Modeling Travel Behavior with the Advent of Electric and Automated Vehicle Technologies

By

FATEMEH NAZARI

M.S., Tarbiat Modares University, Iran, 2013

B.S., University of Zanjan, Iran, 2010

Dissertation

Submitted as partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Civil Engineering
in the Graduate College of the
University of Illinois at Chicago, 2019

Chicago, Illinois

Defense Committee:

Dr. Abolfazl (Kouros) Mohammadian, Chair and Advisor
Dr. Jie (Jane) Lin
Dr. Bo Zou
Dr. Kazuya Kawamura, College of Urban Planning and Public Affairs
Dr. Joshua Auld, Argonne National Laboratory

Dedicated to

My parents,

My husband,

My brother & sister

ACKNOWLEDGEMENTS

This dissertation is accomplished with the encouragement, company, and help of many others, a thorough list of whom requires many lines. I would hereby like to acknowledge some of them.

Foremost, I would like to express my special gratitude to my PhD advisor, Professor Abolfazl (Kouros) Mohammadian, whose supportive advice had lasting effects. His generosity, integrity, and dignity taught me how to use my engineering and research skills for promoting communities' well-being.

I am grateful to my advisory committee members Professors Jane Lin, Bo Zou, and Kazuya Kawamura, and Dr. Joshua Auld for their invaluable comments and ideas. My special thanks goes to Professor Bo Zou for all his skillful guidance over these years. In addition, a thank you to Dr. Thomas Stephens for his support and guidance in these years. I am also thankful to Argonne National Laboratory for financial support.

Next, I would like to extend my sincere thanks to my Master's supervisors and advisors, Professors Seyedehsan Seyedabrishami, AmirReza Mamdoohi, and Mahmoud Saffarzadeh, at Tarbiat Modares University in Iran. I am deeply indebted to them for their unconditional support and guidance that steered my research life into good directions. I am also grateful to my Bachelor's advisor, Professor Amir Masoud Rahimi, who inspired me to pursue my studies in transportation engineering.

I have been fortunate to have good friends who supported me and made Chicago home for me, especially Mojdeh Taghizadeh Khamesi, Hooman Motahari, Ghazaleh Arabkheradmand, Hossein Taghizadeh Khamesi, Marzieh Ezzatipour, and Hossein Joshaghani. My next appreciation goes to my lab mates for their company during these years, especially Homa Taghipour, Tanvir Ahamed, Amir Bahador Parsa, and Limon Barua.

I am very grateful to God for all his blessings and my family; my beloved mother and father, my sister Negin, my brother Mohammadreza, my husband Hossein, and my parents-in-law for their encouragement and prayers.

Contribution of Authors

Chapter 1 introduces two parts of the dissertation by presenting the overall framework and contributions of the research. Chapter 2 presents a published manuscript ("Nazari, F., Noruzoliaee, M., Mohammadian, A., 2018. Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. Transportation Research Part C: Emerging Technologies 97, 456-477."), for which I was the primary author and major driver of the research. My advisor, Dr. Abolfazl (Kouros) Mohammadian, and Dr. Mohamadhossein Noruzoliaee contributed to the writing of the manuscript. Chapter 3 presents an unpublished work, for which I was the primary author and major driver of the research. My advisor, Dr. Abolfazl (Kouros) Mohammadian, contributed to the writing of the manuscript. Chapter 3 investigates people's adoption of autonomous vehicles considering their safety concerns. Chapter 4 and Chapter 5 present a partially published work ("Nazari, F., Mohammadian, A., Stephens, T., 2019. Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. Transportation Research Part D: Transport and Environment 72, 65-82."), for which I was the primary author and major driver of the research. My advisor, Dr. Abolfazl (Kouros) Mohammadian, and Dr. Thomas Stephens contributed to the writing of the manuscript. Chapter 4 and Chapter 5 address adoption of electric vehicles considering people's historical vehicle decisions as well as their subjective attitude, perception, and lifestyle preferences. Chapter 6 presents concluding remarks and provides suggestions for future work.

TABLE OF CONTENTS

1. Introduction **1**
1.1. Part I: Autonomous vehicles 1
1.2. Part II: Electric vehicles 2

2. Shared Versus Private Mobility: Modeling Public Interest in Autonomous Vehicles Accounting for Latent Attitudes **5**
2.1. Introduction 5
2.2. Methodology 12
2.2.1. Latent variable measurement and structural equation models 12
2.2.2. Multivariate ordered probit model 13
2.3. Data 16
2.3.1. Ordered outcome variables 16
2.3.2. Socio-economic and built environment characteristics 18
2.3.3. Current daily and commute travel behavior characteristics 21
2.3.4. Indicators of the latent attitudinal/preferential variables 22
2.4. Results 25
2.4.1. Estimated latent variable structural and measurement equation models 25
2.4.2. Estimated multivariate ordered probit model of AV mobility types for daily travel ... 28
2.4.3. Estimated bivariate ordered probit model of AV mobility types for commute travel.. 34
2.4.4. Policy implications 39

3. Adoption of Autonomous Vehicles with Endogenous Safety Concerns: A Recursive Bivariate Ordered Probit Model **41**
3.1. Introduction 41
3.2. Methodology: recursive bivariate ordered probit model 44
3.3. Data 46
3.4. Results 51
3.4.1. Socio-economic characteristics 57
3.4.2. Demographic factor 58
3.4.3. Travel behavior factor 59
3.4.4. Vehicle decision factors 60

4. Revelations from a National Retrospective Vehicle Survey **61**
4.1. Introduction 61
4.2. Analysis of retrospective vehicle survey 63
4.2.1. Sample data for households 65
4.2.1.1. Socio-economic characteristics 65
4.2.1.2. Demographic attributes 67
4.2.2. Sample data for individuals 71
4.2.2.1. Socio-economic characteristics 71
4.2.2.2. Latent factors describing attitude, perception, and lifestyle preference 73
4.2.3. Sample data for vehicles 81
4.2.4. Sample data for principal drivers 86
4.2.4.1. Socio-economic characteristics 86
4.2.4.2. Travel behavior 90

4.2.5. Sample data for dynamics of household characteristics and their vehicles (over the past 10 years) ... 90

5. Dynamic Vehicle Transaction and Fuel Type Choice: An Integrated Choice Model with Latent Vehicle Perception and Lifestyle Preference ... 92

5.1. Introduction ... 92
5.2. Methodology: integrated choice model with latent variables ... 96
5.3. Results ... 101
5.3.1. Measurement equations ... 101
5.3.2. Structural equations ... 103
5.3.3. Choice model ... 104
5.3.3.1. Vehicle attributes ... 107
5.3.3.2. Change in household socio-economic characteristics over the past 10 years ... 107
5.3.3.3. Latent constructs ... 108
5.3.4. Sensitivity Analysis ... 109

6. Conclusions and Future Research Directions ... 111

6.1. Autonomous vehicles ... 111
6.2. Electric vehicles ... 113

References ... 115
Appendix A. Permission for reuse of the previously published materials ... 123
Appendix B. Permission for reuse of the previously published materials ... 124
VITA ... 125

LIST OF TABLES

Table 2.1. Survey questions inquiring about the interest level in (S)AV types for use in (all-purpose) daily and commuter travels (Puget Sound Regional Council, 2017) ... 17
Table 2.2. Sample data for socio-economic and built environment characteristics (sample size = 2,726). 20
Table 2.3. Sample data for current daily and commute travel behavior characteristics (sample size = 2,726) ... 23
Table 2.4. Sample data for the latent attitudinal/preferential indicator variables (sample size = 2,726) ... 24
Table 2.5. Estimation results of the latent variable structural and measurement equation models ... 26
Table 2.6. Estimated multivariate ordered probit model of public interest in AV types for daily travel ... 29
Table 2.7. Marginal effects for multivariate ordered probit model of public interest in AV mobility types for daily travel ... 31
Table 2.8. Estimated bivariate ordered probit model of public interest in AV types for commute travel ... 35
Table 2.9. Marginal effects for bivariate ordered probit model of public interest in AV mobility types for commute travel ... 36

Table 3.1. Sample data for socio-economic and demographic characteristics at individual- and household-level (sample size = 3,574) ... 49
Table 3.2. Sample data for travel behavior and vehicle decision factors (sample size = 3,574) ... 50
Table 3.3. Estimation results of recursive bivariate ordered probit model ... 52
Table 3.4. Marginal effects for recursive bivariate ordered probit model ... 55

Table 4.1. Statistical distribution of socio-economic characteristics (households, sample size = 1,691) ... 66
Table 4.2. Statistical distribution of socio-economic characteristics (individuals, , sample size = 1,691). 72
Table 4.3. Estimation results of confirmatory factor analysis ... 82
Table 4.4. Statistical distribution of commute factors (principal drivers, , sample size = 3,326) ... 90

Table 5.1. Overview of studies with economic approach on electric vehicle adoption behavior using stated preferences dataset ... 94
Table 5.2. Estimation results of measurement equations ... 102
Table 5.3. Estimation results of structural equations ... 104
Table 5.4. Number of observations for the choice alternatives ... 105
Table 5.5. Estimation results of choice model ... 106
Table 5.6. Elasticity of explanatory variables of the choice model ... 110

LIST OF FIGURES

Figure 2.1. The overarching two-stage modeling framework 9
Figure 2.2. Sample data for public interest in: (a) AV ownership and SAV use in daily travel (sample size = 2,726); and (b) using AV-alone and AV-carpool in commute travel (sample size = 1,775) 18

Figure 3.1. Framework of the recursive bivariate ordered probit model of AV adoption and AV safety concern 45
Figure 3.2. Response of the five regions of the state of California to: (a) AV adoption and (b) AV safety concern (note: the numbers in the parenthesis are the number of observations for the corresponding region) 47

Figure 4.1. Location of respondents to retrospective vehicle survey 64
Figure 4.2. Number of vehicles held by households with respect to BEV ownership 67
Figure 4.3. Residential duration of households with respect to BEV ownership 68
Figure 4.4. Residential ownership of households with respect to BEV ownership 68
Figure 4.5. Residential type of households with respect to BEV ownership 69
Figure 4.6. Importance of factors at the time of choosing household residential neighborhood with respect to BEV ownership 70
Figure 4.7. Frequency of charging PHEVs/BEVs at home, workplace, and public stations 71
Figure 4.8. Travel attitudes measured by frequency of using transportation modes in the past 30 days: (a) green travel modes and (b) shared mobility modes with respect to BEV ownership 74
Figure 4.9. Latent constructs and the corresponding measurement indicators 75
Figure 4.10. Measurement indicators of perception at vehicle purchase time with respect to BEV ownership 78
Figure 4.11. Measurement indicators of lifestyle preference with respect to BEV ownership 80
Figure 4.12. (a) Current odometer reading of vehicles and (b) Vehicle mileage driven in the past 12 months with respect to fuel type (# CVs = 2,060 — # HEVs = 905 — # PHEVs = 141 — # BEVs = 277) 84
Figure 4.13. Vehicle price with respect to fuel type 85
Figure 4.14. (a) Vehicle ownership type and (b) vehicle purchase type 86
Figure 4.15. Gender of principal drivers with respect to vehicle fuel type 87
Figure 4.16. Age of principal drivers with respect to vehicle fuel type 87
Figure 4.17. Education of principal drivers with respect to vehicle fuel type 88
Figure 4.18. Employment type of principal drivers of (a) CVs, (b) HEVs, (c) PHEVs, and (d) BEVs 89
Figure 4.19. Number of changes in household socio-economic characteristics over the past 10 years 91

Figure 5.1. Framework of integrated vehicle transaction choice model with latent constructs 98

SUMMARY

Focusing on humans' transportation needs among many other aspects of humans' life, this dissertation presents an investigation of humans' travel behavior in the new era with autonomous/automated vehicles (AVs) and electric vehicles (EVs). Given the significant share of private vehicles in the Americans' trips, their travel behavior is influenced by vehicle ownership decisions. In view of this, the dissertation presents a modeling framework of household vehicle decisions with the advent of the transformative AVs and EVs. For this purpose, this dissertation uses the state-of-the-art discrete choice models with latent variables which enhance the classical models to a higher explanatory level. In details, this novel method explains a person's decision-making process considering unobservable (*latent*) subjective attitude, perception, and preferences, in addition to observable characteristics and alternative-specific attributes.

The first part of this dissertation contributes to the studies on AV adoption behavior by considering two AV forms including privately-owned AVs and multiple configurations of AVs in a shared system, i.e., shared AV (SAVs). For this purpose, multivariate and bivariate ordered probit models with latent variables are estimated, which accommodate the correlations across the (S)AV types and explicitly treat the latent attitudes/preferences explaining safety concern about AV, green travel pattern, and mobility-on-demand savviness. Given the considerable impact of safety concern on AV adoption behavior, one should more deeply investigate the causality between travelers' safety concern about the AV technology and their AV adoption behavior. In light of this, the first part further addresses this question by explaining AV adoption behavior and endogenous AV safety concern in a joint modeling framework. The model answers this question by estimating a recursive bivariate ordered probit model, which is implemented for the first time in the transportation context.

The second part of this dissertation focuses on EVs, which already exist in the market and thus are an experienced vehicle technology. This dissertation contributes to the existing research on understanding EV adoption behavior in four ways. First is the exploration of persons' actual EV choice instead of intention to adopt EVs, thereby avoiding "hypothetical bias". Second, unlike most studies in this area, the proposed

modeling framework distinguishes between various EV types including hybrid EVs (HEVs), plug-in HEVs (PHEVs), and battery EVs (BEVs). Third, this study takes into accounts persons' historical vehicle decisions on their choice of an EV type versus conventional gasoline and diesel vehicles. To add more explanatory power to the model, the proposed framework explicitly accounts for the *latent* attitude, perception, and lifestyle preference influencing decision-making, along with the observable factors such as socio-economic characteristics of decisions-makers, features of their surrounding built environment, and their current daily and commute travel behavior characteristics.

To address the above-mentioned four main gaps, the second part also presents the design, collection, and comprehensive analysis of a revealed preference survey, as well as a novel modeling framework. In particular, a national-level retrospective vehicle survey (RVS) is conducted, which asks about revealed preferences of 1,691 American households who own 3,326 vehicles. The survey further retrospectively collects information of the households' socio-economic changes and vehicle decisions over the past 10 years (from 2008 to 2017). Using RVS, the individuals' latent behavior is analyzed in three groups capturing perceptions (cost sensitivity, vehicle quality, vehicle specification, and social influence), lifestyle preferences (environmental consciousness, technology savviness, and pro-drive alone), and attitudes (green travel pattern and shared mobility use). The latent constructs are then integrated into a choice model to explain persons' simultaneous decision on vehicle transaction and fuel type as a function of their socio-economic characteristics, vehicle attributes, and dynamics of their households over the past 10 years.

1. Introduction

A large body of travel demand modeling literature has been centered on modeling vehicle ownership decisions and the corresponding aspects such as body type, fuel type, and usage. The advent of electric vehicle (EV) and the emerging autonomous vehicle (AV) technologies call for developing new models to get to know the public adoption behavior of these vehicle technologies. Motivated by this need, my two-part dissertation encompasses two chapters (in part I) focusing on AV adoption behavior and two chapters (in part II) investigating EV adoption. In what ensues, I summarize the two parts.

1.1. Part I: Autonomous vehicles

Emerging AVs and shared mobility systems *per se* will transform urban passenger transportation. Coupled together, shared AVs (SAVs) can facilitate widespread use of shared mobility services by providing flexible public travel modes comparable to private AV. Hence, it may be conjectured that future urban mobility is likely an on-demand service and AV private ownership is unappealing. Nonetheless, it is still unclear what observable and latent factors will drive public interest in (S)AVs, the answer to which will have important implications on transportation system performance. In the first chapter, I attempted to jointly model public interest in private AVs and multiple SAV configurations (including carsharing, ridesourcing, ridesharing, and access/egress mode) in both daily and commute travels with explicit treatment of the correlations across the (S)AV types. To this end, multivariate ordered outcome models with latent variables are employed, whereby latent attitudes and preferences describing traveler safety concern about AV, green travel pattern, and mobility-on-demand (MOD) savviness are accounted for using structural and measurement equations. Drawing from a stated preference survey in the State of Washington, important insights are gained into the potential user groups based on the socio-economic, built environment, and daily/commute travel behavior attributes. Results indicate that safety concern hinders public acceptance of (S)AVs, whereas green travel pattern and MOD savviness promote interest in (S)AVs. It is noteworthy that the marginal effects of safety concern are greater than those of green travel pattern and MOD savviness, which also suggest increasing returns to investments in policies aimed at reducing public safety concern about AVs.

Given that public safety concern about AVs was found in the first chapter to have the greatest impact on traveler behavior —and noting the recent AV-involved accidents in road tests and empirical evidence— the second chapter digs deeper to ascertain the causality between the travelers' safety concern about AVs and their AV adoption behavior, besides exploring the determinants thereof. To this end, a recursive bivariate ordered probit model is estimated, which explicitly accounts for the endogeneity of safety concern in the AV adoption behavior as well as providing a joint modeling framework. Drawing from a stated preference survey in the state of California, results suggest a significant negative association between safety concern and AV adoption. The results further verify the joint estimation of AV adoption and safety concerns. Important insights are also obtained into the impact on shaping travelers' behavior of several socioeconomic and demographic characteristics, current travel behavior factors, and vehicle decision factors and attributes.

1.2. Part II: Electric vehicles

As the most recent and publicly available development in vehicle fuel technology, EVs promise for positive impacts on energy security, climate change, and public health. However, EV benefits are not entirely manifested yet (especially in the U.S.) since this would require widespread adoption of EVs. Promoting public EV adoption calls for an in-depth understanding of the influencing factors on EV adoption behavior. Despite the growing number of such economic and psychological studies, four drawbacks are of note. *First*, most of these studies use stated preference (SP) datasets, which neglect the discrepancies between choices determined by SP data and people's actual choice in the market, referred to as "hypothetical bias". Revealed preference (RP) datasets are required to estimate more realistic models, which describe EV adoption behavior rather than intention to adopt EV. *Second*, most of the studies do not distinguish between the EV types (including hybrid EV (HEV), plug-in HEV (PHEV), and battery EV

(BEV)). For instance, both EV types with plug-in capability (i.e., PHEV and BEV) are charged by plugging to an electricity grid, however, they have several differences and thus attract different consumers. *Third*, EV adoption behavior could be better captured by probing into history of household vehicle decision. This issue could be resolved by collecting a panel data and modeling household vehicle decision in a dynamic framework. *Fourth*, to gain a more behaviorally realistic insight into EV adoption behavior, it is critical to explicitly account for the unobservable (latent) subjective attitude, perception, and lifestyle preference influencing decision-making, along with the observable factors (such as socio-economic characteristics of decisions-makers, features of their surrounding built environment, and their current daily and commute travel behavior characteristics).

Motivated by the above gaps in modeling EV adoption, the second part of this dissertation makes an attempt to more realistically model public adoption of EVs. To this end, I conducted a first-of-its-kind national retrospective vehicle survey (RVS), which is thoroughly analyzed in the third chapter. The RVS database contains information of 1,691 American households who own 3,326 vehicles. The respondent of each household is asked about five types of questions including the household's socio-economic characteristics and demographic factors of residence, his/her own socio-economic characteristics, his/her attitude, perception, and lifestyle preference, attributes of the household's vehicles, socio-economic characteristics and travel behavior of the vehicles' principal drivers, and dynamics of the household's characteristics and vehicles over the past 10 years from 2008 to 2017.

The last chapter utilizes the RVS database to model adoption behavior of various EV types, which are competing with conventional gasoline and diesel vehicles. To this end, I investigate the households' vehicle fuel type choice considering their historical vehicle transaction decisions and (latent) subjective attitude, perception, and lifestyle preference. In particular, an integrated choice with latent variables (ICLV) model of households' vehicle transaction and fuel type is estimated with a choice set consisting of ten alternatives: engaging in no vehicle transaction, adding a new vehicle to the household (conventional vehicle (CV), HEV, PHEV, or BEV), selling one of current household vehicles, and trading one of household vehicles with another one (CV, HEV, PHEV, or BEV). The explanatory factors include socio-economic characteristics, vehicle attributes, and dynamics of households in the past 10 years. The ICLV model further considers four latent constructs describing perception of vehicle specification and social influence at vehicle purchase time as well as lifestyle preference for environmental consciousness and technology savviness.

2. Shared Versus Private Mobility: Modeling Public Interest in Autonomous Vehicles Accounting for Latent Attitudes

The materials of the current chapter are partially published with the following citation: "Nazari, F., Noruzoliaee, M., Mohammadian, A., 2018. Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. Transportation Research Part C: Emerging Technologies 97, 456-477." Permission for reuse of the above publication in the dissertation is obtained from Elsevier (see Appendix A).

2.1. Introduction

It is envisioned that sharing economy and vehicle automation will disrupt the future urban mobility. On the one hand, carsharing (e.g., Zipcar), ridesourcing (e.g., Uber), and ridesharing (e.g., UberPOOL) have recently been gaining momentum by providing flexible shared mobility services comparable to private car and show prospect for diminishing private car ownership (Shaheen et al., 2009; Agatz et al., 2012; Nie, 2017). On the other hand, emerging autonomous/automated vehicles (AVs) will render human input unnecessary and promise numerous benefits such as efficient traffic operations, self-parking patterns, and productive in-vehicle time use (Fagnant and Kockelman, 2015; Liu, 2018). Combined together, shared AVs (SAVs) could foster shared mobility by overcoming the inherent barriers in the existing on-demand services. Specifically, car/ride sharing services will be more accessible and convenient as SAVs can reposition to balance vehicle supply-demand and pick up waiting customers at desired locations. In light of this, it may be conjectured that future urban mobility is likely an on-demand service and AV private ownership is unappealing (Fagnant and Kockelman, 2014; Greenblatt and Shaheen, 2015). It is, however, still unclear what observable and unobservable factors will drive public interest in private and shared AVs, which may of course differ based on trip purpose.

This research aims at *jointly* modeling public interest in privately owned AVs and multiple SAV configurations based on trip purpose and with explicit treatment of the possible correlations across the (S)AV (i.e., AV and SAV, for brevity) types caused by possible common unobserved factors. For (all-purpose) *daily* trips, a multivariate ordered probit model is estimated to gain insight into the interest level of travelers in privately owned AV (denoted by AV-own) and four types of SAV. Specifically, I distinguish carsharing programs with AV (AV-rental), which refer to short-term car rentals such as Zipcar, from two types of point-to-point mobility services: AV as taxi (AV-taxi), which is analogous to the current ridesourcing services[1], and AV as access/egress mode in multimodal trips (namely, AV-access/egress).[2] To better capture the safety concern about the AV technology — besides using the unobserved safety concern factor as elaborated below — I further distinguish between AV-taxi with no (backup) driver and AV-taxi with a driver present. Narrowing focus to *commute* trips, I estimate a bivariate ordered probit model to realize commuter level of interest in two types of AVs: commuting alone in an AV (i.e., AV-alone), and ridesharing with others when commuting using AV (i.e., AV-carpool).

To gain a more behaviorally realistic insight into the public interest in (S)AVs, it is critical to explicitly account for the unobservable (*latent*) subjective attitudes and preferences influencing decision-making, along with the observable factors (such as socio-economic characteristics of decisions-makers, features of their surrounding built environment, and their current daily and commute travel behavior characteristics) explaining the decision-making process (McFadden, 1986; Train et al., 1987). Of note is the psychological attitude toward the safety of AV technology, which can be surmised as a potential barrier for (S)AV adoption (at least before their emergence into markets and public acquaintance with the AV technology),

[1] To be exact, ridesourcing refers to sourcing a ride from a driver pool (Zha et al., 2016). However, I use this term for AV-taxi as it will be likely operated by transportation network companies (TNCs) who source rides from their own SAV fleet.

[2] Note that SAVs will blur the difference between carsharing and taxi services in the sense that both can pick up passengers at their requested locations, thereby obviating the need for walking to a carsharing vehicle as required in existing carsharing systems such as Zipcar and Car2Go. However, the two services will still be distinguished in the era of AVs in terms of the service time window and thus possibly the associated costs. Specifically, AV-rental refers to an autonomous carsharing system, whereby a traveler can rent an AV for a specific amount of time (i.e., time-based such as on a daily or hourly basis) regardless of the number of trips made in that period. In this sense, AV-rental is similar to existing carsharing systems. By contrast, AV-taxi refers to an autonomous taxi system, whereby a traveler can make a single trip from one specific location (point) to another point, thereby making it a point-to-point (i.e., trip-based) system. In this sense, AV-taxi is analogous to existing ridesourcing services such as Uber and Lyft.

notwithstanding the anticipated — from managerial standpoint — reduction in crashes with (S)AVs (Fagnant and Kockelman, 2015; Zmud et al., 2016). In view of this, I take into account people's safety concerns of (S)AVs using five questions capturing perceptions about vehicle equipment and system safety, control, legal liability, and security. The answers to these questions generate five perception indicators to construct the latent factor reflecting *safety concern*, which is used to find how public interest in using private and shared AVs in daily/commute trips is affected. To the authors' best knowledge, previous studies have not examined the impacts of such a latent safety concern on the interest in AV technology.

Furthermore, travelers' preferences for the current on-demand mobility technologies (i.e., ridesourcing and carsharing), which are herein referred to as *mobility-on-demand (MOD) savviness*, could affect their interests in the likely analogous services with (S)AVs in the future. MOD services, as relatively new modes of urban transportation, diminish private car use by improving accessibility while reducing costs of vehicle ownership and use as well as the associated environmental impacts (Shaheen et al., 2009; Agatz et al., 2012; Metcalfe and Warburg, 2012; Laurent, J., Katz, A., 2013; Schaefers, 2013; Silver and Fischer-Baum, 2015; Nie, 2017). Most of the studies on MOD services view them as new technologies to analyze the related impacts on transportation systems (e.g., Clewlow (2016), Dias et al. (2017), and El Zarwi et al. (2017)). In this research, I examine the impact of these services on public interest in (S)AVs as the future technological development. Specifically, indicators of the usage frequency of MOD services along with the possession of smartphone, through which these services are hailed, are bundled to construct the latent factor explaining MOD savviness. To my knowledge, only Lavieri et al. (2017) used the same indicators to investigate the role of technology savviness on AV adoption.

There is also a growing interest in understanding the behavioral mobility within individuals by deriving individuals' mobility patterns and analyzing their multimodality (Molin et al., 2016; Garikapati et al., 2016; Astroza et al., 2017). Previous research highlights the limited understanding of how *(green) travel pattern* preference, which alludes to non-vehicle oriented travels and neighborhoods, influences interest in (S)AVs (Lavieri et al., 2017). In light of this, I consider the role of non-vehicle modes of travel in one person's mobility to derive the latent construct describing green travel pattern, which encapsulates two types of indicators. The first type measures the usage frequency of non-vehicle travel modes including transit, bike, and walk. Given the key role of the residential location choice in one's travel attitude (a comprehensive analysis could be found in Bhat and Guo (2007)), the second type of indicators measures the importance of three factors in choosing residential neighborhood (i.e., being in a walkable neighborhood, close to public transit, and within a fairly short commute to work). It is worth highlighting that these indicators are unique in the database used in this study.

Overall, this research employs a two-stage modeling framework shown in Figure 2.1. In stage 1, the latent variables (i.e., safety concern, green travel pattern, and MOD savviness) are modeled using latent variable measurement and structural equations. This approach, originating from the social sciences and developed based on the work of (Jöreskog, 1977), models the observed indicators as functions of latent constructs, which are called measurement equations that consider measurement error accompanied with each indicator. The latent constructs, on the other hand, are related to observed covariates via structural equations accounting for the cross-equation correlations caused by common unobserved factors. This approach is a parsimonious attempt to define the covariance relationship among observed indicators through a smaller number of latent constructs (examples of this approach can be found in Gates et al. (2011), Hoshino and Bentler (2011), Correia et al. (2013)). Subsequently, two separate models are estimated in Stage 2 to examine people's levels of interest in the above-mentioned (S)AV types based on trip purpose. Specifically, a multivariate (respectively, bivariate) ordered probit model is estimated for all-purpose daily (respectively, commute) trips given two sets of exogenous variables: (1) observable factors such as individuals' socio-economic characteristics, current daily and commute travel behavior attributes, and built environment factors; and (2) the expected (predicted) values of the three latent constructs estimated in stage 1.

Despite the potential limitations of sequential estimation compared to more rigorous simultaneous frameworks that jointly estimate the latent variables with the main outcomes in a single-stage estimation procedure (see, e.g., Bhat (2015) and Lavieri et al. (2017)), the sequential approach could bring empirical contributions by providing acceptable parameter estimates when the latent variables' random error terms in the structural equations are small. In fact, the small error terms of the structural equations lead to sufficient reduction of the measurement errors for larger sample sizes (Ben-Akiva et al., 2002). In this study, the sample size is relatively large and the estimated variances of the error terms of structural equations are small as well (less than 1 for each of the three latent factors). My choice of sequential estimation is further justified by noting the empirical finding of Raveau et al. (2010), who showed a small improvement brought by the simultaneous approach compared to the sequential method, notwithstanding the involved computational burden in the former.

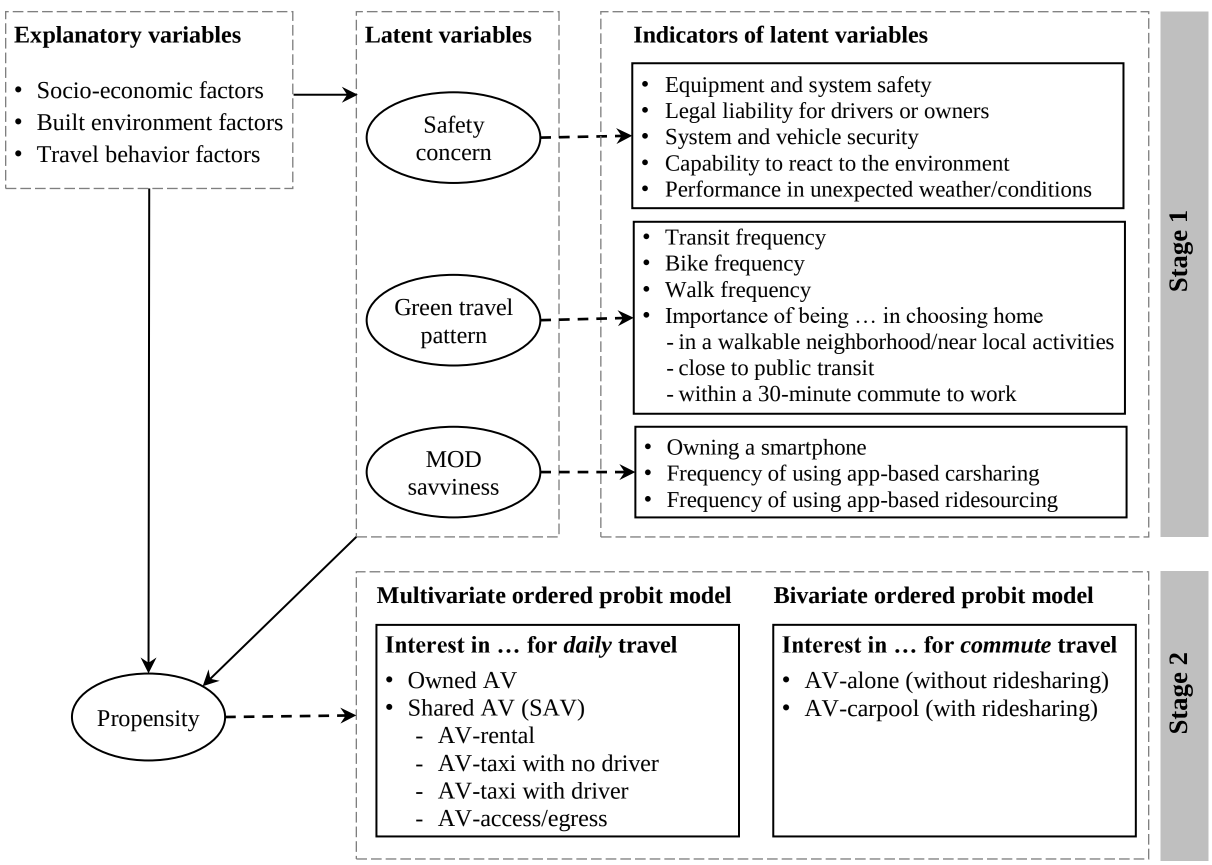


Figure 2.1. The overarching two-stage modeling framework

This empirical study departs from the literature on modeling public interest in (S)AVs[1] in the following three directions. It is worth mentioning that the first two contributions below are identified as two pressing research needs in a recent literature review of this field by Becker and Axhausen (2017).

