Migration*.

Chang, H., Dong, X. Y., & MacPhail, F. (2011). Labor migration and time use patterns of the left-behind children and elderly in rural China. *World Development*, *39*(12), 2199-2210.

Chang, H. L., & Lai, C. Y. (2015). Using travel socialization and underlying motivations to better understand motorcycle usage in Taiwan. *Accident Analysis & Prevention*, *79*, 212-220.

Chataway, E. S., Kaplan, S., Nielsen, T. A. S., & Prato, C. G. (2014). Safety perceptions and reported behavior related to cycling in mixed traffic: A comparison between Brisbane and Copenhagen. *Transportation Research Part F: Traffic Psychology and Behaviour*, *23*, 32-43.

Chen, S., Saeed, T. U., Alqadhi, S. D., & Labi, S. (2019). Safety impacts of pavement surface roughness at two-lane and multi-lane highways: accounting for heterogeneity and seemingly unrelated correlation across crash severities. *Transportmetrica A: Transport Science*, *15*(1), 18-33.

Cheng, Z., Wang, H., & Smyth, R. (2014). Happiness and job satisfaction in urban China: A comparative study of two generations of migrants and urban locals. *Urban Studies*, *51*(10), 2160-2184.

Cherry, C. R., Weinert, J. X., & Xinmiao, Y. (2009). Comparative environmental impacts of electric bikes in China. *Transportation Research Part D: Transport and Environment*, *14*(5), 281-290.

Chib, S., & Greenberg, E. (1998). Analysis of multivariate probit models. *Biometrika*, *85*(2), 347-361.

China Daily (2017). Top 10 Chinese cities with highest average monthly salary. Retrieved from http://www.chinadaily.com.cn/business/2017top10/2017-06/23/content_29853826.htm

Chong, Y., Sethi, D. K., Loh, C. H. Y., & Lateef, F. (2018). Going forward with Pokemon Go. *Journal of Emergencies, Trauma, and Shock*, *11*(4), 243.

Choocharukul, K., Van, H. T., & Fujii, S. (2008). Psychological effects of travel behavior on preference of residential location choice. *Transportation Research Part A: Policy and Practice*, *42*(1), 116-124.

Chorus, C. G., Arentze, T. A., Molin, E. J., Timmermans, H. J., & Van Wee, B. (2006). The value of travel information: Decision strategy-specific conceptualizations and numerical examples. *Transportation Research Part B: Methodological*, *40*(6), 504-519.

Christoforou, Z., Cohen, S., & Karlaftis, M. G. (2010). Vehicle occupant injury severity on highways: an empirical investigation. *Accident Analysis & Prevention*, *42*(6), 1606-1620.

Comscore. *2017 U.S. Cross-Platform Future in Focus*. 2017. Retrieved from https://www.comscore.com/Insights/Presentations-and-Whitepapers/2017/2017-US-Cross-Platform-Future-in-Focus

Costa Jr, P. T., Terracciano, A., & McCrae, R. R. (2001). Gender differences in personality traits across cultures: robust and surprising findings. *Journal of Personality and Social Psychology*, *81*(2), 322.

Coulton, C. J., Korbin, J., Chan, T., & Su, M. (2001). Mapping residents' perceptions of neighborhood boundaries: a methodological note. *American Journal of Community Psychology*, *29*(2), 371-383.

Credit Suisse (2015). Credit Suisse Emerging Consumer Survey. Retrieved from https://www.credit-suisse.com/media/assets/corporate/docs/about-us/research/publications/emerging-consumer-survey-2015.pdf

Dai, D., & Wang, F. (2011). Geographic disparities in accessibility to food stores in southwest Mississippi. *Environment and Planning B: Planning and Design*, *38*(4), 659-677.

Dang, Y., Liu, Z., & Zhang, W. (2014). Land-based interests and the spatial distribution of affordable housing development: The case of Beijing, China. *Habitat International*, *44*, 137-145.

Deng, X., Xu, J., & Wang, B. (2009). Traffic countermeasures research for Guangzhou City in traffic mode transferring period after "Motorcycle Forbidden Ban" effect. *Journal of Transportation Systems Engineering and Information Technology*, *9*(4), 145-150.

de Kruijf, J., Ettema, D., Kamphuis, C. B., & Dijst, M. (2018). Evaluation of an incentive program to stimulate the shift from car commuting to e-cycling in the Netherlands. *Journal of Transport & Health*, *10*, 74-83.

Dennison, L., Morrison, L., Conway, G., & Yardley, L. (2013). Opportunities and challenges for smartphone applications in supporting health behavior change: qualitative study. *Journal of Medical Internet research*, *15*(4), e86.

Di Dio, S., Rizzo, G., & Vinci, I. (2015). How to track behaviours' changes toward more sustainable mobility habits: the serious game of TrafficO2. In *Proceedings of the international Conference on Design, Social Media and Technology to Foster Civic Self-Organisation Conference, Hasselt (BE)*.

Di Dio, S., Lissandrello, E., Schillaci, D., Caroleo, B., Vesco, A., & D'Hespeel, I. (2018, December). MUV: A game to encourage sustainable mobility habits. In *International Conference on Games and Learning Alliance* (pp. 60-70). Springer, Cham.

Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences*, *113*(10), 2636-2641.

Dirin, A., & Laine, T. (2018). User experience in mobile augmented reality: emotions, challenges, opportunities and best practices. *Computers*, *7*(2), 33.

Dissanayake, D., & Morikawa, T. (2010). Investigating household vehicle ownership, mode choice and trip sharing decisions using a combined revealed preference/stated preference Nested Logit model: case study in Bangkok Metropolitan Region. *Journal of Transport Geography*, *18*(3), 402-410.

Du, Y., Park, A., & Wang, S. (2005). Migration and rural poverty in China. *Journal of Comparative Economics*, *33*(4), 688-709.

Eliasson, J., & Mattsson, L. G. (2006). Equity effects of congestion pricing: quantitative methodology and a case study for Stockholm. *Transportation Research Part A: Policy and Practice*, *40*(7), 602-620.

Emmerink, R. H., Axhausen, K. W., Nijkamp, P., & Rietveld, P. (1995). Effects of information in road transport networks with recurrent congestion. *Transportation*, *22*(1), 21-53.

Ethan, D., Basch, C. H., Johnson, G. D., Hammond, R., Chow, C. M., & Varsos, V. (2016). An analysis of technology-related distracted biking behaviors and helmet use among cyclists in New York City. *Journal of Community Health*, *41*(1), 138-145.

Ettema, D., Knockaert, J., & Verhoef, E. (2010). Using incentives as traffic management tool: empirical results of the" peak avoidance" experiment. *Transportation Letters*, *2*(1), 39-51.

Ewing, R., & Cervero, R. (2010). Travel and the built environment: A meta-analysis. *Journal of the American Planning Association*, *76*(3), 265-294.

Federal Highway Administration (FHWA). (2016). *Average Annual Miles per Driver by Age Group*. Retrieved from https://www.fhwa.dot.gov/ohim/onh00/bar8.htm

Flora, H. K., Wang, X., & Chande, S. V. (2014). An investigation on the characteristics of mobile applications: A survey study.

Foshan Public Security Bureau, 2016. Information for foreigners. Retrieved from http://www.fsga.gov.cn/en/inffn/

Fountas, G., & Anastasopoulos, P. C. (2017). A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. *Analytic Methods in Accident Research*, *15*, 1-16.

Fountas, G., & Anastasopoulos, P. C. (2018). Analysis of accident injury-severity outcomes: The zero-inflated hierarchical ordered probit model with correlated disturbances. *Analytic methods in accident research*, *20*, 30-45.

Fountas, G., Anastasopoulos, P. C., & Abdel-Aty, M. (2018). Analysis of accident injury-severities using a correlated random parameters ordered probit approach with time variant covariates. *Analytic Methods in Accident Research*, *18*, 57-68.

Fountas, G., Anastasopoulos, P. C., & Mannering, F. L. (2018). Analysis of vehicle accident-injury severities: a comparison of segment-versus accident-based latent class ordered probit models with class-probability functions. *Analytic Methods in Accident Research*, *18*, 15-32.

Frank, L., Bradley, M., Kavage, S., Chapman, J., & Lawton, T. K. (2008). Urban form, travel time, and cost relationships with tour complexity and mode choice. *Transportation*, *35*(1), 37-54.

Froehlich, J., Dillahunt, T., Klasnja, P., Mankoff, J., Consolvo, S., Harrison, B., & Landay, J. A. (2009, April). UbiGreen: investigating a mobile tool for tracking and supporting green transportation habits. In *Proceedings of the sigchi conference on human factors in computing systems* (pp. 1043-1052). ACM.

Gaziano, T. A., Galea, G., & Reddy, K. S. (2007). Scaling up interventions for chronic disease prevention: the evidence. *The Lancet*, *370*(9603), 1939-1946.

Gärling, T., Eek, D., Loukopoulos, P., Fujii, S., Johansson-Stenman, O., Kitamura, R., ... & Vilhelmson, B. (2002). A conceptual analysis of the impact of travel demand management on private car use. *Transport Policy*, *9*(1), 59-70.

Gauld, C. S., Lewis, I., & White, K. M. (2014). Concealed texting while driving: What are young people's beliefs about this risky behaviour?. *Safety Science*, *65*, 63-69.

Gerlich, R.N., Drumheller, K., Babb, J., and De'Armond, D.A. (2015). App consumption: An exploratory analysis of the uses and gamification of mobile apps. *Academy of Marketing Studies Journal*, 19(1).

Goldenbeld, C., Houtenbos, M., Ehlers, E., & De Waard, D. (2012). The use and risk of portable electronic devices while cycling among different age groups. *Journal of Safety Research*, *43*(1), 1-8.

Greene, W.H. (2000). *Econometric Analysis*, 4th edition. Prentice Hall, New Jersey.

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: contrasts with mixed logit. *Transportation Research Part B: Methodological*, *37*(8), 681-698.

Greene, W. H., & Hensher, D. A. (2010). *Modeling Ordered Choices: A Primer*. Cambridge University Press.

Guo, Z. (2011). Mind the map! The impact of transit maps on path choice in public transit. *Transportation Research Part A: Policy and Practice*, *45*(7), 625-639.

Guo, Y., Agrawal, S., Peeta, S., & Somenahalli, S. (2016). Impacts of property accessibility and neighborhood built environment on single-unit and multiunit residential property values. *Transportation Research Record*, *2568*(1), 103-112.

Guo, F., Klauer, S. G., Fang, Y., Hankey, J. M., Antin, J. F., Perez, M. A., ... & Dingus, T. A. (2017). The effects of age on crash risk associated with driver distraction. *International Journal of Epidemiology*, *46*(1), 258-265.

Guo, Y., & Peeta, S. (2015). Rail–truck multimodal freight collaboration: truck freight carrier perspectives in the United States. *Journal of Transportation Engineering*, *141*(11), 04015023.

Guo, Y., & Peeta, S. (2017). *Impacts of an interactive accessibility information intervention strategy on residential location choice and travel-related behavior* (No. 17-00521).

Guo, Y. & Peeta, S. (2019). Impacts of personalized accessibility information on residential location choice and travel behavior. Submitted to *Travel Behaviour and Society.*

Guo, Y., Peeta, S., Agrawal, S., & Benedyk, I. (2019). Impacts of Pokémon GO on Route and Mode Choice Decisions: Exploring the Potential for Integrating Augmented Reality, Gamification and Social Interactions in Mobile Apps to Influence Travel Decisions. Submitted to *Transportation Research Part A: Policy and Practice*.

Guo, Y., Peeta, S., & Mannering, F. (2016). Rail-truck multimodal freight collaboration: a statistical analysis of freight-shipper perspectives. *Transportation Planning and Technology*, *39*(5), 484-506.

Guo, Y., Peeta, S., & Somenahalli, S. (2017). The impact of walkable environment on single-family residential property values.

Guo, Y., Wang, J., & Peeta, S. (2016). *The impacts of household registration and head of household travel behavior on travel mode choice in China* (No. 16-0693).

Guo, Y., Wang, J., Peeta, S., & Anastasopoulos, P. C. (2018). Impacts of internal migration, household registration system, and family planning policy on travel mode choice in China. *Travel Behaviour and Society*, *13*, 128-143.

Hadiji, F., Sifa, R., Drachen, A., Thurau, C., Kersting, K., & Bauckhage, C. (2014, August). Predicting player churn in the wild. In *2014 IEEE Conference on Computational Intelligence and Games* (pp. 1-8). IEEE.

Hamari, J., & Koivisto, J. (2013, June). Social Motivations To Use Gamification: An Empirical Study Of Gamifying Exercise. In *ECIS* (Vol. 105).

Hamari, J., Koivisto, J., & Sarsa, H. (2014, January). Does Gamification Work?-A Literature Review of Empirical Studies on Gamification. In *HICSS* (Vol. 14, No. 2014, pp. 3025-3034).

Handy, S., Cao, X., & Mokhtarian, P. (2005). Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, *10*(6), 427-444.

Harmon-Jones, E., & Mills, J. (1999). An introduction to cognitive dissonance theory and an overview of current perspectives on the theory. *Cognitive Dissonance: Progress on a Pivotal Theory in Social Psychology*, 3-21.

Hårsman, B., & Quigley, J. M. (2010). Political and public acceptability of congestion pricing: Ideology and self-interest. *Journal of Policy Analysis and Management*, *29*(4), 854-874.

Hasegawa, H. (2010). Analyzing tourists' satisfaction: A multivariate ordered probit approach. *Tourism Management*, *31*(1), 86-97.

Hechter, M., & Kanazawa, S. (1997). Sociological rational choice theory. *Annual Review of Sociology*, *23*(1), 191-214.

He, K., Huo, H., & Zhang, Q. (2002). Urban air pollution in China: current status, characteristics, and progress. *Annual Review of Energy and the Environment*, *27*(1), 397-431.

He, D., Liu, H., He, K., Meng, F., Jiang, Y., Wang, M., ... & Wang, Q. (2013). Energy use of, and CO2 emissions from China's urban passenger transportation sector–Carbon mitigation scenarios upon the transportation mode choices. *Transportation Research Part A: Policy and Practice*, *53*, 53-67.

Hessing, D. J., Elffers, H., & Weigel, R. H. (1988). Exploring the limits of self-reports and reasoned action: An investigation of the psychology of tax evasion behavior. *Journal of Personality and Social Psychology*, *54*(3), 405.

Higgins, L., Avelar, R., & Chrysler, S. (2017). Effects of Distraction Type, Driver Age, and Roadway Environment on Reaction Times–An Analysis Using SHRP-2 NDS Data.

Hopkins, D. (2016). Can environmental awareness explain declining preference for car-based mobility amongst generation Y? A qualitative examination of learn to drive behaviours. *Transportation Research Part A: Policy and Practice*, *94*, 149-163.

Hopkins, D., & Stephenson, J. (2014). Generation Y Mobilities through the lens of energy cultures: a preliminary exploration. *Journal of Transport Geography*, *38*, 88-91.

Hou, Q., Tarko, A. P., & Meng, X. (2018). Analyzing crash frequency in freeway tunnels: A correlated random parameters approach. *Accident Analysis & Prevention*, *111*, 94-100.

Hsiao, K. L., & Chen, C. C. (2016). What drives in-app purchase intention for mobile games? An examination of perceived values and loyalty. *Electronic Commerce Research and Applications*, *16*, 18-29.

Hu, X., Chiu, Y. C., & Zhu, L. (2015). Behavior insights for an incentive-based active demand management platform. *International Journal of Transportation Science and Technology*, *4*(2), 119-133.

Ichikawa, M., & Nakahara, S. (2008). Japanese high school students' usage of mobile phones while cycling. *Traffic Injury Prevention*, *9*(1), 42-47.

Iqbal, M. (2019). Uber Revenue and Usage Statistics (2018). Retrieved from http://www.businessofapps.com/data/uber-statistics/

Ivan, C., & Penev, A. (2011). Chinese consumer attitudes towards the electric vehicle.

Jariyasunant, J., Abou-Zeid, M., Carrel, A., Ekambaram, V., Gaker, D., Sengupta, R., & Walker, J. L. (2015). Quantified traveler: Travel feedback meets the cloud to change behavior. *Journal of Intelligent Transportation Systems*, *19*(2), 109-124.

Jiang, B., Liang, S., Peng, Z. R., Cong, H., Levy, M., Cheng, Q., ... & Remais, J. V. (2017). Transport and public health in China: the road to a healthy future. *The Lancet*, *390*(10104), 1781-1791.

Jin, S. T., Kong, H., Wu, R., & Sui, D. Z. (2018). Ridesourcing, the sharing economy, and the future of cities. *Cities*, *76*, 96-104.

Pill, R. (1984). Accessibility and utilization: Geographical perspectives on health care delivery. *The Journal of the Royal College of General Practitioners*, *34*(265), 452.