I distinguish multiple *SAV configurations* (i.e., carsharing, ridesourcing, ridesharing, and access/egress mode), which is necessary due to their different implications on transportation system performance. Previous studies either did not distinguish various SAV services (Bansal et al., 2016; Lavieri et al., 2017) or focused on only one/some of the SAV forms (Krueger et al. (2016) explored ridesharing with driverless taxis, Yap et al. (2016) studied SAV as access/egress mode, Haboucha et al. (2017) considered carsharing with SAVs, and Nair et al. (2017) examined all SAV types except access/egress mode). In addition, I *jointly* investigate public interest in shared and private AVs by explicitly considering the associated *correlations*. I am aware of a few recent studies exploring both private and shared AVs, however with independent models for AV and SAV (Bansal et al., 2016) and mutually exclusive (S)AV choices which restrict respondents to choose only one of the alternatives (Haboucha et al., 2017). To my knowledge, only Lavieri et al. (2017) and Nair (2017) modeled interdependent (S)AV outcomes to address similar questions using the same dataset as in this research.

I explicitly account for the taste heterogeneity rooted in the subjective attitudes/preferences by considering *latent* variables explaining safety concern, green travel pattern, and MOD savviness in the decision-making process. Few studies on (S)AVs have considered latent factors using three modeling approaches. Bansal et al. (2016) and Nazari et al. (2018a) directly plugged the observable indicators of technology awareness and safety concern into the choice model. Factor analysis was employed by Haboucha et al. (2017) to explore technology interest and environmental concerns, and by Yap et al. (2016)

[1] As this thsis focuses on the econometric modeling of traveler interest in (S)AVs and for brevity, I do not herein include studies viewing this problem from a systems perspective. Readers interested in the latter approach are referred to van den Berg and Verhoef (2016) for analytical models, Correia and van Arem (2016), Chen et al. (2016), Chen et al. (2017), Noruzoliaee et al. (2018), and Zhang et al. (2018) for optimization-based network models, and Fagnant and Kockelman (2014), Fagnant et al. (2015), Levin et al. (2017), Nieuwenhuijsen et al. (2018), Lokhandwala and Cai (2018), Farhan and Chen (2018), Hyland and Mahmassani (2018), and Talebian and Mishra (2018) for simulation-based models, among others.

to inquire into safety concern. More recently, Lavieri et al. (2017) used structural and measurement equations in a joint estimation procedure with the main outcomes, which also accounts for the self-selection of other endogenous travel behavior attributes, to capture green lifestyle and technology savviness. While the latter approach has more merits, readers are referred to Bhat and Dubey, (2014) for a detailed discussion on the pros and cons of each approach.

I explore public interest in (S)AVs with a global view on all-purpose daily travels (e.g., as in Bansal et al. (2016) and Yap et al. (2016)) as well as a local view on a specific trip purpose (i.e., commute trips, as in Haboucha et al. (2017) and de Looff et al. (2018)).

The stated preference data for this study are obtained from the Puget Sound regional travel survey program (Puget Sound Regional Council, Jan. 7, 2017) in the State of Washington. I find that the error components of the (S)AV types are highly positively correlated, suggesting that the common unobserved factors tend to jointly increase (or decrease) the interest level of the individuals in private and shared AVs. Overall, results indicate that safety concern hinders public acceptance of (S)AVs, whereas green travel pattern and MOD savviness promote interest in (S)AVs, as expected. Important policy implications are offered by scrutinizing the marginal effects of the latent variables. It is worth highlighting that the marginal effects of safety concern on all interest levels of (S)AV types are greater than those of green travel pattern and MOD savviness in both (all-purpose) daily and commute travels, which also suggest increasing returns to investments in policies aimed at decreasing people's safety concerns about (S)AVs.

Potential user groups of (S)AVs are identified based on the socio-economic, built environment, and current travel behavior characteristics. Young men who are accustomed to private car use and live in multi-member households and in monofunctional neighborhoods, ceteris paribus, are likely interested in private AVs. I find opposing opinions about (S)AVs vis-à-vis daily and commute travel distance. While those with longer commute times embrace (S)AVs with a greater proclivity toward carpool commute, persons who travel more — in terms of total daily vehicle-miles traveled (VMT) — disfavor the AV technology for use in daily travel. This might imply a trip purpose-based heterogeneity in time valuation as commuters likely enjoy productive use of their in-vehicle time conducting work-related tasks, yet people do not similarly value in-vehicle time saving for conducting less urgent/important activities in other trip purposes. Besides total daily VMT, which is ascribed to one or multiple trips, it is noteworthy that individuals with higher fluctuating daily travel profiles (i.e., larger inter-trip VMT variations) are more inclined toward SAVs. Last but not the least, driving commuters appreciate the self-parking benefit of AVs.

The next section presents the methodology used in this study. Data analysis and model estimation results are elaborated in sections 2.3 and 2.4, respectively.

2.2. Methodology

This section presents in sequence the formulation of the latent variable structural and measurement equation models (section 2.2.1) and the multivariate ordered probit model (section 2.2.2).

2.2.1. Latent variable measurement and structural equation models

The connections among the observable attitudinal/preferential indicators and the underlying latent variables are represented by the dashed arrows in Figure 2.1 and are characterized by the following measurement equations. For brevity, I will suppress the index $q \in \{1,2,\dots,Q\}$ for decision makers (i.e., individuals) in the current and the following sub-section.

$$h_r = \boldsymbol{\gamma_r}'\boldsymbol{z}^* + \vartheta_r \qquad \forall r \in \{1,2,\dots,R\} \tag{2.1}$$

where r is the index for attitudinal/preferential indicator $r \in \{1,2,\dots,R\}$. h_r signifies the r^{th} indicator variable. $\boldsymbol{z}^*$ is the $\mathcal{L} \times 1$ vector of latent variables $\boldsymbol{z}^* = (z_1^*, z_2^*, \dots, z_{\mathcal{L}}^*)'$ and $\boldsymbol{\gamma_r}$ is the associated $\mathcal{L} \times 1$ vector of latent variable loadings on the r^{th} indicator variable. The error term of the r^{th} indicator (ϑ_r) captures the impact of unknown factors and is assumed to be standard normally distributed: $\boldsymbol{\vartheta} \sim [\boldsymbol{0}, \boldsymbol{\Gamma}]$, where $\boldsymbol{\Gamma}$ indicates its covariance matrix.

The latent variable structural equation model further ties the latent attitudinal/preferential variables to the observable explanatory variables using the following set of linear equations. The solid arrow connecting the explanatory variables to the latent variables in Figure 2.1 represents these relationships.

$$z_\ell^* = \boldsymbol{\alpha_\ell}'\boldsymbol{w_\ell} + \eta_\ell \qquad \forall \ell \in \{1,2,\dots,\mathcal{L}\} \tag{2.2}$$

where ℓ denotes the index for latent variables $\ell \in \{1,2,\dots,\mathcal{L}\}$. z_ℓ^* refers to the ℓ^{th} latent variable. $\boldsymbol{w_\ell}$ is a $D \times 1$ vector of exogenous variables for the ℓ^{th} latent variable and $\boldsymbol{\alpha_\ell}$ is the corresponding $D \times 1$ vector of coefficients. η_ℓ is a random error term of ℓ^{th} equation and is assumed to be standard multivariate normally distributed: $\boldsymbol{\eta} \sim [\mathbf{0}, \boldsymbol{\Sigma_z}]$, where $\boldsymbol{\Sigma_z}$ denotes its correlation matrix.

The latent variable measurement and structural equations are estimated using the maximum likelihood estimation method. While there exist rigorous methodologies to explicitly model ordinal indicators as ordered outcomes (Bhat, 2015; Lavieri et al., 2017), I bring empirical contributions by following the tradition and treating the ordinal indicators as continuous outcomes (see, e.g., Johansson et al., 2006; Yáñez et al., 2010; R. Daziano and Barla, 2012; F. Bahamonde-Birke and de Dios Ortúzar, 2014; Gao et al., 2017, among others). This treatment concerns goodness-of-fit of the model (F. J. Bahamonde-Birke and de Dios Ortúzar, 2017). As a remedy, the method of Satorra and Bentler (1994) is used to correct the model chi-square and the estimated standard errors.

2.2.2. Multivariate ordered probit model

In general, multivariate ordered probit models take as input a set of observed ordered outcomes (in the context of this study, each set element refers to an (S)AV type and each ordered outcome corresponds to the stated level of interest of an individual in an (S)AV type) and maps it onto intervals associated with a set of continuous latent propensities. Using a general covariance matrix for the latent propensities further allows for explicitly considering the correlations among the observed ordered outcomes. Previous transportation studies have applied this model in other contexts such as activity-travel planning (Bhat and

Srinivasan, 2005; Ferdous et al., 2010), travel behavior attitudes (Guo et al., 2007; Seraj et al., 2012), and infrastructure management (Saeed et al., 2017).

Expression (2.3) relates each continuous latent propensity y_i^*, where $i \in \{1,2,\dots,I\}$ refers to an (S)AV type, to the associated observed ordered outcome y_i using threshold bounds θ_i^k, wherein $k \in \{1,2,\dots,K_i\}$ indicates the ordered level of interest for (S)AV type i. The latent propensity y_i^* is further linked to the explanatory and latent attitudinal/preferential variables.

$$y_i^* = \boldsymbol{\beta_i}'\boldsymbol{x_i} + \boldsymbol{\omega_i}'\boldsymbol{z}^* + \varepsilon_i, \quad y_i = k \qquad \text{if } \theta_i^{k-1} < y_i^* < \theta_i^k \qquad \forall i \in \{1,2,\dots,I\} \tag{2.3}$$

where $\boldsymbol{x_i}$ is a $\overline{D} \times 1$ vector of exogenous variables and $\boldsymbol{\beta_i}$ is the corresponding $\overline{D} \times 1$ vector of coefficients. The $\mathcal{L} \times 1$ coefficient vector $\boldsymbol{\omega_i}$ incorporates the effects of the latent attitudinal/preferential variables, which were already constructed by jointly solving the set of structural and measurement equations in section 2.2.1. For notational simplicity, the terms $\boldsymbol{\beta_i}'\boldsymbol{x_i} + \boldsymbol{\omega_i}'\boldsymbol{z}^*$ are replaced with $\boldsymbol{\chi_i}'\boldsymbol{f_i}$, in which $\boldsymbol{f_i}$ denotes a $(\overline{D} + \mathcal{L}) \times 1$ vector of observed and latent explanatory variables and $\boldsymbol{\chi_i}$ is the corresponding $(\overline{D} + \mathcal{L}) \times 1$ vector of coefficients. θ_i^k is the upper bound threshold for interest level k of each ordered outcome i ($\theta_i^0 = -\infty < \theta_i^1 < \dots < \theta_i^{K_i} = +\infty$). The threshold bounds delimit intervals of the continuous latent propensity variable associated with the observed ordered outcome. ε_i is the standard normal error term of outcome i. For simplification, the error terms ε_i are assumed to be independent and identical across individuals for each outcome i.

The error correlations across ordered outcomes i are explicitly considered by defining $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_I)'$, where $\boldsymbol{\varepsilon}$ is standard multivariate normal distributed, i.e., $\boldsymbol{\varepsilon} \sim [\boldsymbol{0}, \boldsymbol{\Sigma_\varepsilon}]$, as shown in Eq. (2.4). The variance of each error term ε_i is normalized to one for identification reasons.

$$\boldsymbol{\varepsilon} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1I} \\ & 1 & \cdots & \rho_{2I} \\ & & \ddots & \vdots \\ & & & 1 \end{pmatrix}\right] \tag{2.4}$$

where the correlation parameters $\rho_{ii'}$ $(i \neq i')$ reflect the impact of unobserved factors that affect the propensities of ordered interest levels for outcomes i and i'. Clearly, the model collapses to a set of independent ordered probit models if all off-diagonal elements of the covariance matrix are zero.

Given m_i as the observed ordered interest level for outcome i, the model parameters $\boldsymbol{\chi_i}$, $\boldsymbol{\theta_i} = (\theta_i^1, \theta_i^2, \dots, \theta_i^{K_i-1})$, and vector $\boldsymbol{\Omega}$ containing $\rho_{ii'}$ $(i \neq i')$ can be estimated using the following likelihood function. For notational simplicity, a vector of parameters is defined as $\boldsymbol{\delta} = (\boldsymbol{\chi_i}; \boldsymbol{\theta_i}; \boldsymbol{\Omega})', \forall i$.

$$L(\boldsymbol{\delta}) = \Pr(y_1 = m_1, y_2 = m_2, \dots, y_I = m_I) \tag{2.5}$$

The above likelihood function is written as an I-dimensional rectangular integral as follows, which can be evaluated using Monte Carlo integration. Note in Eq. (2.6) that $\phi_I(.)$ denotes a probability density function of an I-dimensional integral.

$$L(\boldsymbol{\delta}) = \int_{v_1=\theta_1^{m_1}-\chi_1'\boldsymbol{f_1}}^{\theta_1^{m_1+1}-\chi_1'\boldsymbol{f_1}} \cdots \int_{v_I=\theta_I^{m_I}-\chi_I'\boldsymbol{f_I}}^{\theta_I^{m_I+1}-\chi_I'\boldsymbol{f_I}} \phi_I(v_1, \dots, v_I | \boldsymbol{\Omega})\, dv_1 \dots dv_I \tag{2.6}$$

An estimated coefficient ($\boldsymbol{\chi_i}$) for outcome i in an ordered outcome model is only used to interpret the highest and the lowest ordered levels (Greene and Hensher, 2010). Specifically, a positive coefficient ($\boldsymbol{\chi_i}$) for outcome i implies that an increase in $\boldsymbol{f_i}$ increases the probability of the highest ordered level ($y_I = m_I$) and decreases the probability of the lowest ordered level ($y_1 = m_1$). To interpret each intermediate ordered level ($y_2 = m_2, y_3 = m_3, \dots, y_{I-1} = m_{I-1}$), one should calculate the marginal effect for the corresponding level. To do so, it is assumed that $\rho_{ii'}$ $(i \neq i')$ equals zero which is an admittedly trivial extension of bivariate and multivariate ordered probit models (Greene, 2000; Greene and Hensher, 2010; Washington et al., 2010). For a continuous variable explaining outcome i, the marginal effect of ordered level k for each individual is computed as in Eq. (2.7), which are then averaged over the sample (Greene, 2000; Greene and Hensher, 2010; Washington et al., 2010).

$$\boldsymbol{ME_k}(\boldsymbol{f_i}) = \frac{\partial \text{Prob}\,(y_i = k | \boldsymbol{f_i})}{\partial \boldsymbol{f_i}} = [\varphi(\theta_{k-1} - \boldsymbol{\chi_i}'\boldsymbol{f_i}) - \varphi(\theta_k - \boldsymbol{\chi_i}'\boldsymbol{f_i})]\,\boldsymbol{\chi_i} \qquad \forall i \in \{1,2,\dots,I\} \tag{2.7}$$

where $\varphi(\cdot)$ is the probability density function of normal distribution. For a dummy variable d_i with its corresponding coefficient denoted by τ_i, the marginal effect of ordered level k is computed according to Eq. (2.8), in which $\Phi(\cdot)$ is the cumulative density function of normal distribution. The equation measures the effect of a change in d_i from 0 to 1 while all other variables are held at their arithmetic mean (Greene, 2000; Greene and Hensher, 2010; Washington et al., 2010).

$$\boldsymbol{ME_k}(d_i) = [\Phi(\theta_k - \boldsymbol{\chi_i}'\boldsymbol{f_i} + \tau_i) - \Phi(\theta_{k-1} - \boldsymbol{\chi_i}'\boldsymbol{f_i} + \tau_i)] - [\Phi(\theta_k - \boldsymbol{\chi_i}'\boldsymbol{f_i}) - \Phi(\theta_{k-1} - \boldsymbol{\chi_i}'\boldsymbol{f_i})] \quad \forall i \in \{1,2,\dots,I\} \tag{2.8}$$

2.3. Data

I draw from the stated preference data gathered in the Puget Sound regional travel survey program (Puget Sound Regional Council, Jan. 7, 2017) in the State of Washington. AVs were defined in the survey as follows: “Autonomous cars, also known as self-driving or driverless cars, are capable of responding to the environment and navigating without a driver controlling the vehicle. Advantages of autonomous car usage include the potential for reduced congestion, increases in parking capacity, and faster travel times”. This section itemizes the dependent (outcome) variables and the observable independent (explanatory) variables including the socio-economic, built environment, and current travel behavior characteristics, and the indicators of latent attitudinal/preferential variables. For brevity, only the explanatory variables that are significant in the estimated models are presented.

2.3.1. Ordered outcome variables

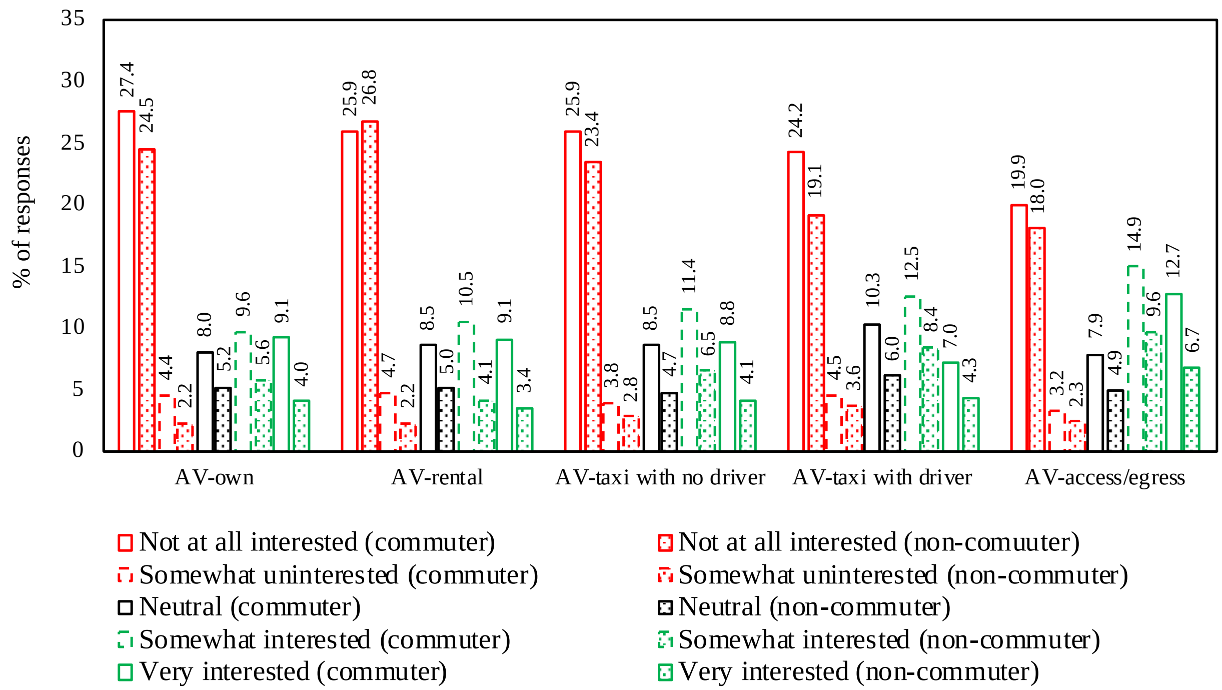
The stated preference survey involves two sets of questions inquiring about public interest in (S)AVs, wherein the interest level is measured on a five-point scale ranging from 1 (not at all interested) to 5 (very interested). Table 2.1 shows the questions presented to the respondents. First, respondents are asked to express their interest in five (S)AV types for use in **(all-purpose) daily travel** comprising privately owned AV (denoted by AV-own) and four SAV configurations (namely, AV-rental, AV-taxi with no driver, AV-taxi with driver, and AV-access/egress). Second, employed respondents are further asked to rate their interest in using AV without ridesharing (AV-alone) and with ridesharing (AV-carpool) for **commute travel**.[1] After cleaning the dataset, the two samples contain respectively 2,726 and 1,755 individual records. Figure 2.2 exhibits the distribution of the respondents' interest levels across the (S)AV types. Overall, almost half of the respondents are not inclined (not all interested/somewhat uninterested) toward any (S)AV type for daily and commute travels, while nearly one third of the sample show positive tendency (very/somewhat interested) to use (S)AVs.[2] The level of interest in the five (S)AV types for daily travel is further classified based on the respondents' commute status. As shown in Figure 2.2 (a), commuters are more interested in both owing AVs and using shared AVs than non-commuters. The responses are further scaled using the reported weights in the dataset so as to represent the associated population.

Table 2.1. Survey questions inquiring about the interest level in (S)AV types for use in (all-purpose) daily and commuter travels (Puget Sound Regional Council, 2017)

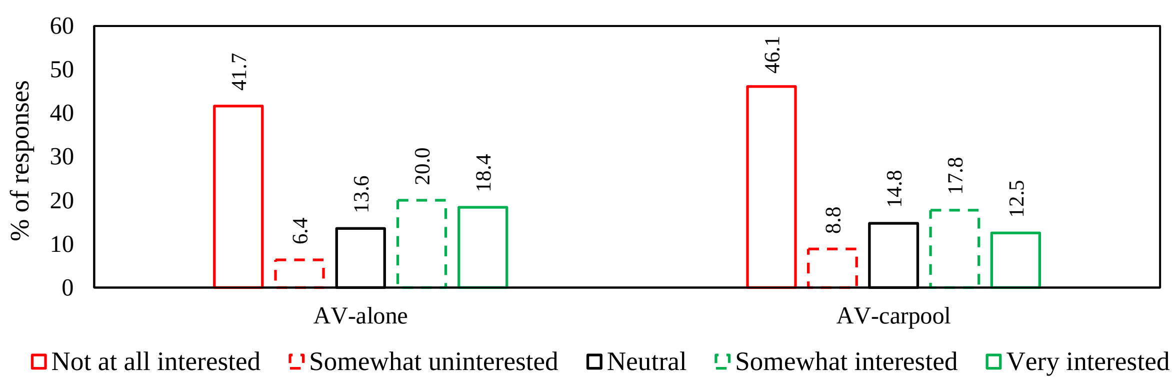
	Very interested	Somewhat interested	Neutral	Somewhat uninterested	Not at all interested
Daily travel					
(1) Owning an autonomous vehicle	□*	□	□	□	□
(2) Participating in an autonomous carsharing system for daily travel	□	□	□	□	□
(3) Taking a taxi ride in an autonomous vehicle with no driver present	□	□	□	□	□
(4) Taking a taxi ride in an autonomous vehicle with a back-up driver present	□	□	□	□	□
(5) Riding in an autonomous vehicle for a short trip to get to a vehicle	□	□	□	□	□
Commute travel					
(1) Commuting alone using an autonomous vehicle	□	□	□	□	□
(2) Commuting with others (carpool) using a shared autonomous vehicle	□	□	□	□	□

[1] I assume that a respondent can distinguish the (S)AV types by making analogies with the existing mobility types by human-driven cars corresponding to each (S)AV mobility type in Table 2.1, and based on the definition and benefits of (S)AVs provided to him/her (as mentioned in the beginning of section 2.3).

[2] Note that relatively large portions of the samples collected in other North American studies (Haboucha et al., 2017) are also associated with uninterested persons in AV technology. Analogous trends have also been reported even in case of technologically well-informed Dutch society (Yap et al., 2016).



(a)



(b)

Figure 2.2. Sample data for public interest in: (a) AV ownership and SAV use in daily travel (sample size = 2,726); and (b) using AV-alone and AV-carpool in commute travel (sample size = 1,775)

2.3.2. Socio-economic and built environment characteristics

Table 2.2 lists a host of socio-economic characteristics at both individual and household levels. The dataset includes only adults (age ≥ 18) who are almost evenly distributed between men and women. More than half of the respondents are middle-aged (35 ≤ age < 65), while the number of youth (18 ≤ age < 35) and the elderly (age ≥ 65) are almost equal. Students contribute to only a small portion (6.7%) of the sample. Approximately two thirds of the sample represent well-educated (bachelor's degree or more) and employed individuals whose households earn either around or above the median US household income in 2015 (US Census Bureau, 2016). The number of adults in a household ranges between 1 and 5 with its average and median values being respectively 1.85 and 2. Almost 73% and 79% of the respondents live together with other household members and do not have children (age < 18) in their households, respectively. The last socio-economic factor indicates a wide range of household vehicle ownership level (between 0 and 10 vehicles per household) with the corresponding average and standard deviation values at 1.67 and 1.06, respectively.

It might be expected that people who reside in similar neighborhoods show identical travel behaviors because of the potential homogeneity in their social and economic attributes. In light of this, I consider built environment characteristics describing residential location, residential type, and land-use. Although residential location and type are decided at the household level, they can play important roles in shaping the travel behavior of each household member. Table 2.2 shows that almost one third of the respondents reside in urban areas and live in apartments/condos and townhouses. Furthermore, a land-use mix diversity index (e.g., as in Bhat and Guo (2007)) is computed based on the land-use composition measures shown in Eq. (2.9) to capture the neighborhood design. The index measures accessibility to various land-uses in the traffic analysis zone (TAZ) corresponding to the residential neighborhood of a respondent. Those living in neighborhoods with larger land-use mix diversity values (i.e., closer to 1) have greater access to various land-uses, while smaller land-use mix diversity values (i.e., closer to 0) indicate a quite uniform TAZ.

$$\text{Land-use mix diversity} = 1 - \frac{3}{4}\left\{\left|\frac{A_1}{A} - \frac{1}{3}\right| + \left|\frac{A_2}{A} - \frac{1}{3}\right| + \left|\frac{A_3}{A} - \frac{1}{3}\right|\right\} \tag{2.9}$$

where A_1 is the zonal acreage in residential use, A_2 is the zonal acreage in commercial/industrial use, A_3 is the zonal acreage in other uses (e.g., governmental use), and $A = A_1 + A_2 + A_3$. The required data for computing these land-use composition measures are borrowed from Silva and Goulias (2007). I find that half of the respondents live in neighborhoods with land-use mix diversity values below 0.22, indicating a relatively poorly diversified study area.

Table 2.2. Sample data for socio-economic and built environment characteristics (sample size = 2,726)

Independent variables	Category	Observations	Share (%)
Socio-economic characteristics			
Gender	Female	1,260	46.22
	Male	1,466	53.78
Age	Young (18 ≤ age < 35)	632	23.18
	Mid-age (35 ≤ age < 65)	1,476	54.15
	Elderly (age ≥ 65)	618	22.67
Employment status	Full-time employed	1,324	48.57
	Part-time employed	243	8.91
	Self-employed	171	6.27
	Unpaid employed (e.g., volunteer work)	32	1.17
	Homemaker	143	5.25
	Retired	639	23.44
	Not currently employed	174	6.38
Education level	High school graduate or less	227	8.33
	Some college/vocational/technical training/associate degree	667	24.47
	Bachelor's degree or more	1,832	67.20
Student	Yes	183	6.71
	No	2,543	93.29
Number of adults in household	Mean = 1.85, SD* = 0.66	[1-5]	-
Household structure	Living alone	743	27.26
	Not living alone	1,983	72.74
Household income	< 50K	748	27.44
	50K ≤ < 75K	417	15.30
	75K ≤ < 100K	402	14.75
	100K ≤ < 150K	519	19.04
	≥ 150K	410	15.04
	Not reported	230	8.44
Presence of children (age < 18) in household	Yes	565	20.73
	No	2,161	79.27
Number of vehicles in household	Mean = 1.67, SD = 1.06	[0-10]	-
Built environment characteristics			
Residential location	Urban	973	35.69
	Suburb	1,753	64.31
Land-use mix diversity of residential TAZ	Mean = 0.22, SD = 0.19	(0-1)	-
Residential type	Single-family detached house	1,592	58.40
	Single-family attached house (townhouse)	138	5.06
	Multifamily house	85	3.12
	Apartment/condo	874	32.06
	Other	37	1.36

2.3.3. Current daily and commute travel behavior characteristics

To examine the potential impacts of the respondents' current travel behaviors on their interests in (S)AVs, an array of the related daily and commute travel characteristics is presented in Table 2.3. Regarding daily travel, I consider four factors reflecting the daily-based and trip-based vehicle-miles traveled (VMT) of a person, as well as his/her potential and de facto driving status. An individual's daily VMT may affect his/her interest in (S)AVs based on the hypothesis that the person can use in-vehicle time more productively (Fagnant and Kockelman, 2015; Bansal et al., 2016). The sample represents a wide range of daily VMT up to 174 miles per day per person with its median, average, and standard deviation values at 17.6, 24.1, and 21.9, respectively. However, as the total daily VMT could be attributed to one or multiple trips in a day, I also account for the trip-based VMT and inter-trip VMT variation. This is achieved by computing the coefficient of variation (COV) of daily VMT for each individual using information on the number of his/her trips in a day and the VMT of each trip. Specifically, the COV of daily VMT is defined as the ratio of the standard deviation to the mean of trip-based VMT throughout a day. This factor ranges between 0 and 2 for the respondents with its average and standard deviation values being respectively 0.58 and 0.44. While holding a driver's license and household vehicle ownership (as a socio-economic factor in Table 2.2) reflect an individual's driving potential, the person may not actually drive. Therefore, I also take into account the vehicle usage at the individual level using a dummy variable (i.e., whether a person is the primary driver of a vehicle of household). Table 2.3 shows that a majority of the respondents are licensed to drive and do so as the primary driver of a vehicle of household.

With respect to commute travel characteristics, I consider the current commute time, mode, departure time flexibility, as well as parking decision at work, telecommute frequency, commute subsidy (e.g., transit pass), commute history, and work schedule. Commute time helps capture the impact of home-work distance as well as the associated congestion effects on the interest in AVs. The commute time of the respondents is reported up to 130 minutes with its median, average, and standard deviation values equal to 30, 30, and 20 minutes. Driving alone, public transit, and biking/walking are the most popular commute modes in descending order, while only a small portion of the respondents (4%) share rides when commuting. 17% of the sample receive subsidized commute benefits such as transit pass. It is worth noting that almost 13% of the respondents telecommute at least a few times per month. I also account for the parking location at work when driving to work, which is hypothesized to be a critical factor in shaping the commute behavior of the workers. Table 2.3 indicates that more than one third of the respondents park their vehicles at the work place (i.e., benefit from subsidized parking), while only 4% of them experience on-street parking. Almost 23% of the respondents enjoy the flexibility in choice of commute departure time (Nazari et al., 2015) to avoid congestion. To further account for commute habits formed over time, I consider commute history that refers to the duration of commuting to the current work place. More than a quarter of the respondents have been commuting to their current work place for less than three years. Lastly, less than 10% of the sample corresponds to work schedules with a night shift.

2.3.4. Indicators of the latent attitudinal/preferential variables

An individual's attitude toward the safety of AVs corresponds to five questions in the survey, which indicate his/her concerns about equipment and system safety, legal liability for drivers or owners, system and vehicle security, capability to react to the environment, and performance in poor weather or other unexpected conditions. It is interesting to note in Table 2.4 that almost two thirds of the respondents are very/somewhat concerned about the safety of AVs. Furthermore, the preference of a person for a green travel pattern is described based on the usage frequency of non-motorized travel modes (bike and walk) and public transit, as well as the importance of residing in a non-vehicle oriented neighborhood. Finally, a respondent's MOD savviness is defined based on his/her usage frequency of the current MOD services including carsharing and ridesourcing, as well as his/her smartphone ownership status through which these shared mobility services are provided.

Table 2.3. Sample data for current daily and commute travel behavior characteristics (sample size = 2,726)

Independent variables	Category	Observations	Share (%)
Daily travel behavior characteristics			
Daily VMT	Mean = 24.08, SD = 21.94	(0-174)	-
COV of daily VMT	Mean = 0.58, SD = 0.44	[0-2]	-
Primary driver of a vehicle of household	Yes	2,335	85.66
	No	391	14.34
Having driver's license	Yes	2,574	94.42
	No	152	5.58
Commute travel behavior characteristics			
Commute travel time (minute)	Mean = 30.09, SD = 20.12	[0-130]	-
Commute mode	Vehicle-alone	883	32.39
	Carpool with household member	84	3.08
	Carpool with non-household member	27	0.99
	Public Transit (bus and train)	362	13.28
	Bicycle or walk	182	6.68
	Other	58	2.13
	Not applicable	1,130	41.45
Telecommute frequency	Not applicable	1,196	43.87
	Never	926	33.97
	Less than monthly	260	9.54
	A few times per month	148	5.43
	1 day a week	78	2.86
	2 days a week	34	1.25
	3 days a week	23	0.84
	4 days a week	12	0.44
	5 days a week	27	0.99
	6-7 days a week	22	0.81
Using subsidized commute benefit (e.g., transit)	Yes	470	17.24
	No	2,256	82.76
Parking location when drive to work	At work (e.g., garage and driveway)	996	36.54
	On street at work	111	4.07
	Different location	67	2.46
	Get dropped off when drive to work	25	0.92
	I don't drive to work	392	14.38
	Other	5	0.18
	Not applicable	1,130	41.45
Choose commute departure time to avoid congestion	Yes	626	22.96
	No	970	35.58
	Not applicable	1,130	41.45
Commute history	Less than a year	299	10.97
	Between 1 and 2 years	265	9.72
	Between 2 and 3 years	191	7.01
	Between 3 and 5 years	210	7.70
	Between 5 and 10 years	305	11.19
	Between 10 and 20 years	210	7.70
	More than 20 years	116	4.26
	Not applicable	1,130	41.45
Having night shift	Yes	250	9.17
	No	1,488	54.59
	Not applicable	988	36.24

Table 2.4. Sample data for the latent attitudinal/preferential indicator variables (sample size = 2,726)

Indicators	% of observations within each category						
	Not at all concerned	Somewhat unconcerned	Neutral	Somewhat concerned	Very concerned		
Safety concern indicators							
Equipment and system safety	14.16	4.81	13.54	26.52	40.98		
Legal liability for drivers or owners	13.87	4.33	14.42	27.84	39.55		
System and vehicle security	15.92	5.87	17.13	26.78	34.30		
Capability to react to the environment	13.28	3.63	9.50	23.00	50.59		
Performance in poor weather/other unexpected conditions	14.05	4.29	12.22	26.89	42.55		
	Very unimportant	Somewhat unimportant	Neutral	Somewhat important	Very important		
Green travel pattern indicators							
Importance of being … in choice of home location							
in a walkable neighborhood & near local activities	10.75	6.38	16.73	21.68	44.46		
close to public transit	15.19	11.41	18.16	25.46	29.79		
within a 30-minute commute to work	10.75	6.38	16.73	21.68	44.46		
	Never	Not in past 30 days	1-3 times in past 30 days	1 day/week	2-4 days/week	5 days/week	6-7 days/week
Transit frequency (in past 30 days)	31.73	24.94	14.93	5.50	8.95	8.84	5.10
Bike frequency (in past 30 days)	62.44	20.84	5.87	3.08	4.99	1.83	0.95
Walk frequency (in past 30 days)	9.43	6.27	9.76	9.76	29.02	12.95	22.82
MOD savviness indicators							
Frequency of using app-based carsharing (e.g., Zipcar, Car2Go)	90.87	4.40	3.15	0.62	0.73	0.22	0
Frequency of using app-based ridesourcing (e.g., Uber, Lyft)	84.92	6.42	6.35	1.28	0.95	0.04	0.04
	Yes	No					
Own a smartphone	70.84	29.16					

2.4. Results

In this section, I present and discuss the estimation results of the latent variable measurement and structural equation models (section 2.4.1), the multivariate ordered probit model of five AV mobility types for daily travel (section 2.4.2), the bivariate ordered probit model of two AV mobility types for commute travel (section 2.4.3), and the policy implications (section 2.4.4). I used the procedures CALIS (SAS, 2013) and QLIM (SAS, 2014) of the statistical analysis system (SAS) for estimating the latent variable's structural/measurement equations and the multivariate/bivariate ordered probit models, respectively.

2.4.1. Estimated latent variable structural and measurement equation models

Table 2.5 shows the estimation results of the latent variable model's measurement and structural equations with three latent variables reflecting the attitude toward safety of AV technology and the propensity for green travel pattern and MOD savviness. The estimated coefficients are highly significant as evidenced by the large t-statistics. The model fits the data well based on the following indices and their corresponding commonly used criteria for a good fit: goodness of fit index (GFI) = 0.934 (> critical value of 0.9 based on Gao et al. (2017)), adjusted GFI = 0.914 (> critical value of 0.9 based on Gao et al. (2017)), standardized root mean square residuals (SRMR) = 0.038 (< critical value of 0.05 based on Byrne (2016)), and the root mean square of error approximation (RMSEA) = 0.046 (< critical value of 0.05 based on Steiger (1990) and Browne and Cudeck (1992)). In addition, the model chi-square is significant at p-value < 0.001 (Golob, 2003).

Recall from section 2.2.1 that the upper-triangle elements of the correlation matrix $\boldsymbol{\Sigma_z}$ in Eq. (2.2) are free parameters, which are determined in the estimation process. I note trivial and negative correlations between the error terms of the structural equations of the three latent variables. In detail, the error term of green travel pattern is correlated with those of MOD savviness and safety concern with values -0.014 and -0.002, respectively. The correlation of the error terms of MOD savviness and safety concern is -0.032.

Table 2.5. Estimation results of the latent variable structural and measurement equation models

Explanatory variables / indicators	Safety concern		Green travel pattern		MOD savviness	
	coef.	t-stat	coef.	t-stat	coef.	t-stat
Measurement equation model						
Indicators of safety concern						
Equipment and system safety	0.933	4771.8				
Legal liability for drivers or owners	0.888	2970.2				
System and vehicle security	0.888	3045.0				
Capability to react to the environment	0.929	4668.5				
Performance in poor weather/other unexpected conditions	0.939	5356.1				
Indicators of green travel pattern						
Transit frequency			0.486	629.8		
Bike frequency			0.155	184.3		
Walk frequency			0.275	313.4		
Importance of being … in choice of home location						
in a walkable neighborhood & near local activities			0.543	750.1		
close to public transit			0.774	1014.8		
within a 30-minute commute to work			0.295	327.3		
Indicators of MOD savviness						
Own a smartphone						
Yes = 1					0.568	525.6
Frequency of using app-based carsharing					0.205	254.3
Frequency of using app-based ridesourcing					0.260	246.8
Structural equation model						
Socio-economic characteristics						
Gender						
Female	-0.045	-59.70	-0.010	-11.69	-0.026	-24.09
Age						
Young (18 ≤ < 35)	-0.017	-23.06	—	—	0.329	257.3
Elderly (≥ 65)	—	—	-0.143	-151.8	-0.390	-293.7
Education level						
Some college/vocational/technical training/associate degree	0.081	61.01	—	—	0.178	88.73
Bachelor's degree or more	0.119	89.46	0.216	250.4	0.383	184.5
Household income						
≥ 75K	—	—	-0.087	-101.1	0.289	238.0
Presence of children in household						
Yes = 1	—	—	-0.049	-56.80	0.057	52.16

The estimated measurement equation model ties the latent attitudinal/preferential variables to the underlying observable indicators through the loading factors (see $\boldsymbol{\gamma_r}$ in Eq. (2.1)), which are all shown to be significant with expected signs (Table 2.5). The latent variable pertaining to **safety concern** has positive loadings on all of its indicators, which clearly implies that the safety-concerned individuals distrust the automated vehicle technology. This is not surprising as AVs are not yet commercially available and are not well known to the public, notwithstanding the anticipated eventual improvement in road safety due to removing human error related accidents (Mamdoohi et al., 2014; Fagnant and Kockelman, 2015). It is worth noting that the latent safety concern contributes more to the loadings on indicators related to vehicle equipment and control (i.e., equipment and system safety, capability to react to the environment, and performance in poor weather or other unexpected conditions) than to those regarding legal liability and security. The latent construct explaining **green travel pattern** has positive impacts in descending order on the proximity to and usage frequency of public transit, usage capability and frequency of non-motorized travel modes (bike and walk), and living close (within 30 minutes) to work place. Finally, the latent **MOD savviness** variable places a greater positive loading on owning a smartphone, through which MOD services are requested, than on the usage frequency of ridesourcing services (e.g., Uber) and carsharing systems (e.g., Zipcar).

The estimated structural equation model reveals the influence of individual- and household-level socio-economic characteristics on the safety concern about the AV technology, green travel pattern preference, and MOD savviness. Compared to **women,** men are more disposed to be MOD-savvy, concerned about safety of AVs, and have green travel pattern. Whereas **young** adults are likely less safety-conscious and more aware of on-demand technology than the elderly and the middle-aged, the elderly show smaller propensity toward green travel pattern and MOD savviness compared to the other age groups. Those with higher **education** levels (bachelor’s degree or more) have greater proclivity for green travel pattern and MOD savviness. However, they are more concerned about AV safety than lower educated persons are, probably due to their better understanding of the technology maturing process. Individuals whose households earn higher than the average US household **income** (US Census Bureau, 2016) are less inclined toward a green travel pattern and are more likely MOD-savvy. Those who live in **households with children** (age < 18) have negative tendency toward green travel pattern, which could be caused by their potentially higher number of trips (e.g., more shopping and children pickup/drop-off trips) and more convenience in using owned vehicles. The positive association of the presence of children in a household with MOD savviness of a household member highlights the role of intra-household interactions in shaping travel behavior.

2.4.2. Estimated multivariate ordered probit model of AV mobility types for daily travel

Table 2.6 reports the estimated multivariate ordered probit model of public interest in owning AV and four configurations of SAV (i.e., renting AV, using AV as taxi with and without backup driver, and using AV as the access/egress mode in multimodal trips) for daily travel. The estimated model fits the data according to the model chi-squared test (Greene and Hensher, 2010) compared to a model with only constants, i.e., $\chi^2_{model} = -2[LL(c) - LL(\beta)] = 624$ at p-value << 0.001.

The estimated model also captures the cross-equation error correlations, i.e., $\rho_{ii'}$ $(i \neq i')$ in Eq. (2.4), which appropriately absorb any propensity for the (S)AV types due to unobserved factors. I find significant and highly positive correlations (> 0.83) across the unobserved factors of the five outcome variables. This suggests that the common unobserved factors tend to jointly increase (or decrease) the interest level of the individuals in the five (S)AV types. To test the hypothesis of zero correlation of the error terms, I use the likelihood ratio test by comparing the estimated model with a restricted model which corresponds to independent ordered outcome estimation of each of the five (S)AV types (Greene and Hensher, 2010). The likelihood ratio test shows that in this particular empirical context, it cannot be rejected to model the public interest in (S)AV types considering the correlation across the error components of the equations.

Table 2.6. Estimated multivariate ordered probit model of public interest in AV types for daily travel

Explanatory variables	AV-own		SAV							
			AV-rental		AV-taxi with no driver		AV-taxi with driver		AV-access/ egress	
	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat	coef.	t-stat
Constant	—	—	—	—	—	—	0.260	5.03	0.223	4.54
Socio-economic characteristics										
Gender										
Female	-0.072	-2.44	—	—	—	—	—	—	—	—
Age										
Young (18 ≤ < 35)	0.132	3.27	0.098	2.65	—	—	—		—	—
Elderly (≥ 65)	—	—	—	—	0.210	3.90	0.279	4.80	0.109	1.88
Employment status										
Full-time employed	—	—	—	—	0.074	3.18	—	—	—	—
Self-employed	0.183	3.58	0.197	4.16	0.153	3.50	—	—	0.178	3.93
Retired	-0.098	-2.05	-0.244	-5.18	—	—	—	—	0.149	3.60
Student										
Yes = 1	-0.311	-3.51	-0.236	-2.70	-0.211	-2.44	-0.309	-3.56	-0.388	-4.53
Household structure										
Living alone	-0.085	-2.79	—	—	—	—	—	—	—	—
Built environment factors										
Land-use mix diversity	—	—	—	—	0.259	4.44	0.215	3.19	0.245	3.85
Residential location										
Suburb = 1	-0.154	-3.22	-0.187	-3.89	-0.228	-4.87	-0.241	-5.06	-0.207	-4.41
Daily travel behavior factors										
Log of daily VMT	-0.041	-2.47	-0.082	-4.89	-0.101	-6.26	-0.092	-5.37	-0.059	-3.61
COV of daily VMT	—	—	0.061	2.07	0.086	3.34	0.078	2.53	—	—
Primary driver of a household vehicle										
Yes = 1	0.125	3.27	0.124	2.89	—	—	—	—	—	—
Having driver's license										
No = 1	—	—	0.223	3.59	—	—	0.130	2.59	—	—
Latent variables										
Safety concern	-3.435	-5.23	-3.173	-5.38	-4.372	-7.39	-4.222	-7.08	-2.908	-4.99
Green travel pattern	1.137	4.58	1.347	5.58	1.367	5.66	1.491	6.16	0.875	3.71
MOD savviness	0.674	7.35	0.576	6.62	0.874	10.86	0.623	7.59	0.851	10.44
Error correlations										
Owned AV	1.00		**0.884**	134.09	**0.886**	134.56	**0.828**	90.22	**0.852**	105.31
AV-rental			1.00		**0.884**	135.66	**0.864**	119.00	**0.861**	115.79
AV-taxi with no driver					1.00		**0.900**	152.95	**0.913**	172.07
AV-taxi with driver							1.00		**0.875**	128.12
AV-access/egress									1.00	
Thresholds										
Threshold 2	0.154	12.94	0.125	11.94	0.143	13.06	0.168	13.83	0.173	13.05
Threshold 3	0.515	26.09	0.523	26.50	0.454	25.26	0.573	28.17	0.514	26.61
Threshold 4	0.983	34.23	1.050	35.26	0.964	34.76	1.225	37.32	1.062	38.94

Furthermore, the estimated coefficients in Table 2.6 are statistically significant at the 0.05 level and intuitively signed. The sign of each estimated coefficient is of particular interest: a positive sign means increase in the highest interest level (i.e., very interested) or decrease in the lowest interest level (i.e., not at all interested) in the (S)AV types (Greene and Hensher, 2010). However, analysis of the intermediate ordered levels of an ordered probit model (i.e., the three middle interest levels in this model) requires computing the associated marginal effects, as illustrated in section 2.2.2. Table 2.7 presents the marginal effects of the exogenous variables explaining each level of interest in (S)AV types, which refer to the approximate change in the probability of each interest level of an (S)AV type in response to a unit change in the desired exogenous variable while other variables are held constant at their respective population mean.

Among the socio-economic characteristics, gender, age, employment status, studentship, and household structure are found to explain public interest in the five AV mobility types, in addition to education level and household income that influence through the latent attitudinal/preferential variables (see section 2.4.1). **Women** are more likely to be not at all interested in AV ownership. This variable also appears as an explanatory variable of the latent variable model in section 2.4.1, implying that the impact of gender on interest in AVs goes beyond what penetrates through the latent variables. While the cohort of **young** adults are more likely inclined toward AV ownership and rental, the elderly favor AV as taxi and as access/egress mode. This makes sense as point-to-point AV-taxi service offers enhanced mobility to seniors whose driving capabilities and daily activities are potentially reduced, as well as improved accessibility to public transit using AV as an access/egress mode.

Table 2.7. Marginal effects for multivariate ordered probit model of public interest in AV mobility types for daily travel

	AV-own					AV-rental					AV-taxi with no driver					AV-taxi with driver					AV-access/egress				
	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested
Socio-economic																									
Gender																									
Female	0.029	-0.001	-0.004	-0.008	-0.017	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Age																									
Young (18 ≤< 35)	-0.053	0.001	0.006	0.014	0.032	-0.039	0.001	0.006	0.012	0.020	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Elderly (≥ 65)	—	—	—	—	—	—	—	—	—	—	-0.084	0.001	0.008	0.024	0.050	-0.110	-0.001	0.011	0.040	0.060	-0.042	-0.001	0.001	0.011	0.032
Employment status																									
Full-time	—	—	—	—	—	—	—	—	—	—	-0.029	0.001	0.003	0.009	0.017	—	—	—	—	—	—	—	—	—	—
Self-employed	-0.073	0.001	0.008	0.019	0.046	-0.078	0.001	0.011	0.024	0.043	-0.061	0.001	0.006	0.017	0.037	—	—	—	—	—	-0.068	-0.003	0.001	0.016	0.054
Retired	0.039	-0.001	-0.005	-0.011	-0.022	0.095	-0.003	-0.017	-0.030	-0.044	—	—	—	—	—	—	—	—	—	—	-0.057	-0.002	0.001	0.014	0.044
Student																									
Yes = 1	0.121	-0.005	-0.020	-0.034	-0.062	0.091	-0.003	-0.018	-0.029	-0.041	0.082	-0.003	-0.011	-0.025	-0.043	0.122	-0.004	-0.020	-0.047	-0.052	0.154	-0.001	-0.014	-0.045	-0.094
Household structure																									
Living alone	0.034	-0.001	-0.005	-0.009	-0.019	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Built environment																									
Land-use mix diversity	—	—	—	—	—	—	—	—	—	—	-0.103	0.002	0.010	0.029	0.063	-0.085	-0.0001	0.009	0.031	0.045	-0.093	-0.003	0.002	0.023	0.073
Residential location																									
Suburb = 1	0.061	-0.001	-0.008	-0.016	-0.036	0.074	-0.002	-0.012	-0.023	-0.038	0.091	-0.002	-0.010	-0.026	-0.053	0.096	-0.0002	-0.011	-0.035	-0.050	0.080	0.002	-0.002	-0.020	-0.060
Daily travel behavior																									
Log of daily VMT	0.015	-0.0003	-0.002	-0.004	-0.009	0.030	-0.001	-0.004	-0.009	-0.017	0.038	-0.001	-0.004	-0.010	-0.023	0.035	-0.0003	-0.004	-0.012	-0.018	0.022	0.001	-0.001	-0.005	-0.016
COV of daily VMT	—	—	—	—	—	-0.022	0.0004	0.003	0.006	0.012	-0.032	0.001	0.003	0.009	0.019	-0.030	0.0002	0.003	0.011	0.016	—	—	—	—	—
Primary driver of a vehicle of household																									
Yes = 1	-0.050	0.001	0.007	0.014	0.027	-0.049	0.002	0.009	0.015	0.023	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Having driver's license																									
Yes = 1	—	—	—	—	—	-0.089	0.001	0.012	0.027	0.049	—	—	—	—	—	-0.052	-0.001	0.005	0.019	0.027	—	—	—	—	—
Latent variables																									
Safety concern	1.283	-0.024	-0.149	-0.316	-0.794	1.167	-0.024	-0.166	-0.335	-0.641	1.629	-0.036	-0.166	-0.436	-0.991	1.617	-0.012	-0.188	-0.573	-0.844	1.082	0.025	-0.038	-0.260	-0.809
Green travel pattern	-0.425	0.008	0.049	0.104	0.263	-0.495	0.010	0.071	0.142	0.272	-0.509	0.011	0.052	0.136	0.310	-0.571	0.004	0.066	0.202	0.298	-0.326	-0.008	0.011	0.078	0.243
MOD savviness	-0.252	0.005	0.029	0.062	0.156	-0.213	0.004	0.030	0.061	0.117	-0.326	0.007	0.033	0.087	0.198	-0.239	0.002	0.028	0.085	0.125	-0.317	-0.007	0.011	0.076	0.237

Regarding **employment status**, I find that the retired persons tend to be not at all interested in owning and renting an AV and are inclined (with neutral to very interested levels, according to Table 2.7) towards AV only as access/egress mode. Whereas self-employed individuals are interested in AV ownership and SAV types without a human driver, full-employed persons are interested in AV taxi without driver. **Students** disfavor all (S)AV types. **Household structure** appears in the model as a dichotomous variable indicating whether a person lives alone. Those who live alone show a less penchant for owning AV than the ones living with other household members, which might be rooted in the fewer trips made by the single-member households.

Results highlight the key role of the built environment factors in forming public interest in (S)AVs. Those who live in **urban areas** with a greater **land-use mix diversity** (closer to 1), ceteris paribus, are interested in using AV-taxi and AV-access/egress services. This is intuitive because of easier accessibility of these residents to different land-use types (e.g., residential, industrial, and governmental) by making short trips, besides parking cost and searching time constraints in such neighborhoods. It is not surprising to note that suburban residents are likely not interested in private and shared AVs given the associated lower accessibility to other land-uses and public transit, which casts doubts on the availability and reliability of SAVs at the request time.

It is interesting to note the public interest in (S)AV types vis-à-vis the current travel behavior attributes. Those who travel more (in terms of **daily VMT**) are negatively associated with proclivity toward private and shared AVs. The corresponding marginal effects in Table 2.7 suggest that one unit increase in the logarithm of daily VMT increases the probability of "not at all interested" for all (S)AV types. This logarithmic functional form also implies an opposite behavior by those who travel less than one mile a day, who show interest in all (S)AV types. Surprisingly, AV ownership is also disfavored by those who travel more, a finding that may cast doubts on the general conjecture about in-vehicle time saving benefits with AVs (Fagnant and Kockelman, 2015). This is in line with the finding of Yap et al. (2016), who showed that travelers associate a higher disutility for trips of equal duration by an AV being driven automatically compared to a manually driven AV.

In addition to the aggregate daily mileage traveled, results highlight the role of daily travel profile (in terms of **inter-trip VMT variations**) in affecting public interest in (S)AVs. Persons whose daily trips are less similar in distance (i.e., higher values of COV of daily VMT) are more inclined toward renting an AV and using AV as taxi, regardless of the presence of a backup driver. The higher interest of such individuals in AV taxi is intuitive since their shorter trips within a day can be made more conveniently (e.g., less parking search time and cost) with AV taxi.

As an indicator of a person's travel behavior, it is important to consider his/her access to a vehicle of household aside from the number of household vehicles. To this end, I used a dummy variable to show whether a person is a **primary driver of a vehicle of household**. Individuals with a positive answer to this question show greater propensities for owned and rented AVs. In other words, those who have become accustomed to the private car use are likely to buy private AV and follow their driving habits. It is also revealed that persons without **driver's license** are open to AV technology in the forms of short-term rental and taxi with driver, indicating that such currently captive travelers enjoy enhanced mobility provided by SAVs.

When it comes to the latent constructs, I find that **safety concern** hinders public inclination toward (S)AVs, whereas **MOD savviness** and **green travel pattern** can promote interest in AV technology. Recall from section 2.4.1 that individuals with green travel pattern are frequent users of non-vehicle modes of travel and live in neighborhoods with higher potential for using non-vehicle modes. Given the positive signs of this latent construct in all (S)AV types, it could be inferred that the emergence of (S)AVs will likely also attract persons who currently are not vehicle-oriented, assuming other factors constant. Thus, it is possible to observe a modal shift from non-vehicle modes to (S)AVs in the future. MOD savvy persons, who are defined as frequent users of MOD services, will likely be more interested in (S)AVs. Furthermore, comparison of the marginal effects of the three latent constructs reveals that a unit change in safety concern of individuals will potentially cause the largest changes in the probabilities of all interest levels in the (S)AV types. Besides, a unit change in green travel pattern of individuals induces larger changes in the propensities of all (S)AV types than those caused by a unit change in MOD savviness.

2.4.3. Estimated bivariate ordered probit model of AV mobility types for commute travel

With a focus on merely the commute trips, this section analyzes public interest in commuting alone with AV and sharing AV rides in commute to work. To explore the possible correlation between the unobserved factors, i.e., $\rho_{ii'}$ $(i \neq i')$ in Eq. (2.4), that affect the level of interest in the two AV types, a bivariate ordered probit model is estimated (Table 2.8). Based on the model chi-squared test (Greene and Hensher, 2010), the estimated model fits the data better than a model with only constants; i.e., $\chi^2_{model} = -2[LL(c) - LL(\beta)] = 1274$ at p-value << 0.001.

The significant and highly positive error correlation between the two AV commute equations (ρ = 0.868) reflects the correlation between the unobserved factors affecting interest in the two AV types. In other words, the common unobserved factors tend to jointly increase (or decrease) the interest level of the individuals in commuting with AV-alone and AV-carpool. To test the hypothesis of zero correlation between the error terms, I use the likelihood ratio test by comparing the estimated model with a restricted model which corresponds to two independent ordered response models (zero correlation between the error terms) of the two AV commute types (Greene and Hensher, 2010). The test shows that in this particular empirical context, it cannot be rejected to model the public interest in AV commute types considering the correlation across the error components of the equations.

The estimated coefficients are statistically significant with meaningful signs. As stated in section 2.4.2, the positive sign of an estimated variable reveals the increase (respectively, decrease) in the highest (respectively, the lowest) interest level. To analyze the impact of the exogenous variables on the intermediate interest levels, the marginal effects are presented in Table 2.9.

Table 2.8. Estimated bivariate ordered probit model of public interest in AV types for commute travel

Explanatory variables	AV-alone		AV-carpool	
	coef.	t-stat	coef.	t-stat
Constant	-0.427	-3.83	-0.673	-5.01
Socio-economic characteristics				
Employment status				
Full-time employed	0.115	1.66	0.238	3.00
Self-employed	—	—	0.164	1.83
Number of adults in household	—	—	0.052	2.10
Presence of children in household				
Yes = 1	—	—	0.144	3.46
Built environment factors				
Land-use mix diversity of residential TAZ	—	—	0.246	2.61
Residential type				
Single family attached house	0.177	1.87	0.214	1.68
Apartment	0.509	6.63	0.462	5.84
Commute travel behavior factors				
Log of commute travel time (minute)	0.084	4.66	0.100	5.51
Choose commute departure time to avoid congestion				
Yes = 1	0.177	4.67	—	—
Commute history	-0.053	-3.27	-0.062	-3.78
Parking location when drive to work				
At work (e.g., garage and driveway)	0.274	4.54	0.153	2.49
On street at work	0.555	4.69	0.397	3.38
Having night shift				
Yes = 1	—	—	-0.163	-3.19
Having driver's license				
No = 1	—	—	0.309	3.31
Latent variables				
Safety concern	-3.813	-4.40	-3.894	-4.44
Green travel pattern	0.566	1.99	1.003	2.76
MOD savviness	0.582	4.91	0.491	4.03
Error correlations				
Commute-alone	1.00	—	**0.868**	88.27
Commute-carpool			1.00	—
Thresholds				
Threshold 2	0.142	8.87	0.188	10.75
Threshold 3	0.510	18.91	0.611	20.90
Threshold 4	1.045	26.92	1.128	27.24

Table 2.9. Marginal effects for bivariate ordered probit model of public interest in AV mobility types for commute travel

	AV-alone					AV-carpool				
	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested	Not at all interested	Somewhat uninterested	Neutral	Somewhat interested	Very interested
Socio-economic characteristics										
Employment status										
Full-time employed	-0.046	-0.0002	0.004	0.013	0.029	-0.095	0.003	0.016	0.029	0.047
Self-employed	—	—	—	—	—	-0.065	0.001	0.008	0.019	0.038
Number of adults in household	—	—	—	—	—	-0.019	0.0002	0.002	0.005	0.011
Presence of children in household										
Yes = 1	—	—	—	—	—	-0.057	0.0005	0.008	0.017	0.032
Built environment factors										
Land-use mix diversity	—	—	—	—	—	-0.098	0.0003	0.012	0.029	0.056
Residential type										
Single family attached house	-0.069	-0.001	0.003	0.018	0.050	-0.085	-0.0002	0.010	0.024	0.051
Apartment	-0.196	-0.004	0.007	0.049	0.144	-0.182	0.0001	0.022	0.052	0.108
Commute travel behavior factors										
Log of commute travel time (minute)	-0.030	-0.0003	0.002	0.007	0.022	-0.036	0.0004	0.004	0.010	0.022
Choose commute departure time to avoid congestion										
Yes = 1	-0.070	-0.001	0.004	0.019	0.048	—	—	—	—	—
Commute history	0.019	0.0002	-0.001	-0.004	-0.014	0.023	-0.0002	-0.003	-0.006	-0.014
Parking location when drive to work										
At work (e.g., garage and driveway)	-0.108	-0.001	0.007	0.029	0.073	-0.061	0.001	0.009	0.018	0.033
On street at work	-0.204	-0.009	-0.004	0.041	0.176	-0.155	-0.003	0.013	0.042	0.102
Having night shift										
Yes = 1	—	—	—	—	—	0.065	-0.002	-0.011	-0.020	-0.033
Having driver's license										
Yes = 1	—	—	—	—	—	-0.121	-0.001	0.012	0.034	0.077
Latent variables										
Safety concern	1.374	0.012	-0.075	-0.321	-0.990	1.417	-0.015	-0.172	-0.375	-0.856
Green travel pattern	-0.204	-0.002	0.011	0.048	0.147	-0.365	0.004	0.044	0.097	0.220
MOD savviness	-0.210	-0.002	0.011	0.049	0.151	-0.179	0.002	0.022	0.047	0.108

Looking at the socio-economic characteristics, **employment status** is a significant factor in describing the commute mode of interest. Full-time employees show positive inclination towards commuting with AVs in both forms, whereas self-employed individuals show positive propensity for carpooling with AVs. The marginal effects reveal that full-time employees likely go for carpooling with AVs more than the self-employed persons do. It is noteworthy to find that the **presence of children** and greater **number of adults** in a household, especially presence of children, contribute to a higher propensity of the household members for carpooling with AV for commute trips. This is intuitive as more adults and children in a household will likely translate into more work and school related commute trips, which can be consolidated into shared rides using fewer vehicles and thus incurring lower (capital) costs. Besides cost incentives, intra-household ridesharing can also be motivated by its spatial (e.g., common home-end of the commute) and temporal (e.g., sustainably- and reliably-matched itineraries with household members) convenience.

With respect to the built environment attributes, commuters who live in neighborhoods with higher **land-use mix diversity** are more disposed to share rides in commuting trips. This makes sense as such individuals are in close proximity to various land-use types (e.g., residential, industrial, and governmental), which facilitates the ride matching process with neighboring commuters. **Residential type** also plays a key role in commuters' inclination toward AV. Apartment and single-family attached house residents are more interested in commuting with AV than those living in other housing types (e.g., single-family detached and multifamily houses). This could be due to the likely higher population densities and more stringent parking constraints of the neighborhoods encompassing apartments and single-family attached houses. In addition, apartment residents are more interested in commuting using AVs (with or without carpooling) than the residents of single-family attached houses, as suggested by the larger marginal effects of the positive interest levels for the apartment residents.

Several important insights are gained into the effects of the current commute travel behavior on inclination toward using AV for commuting in the future. First, those who commute longer (in terms of **commute travel time**) are more interested in both AV types. While corroborating the empirical finding of

Haboucha et al. (2017), this might seem in contrast with my earlier finding in section 2.4.2 about the negative association of total daily (i.e., all trip purposes) VMT with public interest in owned AVs and SAVs. However, it can be explained by noting that people likely enjoy productive use of their commute time conducting work-related activities (e.g., preparing for a business meeting), yet do not similarly value time saving for doing less urgent/important activities in other trip purposes. Such a trip purpose based heterogeneity in time valuation becomes more evident by noting that commuters consider both uncongested and congested travel times, while merely travel distance (regardless of congestion) was shown to describe public interest in AV for (all-purpose) daily trips (see Table 2.6). It is worth mentioning that commute time valuation with AV diminishes in longer commutes as it appears with logarithmic form.

Second, those who currently **choose commute departure time to avoid congestion** are willing to commute alone with AV compared to those with inflexible departure time. This is not surprising as the congestion-averse commuters are likely associated with higher values of time. Third, individuals with a longer **commute history** (which refers to the duration of commuting to the same work place) disfavor commuting with AV in both forms, indicating the role of habitual inertia in shaping travel behavior.

Fourth, commuters who currently drive to work and park their cars at work (i.e., benefit from subsidized parking) and, especially, on street at work appreciate the facilitated **parking** with AVs, which is evidenced by the corresponding positive coefficients in the propensities of both AV types. This is expected since AVs can drop off their passengers at the work place and then move unoccupied to find inexpensive and close parking locations, thereby relieving parking cost, parking search time, and walking distance from the parking location to/from the work place. Finally, commuters who have **night shift** in their work schedule are more likely to be not at all interested in ridesharing with AVs. This is reasonable considering the lower possibility of finding ride matches when the night shift workers' depart from home/work. Finally, workers who do not hold a **driver's license** more likely prefer sharing ride in commuting to commuting alone in AV.

The latent attitudinal and preferential constructs are found crucial in explaining commuters' interests in AV. Consistent with my previous finding for daily travel (section 2.4.2), **safety-concerned** individuals are highly reluctant to commute by AV. Those experiencing a **green travel pattern** and **MOD-savvy** individuals are more interested in commuting with AV in both types. Similar to the model of all-purpose trips (section 2.4.2), the marginal effects of the safety concern construct on all interest levels of (S)AVs are larger than those of the other two latent factors. The marginal effects of the green travel pattern and MOD savviness, however, do not follow the same pattern observed in the model of daily trips. Specifically, a unit change in either of these two latent factors leads to almost equal changes in the probabilities of all interest levels for the AV-alone, whereas the corresponding probabilities of AV-carpool will be impacted more by a unit change in green travel pattern than by that of MOD savviness.