Jylhä, A., Nurmi, P., Sirén, M., Hemminki, S., & Jacucci, G. (2013, September). Matkahupi: a persuasive mobile application for sustainable mobility. In *Proceedings of the 2013 ACM conference on Pervasive and ubiquitous computing adjunct publication* (pp. 227-230). ACM.

Kamargianni, M., Dubey, S., Polydoropoulou, A., & Bhat, C. (2015). Investigating the subjective and objective factors influencing teenagers' school travel mode choice–An integrated choice and latent variable model. *Transportation Research Part A: Policy and Practice*, *78*, 473-488.

Kang, L., & Fricker, J. D. (2013). Bicyclist commuters' choice of on-street versus off-street route segments. *Transportation*, *40*(5), 887-902.

Kazhamiakin, R., Marconi, A., Perillo, M., Pistore, M., Valetto, G., Piras, L., ... & Perri, N. (2015, October). Using gamification to incentivize sustainable urban mobility. In *2015 IEEE First International Smart Cities Conference (ISC2)* (pp. 1-6). IEEE.

Kenworthy, J. R., & Laube, F. B. (1999). Patterns of automobile dependence in cities: an international overview of key physical and economic dimensions with some implications for urban policy. *Transportation Research Part A: Policy and Practice*, *33*(7-8), 691-723.

Kenyon, S., & Lyons, G. (2003). The value of integrated multimodal traveller information and its potential contribution to modal change. *Transportation Research Part F: Traffic Psychology and Behaviour*, *6*(1), 1-21.

Khoo, H. L., & Asitha, K. S. (2016). User requirements and route choice response to smart phone traffic applications (apps). *Travel Behaviour and Society*, *3*, 59-70.

Klein, N. J., & Smart, M. J. (2017). Millennials and car ownership: Less money, fewer cars. *Transport Policy*, *53*, 20-29.

Kogan, L., Hellyer, P., Duncan, C., & Schoenfeld-Tacher, R. (2017). A pilot investigation of the physical and psychological benefits of playing Pokémon GO for dog owners. *Computers in Human Behavior*, *76*, 431-437.

Kong, H., Wang, S., & Fu, X. (2015). Meeting career expectation: can it enhance job satisfaction of Generation Y?. *International Journal of Contemporary Hospitality Management*, *27*(1), 147-168.

Kortum, K., Paleti, R., Bhat, C. R., & Pendyala, R. M. (2012). Joint model of residential relocation choice and underlying causal factors. *Transportation Research Record*, *2303*(1), 28-37.

Krittanawong, C., Aydar, M., & Kitai, T. (2017). Pokémon Go: digital health interventions to reduce cardiovascular risk. *Cardiology in the Young*, *27*(8), 1625-1626.

Krizek, K. J. (2003). Neighborhood services, trip purpose, and tour-based travel. *Transportation*, *30*(4), 387-410.

Lachapelle, U., & Frank, L. D. (2009). Transit and health: mode of transport, employer-sponsored public transit pass programs, and physical activity. *Journal of Public Health Policy*, *30*(1), S73-S94.

Lam, W. H., & Chan, K. S. (2001). A model for assessing the effects of dynamic travel time information via variable message signs. *Transportation*, *28*(1), 79-99.

LaMagna M. *Should you Let your Kids Play Pokémon Go? Market Watch*. Retrieved from http://www.marketwatch.com/story/do-your-kids-playpokemon-go-what-to-watch-out-for-2016-07-11

Langenbucher, J., & Merrill, J. (2001). The validity of self-reported cost events by substance abusers: Limits, liabilities, and future directions. *Evaluation Review*, *25*(2), 184-210.

Lau, J. C. Y. (2013). Sustainable urban transport planning and the commuting patterns of poor workers in a historic inner city in Guangzhou, China. *Habitat International*, *39*, 119-127.

Lee, Y. K., Chang, C. T., Lin, Y., & Cheng, Z. H. (2014). The dark side of smartphone usage: Psychological traits, compulsive behavior and technostress. *Computers in human behavior*, *31*, 373-383.

Lee, J., & Shin, D. H. (2016). Targeting potential active users for mobile app install advertising: An exploratory study. *International Journal of Human–Computer Interaction*, *32*(11), 827-834.

Lee, B. H., & Waddell, P. (2010). Residential mobility and location choice: a nested logit model with sampling of alternatives. *Transportation*, *37*(4), 587-601.

Lehto, T., & Oinas-Kukkonen, H. (2010, June). Persuasive features in six weight loss websites: A qualitative evaluation. In *International Conference on Persuasive Technology* (pp. 162-173). Springer, Berlin, Heidelberg.

Li, S. M. (2004). Life course and residential mobility in Beijing, China. *Environment and Planning A*, *36*(1), 27-43.

Li, Y., Guo, Y., Lu, J., & Peeta, S. (2019). Impacts of congestion pricing and reward strategies on automobile travelers' morning commute mode shift decisions. *Transportation Research Part A: Policy and Practice*, *125*, 72-88.

Li, J., Walker, J. L., Srinivasan, S., & Anderson, W. P. (2010). Modeling private car ownership in China: investigation of urban form impact across megacities. *Transportation Research Record*, *2193*(1), 76-84.

Lin, M. I. B., & Huang, Y. P. (2017). The impact of walking while using a smartphone on pedestrians' awareness of roadside events. *Accident Analysis & Prevention*, *101*, 87-96.

Liu, F., Yun, M., & Liu, G. (2016). *Will Motorcyclist Shift to Bus or Car in Commuting: A Case Study of Zhongshan, China* (No. 16-5303).

Loo, B. P., & Li, L. (2012). Carbon dioxide emissions from passenger transport in China since 1949: Implications for developing sustainable transport. *Energy Policy*, *50*, 464-476.

Luo, W. (2004). Using a GIS-based floating catchment method to assess areas with shortage of physicians. *Health & Place*, *10*(1), 1-11.

Luo, W., & Qi, Y. (2009). An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. *Health & Place*, *15*(4), 1100-1107.

Ma, J., Xu, X., Zhao, C., & Yan, P. (2012). A review of atmospheric chemistry research in China: Photochemical smog, haze pollution, and gas-aerosol interactions. *Advances in Atmospheric Sciences*, *29*(5), 1006-1026.

Macfarlane, G. S., Garrow, L. A., & Mokhtarian, P. L. (2015). The influences of past and present residential locations on vehicle ownership decisions. *Transportation Research Part A: Policy and Practice*, *74*, 186-200.

Magliocchetti, D., Gielow, M., De Vigili, F., Conti, G., & De Amicis, R. (2011). A personal mobility assistant based on ambient intelligence to promote sustainable travel choices. *Procedia Computer Science*, *5*, 892-899.

Majid, M. R., Nordin, A. N., & Medugu, I. N. (2014). Influence of housing development designs on household vehicle miles traveled: A case of Iskandar Malaysia. *Transportation Research Part D: Transport and Environment*, *33*, 63-73.

Mannering, F. L., Shankar, V., & Bhat, C. R. (2016). Unobserved heterogeneity and the statistical analysis of highway accident data. *Analytic Methods in Accident Research*, *11*, 1-16.

Matthies, E., Kuhn, S., & Klöckner, C. A. (2002). Travel mode choice of women: the result of limitation, ecological norm, or weak habit?. *Environment and Behavior*, *34*(2), 163-177.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior.

McFadden, D. (1981). Econometric models of probabilistic choice. *Structural Analysis of Discrete Data with Econometric Applications*, *198272*.

McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, *15*(5), 447-470.

McEvoy, S. P., Stevenson, M. R., & Woodward, M. (2006). Phone use and crashes while driving: a representative survey of drivers in two Australian states. *Medical Journal of Australia*, *185*(11-12), 630-634.

McMillan, T. E. (2007). The relative influence of urban form on a child's travel mode to school. *Transportation Research Part A: Policy and Practice*, *41*(1), 69-79.

Meloni, I., & di Teulada, B. S. (2015). I-Pet Individual Persuasive Eco-travel Technology: A tool for VTBC program implementation. *Transportation Research Procedia*, *11*, 422-433.

Meloni, I., Sanjust, B., Delogu, G., & Sottile, E. (2014). Development of a technological platform for implementing VTBC programs. *Transportation Research Procedia*, *3*, 129-138.

Miles, L. (2007). Physical activity and health. *Nutrition bulletin*, *32*(4), 314-363.

Miralinaghi, M., & Peeta, S. (2016). Multi-period equilibrium modeling planning framework for tradable credit schemes. *Transportation Research Part E: Logistics and Transportation Review*, *93*, 177-198.