2.4.4. Policy implications

Among the significant observable and unobservable (latent) factors in the estimated models for daily and commute travels, it was found (see Table 2.7 and Table 2.9) that the three latent constructs have larger marginal effects for all (S)AV types. Therefore, in this section I scrutinize the marginal effects of the latent attitudes/preferences on the probabilities of interest levels in private and shared AVs. Results provide policymakers and decision-makers with important insights into planning for an era with (S)AVs that will occur ere long.

It is worth highlighting that the largest (in absolute values) marginal effects relate to the latent construct explaining safety concern for all (S)AV types. As the consumers' safety concerns decrease, the induced jumps in the probabilities of being more interested for using (S)AVs in daily/commute travels will be more tangible than those caused by greener travel pattern and more proclivity for MOD savviness. In particular, the absolute values of the marginal effects of safety concern on "not at all interested" are larger than 1 for all (S)AV types in both daily and commute trips. That is, a unit decrease in safety concern about AVs may lead to more than 100% decrease in the probability of being not at all interested in (S)AVs, regardless of the trip purpose. I can conclude that as consumers gain more trust in the safety of the driverless car technology, the propensity for being more interested in (S)AVs for daily and commute travels may rise up to more than 100%. As a consequence, policymakers and planners may expect increasing returns to investments in policies aimed at reducing safety concerns about AVs. For the other two latent factors, results indicate larger marginal effects of green travel pattern than those of MOD savviness for all (S)AV types in daily/commute travels, however with the only exception being almost equal marginal effects of the two latent factors for commuting alone with AV.

The latent attitudinal/preferential factors can be influenced in two ways. First, proactive policies can be undertaken before the emergence of AVs to negate the public concern about the safety of AVs, promote green travel pattern, and enhance MOD savviness. For example, the (social) media can play a key role in informing the public of the navigation/control precision, equipment reliability, and security of the AV technology as well as the consequent benefits in reducing crashes. Public education campaigns can also be held to encourage green travel pattern and advance MOD savviness. In this regard, it should be noted that the data used in this study is from 2015 and people's exposure to information about AV technology might have changed significantly so far. These policies can be more effectively targeted at specific user classes whose socio-economic characteristics are known — through the estimated structural equation model (see Table 2.5) — to potentially impact most on the latent constructs. Second, unprecedented changes in public behavior could occur over time after the introduction of AVs into the markets. For example, the psychological concerns about the safety of AVs could be gradually relieved as travelers observe the adoption of AVs by neighbors and friends (Bansal et al., 2016). People's travel pattern may also change due to, for example, the potentially lower levels of household vehicle ownership because AVs can serve multiple household members with (dis)similar itineraries. The introduction of SAVs could increase the propensity for MOD savviness by improving the service level of shared mobility systems, which are likely operated more efficiently (Fagnant et al., 2015).

3. Adoption of Autonomous Vehicles with Endogenous Safety Concerns: A Recursive Bivariate Ordered Probit Model

3.1. Introduction

It is envisaged that the emergence of autonomous vehicles (AVs) will transform transportation systems through more efficient mobility and enhanced safety. In particular, AVs could remove the leading cause of road crashes, which is human error in 90% of the U.S. road accidents (Fagnant and Kockelman, 2015). Even without full automation, the economic benefits of partially automated vehicle collision avoidance technologies in the U.S. are projected at up to $202 billion (Harper et al., 2016). Notwithstanding, the recent AV crashes in road tests (e.g., see Digital Trends (2018)) could cast doubts on the reliability of future transport safety with AVs in terms of fatalities and injuries. Such a blurred picture of future road safety is even exacerbated by noting that car manufacturers and decision makers cannot simply prove AV reliability through extensive road tests (Kalra and Paddock, 2016). As a consequence, consumers' perceptions about the safety of a ride in an AV could be negatively affected (Bansal et al., 2016; Kyriakidis et al., 2015; Payre et al., 2014). Despite the potentially significant impact of consumers' safety concern on their adoption of AVs, there is a dearth of behavioral studies to explore the causality between the travelers' safety concern about the AV technology and their AV adoption behavior (Becker and Axhausen, 2017).

The literature on modeling the public adoption of the AV technology is rapidly growing. Yap et al. (2016) modeled travelers' preferences for using AVs as last mile public transport of multimodal train trips in the presence of existing travel modes. The authors estimated a mixed logit model to ascertain the extent the share of the existing transport modes will change as a result of using AVs as a last mile mobility solution. Bansal and Kockelman (2017) employed multinomial and binary logit models within a simulation framework to forecast the long-term adoption of AV technology levels and vehicle transaction decisions in the U.S. Bansal et al. (2016) estimated independent ordered probit models to inquire into the public opinion about willingness to pay for different automation levels, adoption of shared AVs, adoption timing of AVs, and home location decisions after AVs become a common travel mode. Daziano et al. (2017) quantified the willingness to pay for different levels of vehicle automation by estimating a semiparametric random parameter logit model. Krueger et al. (2016) estimated a mixed logit model to determine the adoption of shared AVs with and without ridesharing versus public transit. Haboucha et al. (2017) investigated the commuters' vehicle choice among regular car, private AV, and shared AV using a logit kernel model. Lavieri et al. (2017) modeled traveler preferences for private and shared autonomous vehicles using a multinomial probit model. Nazari et al. (2018a) modeled the public interest in private and shared AVs using a multivariate ordered probit model.

However, existing travel behavior studies on AVs mostly ignore safety concern about the AV technology and mainly focus on socio-economic, built-environment, current travel behavior, and instrumental variables. To my knowledge, there are only three exceptions with limited insights. Yap et al. (2016) used a confirmatory factor analysis to investigate the role of trust in AVs, which represents the extent to which travelers trust the safety of a trip using an AV, service reliability, and sustainability. The authors concluded that the attitudinal factor explaining trust in an AV has the second-largest contribution of all attributes in the model to the total utility. The authors concluded that a higher trust perception of travelers regarding AVs leads to lower disutility for AVs and possibly to a higher willingness to use AVs. Lavieri et al. (2017) and Nazari et al. (2018a) incorporated safety concerns into the decision making process by directly plugging psychological attitudes towards safety of AV technology into the utilities.

A main hypothesis in this dissertation is that AV adoption is controlled by, among various factors, the safety concern of travelers, which is itself a function of exogenous factors. For instance, persons who are more familiar with new technologies, especially vehicle technology, could be expected to have lower concerns about AV safety and thus be more interested in AV adoption. In other words, I simultaneously model AV adoption and safety concern while considering the endogeneity between the two dependent variables. To do so, I estimate a recursive bivariate ordered probit (RBOP) model. In addition to treating endogeneity, the model captures the cross-equation error correlation between the two dependent variables.

Ignoring the endogeneity could lead to inconsistent parameter estimates, inaccurate predictions, and erroneous inferences (Washington et al., 2010).

Very few and recent applications of the RBOP model exist in other disciplines. Brunette et al. (2017) employed a RBOP model in an environmental study to characterize the determinants of the forest owner's risk attitude and the associated impact on production (harvesting) decision. In an economic study, Gray (2014) captured the potential endogeneity of the household's financial position in the overall life satisfaction through a RBOP model. Beaumais and Giannoni (2018) estimated a RBOP model in another economic study to explore the causality between the decision to enter a hotel classification system and the hotel rate.

To illustrate the applicability of this method, this study uses a stated preference data recorded in the state of California. The objective is to explore how Californians react to the advent of AVs (in terms of their adoption behavior) and safety concerns tied with AVs. Note that since AVs are not in the markets, existing studies on the travel behavior implications of AVs rely on the stated preference data as well. I find a significant negative association between safety concern and AV adoption. In other words, as a person disagrees more with AV safety concern, he/she agrees less, strongly or moderately, with AV adoption. I also find significant and positive correlation across the error components of the two equations of the two dependent variables, which suggests same-sign association of the outcomes with the unobserved exogenous variables. Important insights are obtained into the impact on shaping public opinion about AV adoption and safety concern of several socioeconomic and demographic characteristics, current travel behavior factors, and vehicle decision factors and attributes.

The rest of the chapter is organized as follows. The next section presents the formulation of recursive bivariate ordered probit models. Data analysis and model estimation results are then discussed and important policy implications are highlighted.

3.2. Methodology: recursive bivariate ordered probit model

To address endogeneity in a bivariate probit model, Burnett (1997) proposed the recursive bivariate probit model, which jointly models two outcomes while addressing variable endogeneity. Later on, Sajaia (2008) extended the recursive bivariate probit to jointly model two ordinal outcomes while addressing endogeneity. In this chapter, I estimate a recursive bivariate ordered probit model to simultaneously model AV adoption and AV safety addressing endogeneity and cross-equation correlation of error terms. The latent ordinal outcomes of AV safety ($y^*_{i,1}$) and AV adoption ($y^*_{i,2}$) for individual $i, i = 1, 2, \dots, N$ are written as Eq. (3.1).

$$
\begin{aligned}
&y^*_{i,1} = \boldsymbol{\beta'_1 x_{i,1}} + \varepsilon_{i,1}, && y_{i,1} = j_1 \text{ if } \mu_{j_1-1} < y^*_{i,1} < \mu_{j_1}, && j_1 = 1, \dots, J_1 \\
&y^*_{i,2} = \boldsymbol{\beta'_2 x_{i,2}} + \theta y^*_{i,1} + \varepsilon_{i,2}, && y_{i,2} = j_2 \text{ if } \mu_{j_2-1} < y^*_{i,2} < \mu_{j_2}, && j_2 = 1, \dots, J_2
\end{aligned} \tag{3.1}
$$

where, $\boldsymbol{x_{i,1}}$ and $\boldsymbol{x_{i,2}}$ are vectors of explanatory variables and $\boldsymbol{\beta'_1}$ and $\boldsymbol{\beta'_2}$ are the corresponding vectors of known coefficients. The error component of the equations, ε_1 and ε_2, are distributed as bivariate normal with correlation ρ. The weight of $y^*_{i,1}$ on $y^*_{i,2}$ is determined by θ, which is an unknown scalar. The explanatory variables in both equations $\boldsymbol{x_{i,1}}$ and $\boldsymbol{x_{i,2}}$ meet the conditions of exogeneity so as $E(\varepsilon_{i,1}|\boldsymbol{x_{i,1}}) = 0$ and $E(\varepsilon_{i,2}|\boldsymbol{x_{i,2}}) = 0$. Given the explanatory variables, the joint probability of $y_{i,1} = j_1$ and $y_{i,2} = j_2$ is written as Eq. (3.2).

$$
\begin{aligned}
Prob&(y_{i,1} = j_1, y_{i,2} = j_2|\boldsymbol{x_{i,1}}, \boldsymbol{x_{i,2}}) \\
&= \Big[\Phi_2\big[(\mu_{j_1} - \boldsymbol{\beta'_1 x_{i,1}}), (\mu_{j_2} - \boldsymbol{\beta'_2 x_{i,2}} - \theta\boldsymbol{\beta'_1 x_{i,1}})\xi, \tilde{\rho}\big] \\
&- \Phi_2\big[(\mu_{j_1-1} - \boldsymbol{\beta'_1 x_{i,1}}), (\mu_{j_2} - \boldsymbol{\beta'_2 x_{i,2}} - \theta\boldsymbol{\beta'_1 x_{i,1}})\xi, \tilde{\rho}\big]\Big] \\
&- \Big[\Phi_2\big[(\mu_{j_1} - \boldsymbol{\beta'_1 x_{i,1}}), (\mu_{j_2-1} - \boldsymbol{\beta'_2 x_{i,2}} - \theta\boldsymbol{\beta'_1 x_{i,1}})\xi, \tilde{\rho}\big] \\
&- \Phi_2\big[(\mu_{j_1-1} - \boldsymbol{\beta'_1 x_{i,1}}), (\mu_{j_2-1} - \boldsymbol{\beta'_2 x_{i,2}} - \theta\boldsymbol{\beta'_1 x_{i,1}})\xi, \tilde{\rho}\big]\Big]
\end{aligned} \tag{3.2}
$$

where Φ_2 is the bivariate standard normal cumulative distribution function. In addition, $\xi = \frac{1}{\sqrt{1+2\theta\rho+\theta^2}}$ and $\tilde{\rho} = \xi(\theta + \rho)$. Assuming that observations are independent, Eq. (3.3) shows the logarithmic likelihood function.

$$\ln \mathcal{L} = \sum_{i=1}^{N} \sum_{j_1=1}^{J_1} \sum_{j_2=1}^{J_2} I(y_{i,1} = j_1, y_{i,2} = j_2) \ln Prob(y_{i,1} = j_1, y_{i,2} = j_2) \tag{3.3}$$

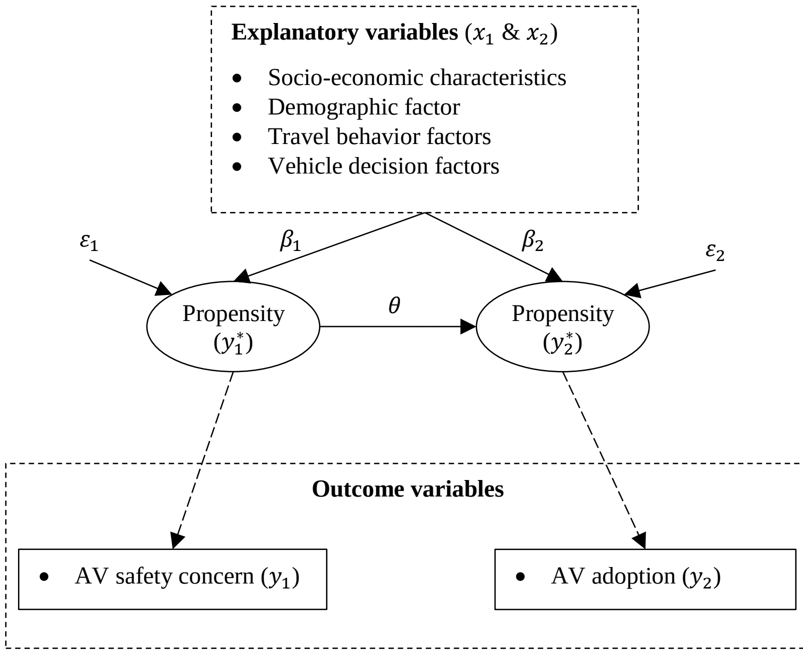


Figure 3.1. Framework of the recursive bivariate ordered probit model of AV adoption and AV safety concern

For outcome m ($m = 1, 2$), the vector of estimated coefficients ($\boldsymbol{\beta}_\mathbf{m}$) in an ordered response model is only used to interpret the highest and the lowest ordered levels (Greene and Hensher, 2010). Specifically, a positive coefficient (β_m) for outcome m implies that an increase in $x_{i,m}$ increases the probability of the highest ordered level ($y_{i,m} = J_m$) and decreases the probability of the lowest ordered level ($y_{i,m} = 1$). To interpret each intermediate ordered level ($y_{i,m} = 2, y_{i,m} = 3, \dots, y_{i,m} = J_m - 1$), one should calculate the marginal effect for the corresponding level. To do so, it is assumed that ρ equals zero, which is an admittedly trivial extension of bivariate ordered probit models (Greene, 2000; Greene and Hensher, 2010; Washington et al., 2010). For a continuous variable explaining outcome m, the marginal effect of ordered level j_m for each individual is computed as in Eq. (3.4), which are then averaged over the sample (Greene, 2000; Greene and Hensher, 2010; Washington et al., 2010).

$$\boldsymbol{ME}_{\boldsymbol{j_m}}(\boldsymbol{x_{i,m}}) = \frac{\partial Prob\ (y_{i,m}=j_m|\boldsymbol{x_{i,m}})}{\partial \boldsymbol{x_{i,m}}} = \left[\varphi\left(\mu_{j_m-1} - \boldsymbol{\beta'_m x_{i,m}}\right) - \varphi\left(\mu_{j_m} - \boldsymbol{\beta'_m x_{i,m}}\right)\right] \boldsymbol{\beta_m} \quad \forall m \in \{1,2\} \tag{3.4}$$

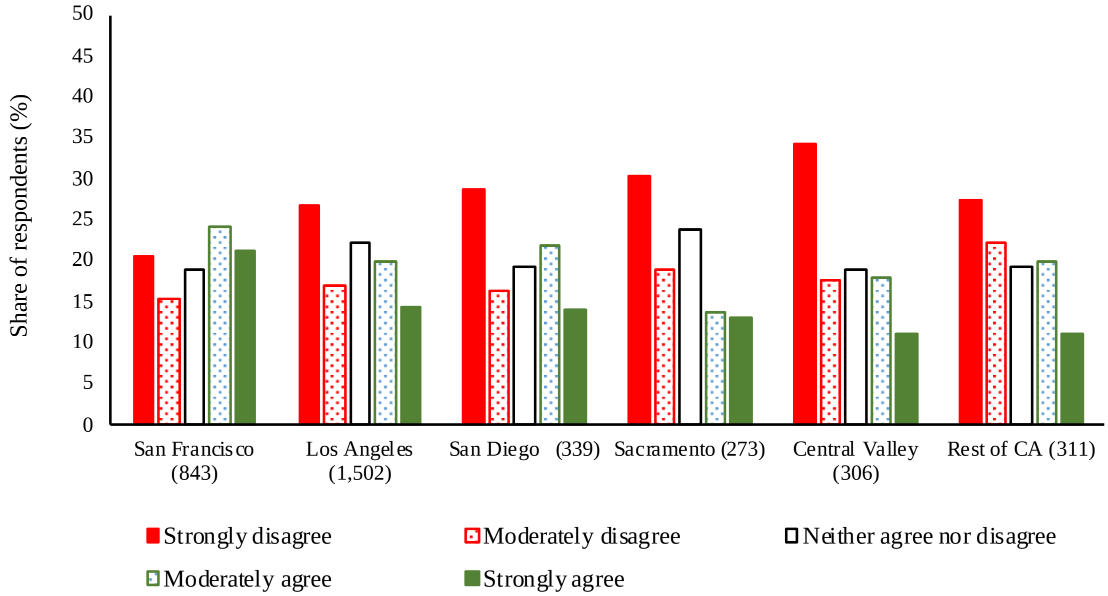
where $\varphi(\cdot)$ is the probability density function of normal distribution. For a dummy variable d_i with its corresponding coefficient denoted by τ_i, the marginal effect of ordered level j_m is computed according to Eq. (3.5), in which $\Phi(\cdot)$ is the cumulative density function of normal distribution. The equation measures the effect of a change in d_i from 0 to 1 while all other variables are held at their arithmetic means (Greene, 2000; Greene and Hensher, 2010; Washington et al., 2010).

$$\begin{aligned}\boldsymbol{ME}_{\boldsymbol{j_m}}(d_i) = &\left[\Phi\left(\mu_{j_m} - \boldsymbol{\beta'_m x_{i,m}} + \tau_i\right) - \Phi\left(\mu_{j_m-1} - \boldsymbol{\beta'_m x_{i,m}} + \tau_i\right)\right] \\ &- \left[\Phi\left(\mu_{j_m} - \boldsymbol{\beta'_m x_{i,m}}\right) - \Phi\left(\mu_{j_m-1} - \boldsymbol{\beta'_m x_{i,m}}\right)\right] \quad \forall m \in \{1,2\}\end{aligned} \tag{3.5}$$

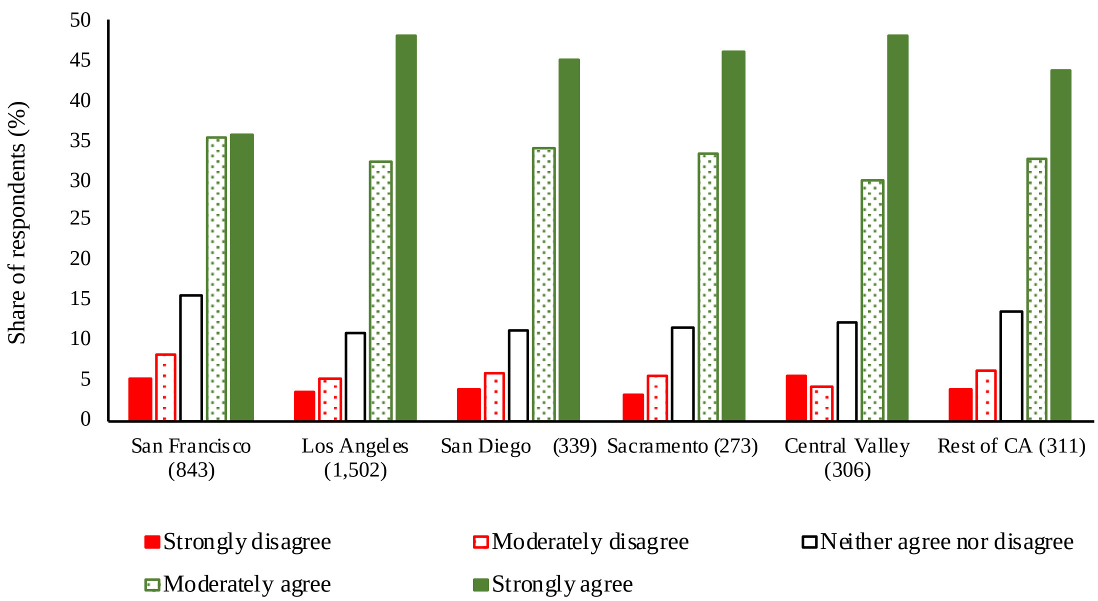
3.3. Data

The majority of the existing studies on AV adoption behavior collect stated preference data sets, in which respondents choose one of the alternatives presented as possible scenarios (see Becker and Axhausen (2017) for a recent review of these studies). Each scenario in a stated preferences survey presents one alternative (e.g., AV, shared AV, and conventional vehicle) with specific features and a respondent could choose one or multiple options. In this research, I estimate a RBOP mode using the stated preference data set provided by California Energy Commission (2016), which does not contain features of AVs, but the respondents are asked about their agreement level with AV adoption and AV safety. Specifically, the respondents answered the following two questions by Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

- AV adoption: “I would consider purchasing a vehicle that is fully self-driving (i.e., the vehicle drives itself)”.
- AV safety concern: “I am concerned about the safety of self-driving vehicles”.



(a)



(b)

Figure 3.2. Response of the five regions of the state of California to: (a) AV adoption and (b) AV safety concern (note: the numbers in the parenthesis are the number of observations for the corresponding region)

I assume that “considering AV as an option for future vehicle decision” could represent potential for adopting an AV in the future. The data set contains Californians’ response to the mentioned questions from five regions of California: San Francisco, Los Angles, San Diego, Sacramento, Central Valley, and the rest of California. Based on the residential region of the respondents, the distribution of the response variables is depicted in Figure 3.2. It is interesting to note that almost half of the respondents in all five regions and the rest of California strongly or moderately disagree with adopting an AV. In addition, majority of them strongly or moderately agree on safety concerns about AVs. Among the five regions, the residents of San Francisco showed more agreement with AV adoption and more disagreement with its safety concerns.

A traveler’s opinion about AV adoption and AV safety concern is related to his/her socio-economic and demographic characteristics, travel behavior, and vehicle decisions. Table 3.1 shows participants’ socio-economic characteristics at both individual- and household-level and their demographic characteristics. Gender, education, and employment type are the significant factors at the individual-level. Their households are also characterized by their income level, structure, number of vehicle, possession of plug-in electric vehicle, and solar panels. The distribution of the respondents over the five regions of the state of California is also shown in the table, which is corresponding to their population share of California.

The other two types of explanatory variables, travel behavior and vehicle decision factors, are listed in two sections of Travel behavior of the respondents are explained by their annual VMT, daily parking cost at residence, and frequency of using mobility-on-demand services. The significant factors of vehicle decision in AV adoption and AV safety are in three variables of attitude towards vehicle decision, vehicle history, and future vehicle decision factors.

Table 3.1. Sample data for socio-economic and demographic characteristics at individual- and household-level (sample size = 3,574)

Explanatory variables	Category	# obs	Share (%)
Socio-economic characteristics (individual-level)			
Gender	Female	1,790	50.08
	Male	1,784	49.92
Education	Level 1 (high school graduate or lower)	243	6.80
	Level 2 (technical school/professional business school, some college, or college graduate (2-year degree))	1,033	28.90
	Level 3 (college graduate (4-year degree))	1,159	32.43
	Level 4 (post-graduate degree)	1,139	31.87
Employment type	Full-time employed	1,736	48.57
	Self-employed	227	6.35
	Part-time employed	389	10.88
	Not employed	1,222	34.19
Socio-economic characteristics (household-level)			
Household income	Low level (< 75K)	1,504	42.08
	Medium level (75K ≤ < 200K)	1,723	48.21
	High level (≥ 200K)	347	9.71
Household structure			
# kids (age < 6)	Mean = 0.144, SD = 0.435	—	—
# teenagers (6 ≤ age < 12)	Mean = 0.172, SD = 0.489	—	—
# young children (12 ≤ age < 16)	Mean = 0.105, SD = 0.360	—	—
# adults (age ≥ 16)	Mean = 2.039, SD = 0.857	—	—
# vehicles in household	Mean = 1.947, SD = 0.936	—	—
# vehicles per # adults (in household)	Mean = 1.013, SD = 0.449	—	—
Household has plug-in electric vehicle	Yes	315	8.81
	No	3,259	91.19
Household has solar panels or plans to purchase	Yes	1,110	31.06
	No	2,464	68.94
Demographic factor			
Residential region	San Francisco	843	23.59
	Log Angeles	1,502	42.03
	San Diego	339	9.49
	Sacramento	273	7.64
	Central Valley	306	8.56
	Rest of California	311	8.70

Table 3.2. Sample data for travel behavior and vehicle decision factors (sample size = 3,574)

Explanatory variables	Category	# obs	Share (%)
Travel behavior factors			
Annual VMT (individual-level)	Mean = 10,133, SD = 11,433	—	—
Daily parking cost at residence	Mean = 5.040, SD = 73.402	—	—
Use of mobility-on-demand services			
Car-sharing frequency	I am not interested in participating	1,898	53.11
	I might participate someday	1,160	32.46
	I have not participated in the past, but I plan to participate	158	4.42
	I have participated in the past, but am not currently participating	214	5.99
	I currently participate	144	4.03
Ride-sourcing frequency	I am not interested in participating	1,361	38.08
	I might participate someday	817	22.86
	I have not participated in the past, but I plan to participate	177	4.95
	I have participated in the past, but am not currently participating	504	14.10
	I currently participate	715	20.01
Vehicle decision factors			
Important attributes of a vehicle			
Reliability	Yes	1,707	47.76
	No	1,867	52.24
Brand	Yes	844	23.61
	No	2,730	76.39
Vehicle history of household in the last 10 years			
# vehicles purchased new	Mean = 1.213, SD = 1.288	—	—
# vehicles purchased used	Mean = 1.003, SD = 1.363	—	—
# vehicles leased	Mean = 0.309, SD = 0.983	—	—
The extent of involvement in future vehicle decisions (purchase or lease)	Sole decision maker	1,651	46.19
	Primary decision maker	867	24.26
	Shared equally with another household member(s)	1,056	29.55
Logarithm of price for replacing one of current vehicles	Mean = 9.813, SD = 1.834	—	—
Logarithm of price for adding a vehicle	Mean = 3.797, SD = 4.896	—	—

3.4. Results

Table 3.3 shows the estimation results of the recursive bivariate ordered probit model of people's AV adoption with endogenous AV safety while accounting for cross-equation correlation. The estimated model has a fair prediction accuracy (indicated by $R^2 = 0.21$). In addition, the ordered levels of both dependent variables are separated by significant estimated thresholds.

The estimated model captures the cross-equation error correlations (i.e., ρ: correlation between error components of the model outcomes in Eq. (3.1)), which appropriately absorb any propensity for AV adoption and AV safety associated with omitted exogenous variables (or unobserved factors). I find significant and positive correlations ($\rho = 0.394$) across the error components of the equations which suggests same-sign association of the outcomes with the omitted exogenous variables. It should be noted that the correlation between the two dependent variables, AV adoption and AV safety, is negative. In fact, the cross-equation error correlation is different from the correlation between the two outcome variables; the former captures the unobserved heterogeneity in the error terms, while the latter shows the linear association between the two variables.

To test the hypothesis of zero correlation of the error terms ($\rho = 0$), I use the likelihood ratio test by comparing the estimated model with a restricted model which corresponds to independent ordered response estimation of each of the two outcomes (Greene and Hensher, 2010). The likelihood ratio test with p-value $<< 0.0001$ shows that in this particular empirical context, it cannot be rejected to model AV adoption and AV safety accounting for the correlation across the error components of the equations.

Table 3.3. Estimation results of recursive bivariate ordered probit model

Explanatory variables	AV adoption		AV safety concern	
	coef.	t-stat	coef.	t-stat
Constant	3.703	11.34	2.414	18.48
Endogenous variable				
AV safety	-0.644	-8.79	—	—
Socio-economic characteristics				
Gender				
Female	-0.110	-2.62	0.156	4.14
Education				
Level 2	—	—	-0.144	-1.83
Level 3	—	—	-0.205	-2.64
Level 4	—	—	-0.268	-3.39
Employment type				
Full-time employed	0.065	1.70	—	—
Self-employed	0.107	1.50	—	—
Household income				
Low level (less than 75K)	-0.086	-2.20	—	—
High level (equal or more than 200K)	0.191	3.02	—	—
Household structure				
# kids (age < 6) and teenagers (6 ≤ age < 12)	0.083	3.25	—	—
# young children (12 ≤ age < 16)	0.139	2.85	—	—
# vehicles per # adults (in household)	-0.181	-4.54	—	—
Household has plug-in electric vehicle				
Yes = 1	—	—	-0.468	-7.50
Household has/ plans to purchase solar panels				
Yes = 1	—	—	-0.082	-2.01
Demographic factor				
Residential region				
San Francisco	0.190	4.01	—	—
Log Angeles	0.069	1.76	—	—
Travel behavior factors				
Logarithm of annual VMT (individual-level)	-0.037	-3.49	-0.031	-2.88
Use of mobility-on-demand services				
Car-sharing frequency	—	—	-0.064	-2.99
Ride-sharing frequency	—	—	-0.046	-3.69
Daily parking cost at residence ($\times 10^{-3}$)	0.724	2.54	—	—
Vehicle decision factors				
Important attributes of a vehicle				
Reliability	—	—	0.081	2.30
Brand	—	—	0.097	2.32
Vehicle history of household in the past 10 years				
# vehicles purchased new	0.028	1.99	—	—
# vehicles leased	0.046	2.58	—	—
Involvement in future vehicle decisions				
Sole decision maker	0.140	3.20	—	—
Shared equally with other household member(s)	-0.082	-1.76	—	—

Table 3.3. Estimation results of recursive bivariate ordered probit model

Explanatory variables	AV adoption		AV safety concern	
	coef.	t-stat	coef.	t-stat
Logarithm of price for replacing one of vehicles	-0.014	-1.49	—	—
Logarithm of price for adding a vehicle	0.014	3.59	—	—
Error correlations				
AV adoption	1.00	—	**0.394**	3.84
AV safety concerns			1.00	—
Thresholds				
Threshold 1	0.00*	—	0.00*	—
Threshold 2	0.486	18.88	0.504	14.55
Threshold 3	1.040	23.10	1.051	24.85
Threshold 4	1.735	25.49	1.953	45.06
Goodness-of-fit measures				
No. of observations = 3,574				
$LL(\beta)$ = -9,877, $LL(0)$ = -12,528, R^2 = 0.21				

Almost all estimated coefficients are statistically significant at the 0.05 level and intuitively signed. The sign of each estimated coefficient is of particular interest: a positive sign means increase in the highest agreement level (i.e., strongly agree) or decrease in the lowest disagreement level (i.e., strongly disagree) of AV adoption and AV safety (Greene and Hensher, 2010). However, analysis of the intermediate order levels of an ordered probit model (i.e., the three middle agreement levels in this model) requires computing the associated marginal effects, as illustrated in the methodology section. Table 3.4 presents the marginal effects of the exogenous variables explaining each level of agreement with AV adoption and AV safety, which refer to the approximate change in the probability of each agreement level with AV adoption and AV safety in response to a unit change in the desired exogenous variable while other variables are held constant at their respective population mean.

The estimated model further accounts for endogeneity of AV safety in the equation of AV adoption, which is signified by the negative coefficient of AV safety in the equation of AV adoption. In fact, as a person disagrees more with AV safety, he/she agrees less, strongly or moderately, with AV adoption. To test the hypothesis of no endogeneity, I use the likelihood ratio test by comparing the estimated model with a restricted model which corresponds to bivariate ordered probit model with no endogeneity (Greene and Hensher, 2010). The likelihood ratio test with $p\text{-value} < 0.05$ shows that in this particular empirical context, it cannot be rejected to jointly model AV adoption and AV safety without endogenous AV safety.

Table 3.4. Marginal effects for recursive bivariate ordered probit model

Explanatory variables	AV adoption					AV safety concern				
	Strongly disagree	Moderately disagree	Neither agree nor disagree	Moderately agree	Strongly agree	Strongly disagree	Moderately disagree	Neither agree nor	Moderately agree	Strongly agree
Endogenous variable										
AV safety	0.190	0.019	-0.019	-0.060	-0.131	—	—	—	—	—
Socio-economic characteristics										
Gender										
Female	0.033	0.003	-0.003	-0.010	-0.022	-0.013	-0.014	-0.019	-0.013	0.060
Education										
Level 2	—	—	—	—	—	0.012	0.013	0.017	0.012	-0.055
Level 3	—	—	—	—	—	0.017	0.019	0.025	0.018	-0.079
Level 4	—	—	—	—	—	0.023	0.024	0.032	0.023	-0.103
Employment type										
Full-time employed	-0.019	-0.002	0.002	0.006	0.007	—	—	—	—	—
Self-employed	-0.032	-0.003	0.003	0.010	0.022	—	—	—	—	—
Household income										
Low level (less than 75K)	0.026	0.002	-0.002	-0.008	-0.018	—	—	—	—	—
High level (equal or more than 200K)	-0.056	-0.006	0.006	0.018	0.039	—	—	—	—	—
Household structure										
# kids (age < 6) and teenagers (6 ≤ age < 12)	-0.024	-0.002	0.002	0.008	0.017	—	—	—	—	—
# young children (12 ≤ age < 16)	-0.041	-0.004	0.004	0.013	0.028	—	—	—	—	—
# vehicles per # adults (in household)	0.053	0.005	-0.005	-0.017	-0.037	—	—	—	—	—
Household has plug-in electric vehicle										
Yes = 1	—	—	—	—	—	0.040	0.042	0.057	0.040	-0.179
Household has/plans to purchase solar panels										
Yes = 1	—	—	—	—	—	0.007	0.007	0.010	0.007	-0.031
Demographic factor										
Residential region										
San Francisco	-0.056	-0.006	0.005	0.018	0.039	—	—	—	—	—
Log Angeles	-0.020	-0.002	0.002	0.006	0.014	—	—	—	—	—
Travel behavior factors										
Logarithm of annual VMT (individual-level)	0.011	0.001	-0.001	-0.003	-0.007	0.003	0.003	0.004	0.003	-0.012
Use of mobility-on-demand services										
Car-sharing frequency	—	—	—	—	—	0.005	0.006	0.008	0.006	-0.024
Ride-sharing frequency	—	—	—	—	—	0.004	0.004	0.006	0.004	-0.017
Daily parking cost at residence ($\times 10^{-2}$)	-0.214	-0.021	0.021	0.067	0.147	—	—	—	—	—
Vehicle decision factors										
Important attributes of a vehicle										
Reliability	—	—	—	—	—	-0.007	-0.007	-0.010	-0.007	0.031
Brand	—	—	—	—	—	-0.008	-0.009	-0.012	-0.008	0.037
Vehicle history of household in the past 10 years										
# vehicles purchased new	-0.008	-0.001	0.001	0.003	0.006	—	—	—	—	—
# vehicles leased	-0.014	-0.001	0.001	0.004	0.009	—	—	—	—	—

Table 3.4. Marginal effects for recursive bivariate ordered probit model

Explanatory variables	AV adoption					AV safety concern				
	Strongly disagree	Moderately disagree	Neither agree nor disagree	Moderately agree	Strongly agree	Strongly disagree	Moderately disagree	Neither agree nor …	Moderately agree	Strongly agree
Involvement in future vehicle decisions										
Sole decision maker	-0.041	-0.004	0.004	0.013	0.028	—	—	—	—	—
Shared equally with other household member(s)	0.024	0.002	-0.002	-0.008	-0.017	—	—	—	—	—
Logarithm of price for replacing one of vehicles	0.004	0.0004	-0.0004	-0.001	-0.003	—	—	—	—	—
Logarithm of price for adding a vehicle	-0.004	-0.0004	0.0004	0.002	0.003	—	—	—	—	—

3.4.1. Socio-economic characteristics

Among socio-economic characteristics, gender appears in both equations as a dummy variable, which takes value 1 for ***females***. It implies that the impact of this factor goes beyond what penetrates to AV adoption equation through the variable AV safety. As the estimation results and the marginal effects reveal, females likely are strongly concerned about the safety of AV and probably strongly or moderately disagree with AV adoption. The ***education level*** of the individuals is the next socio-economic characteristics which is shown to be significant in the response variable pertaining to AV safety concern. Persons who attain degrees higher than high school are less likely to strongly agree with safety issues of AVs and their disagreement decreases as the level of their degree becomes higher. In fact, the lowest possible strong agreement with AV safety concern is ascribed to the graduate degree holders. Two ***employment types***, full-time and self-employment, are positively signed in the AV adoption equation. It means that full-time and self-employed persons, especially self-employed ones, are more likely to agree with AV adoption than part-time employed and unemployed persons.

The rest of the influential socio-economic characteristics relate to the households of the individuals. The variable ***household income*** appears with an expected sign: those who live in a household with low level of income (less than 75K) are more inclined towards disagreement with AV adoption while members of households with high income level (equal or more than 200K) more likely agree with AV adoption. The ***household structure*** also affects the AV adoption behavior of its members through two variables: the number of kids (age < 6) and teenagers ($6 \leq$ age < 12) as well as the number of young children ($12 \leq$ age < 16) in the household. Results indicate that households with more children, especially older ones ($12 \leq$ age < 16), will likely agree with adopting an AV.

In the AV studies, it is still a debate to determine the relationship between the AV adoption and household vehicle ownership. In one side, one group of studies found that persons in households with larger number of vehicles will be more interested in replacing their vehicle(s) with an AV or adding an AV as another vehicle. The other group of studies, on the other side, showed that persons with no vehicles in their household will adopt AVs as the first vehicle. Additionally, it should be noted that how many persons in one household could potentially use its vehicles. In fact, there is a significant difference in travel behavior and vehicle decisions of two households with the same level of vehicle ownership but different number of adults (age $\geq$ 16). A household who assigns one vehicle, or even more, to each one of its adult members show different travel behavior and in turn different vehicle decisions from a household with lower number of vehicles assigned to larger number of adults. Therefore, I define the variable ***number of vehicles per number of adults in a household*** which has a negative sign in the equation of AV adoption. As the number of assigned vehicles to potential drivers, or adults, in one household increases, the household members probably strongly or moderately disagree with AV adoption. These findings imply that the potential AV adopters, ceteris paribus, could be among persons whose households provide less vehicles for its members or probably consider AVs as the first vehicle(s) in the household. In the data set, I also observed that the mean vehicle ownership of individuals with positive agreement with AV adoption is smaller than others with negative agreement.

Since AVs are studied as a new vehicle technology, persons' awareness of and openness to technological development could affect AV adoption. This factor is reflected by two dummy variables. The first variable relates to the adoption of a recent vehicle technology, which is ***plug-in electric vehicles***. The latter is not limited to vehicle technology and is a broader indicator of familiarity with new technologies: whether a household has ***solar panels/plans to purchase them*** or not. The respondents with positive answers to these two questions are more inclined towards not strongly agreeing with AV safety concern. It is also worth noting that these variables are not significant in the equation of AV adoption and its impact on AV adoption only penetrates through the AV safety equation caused by considering the endogeneity.

3.4.2. Demographic factor

As already described in the data section, the data is collected in the five regions of the state of California. Given the role of built environment in travel behavior (Bhat and Guo, 2007) and possibly AV adoption

(Nazari et al., 2018a), I tried the demographic variable denoting the persons' residential region in model estimation, but only two regions appeared significant in only AV adoption equation. It means that the residents of San Francisco and Los Angeles likely agree more with AV adoption than the residents of San Diego, Sacramento, Central Valley, and rest of California. In addition, persons who live in San Francisco have inclination towards AVs almost twice the Los Angeles residents.

3.4.3. Travel behavior factor

The current travel behavior of individuals is undoubtedly crucial in shaping their current vehicle decisions and probably their future decisions. The findings of this research reveal that AV adoption in future will also be influenced by three dimensions of travel behavior. The first dimension is ***annual VMT at individual-level***, whose logarithmic form is negatively signed in both equations. It means that as VMT of an individual increases, his/her strong agreement with AV safety concern will likely decrease and also he/she disagrees more, strongly or moderately, with AV adoption. In fact, it means that persons who drive more (larger VMT) are less concerned about AV safety and at the same time are less interested in adoption of an AV. In other words, these persons are probably less concerned about safety issues of an AV, but they still have other concerns about AVs, which discourage them to adopt an AV. In addition, the logarithmic form of this variable in both equations implies its diminishing impact for larger values of VMT.

The second dimension of travel behavior of a person is defined by his/her ***frequency of using mobility-on-demand services***. Frequent users of these services, especially car-sharing services, tend to have less strong agreement with AV safety concern. Individuals' travel behavior, as the third dimension of travel behavior, is defined by ***daily parking cost at their residence***. The positive sign of the estimated coefficient of this variable indicates that as the cost of parking at residence increases, individuals probably agree more with AV adoption. It can be concluded that the self-driving and especially self-parking feature of AVs is more of interest to persons who live in a dense neighborhood with larger parking cost values.

3.4.4. Vehicle decision factors

This category of the explanatory variables includes three types of factors. The first one captures individuals' attitude towards vehicle decisions among which two of them are significant in the AV safety concern equation. Persons who pick ***reliability*** and ***brand*** as the important attributes of a vehicle at the purchase time likely agree strongly with AV safety concern compared to those with attention to other vehicle attributes (e.g., vehicle price, fuel cost, and vehicle style). The second type of vehicle decision factors relates to ***households' vehicle transaction history***. As the number of purchased and leased, especially leased, vehicles of a household increases, the tendency of its members towards agreeing with AVs increases.

The factors describing the future decisions of an individual places as the third type of vehicle decision factors. I find ***the extent of involvement in the future vehicle decision*** a significant factor explaining the AV adoption behavior such that sole decision-makers on their vehicle adoption are more willing to adopt an AV, while those who share their decision-making with the other household members probably strongly or moderately disagree with AV adoption. Furthermore, two factors of willingness to pay for the future vehicle influence the adoption of AVs with opposing signs and in logarithmic form: ***price for replacing one of the current vehicles with another one*** and ***price for adding a vehicle to the current vehicles***. Larger values of willingness to pay for replacing a vehicle could be translated into negative tendency towards AVs whereas larger values for adding a vehicle increases the probability of adopting an AV. In addition, these tendency for both variables has diminishing impact on AV adoption due to their logarithmic form.

4. Revelations from a National Retrospective Vehicle Survey

The materials of the current chapter are partially published with the following citation: "Nazari, F., Mohammadian, A., Stephens, T., 2019. Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. Transportation Research Part D: Transport and Environment 72, 65-82." Permission for reuse of the above publication in the dissertation is obtained from Elsevier (see Appendix B).

4.1. Introduction

The U.S. is responsible for 20% of the world petroleum consumption, of which 19% is imported (Davis et al., 2018). With a share of 70% in 2017, the transportation sector is the major petroleum consumer in the U.S. (US DOE, Energy Information Administration, 2018). Transportation also accounts for 28% of the U.S. greenhouse gas (GHG) emissions (US EPA, 2018), 60% of which is contributed by light-duty vehicles. In view of the role of transportation and light-duty vehicles in reliance on oil imports and the associated consequences in energy security, climate change, and public health, policy makers, vehicle manufacturers, and technology developers are interested in advancing alternative fuel technologies such as electric vehicles (EVs). Initial attempts in the early 2000s introduced hybrid electric vehicles (HEVs), which combust liquid fuels (e.g., gasoline) while also recapturing the lost energy during braking into batteries. Released in 2010, plug-in electric vehicles (PEVs) draw energy from an electricity grid. PEVs include both plug-in hybrid electric vehicles (PHEVs), which use both liquid fuels and electricity, and battery electric vehicles (BEVs), which use only electricity.

Realization of significant EV[1] benefits requires its mass acceptance and adoption by the public. Despite the growing PEV stock in the U.S. since 2010 —with a greater BEV uptake than that of PHEV— and surpassing 0.6 million vehicles threshold in 2017 and 1.0 million in 2018 (US DOE, Office of Energy Efficiency & Renewable Energy, 2018a), the scale achieved so far in the U.S. is very small as evidenced by a PEV sales share of 1.65% of light-duty vehicles in 2018 (European Alternative Fuels Observatory, 2018; Auto Alliance, 2018). To enhance the context-dependent EV adoption in the U.S., one should develop a disaggregate model on Americans' EV adoption behavior using a detailed dataset collected in a sufficiently large and heterogeneous region of the U.S. A disaggregate-level model in fact brings the capability to characterize EV users by their socio-economic characteristics, demographic factors, attitude/perception/lifestyle preference, and attributes of their vehicles. Furthermore, these models are a tool for better assessing the effectiveness of polices aimed at removing barriers to PEV adoption[2].

Four issues are of note in the existing studies on the adoption of EVs. *First*, due to the recent advent of EVs (especially PEVs), most of the studies use stated preference (SP) datasets. However, there may be discrepancies between choices determined by SP data and people's actual choice in the market that is referred to as "hypothetical bias" (Beck et al., 2016). Revealed preference (RP) datasets are required to estimate more realistic models, which describe EV adoption behavior rather than intention to adopt EV. To my knowledge, the only study using RP data is Javid and Nejat (2017), who estimated a binary choice model to ascertain PEV versus non-PEV adoption behavior in the state of California. *Second*, most of the studies do not distinguish between the two types of PEVs (i.e., PHEVs and BEVs). Although both PHEVs and BEVs are charged by plugging to an electricity grid, they have several differences and thus attract different consumers.

[1] Throughout the dissertation, EVs include HEVs, PHEVs, and BEVs.

[2] A review of these policies (such as incentives, laws, and regulations), which are set by the U.S. federal, state, and local agencies, could be found in Jin et al. (2014), Tal and Nicholas (2016), Hardman et al. (2017), Zambrano-Gutiérrez et al. (2018), and Stephens et al. (2018).

Third, EV adoption behavior could be better captured by probing into history of household vehicle decision. This issue could be resolved by collecting a panel data and modeling household vehicle decision in a dynamic framework. *Fourth*, to gain a more behaviorally realistic insight into EV adoption behavior, it is critical to explicitly account for the unobservable (*latent*) subjective attitudes, perception, and lifestyle preference influencing decision-making, along with the observable factors (such as socio-economic characteristics of decisions-makers, features of their surrounding built environment, and their current daily and commute travel behavior characteristics) explaining the decision-making process (McFadden, 1986; Train et al., 1987). Motivated by the above gaps in modeling EV adoption, this dissertation makes an attempt to more realistically model public adoption of EVs using a U.S. based RP panel data while distinguishing between PHEVs and BEVs adoption behavior as well as taking into account latent constructs. To this end, I conducted a first-of-its-kind national retrospective vehicle survey (RVS) collected by Qualtrics in March-June 2018. The rest of this chapter presents a thorough statistical analysis of the collected database.

4.2. Analysis of retrospective vehicle survey

RVS contains information of 1,691 American households who own 3,326 vehicles. The information of each household is asked from one respondent. Figure 4.1 visualizes location of the respondents, most of whom live in the states of California, Illinois, Texas, New York, and New Jersey. The respondents are asked about five types of questions. *First*, they determined socio-economic characteristics of their households and demographic factors of their residence (section 4.2.1). *Second*, they characterized their own socio-economic attributes. Furthermore, various indicators determined the respondents' attitude, perception, and lifestyle preference (section 4.2.2). *Third*, extensive questions were asked about various attributes of households' vehicles (section 4.2.3). Each vehicle of a household is mostly driven by one person, i.e., principal driver, whose socio-economic characteristics and travel behavior are collected by *fourth* question type (section 4.2.4). *Finally*, the respondents retrospectively were asked about dynamics of household characteristics and their vehicles over the past 10 years from 2008 to 2017 (section 4.2.5). The mentioned survey questions are listed below.

- Household-level
  - Socio-economic characteristics
  - Demographic attributes
- Individual-level
  - Socio-economic characteristics
  - Attitudinal, perceptual, and preferential factors
- Households' vehicles
  - Vehicle attributes
- Principal drivers
  - Socio-economic characteristics
  - Travel behavior
- Dynamics of household characteristics and their vehicles over the past 10 years (2008-2017)
  - Vehicle transaction decisions
  - Change in socio-economic characteristics

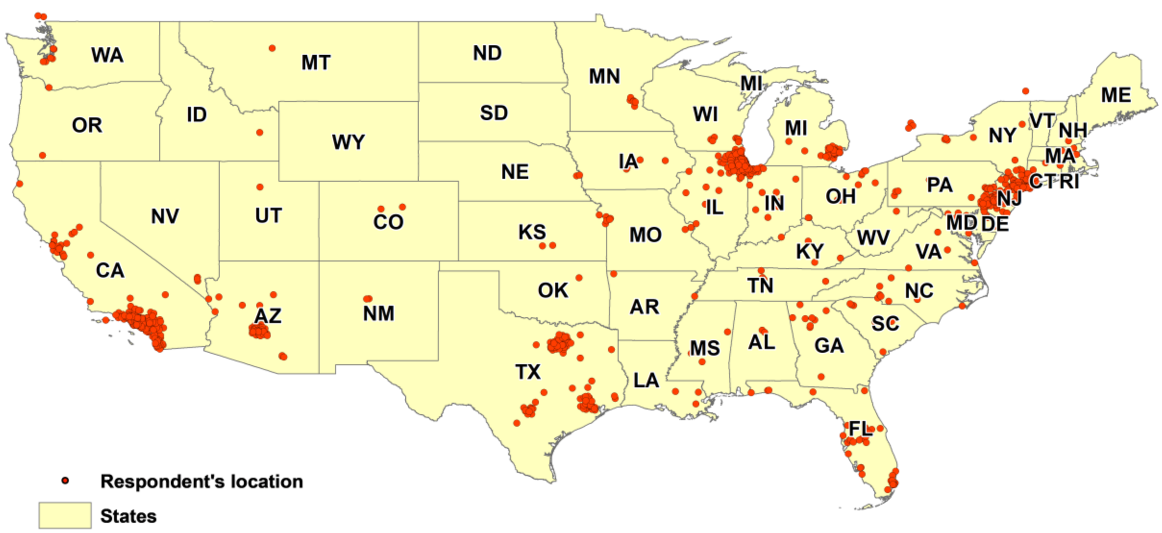


Figure 4.1. Location of respondents to retrospective vehicle survey

4.2.1. Sample data for households

4.2.1.1. Socio-economic characteristics

The collected database is biased towards non-Hispanic two-member households without children who live in urban areas. The sample distribution should be aligned to the population distribution to avoid the biases associated with sampling and to have a robust database (see Yeager et al. (2011) for comparing weighted and unweighted estimates and Stuart (2010) for a review on methods for matching sample and population). To do that, I applied the method of raking adjustment to calculate weight of each household using 2013-2017 American Community Survey 2013-2017 5-year Data Release (United States Census Bureau, 2018). The weights are calculated for four household structure types (household size one, two, three, and four or more), four child-based groups of households (no-child, one child, two children, and three or more children), two ethnicity types (Hispanic and non-Hispanic), five race groups (white, black or African/American, American Indian or Alaska native, Asian, and other), nine income levels, four groups of workers (zero, one worker, two workers, and three or more workers), four vehicles ownership levels (one vehicle, two vehicles, three vehicles, and four or more vehicles), and two residential regions (urbanized and unurbanized residence). Table 4.1 presents a comparison between households' unweighted and weighted socio-economic characteristics. Of importance is the share of households who earn part of their income by their vehicles, which is 22.99%.

Table 4.1. Statistical distribution of socio-economic characteristics (households, sample size = 1,691)

Variables	Unweighted share (%)	Weighted share (%)
Household size		
1	22.89	23.07
2	44.71	34.51
3	16.09	16.67
4+	16.32	25.75
# children		
0	73.27	58.37
1	13.60	17.92
2	9.23	15.52
3+	3.90	8.20
# seniors		
0	63.69	65.94
1	16.74	17.02
2	17.68	14.40
3+	1.89	2.64
Ethnicity		
Hispanic or Latino	9.76	17.24
Non-Hispanic	90.24	82.76
Race		
White	73.74	73.05
Black or African/American	10.29	12.64
American Indian or Alaska native	0.83	0.81
Asian	6.21	5.35
Other	8.93	8.15
Income		
< \$10K	2.48	6.66
\$10K ≤ < \$25K	5.14	14.67
\$25K ≤ < \$35K	5.44	9.53
\$35K ≤ < \$50K	8.99	12.86
\$50K ≤ < \$75K	15.85	17.69
\$75K ≤ < \$100K	17.80	12.36
\$100K ≤ < \$150K	20.64	14.07
\$150K ≤ < \$200K	10.29	5.77
≥ \$200K	13.36	6.38
Part of income is gained by vehicle(s)		
Yes	18.81	22.99
No	81.19	77.01
# workers		
0	22.53	23.65
1	35.19	38.81
2	34.12	30.45
3+	8.16	7.09
# vehicles		
1	35.01	36.00
2	43.58	41.19
3	13.25	15.76
4	8.16	7.06
# driver’s license holders		
1	28.62	31.83
2	55.53	51.14
3	11.12	12.05
4+	4.73	4.99
Region		
Urbanized	86.64	78.92
Unurbanized	13.36	21.08

To assess the role of household vehicle ownership (i.e., number of vehicles held by a household) on purchasing BEVs, Figure 4.2 illustrates share of BEV versus non-BEV owners for each vehicle ownership level from one vehicle to four or more vehicles. As observed, share of BEV ownership for the households with more vehicles is more than those with less vehicles. In two extreme cases, 39.62% of households with four or more vehicles own BEVs whereas only 7.12% of single-vehicle households own BEVs.

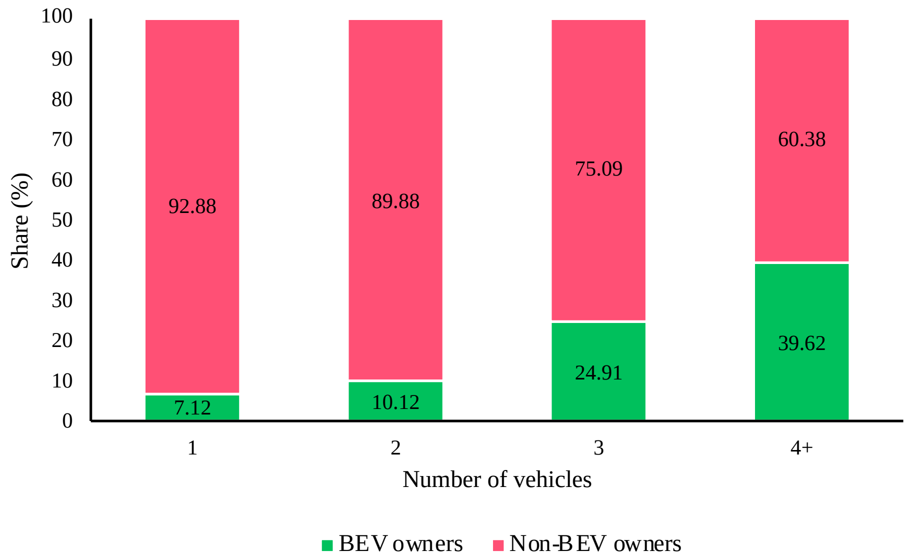


Figure 4.2. Number of vehicles held by households with respect to BEV ownership (#1-vehicle owners = 592 — #2-vehicle owners = 737 — #3-vehicle owners = 224 — #4+-vehicle owners = 138)

4.2.1.2. Demographic attributes

This sub-section discusses weighted statistical distribution of the households' residential demography. To compare demographic attributes of BEV owners with non-BEV owners, Figure 4.3, Figure 4.4, and Figure 4.5 respectively depicts three residential attributes including residential duration, ownership, and type with respect to BEV ownership. As shown in Figure 4.3, majority of non-BEV owners have longer residential duration. In contrast, BEV owners are equally distributed over residential duration with an exemptional jump in the graph which shows that one fourth of them live in their residence between 2 to 3 years.

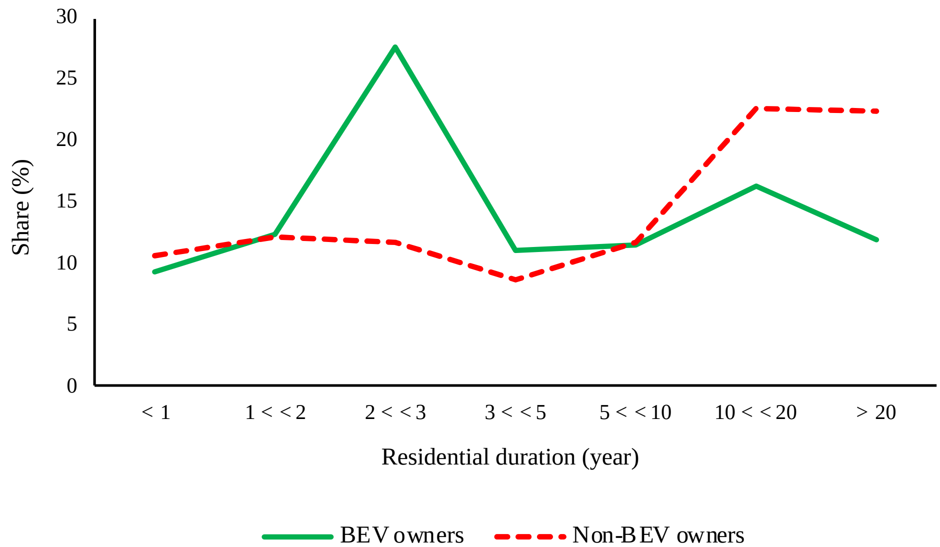


Figure 4.3. Residential duration of households with respect to BEV ownership (# BEV owners = 235 — # non-BEV owners = 1,456)

Distribution of the residential ownership for BEV owners is almost similar to that of non-BEV owners. In fact, more than two third of both groups own/buying (paying mortgage) their houses (Figure 4.4).

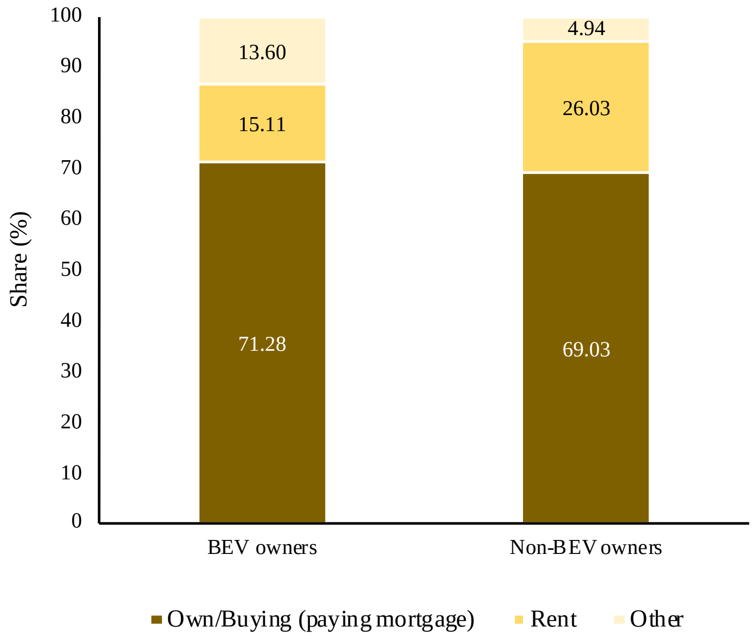


Figure 4.4. Residential ownership of households with respect to BEV ownership (# BEV owners = 235 — # non-BEV owners = 1,456)

Since PEV, especially BEV, users prefer to recharge their PEV at home (US DOE, Office of Energy Efficiency & Renewable Energy, 2018b), it is important to examine the impact of residential type on a household's desire to purchase PEVs. In fact, single-family attached houses provide the possibility of installing charging equipment and therefore, their residents might be more interested in PEV adoption. Figure 4.5 shows distribution of the residential type of BEV and non-BEV owners. As seen, almost two third of both groups live in the single-family detached houses.

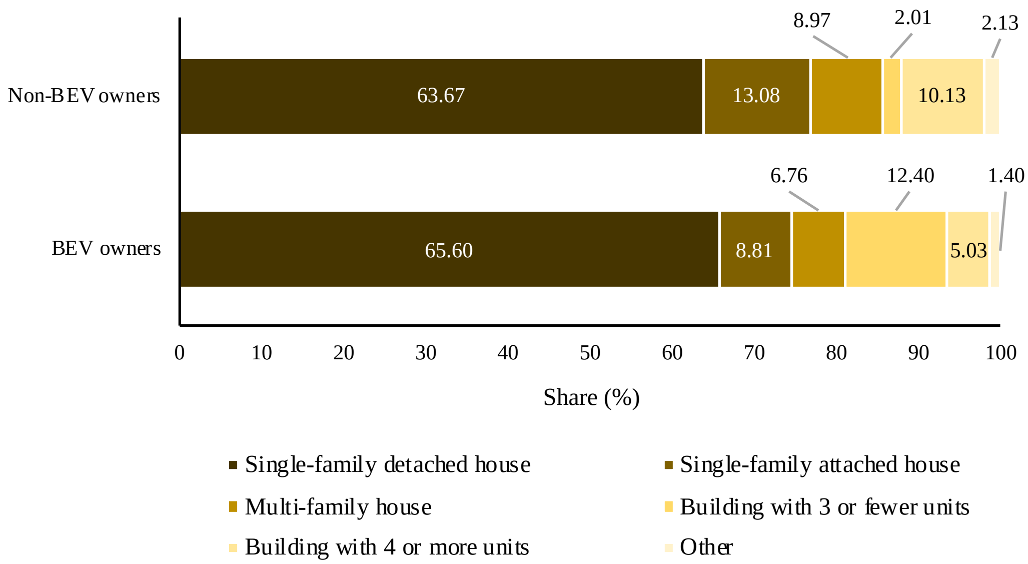


Figure 4.5. Residential type of households with respect to BEV ownership (# BEV owners = 235 — # non-BEV owners = 1,456)

In addition to the residential attributes, the respondents are asked about eight questions on their attitude towards the importance of factors affecting residential neighborhood choice. These attitudinal factors are measured by a five-point Likert scale ranging from 1 "very unimportant" to 5 "very important". Figure 4.6 shows the average value of the responses over BEV owners and non-BEV owners. Overall, BEV owners found these factors more important than non-BEV owners. Of importance is that BEV owners on average pay more attention to being close to their work location than non-BEV owners.