Molin, E., Oppewal, H., & Timmermans, H. (1999). Group-based versus individual-based conjoint preference models of residential preferences: a comparative test. *Environment and Planning A*, *31*(11), 1935-1947.

Moniruzzaman, M., & Páez, A. (2012). Accessibility to transit, by transit, and mode share: application of a logistic model with spatial filters. *Journal of Transport Geography*, *24*, 198-205.

Mun, M., Reddy, S., Shilton, K., Yau, N., Burke, J., Estrin, D., ... & Boda, P. (2009, June). PEIR, the personal environmental impact report, as a platform for participatory sensing systems research. In *Proceedings of the 7th international conference on Mobile systems, applications, and services* (pp. 55-68). ACM.

Mwakalonge, J. L., White, J., & Siuhi, S. (2014). Distracted biking: a review of the current state-of-knowledge. *International Journal of Traffic and Transportation Engineering*, *3*(2), 42-51.

Muth, R. F. (1969). City and Housing: the spatial pattern of urban residential land use.

Nakashima, R., Sato, T., & Maruyama, T. (2017). Gamification approach to smartphone-app-based mobility management. *Transportation Research Procedia*, *25*, 2344-2355.

National Bureau of Statistics (NBS). (2019). Migrant worker report. Retrieved from http://www.stats.gov.cn/tjsj/zxfb/201904/t20190429_1662268.html

National Bureau of Statistics of China (NBSC), 2015. 2014 Population Census.

National Development and Reform Commission., 2010. ＃90 Gasoline price in Guangdong province. Retrieved from http://auto.ifeng.com/news/special/youjia1001/

National Highway Traffic Safety Administration (NHTSA). Traffic Safety Facts: Distracted Driving 2015. 2016. Retrieved from https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/812_381_distracteddriving2015.pdf

Nelson, E., Atchley, P., & Little, T. D. (2009). The effects of perception of risk and importance of answering and initiating a cellular phone call while driving. *Accident Analysis & Prevention*, *41*(3), 438-444.

Newbold, K. B., & Scott, D. M. (2017). Driving over the life course: The automobility of Canada's Millennial, generation X, baby boomer and greatest generations. *Travel Behaviour and Society*, *6*, 57-63.

Nigg, C. R., Mateo, D. J., & An, J. (2017). Pokémon GO may increase physical activity and decrease sedentary behaviors. *American Journal of Public Health*, *107*(1), 37.

Oberholzer-Gee, F., & Weck-Hannemann, H. (2002). Pricing road use: politico-economic and fairness considerations. *Transportation Research Part D: Transport and Environment*, *7*(5), 357-371.

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the American society for Information Science and Technology*, *59*(6), 938-955.

Office of Disease Prevention and Health Promotion (ODPHP). Physical Activity Guidelines for Americans. Retrieved from https://health.gov/paguidelines/guidelines/

Owens, J. M., Antin, J. F., Doerzaph, Z., & Willis, S. (2015). Cross-generational acceptance of and interest in advanced vehicle technologies: A nationwide survey. *Transportation Research Part F: Traffic Psychology and Behaviour*, *35*, 139-151.

Owen, A., & Levinson, D. M. (2015). Modeling the commute mode share of transit using continuous accessibility to jobs. *Transportation Research Part A: Policy and Practice*, *74*, 110-122.

Palm, R., & Danis, M. A. (2001). Residential mobility: The impacts of web-based information on the search process and spatial housing choice patterns. *Urban Geography*, *22*(7), 641-655.

Papa, E., & Bertolini, L. (2015). Accessibility and transit-oriented development in European metropolitan areas. *Journal of Transport Geography*, *47*, 70-83.

Paulssen, M., Temme, D., Vij, A., & Walker, J. L. (2014). Values, attitudes and travel behavior: a hierarchical latent variable mixed logit model of travel mode choice. *Transportation*, *41*(4), 873-888.

Paz, A., & Peeta, S. (2009). Information-based network control strategies consistent with estimated driver behavior. *Transportation Research Part B: Methodological*, *43*(1), 73-96.

Peeta, S., & Mahmassani, H. S. (1995). Multiple user classes real-time traffic assignment for online operations: a rolling horizon solution framework. *Transportation Research Part C: Emerging Technologies*, *3*(2), 83-98.

Pew Research Center. (2017). *Mobile Fact Sheet*. Retrieved from http://www.pewinternet.org/fact-sheet/mobile/

Pew Research Center. (2019). Defining generations: Where millennials end and generation Z begins, Retrieved from http://www.pewresearch.org/fact-tank/2019/01/17/where-millennials-end-and-generation-z-begins/.

Pinjari, A. R., Pendyala, R. M., Bhat, C. R., & Waddell, P. A. (2011). Modeling the choice continuum: an integrated model of residential location, auto ownership, bicycle ownership, and commute tour mode choice decisions. *Transportation*, *38*(6), 933.

Piras, F., Sottile, E., Calli, D., & Meloni, I. (2018). Automatic data collection for detecting travel behavior: the IPET platform. *Procedia Computer Science*, *134*, 421-426.

Ploderer, B., Reitberger, W., Oinas-Kukkonen, H., & Gemert-Pijnen, J. (2014). Social interaction and reflection for behaviour change. *Personal and Ubiquitous Computing*, *18*(7), 1667-1676.

Plous, S. *The Psychology of Judgment and Decision Making*. Mcgraw-Hill Book Company, 1993.

Pope, C. N., Mirman, J. H., & Stavrinos, D. (2019). Adolescents' perspectives on distracted driving legislation. *Journal of Safety Research*, *68*, 173-179.

Pourmand, A., Lombardi, K., Kuhl, E., & O'Connell, F. (2017). Videogame-related illness and injury: a review of the literature and predictions for Pokémon Go!. *Games for Health Journal*, *6*(1), 9-18.

Prashker, J., Shiftan, Y., & Hershkovitch-Sarusi, P. (2008). Residential choice location, gender and the commute trip to work in Tel Aviv. *Journal of Transport Geography*, *16*(5), 332-341.

Pucher, J., Peng, Z. R., Mittal, N., Zhu, Y., & Korattyswaroopam, N. (2007). Urban transport trends and policies in China and India: impacts of rapid economic growth. *Transport Reviews*, *27*(4), 379-410.

Rauschnabel, P. A., Rossmann, A., & tom Dieck, M. C. (2017). An adoption framework for mobile augmented reality games: The case of Pokémon Go. *Computers in Human Behavior*, *76*, 276-286.

Reference USA. U.S. Business, 2014. Retrieved from http://www.referenceusa.com/Home/Home.

Riquelme, H. E., Al-Sammak, F. S., & Rios, R. E. (2010). Social influences among young drivers on talking on the mobile phone while driving. *Traffic Injury Prevention*, *11*(2), 127-132.

Rodriguez, D. A., & Rogers, J. (2014). Can housing and accessibility information influence residential location choice and travel behavior? An experimental study. *Environment and Planning B: Planning and Design*, *41*(3), 534-550.

Roider, O., Wegener, S., Stark, J., Judmaier, P., Michelberger, F., & Barberi, A. (2019). Merging Virtual World with Real-Life Behavior: A Concept for a Smartphone App to Influence Young People's Travel Behavior. *Transportation Research Record*, *2673*(4), 241-250.

Russo, B. J., Savolainen, P. T., Schneider IV, W. H., & Anastasopoulos, P. C. (2014). Comparison of factors affecting injury severity in angle collisions by fault status using a random parameters bivariate ordered probit model. *Analytic Methods in Accident Research*, *2*, 21-29.

Rudisill, T. M., & Zhu, M. (2017). Hand-held cell phone use while driving legislation and observed driver behavior among population sub-groups in the United States. *BMC public health*, *17*(1), 437.

Runge, J., Gao, P., Garcin, F., & Faltings, B. (2014, August). Churn prediction for high-value players in casual social games. In *2014 IEEE conference on Computational Intelligence and Games* (pp. 1-8). IEEE.

Sawano, T., Ozaki, A., Shimada, Y., Leppold, C., Tsubokura, M., Tsukada, M., ... & Ohira, H. (2017). Pokémon GO & driving. *QJM: An International Journal of Medicine*, *110*(5), 311-312.

Scheiner, J., & Holz-Rau, C. (2007). Travel mode choice: affected by objective or subjective determinants?. *Transportation*, *34*(4), 487-511.

Schrammel, J., Busch, M., & Tscheligi, M. (2013, April). Peacox-Persuasive Advisor for CO2-Reducing Cross-Modal Trip Planning. In *PERSUASIVE (Adjunct Proceedings)*.