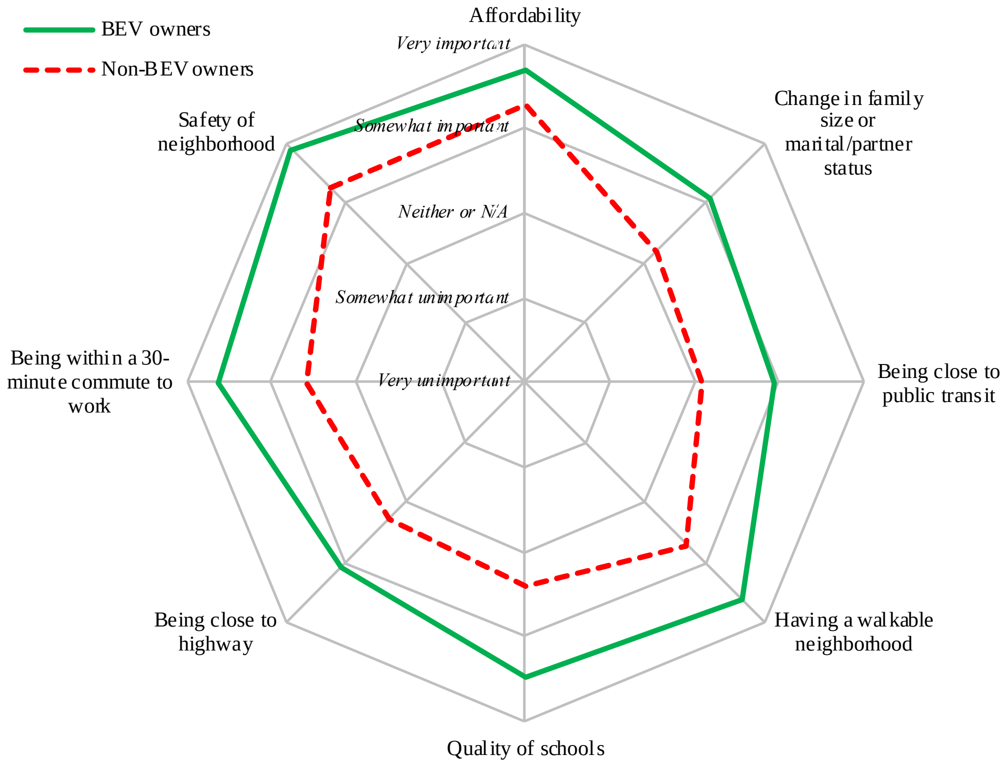


Figure 4.6. Importance of factors at the time of choosing household residential neighborhood with respect to BEV ownership

Although the more preferred charging location of PEV users (number of PEV owners in the dataset is equal to 332) is their detached family houses, they can also use charging equipment installed at workplace or public charging stations. Figure 4.7 shows the frequency of charging PEVs at the three locations. Almost 40% of them charge their vehicles at home with a frequency of 6-7 days per week. The high frequency of charging PEVs at home verifies that PEV users more frequently use home installed equipment. It is also interesting to note that workplace and public charging stations is not applicable for almost half and one third of the PEV users, respectively. At most, 20% of them charge their PEVs daily at workplace. Moreover, one third of PEV users charge their vehicles at public stations.

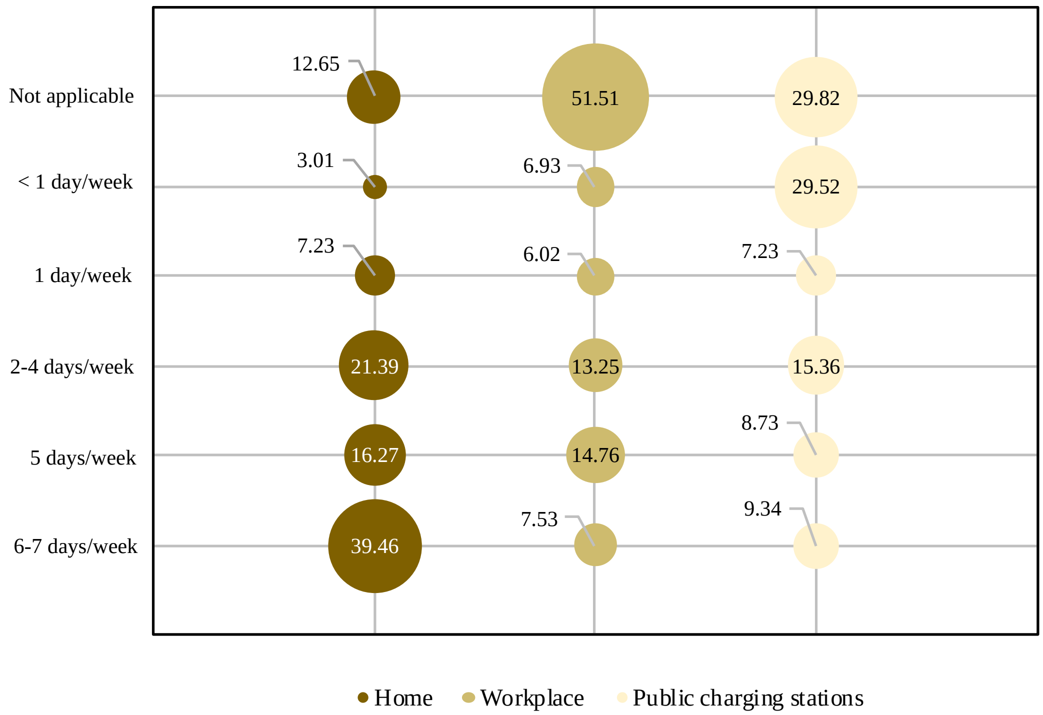


Figure 4.7. Frequency of charging PHEVs/BEVs at home, workplace, and public stations (# PHEV/BEV owners = 332)

4.2.2. Sample data for individuals

4.2.2.1. Socio-economic characteristics

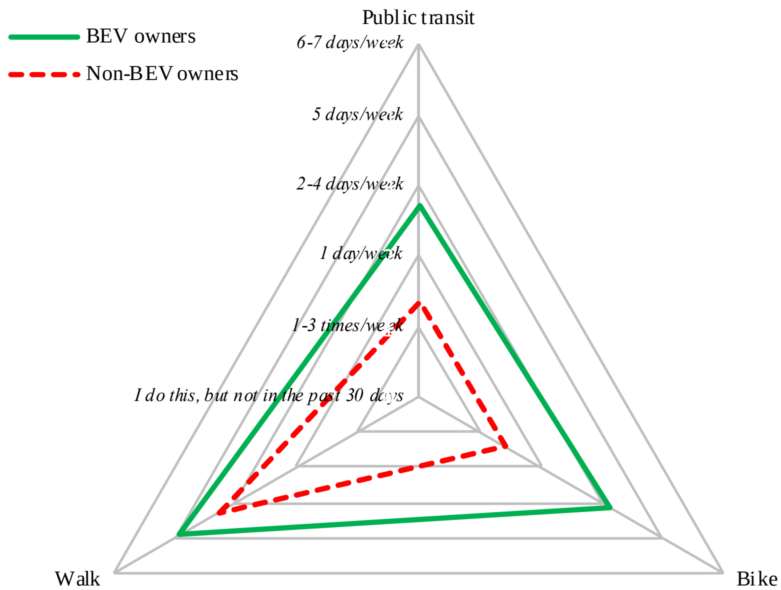
The collected database is further biased towards the respondents who are fully-employed with higher education that are at their mid-age. To avoid the sampling biases, the sample distribution of the respondents (individuals) is aligned to the population distribution. To do that, I applied the method of raking adjustment to calculate weight of each respondent using 2013-2017 American Community Survey 2013-2017 5-year Data Release (United States Census Bureau, 2018). The weights are calculated for two gender types (males and females), nine age categories, seven employment types, and five education levels. Table 4.2 presents the unweighted and weighted share of the individuals for socio-economic characteristics.

Table 4.2. Statistical distribution of socio-economic characteristics (individuals, , sample size = 1,691)

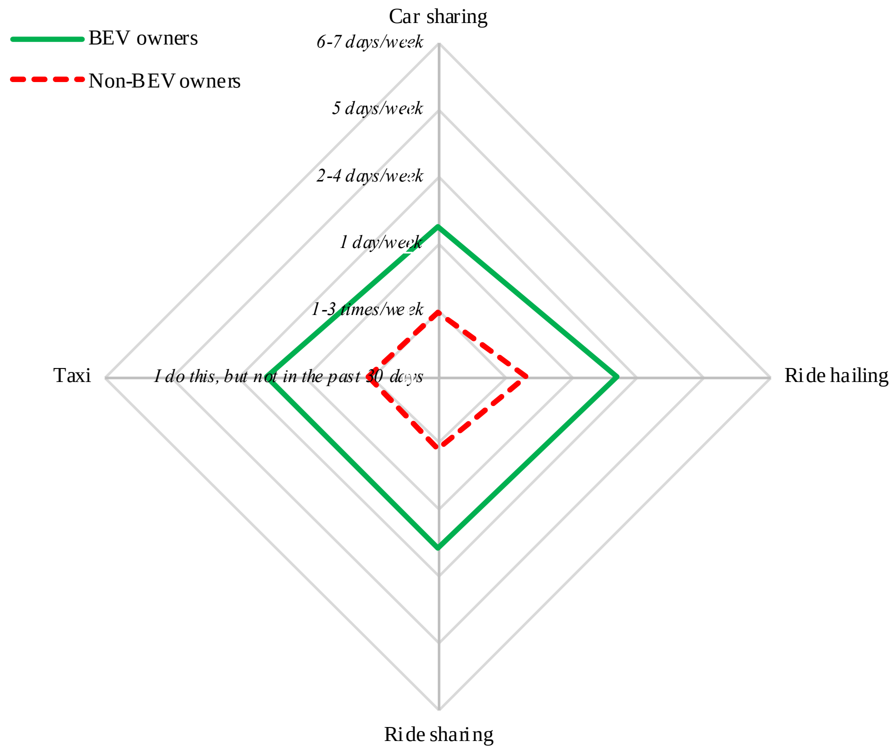
Variables	Unweighted share (%)	Weighted share (%)
Gender		
Male	48.91	53.29
Female	51.09	46.71
Age (years)		
16 ≤ < 18	0.65	4.38
18 ≤ < 25	7.39	12.04
25 ≤ < 35	17.33	17.48
35 ≤ < 45	14.84	15.95
45 ≤ < 55	13.72	17.24
55 ≤ < 65	20.82	15.84
65 ≤ < 75	20.82	9.88
75 ≤ < 85	4.02	4.90
≥ 85	0.41	2.28
Employment		
Full-time	49.32	40.05
Part-time	9.88	8.82
Self-employed	7.39	5.04
Unpaid volunteer or intern	0.65	0.52
Homemaker	4.32	27.43
Retired	25.07	13.43
Not currently employed	3.37	4.71
Education		
Less than high school	0.77	12.78
High school graduate	9.99	27.72
Some college/ technical training/associate degree	27.26	31.15
Bachelor’s degree	34.00	18.04
Graduate/Post-graduate degree	27.97	10.31

4.2.2.2. Latent factors describing attitude, perception, and lifestyle preference

The respondents are questioned about attitude, perception, and lifestyle preference. The first group of the questions determine their *travel attitudes* by asking seven questions, which measure their travel mode use in the past 30 days by a six-point Likert scale from 1 “I do this, but not in the past 30 days” to 6 “6-7 days per week”. The first three questions measure the individuals’ non-vehicle travel mode use including public transit, bike, and walk. The other four questions describe their shared mobility use of four options including carsharing, ridehailing, ridesharing, and taxi. The average value of these seven attitudinal factors over individuals whose households own BEVs and non-BEVs are depicted in Figure 4.8. In general, BEV owners more frequently use all seven travel modes compared to non-BEV owners. Moreover, both groups on average walk more than biking and using public transit. It is also observed that BEV owners use all shared mobility options almost with the same frequency. The same pattern is also observed for non-BEV owners.



(a)



(b)

Figure 4.8. Travel attitudes measured by frequency of using transportation modes in the past 30 days: (a) green travel modes and (b) shared mobility modes with respect to BEV ownership

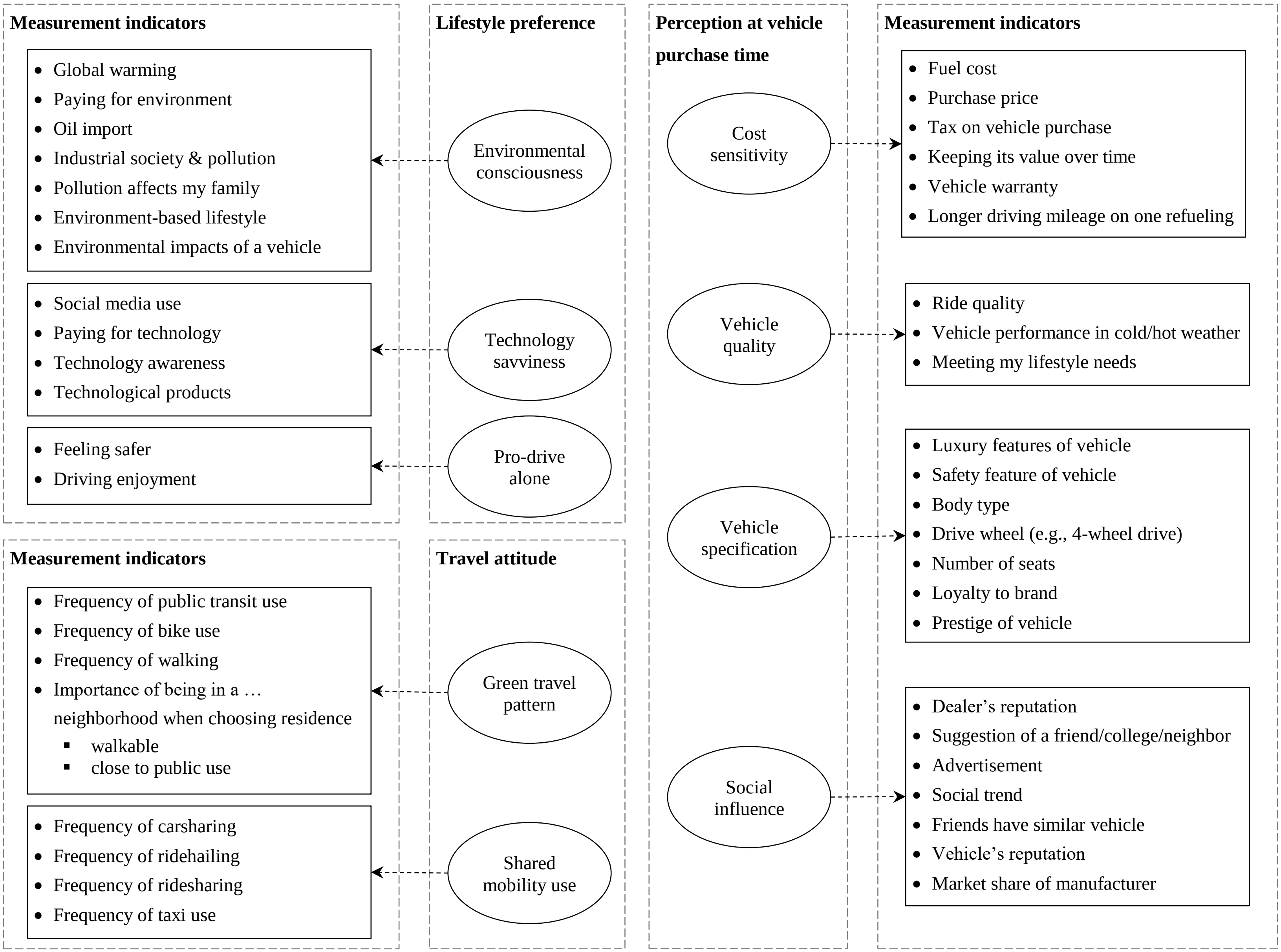
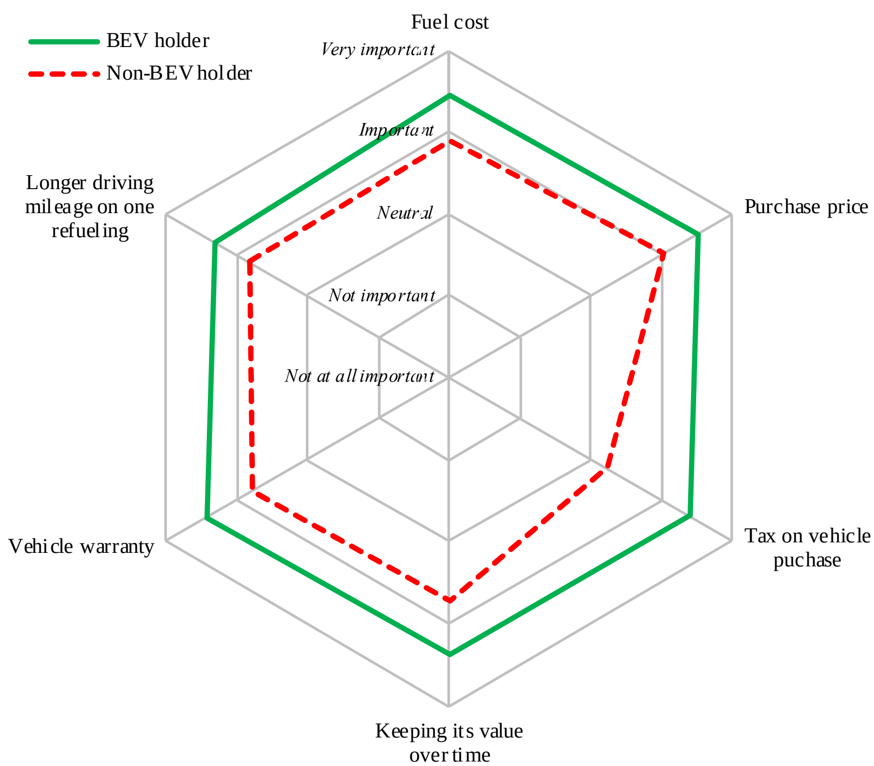
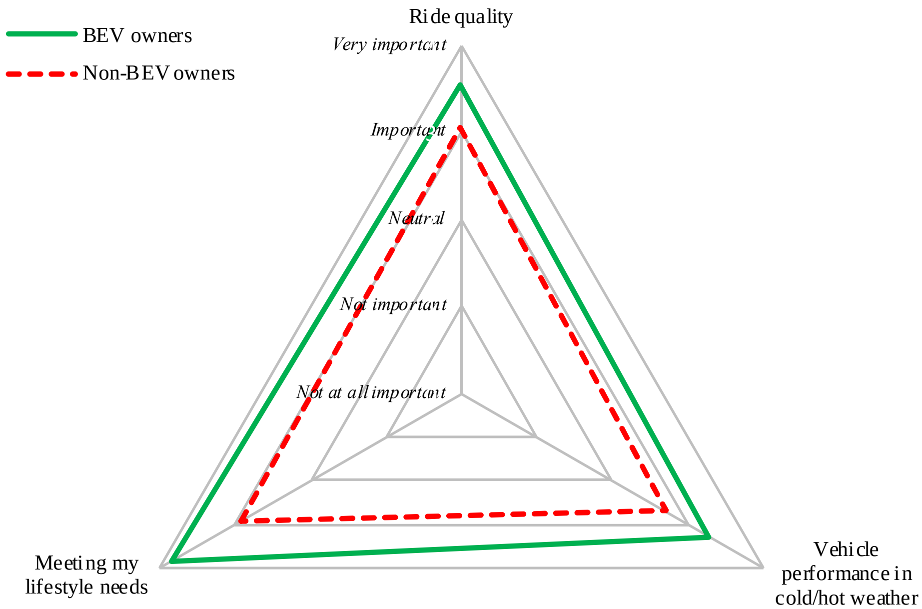


Figure 4.9. Latent constructs and the corresponding measurement indicators

In addition to the revealed travel attitudinal factors, the respondents expressed their opinions about two groups of questions including *perception at vehicle purchase time* and *lifestyle preference*. The indicators of the first group are classified as four factors representing four types of vehicle features that are of importance at vehicle purchase time. These factors include cost sensitivity, vehicle quality, vehicle specification, and social influence. The corresponding indicators of each perceptual factor are measured by a five-point Likert scale ranging from 1 "not at all important" to 5 "very important". The related distribution is overaged out over individuals whose households own BEVs and non-BEVs (Figure 4.10).

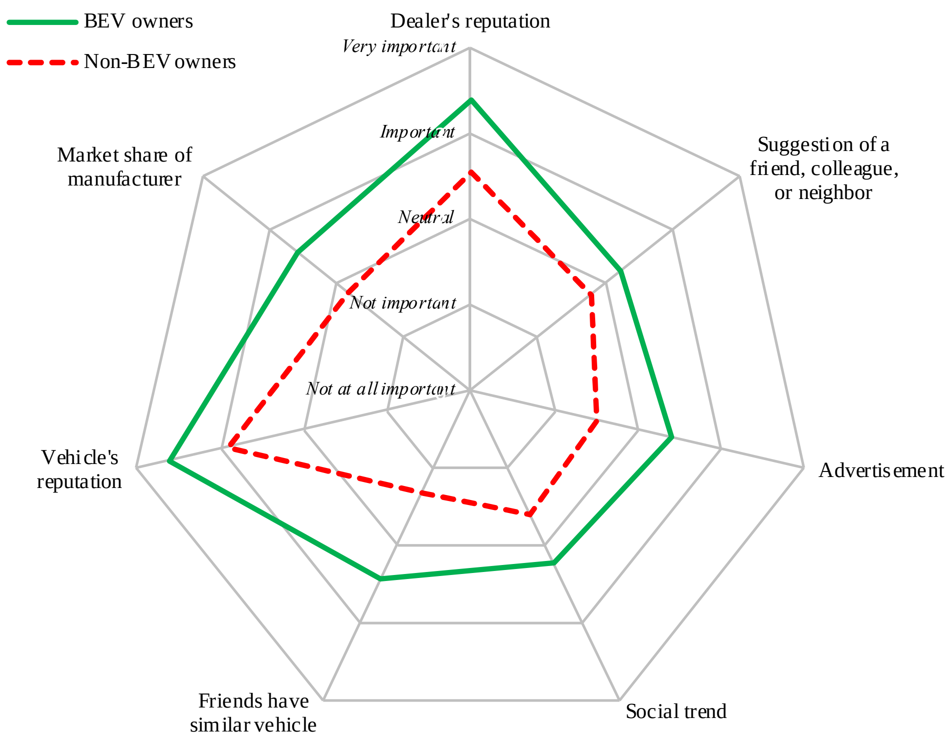


(a) Cost sensitivity



(b) Vehicle quality

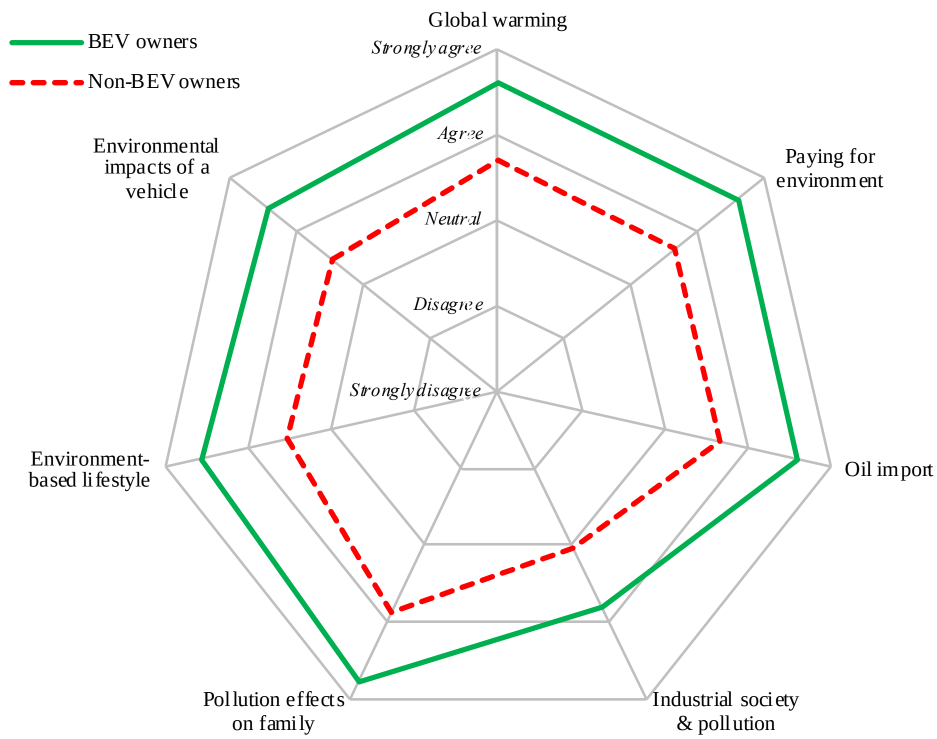
(c) Vehicle specification



(d) Social influence

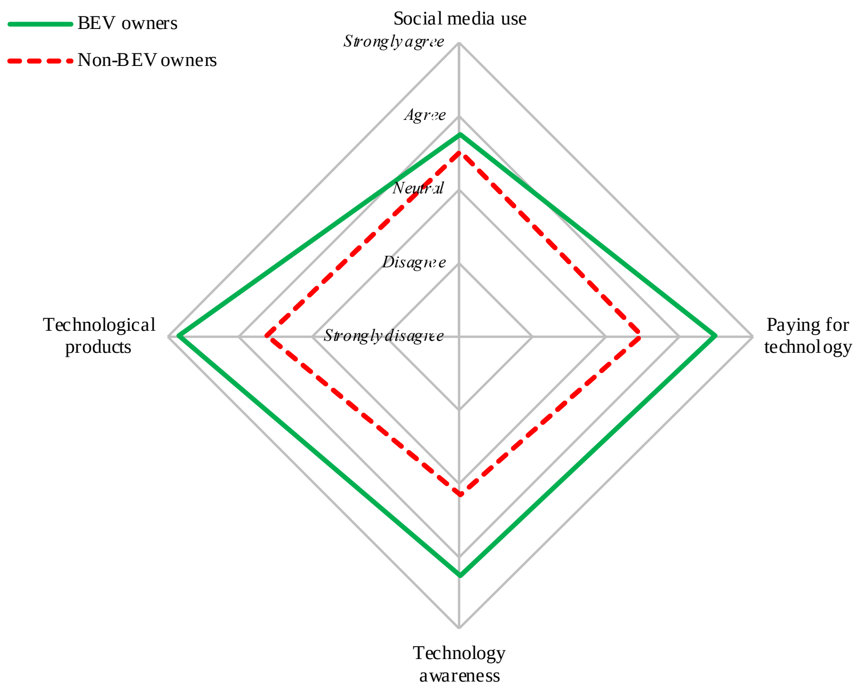
Figure 4.10. Measurement indicators of perception at vehicle purchase time with respect to BEV ownership

The second group determines the respondents' lifestyle preference for environmental consciousness, technology savviness, and pro-drive alone. The corresponding indicators are measured by a five-point Likert scale starting from 1 "strongly disagree" to 5 "strongly agree". Figure 4.11 depicts the average value of the indicators over the respondents with BEVs and non-BEVs in their households. It is observed that BEV owners on average more agree on lifestyle preference factors. Of importance is that both of BEV and non-BEV owners more agree on the statement of pollution effects on family than other environmental consciousness indicators. Moreover, BEV owners almost strongly agree on interest in technological products, whereas non-BEV owners are almost neutral about that. Interestingly, both groups have almost equal social media use. Finally, BEV owners are more pro-drive alone than other ones.



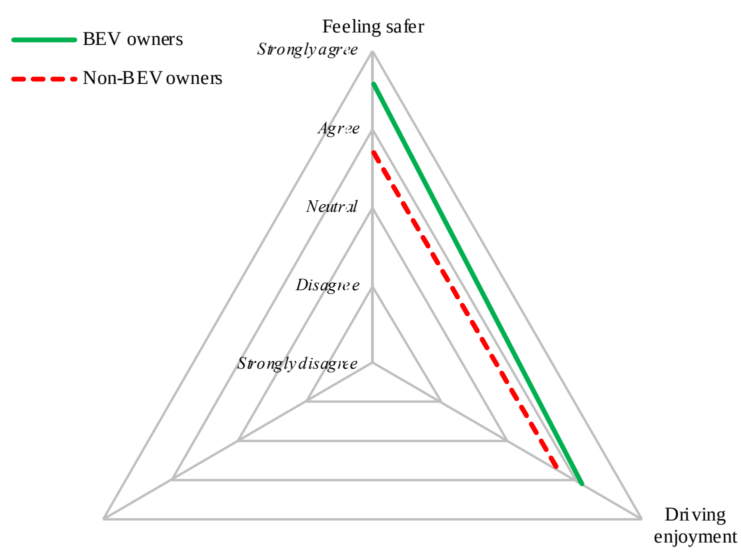
(a) Environmental consciousness

I am concerned about global warming.	Global warming
I am willing to pay for a product which is more environmentally friendly.	Paying for environment
It is important to be independent from oil and the producer countries.	Oil import
It is acceptable for an industrial society such as ours to produce a certain degree of pollution.	Industrial society & pollution
I am concerned about the effects of pollution on myself and my family.	Pollution effects on family
I change my behavior and lifestyle based on concerns for the environment.	Environment-based lifestyle
It is important to consider environmental impacts of a vehicle at its purchase time.	Environmental impacts of a vehicle



(b) Technology savviness

I frequently use social media (e.g., Facebook and Tweeter).	Social media use
I am willing to pay for new technological products.	Paying for technology
I am aware of latest technological products more than others.	Technology awareness
I am interested in new technological products.	Technological products



(c) Pro-drive alone

I feel safer when I myself drive rather than others driving me.	Feeling safer
I enjoy driving.	Driving enjoyment

Figure 4.11. Measurement indicators of lifestyle preference with respect to BEV ownership

To determine weight of the measurement indicators on each latent construct, I estimated a confirmatory factor analysis (CFA) considering individual-level weights (described in section 4.2.2.1). According to the estimation results (Table 4.3), a significant share of explained variance belongs to perception of social influence at vehicle purchase time, travel attitude of shared mobility use, and lifestyle preference for environmental consciousness with the values 18.27%, 17.41%, and 15.26%, respectively.

4.2.3. Sample data for vehicles

The collected database contains information of 3,326 vehicles with four fuel types including CV, HEV, PHEV, and BEV. Figure 4.12 depicts distribution of vehicle miles traveled (VMT) with respect to fuel type. Figure 4.12 (a) shows current odometer reading of vehicles which is equal to total VMT of vehicles in their lifetime, whereas Figure 4.12 (b) shows total driven miles in the past 12 months. On average, total VMT of CVs has the largest VMT followed by HEVs, PHEVs, and BEVs. The reason of this observation is the recent advent of EVs to the vehicle market. In contrast, the average VMT in the past 12 months shows that PHEVs and BEVs are driven the most among all fuel types. Moreover, CVs have the lowest VMT in past 12 months. It can be inferred that the advent of PHEVs and BEVs could increase VMT.

Another vehicle attribute is price, which is statistically distributed according to Figure 4.13 with respect to fuel type. As expected, average price of BEVs is the highest which is followed by PHEVs, HEVs, and CVs.

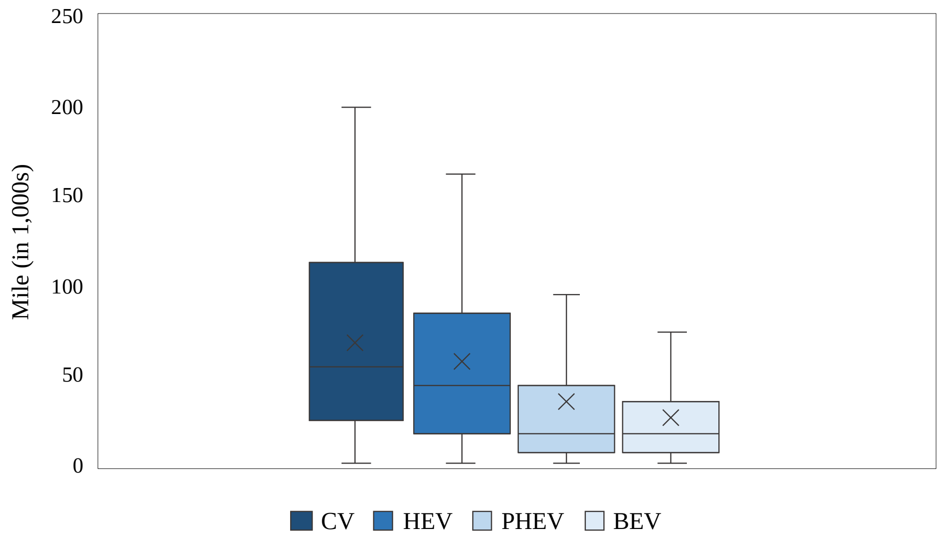
Vehicle ownership and purchase type for the various fuel types are shown in Figure 4.14 (a) and Figure 4.14 (b), respectively. Majority of the vehicles, regardless of the fuel type, are owned or financed by the households. However, share of owned/financed PEVs is less than CVs and HEVs. It is further observed that the share of leased and company vehicles for both BEVs and PHEVs is noticeable. Figure 4.14 (b) divides vehicles based on their age, whether the vehicles are purchased used or new. Share of used and new CVs is almost equal. In addition, share of new non-CVs is more than used ones which makes sense regarding the recent advent of EVs to the vehicle market.