Schwebel, D. C., & Barton, B. K. (2005). Contributions of multiple risk factors to child injury. *Journal of Pediatric Psychology*, *30*(7), 553-561.

Schwanen, T., & Mokhtarian, P. L. (2004). The extent and determinants of dissonance between actual and preferred residential neighborhood type. *Environment and planning B: Planning and Design*, *31*(5), 759-784.

Searcy, S. E., Findley, D. J., Huegy, J. B., Ingram, M., Mei, B., Bhadury, J., & Wang, C. (2018). Effect of residential proximity on university student trip frequency by mode. *Travel Behaviour and Society*, *12*.

Seraneeprakarn, P., Huang, S., Shankar, V., Mannering, F., Venkataraman, N., & Milton, J. (2017). Occupant injury severities in hybrid-vehicle involved crashes: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research*, *15*, 41-55.

Serino, M., Cordrey, K., McLaughlin, L., & Milanaik, R. L. (2016). Pokémon Go and augmented virtual reality games: a cautionary commentary for parents and pediatricians. *Current Opinion in Pediatrics*, *28*(5), 673-677.

Shankar, V., & Mannering, F. (1998). Modeling the endogeneity of lane-mean speeds and lane-speed deviations: a structural equations approach. *Transportation Research Part A: Policy and Practice*, *32*(5), 311-322.

Shen, J. (2013). Increasing internal migration in China from 1985 to 2005: Institutional versus economic drivers. *Habitat International*, *39*, 1-7.

Simma, A., & Axhausen, K. W. (2001). Structures of commitment in mode use: a comparison of Switzerland, Germany and Great Britain. *Transport Policy*, *8*(4), 279-288.

Sima, Y., & Pugsley, P. C. (2010). The rise of a'me culture'in postsocialist China: youth, individualism and identity creation in the blogosphere. *International Communication Gazette*, *72*(3), 287-306.

Simons-Morton, B., Lerner, N., & Singer, J. (2005). The observed effects of teenage passengers on the risky driving behavior of teenage drivers. *Accident Analysis & Prevention*, *37*(6), 973-982.

Simonsohn, U. (2006). New Yorkers commute more everywhere: contrast effects in the field. *Review of Economics and Statistics*, *88*(1), 1-9.

Song, P., & Zhong, C. (2015). Fuzzy Comprehensive Evaluation Research of Goal Attainment of Green Transportation Development Policy—Take Dongguan “Motorcycle Ban” Policy as an Example. *Journal of Transportation Technologies*, *5*(01), 46.

Sparling, P. B., Owen, N., Lambert, E. V., & Haskell, W. L. (2000). Promoting physical activity: the new imperative for public health. *Health Education Research*, *15*(3), 367-376.

Stavrinos, D., Byington, K. W., & Schwebel, D. C. (2011). Distracted walking: cell phones increase injury risk for college pedestrians. *Journal of Safety Research*, *42*(2), 101-107.

Stavrinos, D., Pope, C. N., Shen, J., & Schwebel, D. C. (2018). Distracted walking, bicycling, and driving: Systematic review and meta-analysis of mobile technology and youth crash risk. *Child Development*, *89*(1), 118-128.

Steg, L. (2003). Factors influencing the acceptability and effectiveness of transport pricing. In *Acceptability of Transport Pricing Strategies* (pp. 187-202). Pergamon Press.

Stopher, P. R. (2004). Reducing road congestion: a reality check. *Transport Policy*, *11*(2), 117-131.

Struckman-Johnson, C., Gaster, S., Struckman-Johnson, D., Johnson, M., & May-Shinagle, G. (2015). Gender differences in psychosocial predictors of texting while driving. *Accident Analysis & Prevention*, *74*, 218-228.

Stutts, J., D. Reinfurt, L. Staplin, E. Rodgman. *The Role of Driver Distraction in Traffic Crashes*. 2001. Retrieved from https://ntl.bts.gov/lib/32000/32600/32685/distraction.pdf

Sun, J., & Wang, X. (2010). Value differences between generations in China: A study in Shanghai. *Journal of Youth Studies*, *13*(1), 65-81.

Sunio, V., & Schmöcker, J. D. (2017). Can we promote sustainable travel behavior through mobile apps? Evaluation and review of evidence. *International Journal of Sustainable Transportation*, *11*(8), 553-566.

Tsukayama H. Pokemon Go's Unexpected Side Effect: Injuries. The Washington Post. Retrieved from https://www.washingtonpost.com/news/the-switch/wp/2016/07/08/pokemon-gos-unexpected-side-effect-injuries/

Sween, M., Ceschi, A., Tommasi, F., Sartori, R., & Weller, J. (2017). Who is a Distracted Driver? Associations between Mobile Phone Use while Driving, Domain-Specific Risk Taking, and Personality. *Risk Analysis*, *37*(11), 2119-2131.

Tang, B. J., Li, X. Y., Yu, B., & Wei, Y. M. (2019). How app-based ride-hailing services influence travel behavior: An empirical study from China. *International Journal of Sustainable Transportation*, 1-15.

Tate, D. F., Lyons, E. J., & Valle, C. G. (2015). High-tech tools for exercise motivation: use and role of technologies such as the internet, mobile applications, social media, and video games. *Diabetes Spectrum*, *28*(1), 45-54.

Terzano, K. (2013). Bicycling safety and distracted behavior in The Hague, the Netherlands. *Accident Analysis & Prevention*, *57*, 87-90.

The U.S. Census Bureau. 2010 Population Finder. Retrieved from http://www.census.gov/popfinder/index.php.

The U.S. Census Bureau. 2010-2014 American Community Survey 5-year Estimates. Retrieved from http://factfinder.census.gov/faces/nav/jsf/pages/community_facts.xhtml.

Thornton, D., & Francia III, G. (2014). Gamification of information systems and security training: Issues and case studies. *Information Security Education Journal*, *1*(1), 16-24.

Tielemans, E., Kupper, L. L., Kromhout, H., Heederik, D., & Houba, R. (1998). Individual-based and group-based occupational exposure assessment: some equations to evaluate different strategies. *The Annals of Occupational Hygiene*, *42*(2), 115-119.

Traffic Management Bureau of the Public Security Ministry, 2011. *Annual Safety Report 2010*.

Train, K. E. (2009). *Discrete Choice Methods with Simulation*. Cambridge university press.

Truong, L. T., Nguyen, H. T., & De Gruyter, C. (2016). Mobile phone use among motorcyclists and electric bike riders: a case study of Hanoi, Vietnam. *Accident Analysis & Prevention*, *91*, 208-215.

Tudor-Locke, C., & Bassett, D. R. (2004). How many steps/day are enough?. *Sports Medicine*, *34*(1), 1-8.

Useche, S. A., Alonso, F., Montoro, L., & Esteban, C. (2018). Distraction of cyclists: how does it influence their risky behaviors and traffic crashes?. *PeerJ*, *6*, e5616.

Vasserman, S., Feldman, M., & Hassidim, A. (2015, June). Implementing the wisdom of waze. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*.

Vella, K., Johnson, D., Cheng, V. W. S., Davenport, T., Mitchell, J., Klarkowski, M., & Phillips, C. (2017). A sense of belonging: Pokemon GO and Social Connectedness. *Games and Culture*, 1555412017719973.

Volvo, 2006. *Environment product declaration - Volvo 8500 low-entry report*.

Wagner-Greene, V. R., Wotring, A. J., Castor, T., MSHE, J. K., & Mortemore, S. (2017). Pokémon GO: Healthy or harmful?. *American Journal of Public Health*, *107*(1), 35.

Wang, H., Chen, C., Huang, C., & Fu, L. (2008). On-road vehicle emission inventory and its uncertainty analysis for Shanghai, China. *Science of the Total Environment*, *398*(1-3), 60-67.

Wang, T. J., Lam, K. S., Xie, M., Wang, X. M., Carmichael, G., & Li, Y. S. (2006). Integrated studies of a photochemical smog episode in Hong Kong and regional transport in the Pearl River Delta of China. *Tellus B: Chemical and Physical Meteorology*, *58*(1), 31-40.

Wang, Y., Li, L., Wang, Z., Lv, T., & Wang, L. (2013). Mode shift behavior impacts from the introduction of metro service: Case study of Xi'an, China. *Journal of Urban Planning and Development*, *139*(3), 216-225.

Wang, D., Xiang, Z., & Fesenmaier, D. R. (2016). Smartphone use in everyday life and travel. *Journal of Travel Research*, *55*(1), 52-63.

Washington, S. P., Karlaftis, M. G., & Mannering, F. (2010). *Statistical and econometric methods for transportation data analysis*. Chapman and Hall/CRC.

Weinert, J. X., Ma, C., Yang, X., & Cherry, C. R. (2007). Electric two-wheelers in China: effect on travel behavior, mode shift, and user safety perceptions in a medium-sized city. *Transportation Research Record*, *2038*(1), 62-68.

Wells, S., Forbes, P., Masthoff, J., Gabrielli, S., & Jyllha, A. (2013, September). SUPERHUB: integrating digital behaviour management into a novel sustainable urban mobility system. In *Proceedings of the 27th International BCS Human Computer Interaction Conference* (p. 62). British Computer Society.

Wilks, J., Watson, B. C., Johnston, K. L., & Hansen, J. A. (1999). International drivers in unfamiliar surroundings: The problem of disorientation. *Travel Medicine International*, *17*(6), 162-167.

Williamson, J. W. (2016). Will the ‘Pokémon’be heroes in the battle against physical inactivity. *Sport Exerc Med Open J*, *2*(1), 13-14.

Wogalter, M. S., & Mayhorn, C. B. (2005). Perceptions of driver distraction by cellular phone users and nonusers. *Human Factors*, *47*(2), 455-467.

Wong, F., & Song, H. (2008). The resilience of migrant workers in Shanghai China: the roles of migration stress and meaning of migration. *International Journal of Social Psychiatry*, *54*(2), 131-143.

Wu, M. Y. (2015). Driving an unfamiliar vehicle in an unfamiliar country: Exploring Chinese recreational vehicle tourists’ safety concerns and coping techniques in Australia. *Journal of Travel Research*, *54*(6), 801-813.

Xie, X., Tou, X., & Zhang, L. (2017). Effect analysis of air pollution control in Beijing based on an odd-and-even license plate model. *Journal of Cleaner Production*, *142*, 936-945.

Xiong, W., & Wei, D. (2013). Impaction Analysis of Motorcycle Forbidden Policy's upon Resident's Traveling Time Cost. *Journal of Transportation Systems Engineering and Information Technology*, (1), 32.

Xu, J. (2010). Motorcycle taxi drivers and motorcycle ban policy in the Pearl River Delta. Hong Kong University Dissertation.

Xu, J. (2012). Drive-away policing and situational crime prevention in China: an analysis of motorcycle ban (jinmo) policy in Guangzhou. *International Journal of Offender Therapy and Comparative Criminology*, *56*(2), 239-264.

Xu, J. (2014). Authoritarian policing with Chinese characteristics: A case study of motorcycle bans in the Pearl River Delta. *Crime, Law and Social Change*, *61*(4), 439-460.

Yamamoto, T., & Shankar, V. N. (2004). Bivariate ordered-response probit model of driver's and passenger's injury severities in collisions with fixed objects. *Accident Analysis & Prevention*, *36*(5), 869-876.

Yang, J., Liu, Y., Qin, P., & Liu, A. A. (2014). A review of Beijing′ s vehicle registration lottery: Short-term effects on vehicle growth and fuel consumption. *Energy Policy*, *75*, 157-166.

Yang, M., Li, D., Wang, W., Zhao, J., & Chen, X. (2013). Modeling gender-based differences in mode choice considering time-use pattern: analysis of bicycle, public transit, and car use in suzhou, China. *Advances in Mechanical Engineering*, *5*, 706918.

Ye, L., & Wang, Q. (2011). Case study of motorcycle use and policy analysis in Huizhou, China. *Journal of Transportation Engineering*, *137*(11), 831-836.

YouGov. (2016). *Pokémon Go: 34m downloads, 31m current players, and 10m paying users since U.S. launch*. Retrieved from https://today.yougov.com/topics/entertainment/articles-reports/2016/08/12/pokemon-go-34m-downloads-31m-current-players-and-1.

Yue, Z., Li, S., Feldman, M. W., & Du, H. (2010). Floating choices: A generational perspective on intentions of rural–urban migrants in China. *Environment and Planning A*, *42*(3), 545-562.

Zhang, D., Li, X., & Xue, J. (2015). Education inequality between rural and urban areas of the People's Republic of China, migrants' children education, and some implications. *Asian Development Review*, *32*(1), 196-224.

Zhang, D., Magalhães, D. J. A. V., & Wang, X. C. (2014). Prioritizing bicycle paths in Belo Horizonte City, Brazil: Analysis based on user preferences and willingness considering individual heterogeneity. *Transportation Research Part A: Policy and Practice*, *67*, 268-278.

Zhang, Z., & Wu, X. (2017). Occupational segregation and earnings inequality: Rural migrants and local workers in urban China. *Social Science Research*, *61*, 57-74.

Zhao, P., & Howden-Chapman, P. (2010). Social inequalities in mobility: the impact of the hukou system on migrants' job accessibility and commuting costs in Beijing. *International Development Planning Review*, *32*(3-4), 363-384.

Zhou, J. (2012). Sustainable commute in a car-dominant city: Factors affecting alternative mode choices among university students. *Transportation Research Part A: Policy and Practice*, *46*(7), 1013-1029.

Zhou, R., Wu, C., Rau, P. L. P., & Zhang, W. (2009). Young driving learners' intention to use a handheld or hands-free mobile phone when driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, *12*(3), 208-217.

Zondag, B., & Pieters, M. (2005). Influence of accessibility on residential location choice. *Transportation Research Record*, *1902*(1), 63-70.

Zuo, Z. (2009). Guanyu jiechu chengshi jinmo de ti'an (The proposal for the lift of motorcycle ban policy in cities). *Motuo Xinxi (Motorcycle Informations)*, *5*, 27-29.

VITA

Research Assistant/PhD Candidate

Address: 3000 Kent Ave/NEXTRANS Center, West Lafayette, IN 47906 U.S.A.

Email: guo187@purdue.edu; gyt861211@gmail.com

Phone: +1-765-775-0744

PROFESSIONAL EXPERIENCE

PURUDE UNIVERSITY — **West Lafayette, IN, United States**
Research Assistant — *August 2012 – August 2019*

UNIVERSITY OF CALIFORNIA, RIVERSIDE — **Riverside, CA, United States**
Research Staff — *September 2011 – August 2012*

TWO GROUP RIB CONSTRUCTION — **Guangzhou, Guangdong, China**
Junior Construction Consultant — *December 2009 – August 2010*

EDUCATION

PURDUE UNIVERSITY — **West Lafayette, IN, United States**
Ph.D. Civil Engineering, August 2019
Committee: Srinivas Peeta (co-chair), Samuel Labi (co-chair), John Fricker, Fred Mannering, Tonglin Zhang

UNIVERSITY OF SOUTHERN CALIFORNIA — **Los Angeles, CA, United States**
M.S. Civil Engineering, 2010-2011

HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY — **Hong Kong, China**
B.S. Civil and Structural Engineering, 2005-2009

RESEARCH INTERESTS

- Travel behavior
- Smart growth, livability and accessibility
- Connected and autonomous transportation
- Infrastructure design
- Technology adoption
- Transportation and land use
- Freight transportation
- Econometrics modeling

AWARDS

- ITS Michigan Scholar Award for winning Smart Cities Student Contest, Center for Connected and Automated Transportation, 2019
- Pai Tao Yeh Fellowship, Lyles School of Civil Engineering of Purdue University 2014, 2015
- Intermodal Freight Award for the paper “Rail-truck multimodal freight collaboration: a statistical analysis of freight-shipper perspectives”, the Intermodal Freight Committee of Transportation Research Board, 2015
- Research Assistantship, Purdue Civil Engineering Department, 2012-2019
- Civil Engineering Department Scholarship, Hong Kong University of Science and Technology, 2005