Table 4.3. Estimation results of confirmatory factor analysis

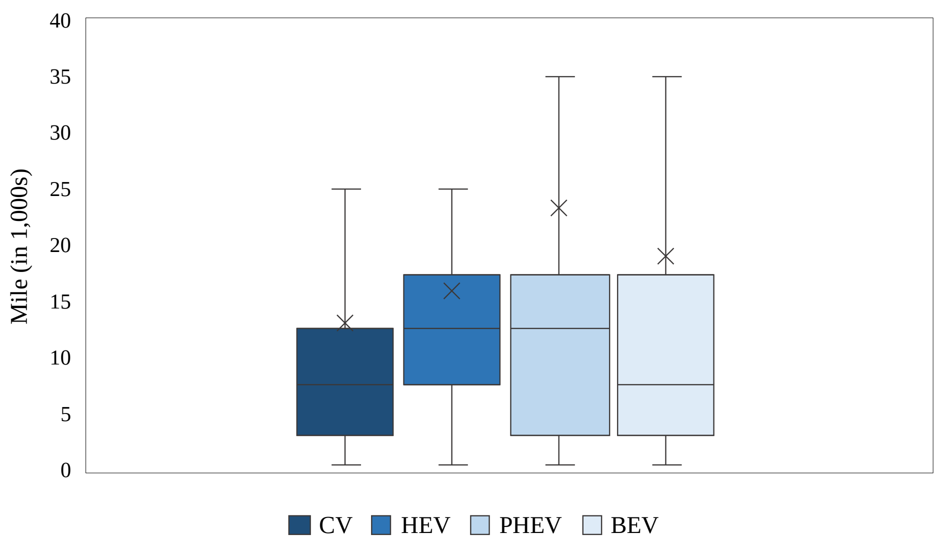
Latent constructs and measurement indicators	Factor loading	T-statistics	Explained variance (%)
Perception at vehicle purchase time			
Cost sensitivity			1.777 (9.58)
Fuel cost	0.563	24.04	0.317
Purchase price	0.389	12.10	0.151
Tax on vehicle purchase	0.439	15.63	0.193
Keeping its value over time	0.577	27.72	0.333
Vehicle warranty	0.623	28.14	0.388
Longer driving mileage on one refueling	0.629	32.21	0.395
Vehicle quality			1.075 (5.80)
Ride quality	0.681	29.78	0.464
Vehicle performance in cold or hot weather	0.569	22.20	0.323
Meeting my lifestyle needs	0.537	21.28	0.288
Vehicle specification			1.978 (10.67)
Luxury features of vehicle	0.596	30.50	0.355
Safety features of vehicle	0.321	13.30	0.103
Body type	0.360	14.24	0.130
Drive wheel (e.g., 2-wheel drive)	0.536	26.15	0.287
Number of seats	0.394	16.97	0.155
Loyalty to brand	0.663	37.45	0.440
Prestige of vehicle	0.713	44.37	0.508
Social influence			3.387 (18.27)
Dealer’s reputation	0.471	25.47	0.222
Suggestion of a friend, colleague, or neighbor	0.756	58.94	0.571
Advertisement	0.843	92.12	0.712
Social trend	0.810	72.10	0.656
Friends have similar vehicle	0.775	69.87	0.601
Vehicle reputation	0.249	11.25	0.062
Market share of manufacturer	0.751	55.17	0.563
Lifestyle preference			
Environmental consciousness			2.829 (15.26)
I am concerned about global warming.	0.693	38.49	0.480
I change my behavior and lifestyle based on concerns about the environment.	0.743	40.23	0.552
I am concerned about the effects of pollution on myself and my family.	0.748	50.54	0.559
I am willing to pay for a product which is more environmentally friendly.	0.698	35.59	0.487
It is important to be independent from oil and the producer countries.	0.603	27.07	0.364
It is important to consider environmental impacts of a vehicle at its purchase time.	0.622	27.42	0.387
Technology savviness			1.750 (9.44)
I am interested in new technological products.	0.668	32.33	0.446
I am aware of latest technological products more than others.	0.766	44.76	0.587
I am willing to pay for new technological products.	0.724	40.36	0.524
I frequently use social media (e.g., Facebook, Tweeter, Instagram).	0.439	16.78	0.193
Pro-drive alone			0.737 (3.98)
I enjoy driving.	0.703	16.51	0.494
I feel safer when I myself drive rather than others driving me.	0.492	12.77	0.243

Table 4.3. Estimation results of confirmatory factor analysis

Latent constructs and measurement indicators	Factor loading	T-statistics	Explained variance (%)
Travel attitude			
Green travel pattern			1.780 (9.60)
Frequency of public transit use	0.801	59.77	0.642
Frequency of bike use	0.833	67.46	0.693
Frequency of walking	0.362	20.51	0.131
Importance of being in a … neighborhood when choosing residence			
walkable	0.224	10.00	0.050
close to public transit	0.513	33.72	0.264
Shared mobility use			3.227 (17.41)
Frequency of carsharing	0.926	130.30	0.858
Frequency of ridehailing	0.871	95.62	0.759
Frequency of ridesharing	0.898	91.05	0.806
Frequency of taxi use	0.897	107.90	0.804



(a)



(b)

Figure 4.12. (a) Current odometer reading of vehicles and (b) Vehicle mileage driven in the past 12 months with respect to fuel type (# CVs = 2,060 — # HEVs = 905 — # PHEVs = 141 — # BEVs = 277)

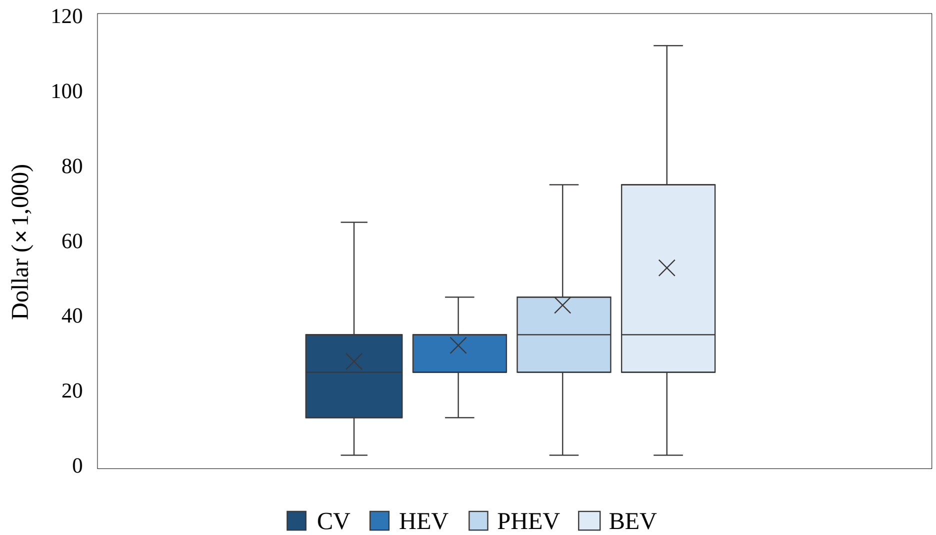
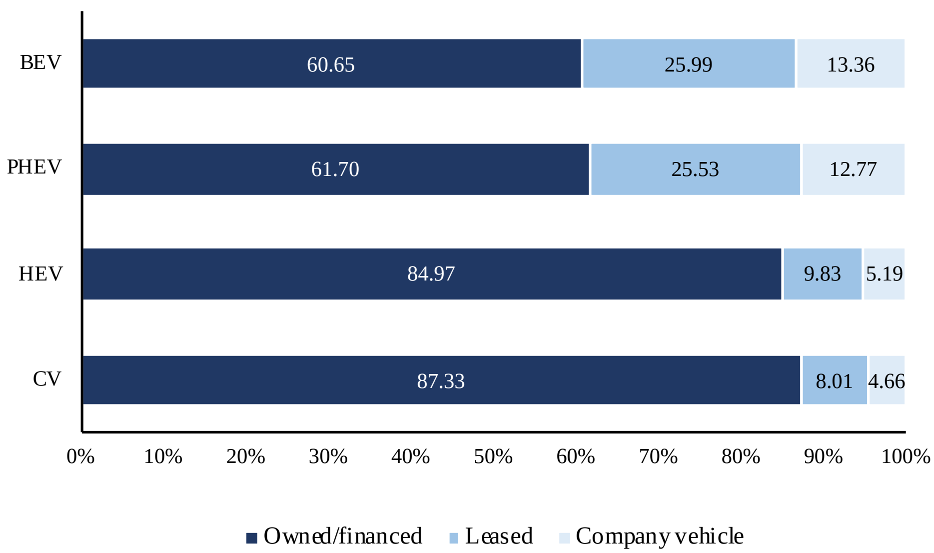
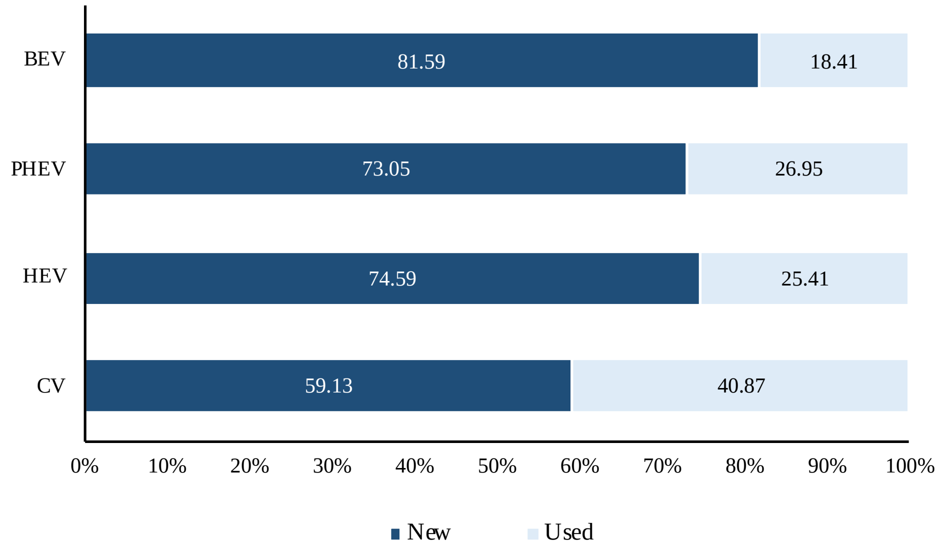


Figure 4.13. Vehicle price with respect to fuel type
(# CVs = 2,060 — # HEVs = 905 — # PHEVs = 141 — # BEVs = 277)



(a)



(b)

Figure 4.14. (a) Vehicle ownership type and (b) vehicle purchase type (# CVs = 2,060 — # HEVs = 905 — # PHEVs = 141 — # BEVs = 277)

4.2.4. Sample data for principal drivers

4.2.4.1. Socio-economic characteristics

The principal drivers are characterized by gender, age, educational attainment, and employment type, which are statistically distributed according to Figure 4.15-Figure 4.18 with respect to vehicle fuel type. The principal drivers are almost equally gender-distributed. Almost half of each fuel type is driven by persons with mid-age (35 ≤ age < 65). In addition, BEVs belong to persons, 88.08% of whom are young (18 ≤ age < 35) or mid-age (35 ≤ age < 65).

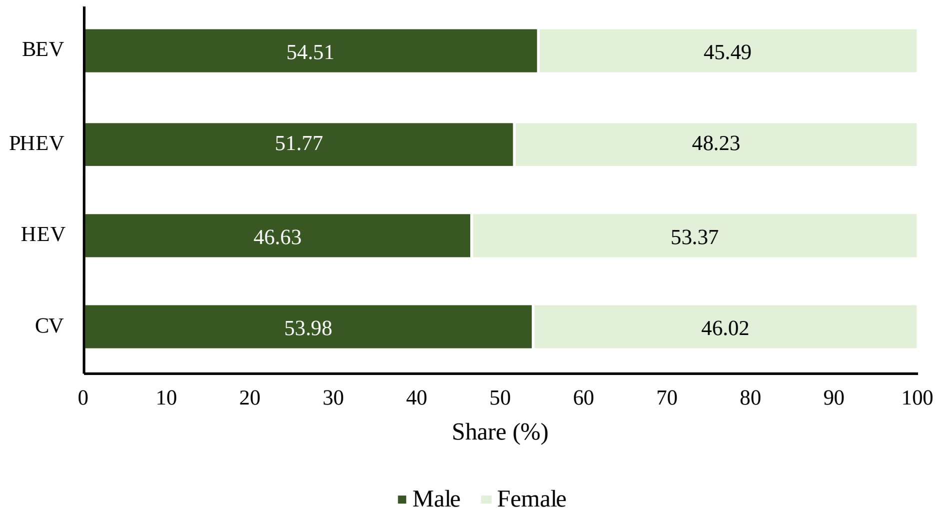


Figure 4.15. Gender of principal drivers with respect to vehicle fuel type

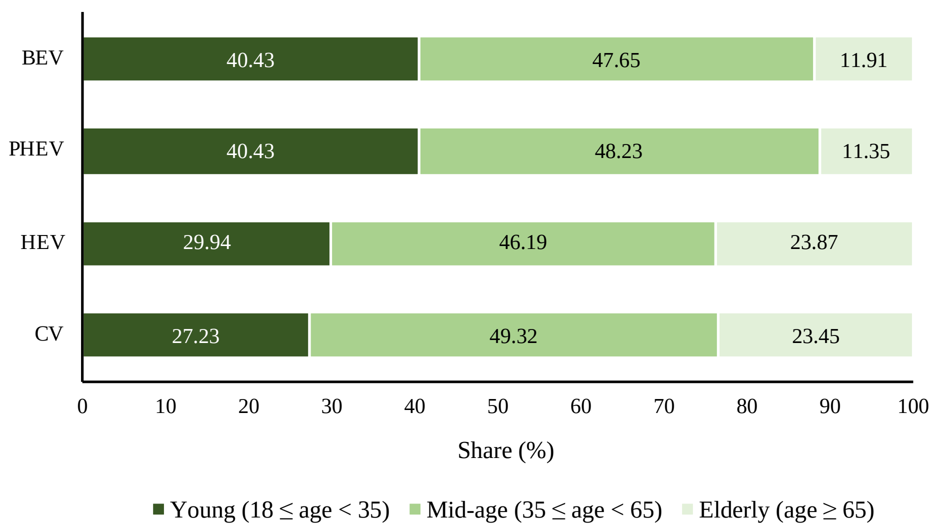
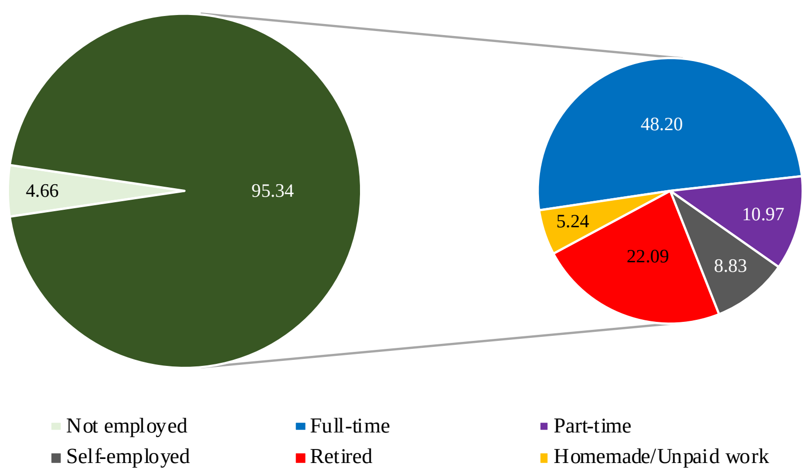


Figure 4.16. Age of principal drivers with respect to vehicle fuel type

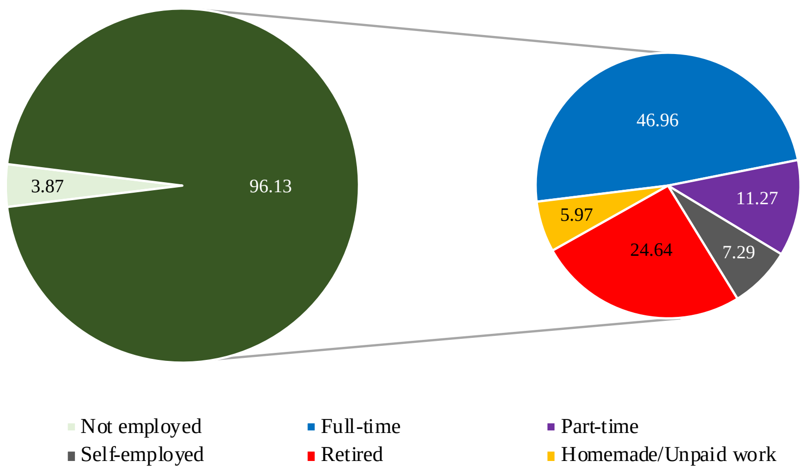
Distribution of educational attainments is such that almost one third of CV drivers have bachelor's degree, however, share of CV drivers with lower educational levels is significant. In contrast, majority of HEV, PHEV, and BEV drivers, especially HEV drivers, have higher education level (bachelor's degree or higher).

Figure 4.17. Education of principal drivers with respect to vehicle fuel type

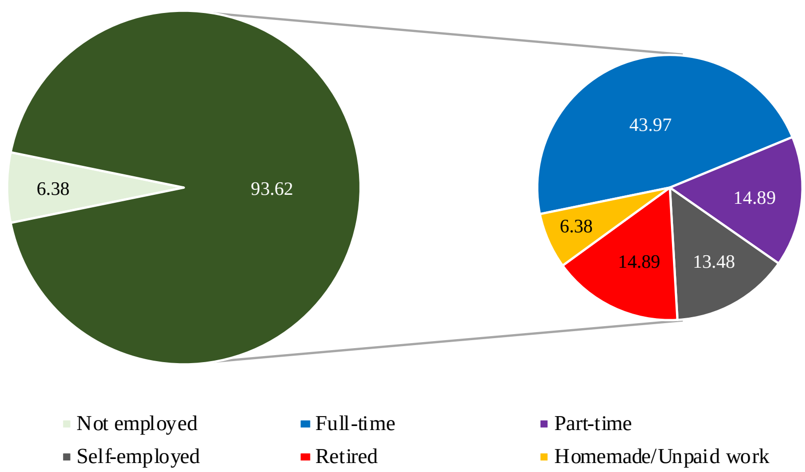
Figure 4.18 presents employment type of the principal drivers with respect to fuel type of their vehicles. It is observed that the difference between employment type of the drivers of various fuel types is negligible.



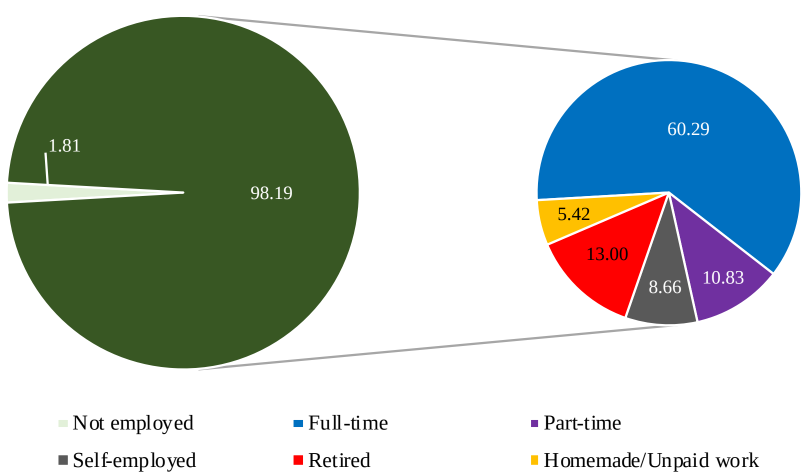
(a)



(b)



(c)



(d)

Figure 4.18. Employment type of principal drivers of (a) CVs, (b) HEVs, (c) PHEVs, and (d) BEVs

4.2.4.2. Travel behavior

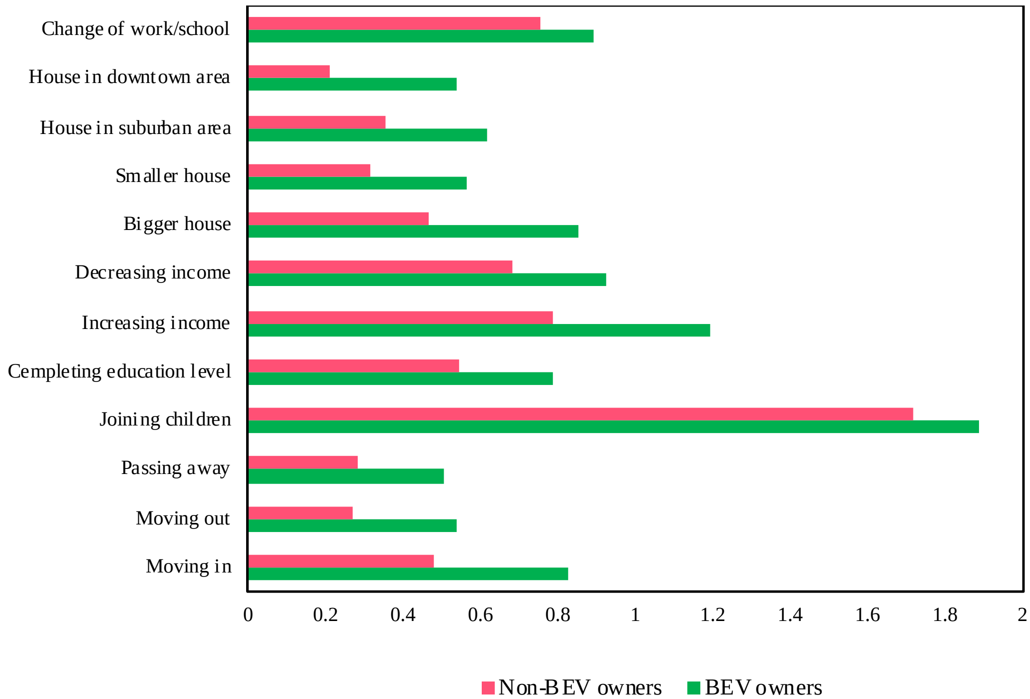
The principal drivers are further characterized by two of their travel behavior factors as shown in Table 4.4. It is noticeable that almost half of the respondents with any fuel type drive alone to their workplace. Moreover, majority of them live in a 30-mile or less distance to their workplace.

Table 4.4. Statistical distribution of commute factors (principal drivers, , sample size = 3,326)

Commute factors	CV		HEV		PHEV		BEV	
	# obs	Share (%)	# obs	Share (%)	# obs	Share (%)	# obs	Share (%)
Commute mode								
Drive alone	665	55.60	451	55.75	58	54.21	162	56.06
Drive/ride with others or vanpool	208	17.39	141	17.43	27	25.23	80	27.68
Bicycle, walk, jog, or wheelchair	6	0.50	5	0.62	2	1.87	7	2.42
Public transit (bus and train)	20	1.67	14	1.73	1	0.93	4	1.38
Taxi	1	0.08	3	0.37	3	2.80	0.00	0.00
Ridesourcing (e.g., Uber, Lyft)	1	0.08	2	0.25	0.00	0.00	2	0.69
Other	8	0.67	7	0.87	0.00	0.00	0.00	0.00
Not applicable	287	24.00	186	22.99	16	14.95	34	11.76
Commute distance (miles)								
1-4.9	155	12.96	69	8.53	9	8.41	27	9.34
5-9.9	173	14.46	102	12.61	11	10.28	51	17.65
10-14.9	155	12.96	131	16.19	13	12.15	52	17.99
15-19.9	113	9.45	84	10.38	16	14.95	39	13.49
20-29.9	120	10.03	100	12.36	14	13.08	40	13.84
30-39.9	59	4.93	46	5.69	11	10.28	22	7.61
40-49.9	26	2.17	22	2.72	3	2.80	3	1.04
50 or more	27	2.26	14	1.73	8	7.48	12	4.15
Not applicable	368	30.77	241	29.79	22	20.56	43	14.88
# observations	1,196		809		107		289	

4.2.5. Sample data for dynamics of household characteristics and their vehicles (over the past 10 years)

The database finally contains information on changes that each household has experienced over the past 10 years from 2008 to 2017. These changes are asked from the respondents in three question groups which cover changes in household structure, income level, and residential statue. Figure 4.19 shows average of these changes over BEV and non-BEV owners. It is interesting to note that BEV owners have experienced more changes than non-BEVs over the past 10 years in all change indices. The largest change of both groups is joining children to their households with an average value of almost 1.5. In addition, BEV owners and non-BEV owners have the largest difference in moving to a house in downtown area so as BEV owners have more experience in this index.



Household structure	
Move in with spouse, partner, or significant other one	Moving in
Move out because of separation, divorce, or other reasons	Moving out
A household member passed away	Passing away
Children were born, adopted, or joined your household	Joining children
You or anyone in the household completed an education level	Completing education level
Income level	
Significant increase in income of any household member	Increasing income
Significant decrease in income of any household member	Decreasing income
Residential status	
Move into a bigger house	Bigger house
Move into a smaller house	Smaller house
Move into a house in suburban area	House in suburban area
Move into a house in downtown area	House in downtown area
Change of work/school location of a household member	Change of work/school

Figure 4.19. Number of changes in household socio-economic characteristics over the past 10 years

5. Dynamic Vehicle Transaction and Fuel Type Choice: An Integrated Choice Model with Latent Vehicle Perception and Lifestyle Preference

The materials of the current chapter are partially published with the following citation: "Nazari, F., Mohammadian, A., Stephens, T., 2019. Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. Transportation Research Part D: Transport and Environment 72, 65-82." Permission for reuse of the above publication in the dissertation is obtained from Elsevier (see Appendix B).

5.1. Introduction

As detailed in introduction section of the previous chapter (section 4.1), there exist four main gaps in the disaggregate-level models of EV adoption behavior, which are rare use of RP datasets, the lack of distinguishing PHEV users from BEV users, ignorance of historical household changes, and absence of unobservable (latent) subjective attitudinal, perceptual, and lifestyle preferential factors. Motivated by these gaps, this empirical study makes an attempt to more realistically model public adoption of EVs. Specifically, an integrated choice with latent variables (ICLV) model of households' vehicle transaction and fuel type is estimated with a choice set consisting of ten alternatives: engaging in no vehicle transaction, adding a new vehicle to the household (CV, HEV, PHEV, and BEV), selling one of current household vehicles, and trading one of household vehicles with another one (CV, HEV, PHEV, and BEV). The explanatory factors include socio-economic characteristics, vehicle attributes, and dynamics of households in the past 10 years. The ICLV model furthermore considers four latent constructs describing perception of vehicle specification and social influence at vehicle purchase time as well as lifestyle preference for environmental consciousness and technology savviness, which are built based on the observed responses to perceptual/preferential questions of the RVS (McFadden, 1986; Koppelman and Hauser, 1978; Ben-Akiva et al., 2002).

Broadly speaking, disaggregate-level studies on EV adoption behavior view the problem from either a *psychological* or an *economic* perspective.[1] The psychological studies reason that EV adoption behavior depends on individual-specific psychological constructs such as perceptions, attitudes, and emotions which are drawn from the related questions of questionnaire (Schuitema et al., 2013). The majority of these studies use SP datasets as in Axsen et al. (2012) and Moons and De Pelsmacker (2012) among others described in a thorough review by Rezvani et al. (2015). A drawback of these studies is the neglect of other fuel type options (e.g., gasoline and diesel), which limits interpretation and application of the findings. The economic approach complements the first method by modeling the tradeoff between various vehicle fuel types to describe decision-makers' choice as a function of their characteristics and vehicle attributes (Liao et al. (2017) presents a comprehensive review of economic-based studies). The focus of this study is on the latter approach. Table 5.1 characterizes the relevant studies that used SP datasets by model, EV type(s) included in choice set, input variable(s), and a summary of highlighted finding(s).

[1] In addition, two other approaches have been used to model market penetration of EVs. The first approach uses agent-based simulation frameworks (e.g., Eppstein et al. (2011) and Querini and Benetto (2014)). The second approach investigates market penetration of EVs at aggregate-level using diffusion rate and time-series models (e.g., Centrone et al. (2007) and McManus and Senter (2009); see Gnann et al. (2018) for a review of diffusion rate models).

Table 5.1. Overview of studies with economic approach on electric vehicle adoption behavior using stated preferences dataset

Study, country	Model	EV types	Explanatory variables	Key finding(s)
Potoglou and Kanaroglou (2007), Canada	NL	HEV	Vehicle attribute: price, fuel/maintenance cost, acceleration, and pollution Charging infrastructure: fuel availability Incentives: purchase tax, parking fees, and access to high occupancy vehicle (HOV) lane/Socio-economic characteristics and travel behavior	Incentives including parking fees and access to HOV lane do not affect preferences towards HEVs.
Hidrue et al. (2011), U.S.	LCMNL	BEV	Vehicle attributes: price, fuel cost, driving range, charging time, pollution, and acceleration	Main concerns about BEVs are range anxiety, long charging time, and high purchase price. BEV battery cost must drop significantly before its mass market without subsidy.
Mabit and Fosgerau (2011), Denmark	MXL	HEV, BEV	Vehicle attributes: acceleration time, costs, refueling frequency, driving range, purchase price, and repair service Socio-economic characteristics	Tax reduction increases HEV and BEV market share to conventional vehicle level.
Musti and Kockelman (2011), U.S.	MNL	HEV, PHEV	Vehicle attribute: purchase price Socio-economic characteristics and residential location	Senior persons probably select HEVs and PHEVs. Women are interested in HEVs. Urban residents prefer PHEVs. Households with more vehicles do not prefer PHEVs.
Qian and Soopramanien (2011), China	MNL, NL	HEV, BEV	Vehicle attributes: purchase price and running cost Incentives: cash subsidy, free parking, and access to priority lane Socio-economic characteristics	HEV and BEV adopters are among women and young persons who live in a household with large size, children, high income, and more vehicles. All three incentives are insignificants in preference for HEVs and BEVs.
Lin and Greene (2011), U.S.	NL	PHEV, BEV	Charging infrastructure: fuel-saving benefits, range anxiety, willingness to pay for workplace, and public charging	Three types of recharge enhancement increase sales of PHEVs and BEVs.
Achtnicht et al. (2012), Germany	MNL	HEV, BEV	Vehicle attribute: purchase price, fuel cost, engine power, emissions, driving range, and mileage Charging infrastructure: fuel availability/Socio-economic characteristics	Preference for HEVs and BEVs decreases with age. BEVs are unpopular among Germans, even with a significant expansion of public PEV charging infrastructure.
Hess et al. (2012), U.S.	Cross NL	HEV, PHEV, BEV	Vehicle attributes: body type, costs, performance, and efficiency Charging infrastructure: fuel availability Incentives: access to HOV lane, free parking, and tax credit Socio-economic characteristics	Incentives including access to HOV lane, free parking, and reduced purchase price are insignificant in preferences for HEVs, PHEVs, and BEVs while tax credit incentive affects the utility of HEVs, PHEVs, and BEVs.
Ziegler (2012), Germany	MNP	HEV, PHEV, BEV	Vehicle attributes: purchase price, power, fuel costs, emissions, age, body type, horsepower, driving range, mileage, and driving vehicle to work Charging infrastructure: fuel availability Socio-economic characteristics and environmentally-friendly purchase	Younger and environmentally aware persons have positive intention towards HEVs, PHEVs, and BEVs.
Hackbarth and Madlener (2013), Germany	MXL	HEV, PHEV, BEV	Vehicle attributes: purchase price, fuel cost, emissions, driving range, refueling time, battery recharging time, and body size Charging infrastructure: fuel availability and equipping parking Incentives: tax exemption, free parking, and access to bus lane Socio-economic, travel characteristics, and environmental awareness	EVs (HEVs, PHEVs, and BEVs) are embraced by younger, well-educated, and environmentally aware persons with many trips. People are willing to pay for greater fuel economy, emission reduction, improved driving range, and enhanced charging infrastructure, as well as EV incentives.
Daziano and Achtnicht (2013), Germany	MNP	HEV, BEV	Vehicle attributes: purchase price, fuel costs, power, and CO_2 emissions Charging infrastructure: fuel availability	Increasing fuel availability could increase greater than threefold increase in HEV and BEV market penetration.