JOURNAL PUBLICATIONS

1. Li, Y., **Y. Guo,** S. Peeta, J. Lu, Y. Li, “Impacts of congestion pricing and reward strategies on automobile travelers’ morning commute mode choice decisions: a case study in Beijing”, *Transportation Research Part A: Policy and Practice*, Vol. 125, 2019, 72-88.
2. Tang, T., S. Zhu, **Y. Guo**, X. Zhou, Y. Cao. “Evaluating the safety risk of rural roadsides using a Bayesian Network Method”, *International Journal of Environmental Research and Public Health*, Vol. 16, No. 7, 2019, pp.1166.
3. Zhu, S., K. Guo, **Y. Guo**, H. Tao, Q. Shi, “An adaptive signal control method with the optimal detector locations”, *Sustainability*, Vol. 11, No. 3, 2019, pp. 727.
4. Zheng, L., **Y. Guo (Corresponding author)**, S. Peeta, B. Wu, “Impacts of Information from Various Sources on the Evacuation Decision-Making Process during No-Notice Evacuations in Campus Environment”, Accept for publication in *Journal of Transportation Safety & Security*, 2018.
5. **Guo, Y.,** J. Wang, S. Peeta, P. Ch. Anastasopoulos, “Impacts of internal population migration, household registration system, and family planning policy on travel mode choice in China”, *Travel Behaviour and Society*, Vol. 13, 2018, pp. 128-143.
6. Zhu, S., **Y. Guo (Corresponding author)**, J. Chen, D. Li, L. Cheng, “Integrating Optimal Heterogeneous Sensor Deployment and Operation Strategies for Dynamic Origin-Destination Demand Estimation”, *Sensors*, Vol. 17, No. 8, 2017, pp. 1767.
7. Zhu, X., X. Yang, **Y. Guo**, “Exploring the Relationship between Heterogeneity of Vehicle Distribution and the Macroscopic Fundamental Diagram under Segment Disruption Conditions”, *Procedia Computer Science*, Vol. 109, 2017, pp. 600-607.
8. **Guo, Y.,** S. Peeta, F. Mannering, “Rail-truck multimodal freight collaboration: a statistical analysis of freight-shipper perspectives”, *Transportation Planning and Technology*, Vol. 39, No. 5, 2016, pp. 484-506.
9. **Guo, Y.,** S. Agrawal, S. Peeta, S. Somenahalli, “Impacts of property accessibility and neighborhood built environment on single-unit and multi-unit residential property values”, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2568, 2016, pp. 103-112.
10. **Guo, Y.,** X. He, S. Peeta, J. Weiss, “Internal curing for concrete bridge decks: integrating a social cost analysis in evaluating the long-term benefit”, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2577, 2016, pp. 17-24.

11. Zhu, S., H. Zheng, S. Peeta, **Y. Guo**, L. Cheng, W. Sun, "Optimal heterogeneous sensor deployment strategy for dynamic origin-destination demand estimation", *Transportation Research Record: Journal of the Transportation Research Board*, No. 2567, 2016, pp. 18-27.
12. Benedyk, I., S. Peeta, H. Zheng, **Y. Guo**, A. Iyer, "Scenario-based dynamic model of investment decision-making process in intermodal facilities under demand uncertainty", *Transportation Research Record: Journal of the Transportation Research Board*, No. 2548, 2016, 24-34.
13. **Guo, Y.,** S. Peeta, "Rail-truck multimodal freight collaboration: truck freight carrier perspectives in the United States", *Journal of Transportation Engineering*, Vol. 141, No. 11, 2015, pp. 1-11.
14. **Guo, Y.,** S. Peeta, S. Somenahalli, "The impacts of walkable environment on single family residential property values", *Journal of Transport and Land Use*, Vol. 10, No. 2, 2015, pp. 1-20.
15. Wang, J., W. Deng, **Y. Guo**, "New Bayesian combination method for short-term traffic flow forecasting", *Transportation Research Part C: Emerging Technologies*, Vol. 43, 2014, pp. 79-94.

PAPERS UNDER REVIEW

1. **Guo, Y.,** S. Peeta, S. Agrawal, and I. Benedyk, "Safety and Health Implications of Location-based Augmented Reality Mobile Apps", submitted to *Accident Analysis & Prevention*, 2019.
2. **Guo, Y.,** S. Peeta, S. Agrawal, I. Benedyk, "Impacts of Pokémon GO on Route and Mode Choice Decisions: Exploring the Potential for Integrating Augmented Reality, Gamification and Social Interactions in Mobile Apps to Influence Travel Decisions", submitted to *Transportation Research Part A: Policy and Practice*, 2019.
3. **Guo, Y.,** S. Peeta, "Impacts of an interactive accessibility information intervention strategy on residential location choice and travel-related behavior", submitted to *Travel Behaviour and Society*, 2019.
4. **Guo, Y.,** J. Wang, S. Peeta, P. Ch. Anastasopoulos, "Personal and Social Impacts of Motorcycle Full Ban Policy on Motorcyclists' Home-to-work Morning Commute in China", submitted to *Transportation*, 2019.
5. **Guo, Y.,** Y. Li, S. Peeta, J. Lu, "China's Millennial Car Travelers' Mode Shift Responses under Congestion Pricing and Reward Policies: A Case Study in Beijing", submitted to *Travel Behaviour and Society*, 2019.
6. Benedyk, I., **Y. Guo,** S. Peeta, "Freight transportation decision-maker perspectives: Does familiarity affect willingness to use the Northern Sea Route?", submitted to *Journal of Transportation Geography*, 2019.
7. Benedyk, I., S. Peeta, H. Zheng, A. Iyer, **Y. Guo**, "Risk management in a system view of intermodal facility investment under demand uncertainty", submitted to *International Journal of Shipping and Transport Logistics*, 2019.
8. Zheng, L. **Y. Guo (Corresponding author),** S. Peeta, B. Wu, "Understanding people's social networking services related behaviors during no-notice evacuations", submitted to *Journal of Safety Research*, 2019.

PAPERS IN PROGRESS

1. **Guo, Y.,** D. Souders, S. Labi, S. Peeta, I. Benedyk, "Paving the Way for CAVs and Multi-modal Transportation: Road User Roadway Design and Policies Preferences and Autonomous Vehicle Adoption Attitudes", 2019.
2. **Guo, Y.,** D. Souders, S. Agrawal, S. Labi, S. Peeta, Y. Chen, "Impacts of Travel Experience and Travel Information on Autonomous Vehicle Adoption", 2019.

FUNDED RESEARCH PROJECTS

1. Design of Urban Landscape and Road Networks to Accommodate Connected and Autonomous Vehicles – Phase II, *USDOT Center for Connected Automated Transportation*, 2018-2019.
2. Adapting land use and infrastructure for automated driving, *USDOT Center for Connected Automated Transportation*, 2018-2019.
3. Design of Urban Landscape and Road Networks to Accommodate Connected and Autonomous Vehicles, *USDOT Center for Connected Automated Transportation*, 2017-2018.
4. Develop In-Vehicle Information Dissemination Mechanisms to Reduce Cognitive Burden in the Information-Rich Driving Environment, *USDOT Center for Connected Automated Transportation*, 2017-2018.
5. Driving Simulator Based Interactive Experiments: Understanding Driver Behavior, Cognition and Technology Uptake under Information and Communication Technologies, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2015 - 2017.
6. Information and Transportation Choices, Long- and Short-Term, that Link Sustainability and Livability – Phase II, NEXTRANS Center, *USDOT Region 5 University Transportation Center*, 2014 - 2017.
7. Effects of Heterogeneous Information Characteristics and Sources on Evacuation Behavior, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2014 - 2017.
8. Intermodal Infrastructure Investment Decisions and Linkage to Economic Competitiveness, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2014 - 2017.
9. Field Data Based Data Fusion Methodologies to Estimate Dynamic Origin-Destination Demand Matrices from Multiple Sensing and Tracking Technologies, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2013 - 2015.
10. Information and Transportation Choices, Long- and Short-Term, that Link Sustainability and Livability, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2013 - 2015.
11. Exploring the Opportunities and Barriers to Intermodal Rail Freight, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2012 - 2014.
12. Driving Simulator based Interactive Experiments: Understanding Driver Behavior, Cognition and Technology Uptake under Information and Communication Technologies, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2012 - 2015.
13. Driving Simulator Laboratory: Traveler Behavior Modeling and Interactive Experiments to Address Mobility and Safety Needs, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2012 - 2015.
14. Internal Curing as a New Tool for Infrastructural Renewal: Reducing Repair Congestion, Increasing Service Life, and Improving Sustainability, *NEXTRANS Center, USDOT Region 5 University Transportation Center*, 2012 - 2014.

TECHNICAL REPORTS FOR FUNDED RESEARCH PROJECTS

1. **Guo, Y.,** S. Peeta, Y. Li, "Information and Transportation Choices, Long- and Short-Term, that Link Sustainability and Livability: Phase II," Technical Research Report, NEXTRANS Project No. 159PUY2.2 of the NEXTRANS Center, USDOT Region 5 Regional University Transportation Center, 2017.
2. **Guo, Y.,** S. Peeta, J. Levine, "Information and Transportation Choices, Long- and Short-Term, that Link Sustainability and Livability: Phase I," Technical Research Report, Project No. 111PUY2.1 of the NEXTRANS Center, USDOT Region 5 Regional University Transportation Center, 2017.
3. Zheng, L., **Y. Guo,** D-Y. Song, S. Peeta, J-H. Chung, "Effects of Heterogeneous Information Characteristics and Sources on Evacuation Behavior," Technical Research Report, Project No. 160PUY2.2 of the NEXTRANS Center, USDOT Region 5 Regional University Transportation Center, 2017.
4. Zhu, S., **Y. Guo,** H. Zheng, S. Peeta, G. Ramadurai, J. Wang, "Field Data Based Data Fusion Methodologies to Estimate Dynamic Origin-Destination Demand Matricies from Multiple Sensing and Tracking Technologies," Technical Research Report, Project No. 109PUY2.1 of the NEXTRANS Center, USDOT Region 5 Regional University Transportation Center, 2017.
5. Benedyk, I., S. Peeta, H. Zheng, **Y. Guo,** A.V. Iyer, "Intermodal Infrastructure Investment Decisions and Linkage to Economic Competitiveness," Technical Research Report, Project No. 161PUY2.2 of the NEXTRANS Center, USDOT Region 5 Regional University Transportation Center, 2017.
6. **Guo, Y.,** S. Peeta, X. He, H. Zheng, T. Barrett, A. Miller, J. Weiss, "Internal curing as a new tool for infrastructural renewal: reducing repair congestion, increasing service life, and improving sustainability". Technical Research Report, Project No. 082PY04 of the NEXTRANS Center, USDOT Region 5 University Transportation Center, 2014.
7. **Guo, Y.,** S. Peeta, H. Zheng, B. Cox, "Exploring the opportunities and barriers to intermodal rail freight". Technical Research Report, Project No. 078PY04 of the NEXTRANS Center, USDOT Region 5 University Transportation Center, 2014.

CONFERENCE PRESENTATION

1. Presenter/first author, "Can autonomous vehicle (AV) travel experience and roadway design impact AV acceptance, adoption, and fuel type choice? A driving simulator study", Road Safety and Simulation, October 14, Iowa City, Iowa, the U.S.A.
2. Presenter/first author, "Can roadway designs and operational policies influence autonomous vehicle adoption: a driving simulator study", *2019 International Conference on Smart Cities*, July 17, Seoul, South Korea.
3. Coauthor, "Elements of municipal infrastructure management in an era of smart cities", *2019 International Conference on Smart Cities*, July 17, Seoul, South Korea.
4. Coauthor, "Segment importance ranking approach for traffic networks based on macroscopic fundamental diagram", *19th COTA conference International Conference of Transportation Professionals*, July 6th, 2019, Nanjing, China.
5. Presenter/first author, "Paving the way for autonomous vehicles in a multi-modal transportation environment: impacts of roadway design and policy on autonomous vehicle

adoption and mode choice”, *ASCE International Conference on Transportation & Development*, June 9th, 2019, Alexandria, Virginia, the U.S.A.

6. Presenter/corresponding author, “Impacts of information sources on evacuation decision during no-notice evacuations in a campus environment”, *98th Transportation Research Board Annual Meeting*, January 15th, 2019, Washington D. C., the U.S.A.
7. Presenter/first author, “Understanding the impacts of internal migration and household registration system on travel mode choice in China”, *98th Transportation Research Board Annual Meeting*, January 13th, 2019, Washington D. C., the U.S.A.
8. Coauthor, “An approach based on macroscopic fundamental diagram for identifying critical segments in urban road network”, *98th Transportation Research Board Annual Meeting*, January 16th, 2019, Washington D. C., the U.S.A.
9. Presenter/first author, “Integrating Augmented Reality, Gamification and Social Interactions in Mobile Apps to Influence Short- and Long-term Travel decisions”, *INFORMS 2018*, November 4th, 2018, Phoenix, Arizona, the U.S.A.
10. Coauthor, "Segment Importance Ranking Approach for Traffic Networks based on Macroscopic Fundamental Diagram", *23rd International Conference of Hong Kong Society for Transportation Studies*, December 8th, 2018, Hong Kong, China.
11. Presenter/first author, “Paving the Way for CAVs and Multi-modal Transportation: Road User Roadway Design and Policies Preferences and CAV Adoption Attitudes”, *2018 Global Symposium on Connected and Automated Transportation and Infrastructure*, March 7th, 2018, Ann Arbor, Michigan, the U.S.A.
12. Coauthor, “Design of Interactive Driving Simulator Experiments to Understand Drivers’ Cognitive and Routing Behavior Under Real-Time Travel Information”, *15th International Conference on Travel Behavior Research*, July 15th, 2018, Santa Barbara, California, the U.S.A.
13. Presenter/coauthor, “A stage model for mode choice decision-making process under congestion pricing and reward strategy: A case study in Beijing”, *97th Transportation Research Board Annual Meeting*, January 13th, 2018, Washington D. C., the U.S.A.
14. Presenter/first author, “Impacts of interactive accessibility information intervention strategy on residential location choice and travel-related behavior”, *96th Transportation Research Board Annual Meeting*, January 13th, 2017, Washington D. C., the U.S.A.
15. Coauthor, “Risk management in s systems view of intermodal facility investment under uncertainty in freight commodity flow”, *96th Transportation Research Board Annual Meeting*, January 13th, 2017, Washington D. C., the U.S.A.
16. Presenter/coauthor, “Optimal heterogeneous sensor deployment strategy for dynamic origin-destination demand estimation”, *95th Transportation Research Board Annual Meeting,* January 13th, 2016, Washington D. C., the U.S.A.
17. Coauthor, “Scenario-based dynamic model of investment decision-making process in intermodal facilities under demand uncertainty”, *95th Transportation Research Board Annual Meeting*, January 13th, 2016, Washington D. C., the U.S.A.
18. Presenter/first author, “The impacts of household registration and head of household travel behavior on travel mode choice in China”, *95th Transportation Research Board Annual Meeting*, January 13th, 2016, Washington D. C., the U.S.A.
19. Presenter/first author, “The impacts of property accessibility and neighborhood built environment on single-unit and multi-unit residential property values”, *95th Transportation Research Board Annual Meeting*, January 12th, 2016, Washington D. C., the U.S.A.

20. Presenter/first author, "Internal curing for concrete bridge decks: integrating a social cost analysis in evaluating the long-term benefit", *95th Transportation Research Board Annual Meeting*, January 11th, 2016, Washington D. C., the U.S.A.
21. Presenter/first author, "A comparison of mixed logit and latent class methods for mode choice analysis", *INFORMS 2015*, November 1st, 2015, Philadelphia, the U.S.A.
22. Coauthor, "Downside risk analysis for planning intermodal facility investments", *INFORMS 2015*, November 1st, 2015, Philadelphia, the U.S.A.
23. Presenter/first author, "The impacts of interactive accessibility information on residential location choice and travel behavior: an experimental study", *4th Symposium of the European Association for Research in Transportation*, September 11th, 2015, Copenhagen, Denmark.
24. Presenter/first author, "Effects of land use mix and property walk accessibility on single-family residential property values", *94th Transportation Research Board Annual Meeting*, January 13th, 2015, Washington D. C., the U.S.A.
25. Presenter/first author, "Rail-truck multimodal freight collaboration: a statistical analysis of freight shipper perspectives", *94th Transportation Research Board Annual Meeting*, January 13th, 2015, Washington D. C., the U.S.A.
26. Presenter/first author, "Analytical model for evaluating the long-term benefits of internal curing", *INFORMS 2014*, November 10th, 2014, San Francisco, the U.S.A.
27. Presenter/first author, "Exploring the opportunities and barriers to rail-truck multimodal freight collaboration: truck freight carrier perspective", *93rd Transportation Research Board Annual Meeting*, January 13th, 2014, Washington D. C., the U.S.A.
28. Presenter/first author, "Cost and benefit of rail and truck freight collaboration", *INFORMS 2013*, October 7th, 2013, Minneapolis, the U.S.A.
29. Presenter/first author, "The opportunities and barriers to rail-truck multimodal freight collaboration", *INFORMS 2013*, October 9th, 2013, Minneapolis, the U.S.A.

EDITORIAL ACTIVITIES & INVITED REVIEWS

- Editorial Advisory Board, *Macro Management & Public Policies*, Bilingual Publishing Co., 2019-present
- Transportation Research Part C: Emerging Technologies: 3
- Transportation Research Part D: Transport and Environment: 3
- Accident Analysis & Prevention: 1
- IET Intelligent Transport: 3
- Transportation Research Record: Journal of the Transportation Research Board: 27
- COTA International Conference of Transportation Professionals: 9

TEACHING EXPERIENCE

CE 594 Transportation System Analysis **2016 Spring**
Instructor: Srinivas Peeta

CE 594 Transportation System Analysis **2015 Spring**
Instructor: Srinivas Peeta