Table 5.1. Overview of studies with economic approach on electric vehicle adoption behavior using stated preferences dataset

Study, country	Model	EV types	Explanatory variables	Key finding(s)
Jensen et al. (2013), Denmark	HCM	BEV	Vehicle attributes: purchase price, fuel cost, driving range, age, emissions, top speed, battery stations, battery life, and body size Socio-economic characteristics, latent environment attitude, charging at work/city centers/larger train stations, and home-work distance	Women in households with more vehicles are interested in BEVs. Individual preferences change significantly after a real experience with a BEV in a household. Environmental concerns have a positive effect on BEV preference.
Barter et al. (2013), U.S.	NL	PHEV, BEV	Vehicle attributes: pace of technological development Incentives: ownership cost, oil price, and battery performance	Reduction of greenhouse gas (GHG) emissions cannot occur only by widespread EV adoption and it requires efficiency improvement of conventional vehicles.
Kim et al. (2014), the Netherlands	HCM	BEV	Socio-economic characteristics, social influence, environmental concerns, and technology acceptance	Males and highly educated persons are interested in BEVs. Preference for a BEV is influenced by social influence, environmental concerns, and technology acceptance.
Hoen and Koetse (2014), the Netherlands	MXL	HEV, PHEV, BEV	Vehicle attributes: driving range, recharging time, additional detour time, and vehicle brand Incentives: free parking, tax exception, and access to bus/taxi lanes	Preference for an EV (HEV, PHEV, and BEV) increases with improving driving range, refueling time, and fuel availability. Increasing annual mileage leads to lower preference for EVs.
Tanaka et al. (2014), U.S. and Japan	MXL	PHEV, BEV	Vehicle attributes: purchase price, fuel cost, driving range, and emissions Charging infrastructure: PEV charging station availability	PHEV and BEV consumers in the U.S. are sensitive to fuel cost reduction and public charging station availability.
Valeri and Danielis (2015), Italy	MXL	HEV, BEV	Vehicle attributes: purchase price, operating cost, acceleration, and driving range Charging infrastructure: refueling distance Socio-economic characteristics and presence of long-distance trips	An increase in driving range does not increase BEV market share whereas a combination of changes such as introduction of a subsidy, decrease of purchase price, increase in battery range and fuel price increases BEV market share.
Helveston et al. (2015), U.S. and China	MXL	HEV, PHEV, BEV	Vehicle attributes: price, powertrain, brand, cost, and performance	Americans have low willingness-to-pay for BEVs and they prefer low-range PHEVs.
Rasouli and Timmermans (2016), the Netherlands	MXL	BEV	Vehicle attributes: capital costs, operating costs, cruising range, time to change the battery, and maximum speed Charging infrastructure: distance to charging station Socio-economic characteristics and social networks	Social network effects play a minor role on BEV adoption. BEV adopters are among persons with high income level.
Cirillo et al. (2017), U.S.	MXL	HEV, BEV	Vehicle attributes: purchase price, recharging range, size, and fuel economy Socio-economic characteristics and energy (electricity and gas) price	Highly educated women prefer HEVs whereas highly educated men are interested in BEVs. Young people more probably buy HEVs and BEVs, especially BEVs.
Higgins et al. (2017), Canada	MNP	HEV, PHEV, BEV	Vehicle attributes: cost, performance, charging characteristics, warranty, and vehicle attribute importance Incentives: cash, free parking, free toll road use, and access to HOV lane Socio-economic characteristics	PHEVs and BEVs are most attractive to households that are younger and highly educated. Those that care about fuel economy and reduced or zero emissions show much higher probabilities of selecting HEV, PHEV, and BEV options.
Nazari et al. (2018b), U.S.	NL	HEV, PEV	Charging infrastructure: accessibility to public PEV charging stations Socio-economic characteristics, built-environment characteristics, and travel attitude factors	Households with higher income and education are more interested in PEVs. Accessibility to PEV charging stations is a critical factor in choosing PEVs.

MNL: multinomial logit, NL: nested logit, MNP: multinomial probit, MXL: mixed logit, LCMNL: latent class MNL, HCM: hybrid choice model
HEV: hybrid electric vehicle, PHEV: plug-in hybrid electric vehicle, BEV: battery electric vehicle, PEV: PHEV or BEV

5.2. Methodology: integrated choice model with latent variables

To gain a more behaviorally realistic insight into the EV adoption behavior, it is critical to explicitly account for the unobservable (*latent*) subjective attitude, perception, and lifestyle preference influencing decision-making, along with the observable factors (such as socio-economic characteristics of decisions-makers, features of their surrounding built environment, and their current daily and commute travel behavior characteristics) explaining the decision-making process (McFadden, 1986; Train et al., 1987). In view of this and with the availability of a rich database (RVS), I take into account people's perception at vehicle purchase time and lifestyle preference. A comparison between the explained variance by perceptual latent constructs shows that a significant share of variance is explained by *vehicle specification* and *social influence* (according to the CFA results as discussed in section 0). Another comparison between the explained variance by lifestyle preference latent constructs also determines that the more influential constructs are *environmental consciousness* and *technology savviness*. Therefore, I estimated an ICLV model of households' vehicle transaction and fuel type choice among a set of ten alternatives (including no vehicle transaction, adding a new vehicle to the household (CV, HEV, PHEV, and BEV), selling one of current household vehicles, and trading one of household vehicles with another one (CV, HEV, PHEV, and BEV)) in addition to considering four latent constructs describing perception of vehicle specification and social influence at vehicle purchase time as well as lifestyle preference for environmental consciousness and technology savviness.

This section presents the modeling framework and the formulation of the ICLV, which is first proposed by Ben-Akiva and colleagues (Ben-Akiva and Boccara, 1995). Figure 5.1 shows framework of the employed ICLV model, where the squared boxes and the circles represent the observable variables (i.e., explanatory variables, measurement indicators of the latent constructs, and choice indicators) and unobservable/latent constructs (vehicle specification, social influence, environmental consciousness, and technology savviness), respectively. The framework integrates a choice model with a latent variable model in which the values of the parameters are determined by simultaneous estimation of the system of the equations. The *first* component of the integrated model is the latent variable model, the upper section of the framework, which determines the latent constructs by two sets of equations. The *second* component is the choice model as shown in the lower section of the framework.

The rest of the section discusses the ICLV formulation. For brevity, I suppress the index $q \in \{1, 2, \dots, Q\}$ for observations, i.e., decision makers, in the equations of this section.

The *first* component of the modeling framework is a latent variable model, which consists of two sets of structural and measurement equations. The structural equations connect the vector of the latent constructs $\boldsymbol{x}^* = (x_1^*, x_2^*, \dots, x_{\mathcal{L}}^*)$ to the vector of the explanatory variables $\boldsymbol{z_\ell}$ as is shown in Figure 5.1 by the full arrows from the explanatory variables towards the latent constructs. This relationship for the ℓ^{th} latent construct x_ℓ^*, $\ell \in \{1, 2, \dots, \mathcal{L}\}$ is formulated as equation (5.1) that creates $\mathcal{L}$ structural equations.

$$x_\ell^* = \boldsymbol{\beta'_\ell} \boldsymbol{z_\ell} + \eta_\ell \quad \forall\, \ell \in \{1, 2, \dots, \mathcal{L}\} \tag{5.1}$$

where, $\boldsymbol{z_\ell}$ is a $\mathcal{S} \times 1$ vector of explanatory variables for the ℓ^{th} latent construct and $\boldsymbol{\beta_\ell}$ is the corresponding vector of parameters. The unobserved factors of ℓ^{th} structural equation is captured by the random error term η_ℓ, which is assumed to be standard normally distributed ($\boldsymbol{\eta} \sim N[0, \boldsymbol{\Sigma_\eta}]$, where $\boldsymbol{\Sigma_\eta}$ is the covariance matrix). In this chapter, the latent constructs are vehicle specification (x_1^*), social influence (x_2^*), environmental consciousness (x_3^*), and technology savviness (x_4^*). Given distribution of error term and conditional on the vector of the explanatory variables, the probability of the structural equation is written as equation (5.2).

$$f_1(\boldsymbol{x}^* | \boldsymbol{z}; \boldsymbol{\beta}, \boldsymbol{\Sigma_\eta}) = \prod_{\ell=1}^{\mathcal{L}} \frac{1}{\sigma_{\eta_\ell}} \varphi \left(\frac{x_\ell^* - \boldsymbol{\beta'_\ell} \boldsymbol{z_\ell}}{\sigma_{\eta_\ell}} \right) \tag{5.2}$$

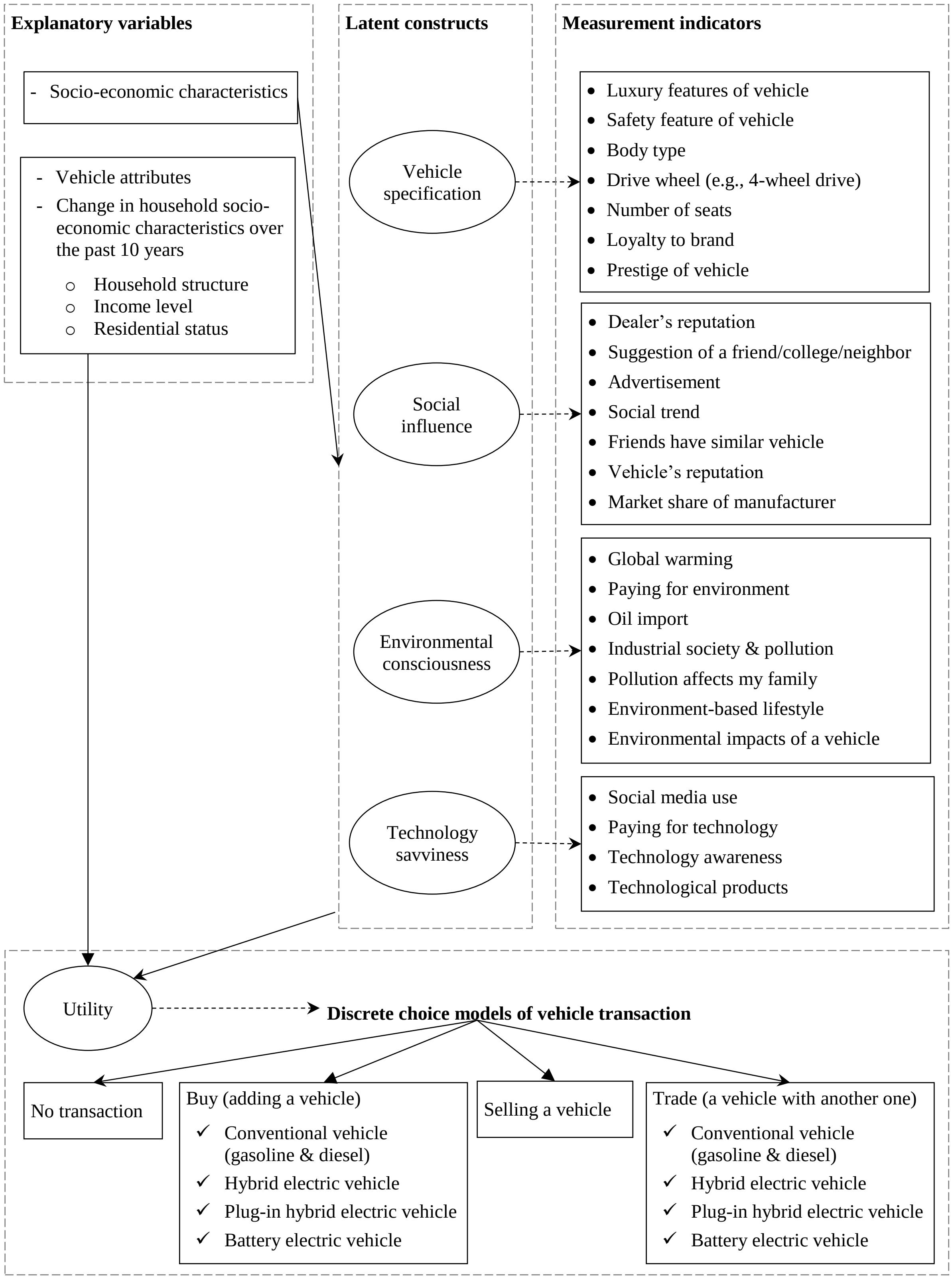


Figure 5.1. Framework of integrated vehicle transaction choice model with latent constructs

The latent constructs, on the other side, are explained by the corresponding indicators. This connection is shown in Figure 5.1 by the dotted lines from the latent constructs to the indicators and is formulated as equation (5.3).

$$I_{\mathscr{r}} = \boldsymbol{\gamma}'_{\mathscr{r}}\boldsymbol{x}^{*} + \mu_{\mathscr{r}} \quad \forall\, \mathscr{r} \in \{1, 2, \ldots, \mathcal{R}\} \tag{5.3}$$

where, $I_{\mathscr{r}}$, $\mathscr{r} \in \{1, 2, \ldots, \mathcal{R}\}$ denotes the $\mathscr{r}^{th}$ attitudinal/perceptual/preferential indicator and thus, there are $\mathcal{R}$ measurement equations. Weight of the vector of the latent constructs $\boldsymbol{x}^{*}$ on the $\mathscr{r}^{th}$ indicator is denoted by $\boldsymbol{\gamma}_{\boldsymbol{\mathscr{r}}}$. The random errors of the $\mathscr{r}^{th}$ measurement equation is shown by the term $\mu_{\mathscr{r}}$ and is assumed to be standard normally distributed such that $\boldsymbol{\mu} \sim N[0, \boldsymbol{\Sigma}_{\boldsymbol{\mu}}]$, where $\boldsymbol{\Sigma}_{\boldsymbol{\mu}}$ is the covariance matrix. In this research, four sets of indicators define the underlying latent constructs vehicle specification, social influence, environmental consciousness, and technology savviness as listed in Figure 5.1. Conditional on the vector of the latent constructs and given the distribution of the error term, the probability of the measurement equation is written as equation (5.4).

$$f_2(\boldsymbol{I} | \boldsymbol{x}^{*}; \boldsymbol{\gamma}, \boldsymbol{\Sigma}_{\boldsymbol{\mu}}) = \prod_{\mathscr{r}=1}^{\mathcal{R}} \frac{1}{\sigma_{\eta_{\mathscr{r}}}} \varphi\left(\frac{I_{\mathscr{r}} - \boldsymbol{\gamma}'_{\mathscr{r}}\boldsymbol{x}^{*}}{\sigma_{\eta_{\mathscr{r}}}}\right) \tag{5.4}$$

The second component of the ICLV is a choice model that explains the decision makers' choice among the set alternatives $i \in \{1, 2, \ldots, I\}$. The first alternative is engaging in no vehicle transaction, which implies that the decision maker continues utilizing the current vehicle fleet. The other alternatives include buying a vehicle (CV, HEV, PHEV, and BEV), selling one of current vehicles, and trading an existing vehicle with another one (CV, HEV, PHEV, and BEV). Equation (5.5) formulates utility of alternative i (U_i) given a $\bar{S} \times 1$ vector of explanatory variables ($\boldsymbol{x}_{\boldsymbol{i}}$) and the $\mathcal{L} \times 1$ vector of latent constructs $\boldsymbol{x}^{*}$.

$$U_i = \underbrace{\boldsymbol{\alpha}'_{\boldsymbol{1i}}\boldsymbol{x}_{\boldsymbol{i}} + \boldsymbol{\alpha}'_{\boldsymbol{2i}}\boldsymbol{x}^{*}}_{V_i} + \varepsilon_i \qquad y_i = 1, if\ U_i = \max_{j}\{U_j\} \tag{5.5}$$

The estimation gives the $\bar{S} \times 1$ vector of parameters for the explanatory variables $\boldsymbol{\alpha_{1i}}$ and the $\mathcal{L} \times 1$ vector of parameters for the latent constructs $\boldsymbol{\alpha_{2i}}$. The error term for alternative i is denoted by ε_i, which has standard Gumbel distribution so as $\boldsymbol{\varepsilon} \sim G[0, \boldsymbol{\Sigma_\varepsilon}]$, where $\boldsymbol{\Sigma_\varepsilon}$ is the covariance matrix. y_i is the choice indicators that equals 1 if a decision maker selects alternative i, which maximizes the related utility equation. The vector of the choice indicators is denoted by $\boldsymbol{y}$**.** Given the assumption about the distribution of the error term and conditional on the vectors of the explanatory variables and the latent construct, the choice probability is derived as equation (5.6).

$$f_3(\boldsymbol{y}|\boldsymbol{x}, \boldsymbol{x}^*; \boldsymbol{\alpha_1}, \boldsymbol{\alpha_2}) = \frac{e^{V_i}}{\sum_{j \in I} e^{V_j}} \tag{5.6}$$

The likelihood equation is the joint choice probability and the latent variables are formulated in equation (5.7) given the vector of the choice indicators and latent construct indicators. The integral degree of the equation is equal to the number of the latent constructs.

$$Likelihood\left(\boldsymbol{y}, \boldsymbol{I} \middle| \boldsymbol{x}; \boldsymbol{\alpha_1}, \boldsymbol{\alpha_2}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\Sigma_\varepsilon}, \boldsymbol{\Sigma_\eta}, \boldsymbol{\Sigma_\mu}\right) = \int f_1(\cdot) \times f_2(\cdot) \times f_3(\cdot)\, d\boldsymbol{x}^* \tag{5.7}$$

Substituting equations (5.2), (5.4), and (5.6) in equation (5.7) gives equation (5.8).

$$\begin{aligned} &L\left(\boldsymbol{y}, \boldsymbol{I} \middle| \boldsymbol{x}; \boldsymbol{\alpha_1}, \boldsymbol{\alpha_2}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\Sigma_\varepsilon}, \boldsymbol{\Sigma_\eta}, \boldsymbol{\Sigma_\mu}\right) \\ &\qquad = \int \prod_{\ell=1}^{\mathcal{L}} \frac{1}{\sigma_{\eta_\ell}} \varphi\left(\frac{x_\ell^* - \boldsymbol{\beta}'_{\boldsymbol{\ell}} \boldsymbol{z_\ell}}{\sigma_{\eta_\ell}}\right) \times \prod_{r=1}^{\mathcal{R}} \frac{1}{\sigma_{\eta_r}} \varphi\left(\frac{I_r - \boldsymbol{\gamma}'_r \boldsymbol{x}^*}{\sigma_{\eta_r}}\right) \times \frac{e^{\boldsymbol{\alpha}'_{\boldsymbol{1i}} \boldsymbol{x_i} + \boldsymbol{\alpha}'_{\boldsymbol{2i}} \boldsymbol{x}^*}}{\sum_{j \in I} e^{\boldsymbol{\alpha}'_{\boldsymbol{1j}} \boldsymbol{x_i} + \boldsymbol{\alpha}'_{\boldsymbol{2j}} \boldsymbol{x}^*}} d\boldsymbol{x}^* \end{aligned} \tag{5.8}$$

The assumption of standard normal distribution for the error term of the structural equation gives $\eta_\ell = \sigma_{\eta_\ell} \tilde{\eta}_\ell$ so as $\tilde{\eta}_\ell \sim N(0,1)$. This assumption convert equation (5.8) to equation (5.9).

$$\begin{aligned} &L\left(\boldsymbol{y}, \boldsymbol{I} \middle| \boldsymbol{x}; \boldsymbol{\alpha_1}, \boldsymbol{\alpha_2}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\Sigma_\varepsilon}, \boldsymbol{\Sigma_\eta}, \boldsymbol{\Sigma_\mu}\right) \\ &= \int \prod_{\ell=1}^{\mathcal{L}} \varphi(\tilde{\eta}_\ell) \times \prod_{r=1}^{\mathcal{R}} \frac{1}{\sigma_{\eta_r}} \varphi\left(\frac{I_r - \boldsymbol{\gamma}'_r (\boldsymbol{\beta}'_{\boldsymbol{\ell}} \boldsymbol{z_\ell} + \sigma_{\eta_\ell} \tilde{\eta}_\ell)}{\sigma_{\eta_r}}\right) \times \frac{e^{\boldsymbol{\alpha}'_{\boldsymbol{1i}} \boldsymbol{x_i} + \boldsymbol{\alpha}'_{\boldsymbol{2i}} (\boldsymbol{\beta}'_{\boldsymbol{\ell}} \boldsymbol{z_\ell} + \sigma_{\eta_\ell} \tilde{\eta}_\ell)}}{\sum_{j \in I} e^{\boldsymbol{\alpha}'_{\boldsymbol{1j}} \boldsymbol{x_i} + \boldsymbol{\alpha}'_{\boldsymbol{2j}} (\boldsymbol{\beta}'_{\boldsymbol{\ell}} \boldsymbol{z_\ell} + \sigma_{\eta_\ell} \tilde{\eta}_\ell)}} d\boldsymbol{\tilde{\eta}_\ell} \end{aligned} \tag{5.9}$$

By applying simulated maximum likelihood, the likelihood equation (5.9) converts to equation (5.10).

$$\tilde{L}\left(\boldsymbol{y},\boldsymbol{I}\middle|\boldsymbol{x};\boldsymbol{\alpha_1},\boldsymbol{\alpha_2},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\Sigma_\varepsilon},\boldsymbol{\Sigma_\eta},\boldsymbol{\Sigma_\mu}\right) = \frac{1}{\mathcal{M}}\sum_{m=1}^{\mathcal{M}}\left(\prod_{r=1}^{\mathcal{R}}\frac{1}{\sigma_{\eta_r}}\varphi\left(\frac{I_r-\boldsymbol{\gamma}'_r\left(\boldsymbol{\beta}'_{\boldsymbol{\ell}}\boldsymbol{z}_{\boldsymbol{\ell}}+\sigma_{\eta_\ell}\tilde{\eta}_\ell^m\right)}{\sigma_{\eta_r}}\right)\times\frac{e^{\boldsymbol{\alpha}'_{1i}\boldsymbol{x}_i+\boldsymbol{\alpha}'_{2i}\left(\boldsymbol{\beta}'_{\boldsymbol{\ell}}\boldsymbol{z}_{\boldsymbol{\ell}}+\sigma_{\eta_\ell}\tilde{\eta}_\ell^m\right)}}{\sum_{j\in I}e^{\boldsymbol{\alpha}'_{1j}\boldsymbol{x}_i+\boldsymbol{\alpha}'_{2j}\left(\boldsymbol{\beta}'_{\boldsymbol{\ell}}\boldsymbol{z}_{\boldsymbol{\ell}}+\sigma_{\eta_\ell}\tilde{\eta}_\ell^m\right)}}\right) \quad (5.10)$$

where, $\mathcal{M}$ is the number of random draws from $\tilde{\eta}_\ell$ for each observation that is denoted by $\tilde{\eta}_\ell^m$, $m \in \{1, 2, \dots, \mathcal{M}\}$. According to equation (5.11), logarithm of the likelihood equation is maximized over the observations $q \in \{1, 2, \dots, Q\}$ to determine the vectors of the parameters $\left(\boldsymbol{\alpha_1},\boldsymbol{\alpha_2},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\Sigma_\varepsilon},\boldsymbol{\Sigma_\eta},\boldsymbol{\Sigma_\mu}\right)$.

$$\ln\tilde{L} = \max_{\alpha_1,\alpha_2,\beta,\gamma,\Sigma}\sum_{q=1}^{Q}\ln\tilde{L}\left(y_q, I_q\middle|x_q;\alpha_{1q},\alpha_{2q},\beta_q,\gamma_q,\Sigma_\varepsilon,\Sigma_\eta,\Sigma_\mu\right) \quad (5.11)$$

5.3. Results

This section discusses the estimation results of the ICLV model in three sub-sections including measurement and structural equations and the choice model. Almost all estimated coefficients are significant at 95% level of confidence and the model has an acceptable goodness-of-fit.

5.3.1. Measurement equations

The measurement equations connect the latent constructs to the corresponding measurement indicators (shown by the dotted lines in the upper section of Figure 5.1). The related coefficients are shown in Table 5.2. The first latent construct, vehicle specification, describes how the individuals perceive various vehicle specifications when they decided on purchasing a vehicle. Comparison of the indicators shows that the latent vehicle specification is mostly defined by prestige of a vehicle. In addition, safety features of a vehicle have the smallest impact on this latent factor. The other perceptual latent construct is social influence which is more influenced by advertisement. Interestingly, vehicle reputation has the smallest influence on this latent factor.

Table 5.2. Estimation results of measurement equations

Indicators of latent constructs	Coefficient	T-statistics
Perception at vehicle purchase time		
Vehicle specification		
Luxury features of vehicle	0.602	30.89
Safety features of vehicle	0.339	13.605
Body type	0.357	13.94
Drive wheel (e.g., 2-wheel drive)	0.514	24.19
Number of seats	0.406	17.23
Loyalty to brand	0.660	36.94
Prestige of vehicle	0.717	45.04
Social influence		
Dealer’s reputation	0.463	23.08
Suggestion of a friend, colleague, or neighbor	0.734	49.80
Advertisement	0.831	81.63
Social trend	0.787	60.78
Friends have similar vehicle	0.750	59.53
Vehicle reputation	0.244	10.47
Market share of manufacturer	0.739	50.03
Lifestyle preference		
Environmental consciousness		
I am concerned about global warming.	0.698	36.97
I change my behavior and lifestyle based on concerns about the environment.	0.157	6.34
I am concerned about the effects of pollution on myself and my family.	0.725	43.44
I am willing to pay for a product which is more environmentally friendly.	0.712	36.36
It is important to be independent from oil and the producer countries.	0.626	28.86
It is important to consider environmental impacts of a vehicle at its purchase time.	0.629	28.38
Technology savviness		
I am interested in new technological products.	0.684	35.13
I am aware of latest technological products more than others.	0.813	59.30
I am willing to pay for new technological products.	0.698	38.58
I frequently use social media (e.g., Facebook, Tweeter, Instagram).	0.431	16.88

The third latent construct describes lifestyle preference for environmental consciousness. The largest and smallest weight of the related indicators belong to the impacts of pollution on oneself and his/her family and changing behavior and lifestyle based on environmental concerns, respectively. Finally, the last latent construct explains how a person is aware of technology, i.e., technology savviness. This factor is highly affected by being aware of new technologies while the indicator with the smallest impact is frequency of social media use.

5.3.2. Structural equations

Besides the connection of the latent constructs to the corresponding indicators, the model ties the latent constructs to the explanatory variables, i.e., individuals' socio-economic characteristics, via the structural equations (shown by the solid lines in the upper section of Figure 5.1). The estimation results signify the role of six socio-economic characteristics as explanatory variables (Table 5.3). **Females** significantly appear in the four structural equations with a negative sign. It means that at vehicle purchase time, females less perceive vehicle specification and social influence compared to males. They are also less environmentally conscious and technology savvy than males.

Age of the persons appears as a categorical variable, which shows it non-linear effect on the latent constructs. When young persons ($18 \leq \text{age} < 35$) decide on purchasing a vehicle, they pay more attention to its specification and are more affected by social influence. In contrast, these two factors have the lowest importance for the elderly ($\text{age} \geq 65$). I also found that the environmentally conscious group are young persons compared to others. Moreover, young persons are more aware of technologies, whereas the elderly have the lowest technology awareness.

It is also interesting to find that higher **education level** (bachelor's degree or higher) decreases the importance of vehicle specification and social influence. In contrast, highly educated persons are more conscious of environmental impacts of products and have higher levels of technology awareness.

Table 5.3. Estimation results of structural equations

Explanatory variables	Vehicle specification		Social influence		Environmental consciousness		Tech. savviness	
	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.	Coeff.	T-stat.
Socio-economic characteristics								
Female	-0.136	-4.98	-0.151	-6.41	-0.094	-3.50	-0.309	-12.47
Age								
Young (18 ≤ age < 35)	0.115	3.86	0.332	13.35	0.168	6.81	0.191	7.53
Elderly (age ≥ 65)	-0.122	-4.86	-0.140	-6.47	—	—	-0.157	-6.69
Education level								
Bachelor's degree or higher	-0.085	-3.10	-0.050	-2.08	0.139	5.29	0.122	4.82
Paid employed								
Yes = 1	0.210	6.40	0.117	4.88	—	—	—	—
Living alone								
Yes = 1	-0.065	-2.54	0.053	2.44	0.046	2.16	—	—

The perceptual latent constructs, i.e., vehicle specification and social influence, are further affected by **employment status** as a dummy variable with value 1 for paid employed (full-time, part-time, and self-employed) persons and 0 otherwise. The positive sign of this variable in the related structural equations reveals the importance of vehicle specification and social influence for paid employees.

Lastly, **household structure** is reflected by a dummy variable with value 1 for those who live alone and 0 otherwise. Persons who live alone less perceive the importance of vehicle specification, while are positively affected by social influence. Furthermore, alone persons have higher environmental consciousness compared to other ones.

5.3.3. Choice model

As discussed in section 5.2, the ICLV model explains households' decision on vehicle transaction among ten alternatives (second section of the modeling framework shown in Figure 5.1). The number of observations for each vehicle transaction and fuel type choice is according to Table 5.4. The summation of the number of observations over the transaction types (except for sell alternative) gives the number of existing vehicles with different fuel types, which is shown in the lower section of Table 5.4 (the reference is The Statistics Portal (2018), Auto Alliance (2018), and US DOE, Office of Energy Efficiency & Renewable Energy (2018c)). Since the market share of EVs, especially PEVs, in the US is very small (shown in Table 5.4), a model of vehicle fuel type choice using a sample data of vehicles with a fuel type distribution according to the market share cannot be estimated (the number of each EV type would be a small number). To cope with this problem, I oversampled EV types. After model estimation, the biases caused by oversampling EV types can be removed by applying the method of Cherchi and Ortúzar (2006). Using this method, the constant terms of the estimated model is adjusted so that the model with only constant terms gives the market share. Table 5.5 present the estimation results of the ICLV vehicle transaction, which is explained by three types of explanatory variables. The rest of the section discusses the impacts of the explanatory variables.

Table 5.4. Number of observations for the choice alternatives

Alternatives of choice model				
Vehicle transaction	*Fuel type*	*# observations*		
No transaction	CV	407		
	HEV	69		
Buy	CV	1,614		
	HEV	476		
	PHEV	91		
	BEV	192		
Sell	—	513		
Trade	CV	1,106		
	HEV	525		
	PHEV	83		
	BEV	148		
		Sum = 5,224		
Existing vehicles				
	Fuel type	*# observations*	*Sample share (%)*	*Market share* (%)*
	CV	3,127	66.38	98.09
	HEV	1,070	22.71	1.65
	PHEV	174	3.69	0.13
	BEV	340	7.22	0.13
		Sum = 4,711		

Table 5.5. Estimation results of choice model

Explanatory variables	Buy								Sell		Trade							
	CV		HEV		PHEV		BEV		Sell		CV		HEV		PHEV		BEV	
	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat	Coeff.	T.stat
Constant	—	—	-4.085	-11.39	-6.626	-15.78	-6.626	-19.74	-0.580	-9.27	—	—	-4.085	-11.00	-6.626	-11.13	-6.626	-15.29
Vehicle attributes																		
Ownership																		
Leased = 1	1.459	6.907	1.611	6.624	—	—	1.672	6.211	—	—	1.883	8.838	1.492	5.945	3.193	10.69	2.940	10.80
Company vehicle = 1	—	—	0.364	2.016	—	—	—	—	—	—	-0.593	-2.755	—	—	—	—	—	—
Part of income is gained by vehicle																		
Yes = 1	0.407	5.953	0.547	5.026	—	—	0.613	4.239	—	—	—	—	—	—	—	—	—	—
Changes in household socio-economic characteristics over the past 10 years																		
# change in household structure																		
Moving in	—	—	0.125	2.547	0.132	1.518	0.111	1.731	0.192	4.718	—	—	—	—	0.225	2.372	—	—
Joining children	—	—	0.149	2.06	—	—	—	—	—	—	0.077	2.37	—	—	—	—	—	—
# change in income level																		
Increasing income	0.212	7.21	—	—	0.266	3.94	0.203	3.59	—	—	0.209	6.63	—	—	—	—	0.155	2.08
Decreasing income	—	—	—	—	—	—	—	—	0.114	2.80	—	—	—	—	—	—	—	—
# change in residential status																		
House in suburban area	0.260	3.90	0.163	1.64	0.857	6.27	0.431	3.41	—	—	0.238	3.08	—	—	—	—	0.301	1.91
House in downtown area	—	—	—	—	—	—	0.489	4.99	0.192	2.41	-0.106	-1.44	—	—	—	—	—	—
Change of work/school	0.121	4.05	—	—	0.156	1.71	—	—	0.090	2.13	—	—	0.141	3.47	—	—	—	—
Latent constructs																		
Vehicle specification	2.983	7.36	—	—	—	—	1.784	1.82	—	—	1.089	3.53	—	—	—	—	—	—
Social influence	0.849	2.99	1.579	4.53	3.042	4.14	3.102	5.04	—	—	—	—	0.518	1.65	—	—	1.324	2.07
Environmental consciousness	—	—	2.191	4.06	—	—	—	—	0.629	1.53	—	—	2.335	4.48	2.488	1.69	—	—
Technology savviness	—	—	—	—	1.411	1.98	—	—	—	—	—	—	—	—	1.793	1.91	1.986	3.16

Goodness-of-fit
observations = 5,224
Log-likelihood at zero = 15,503.589
Log-likelihood with constants = -1,3404.544
Log-likelihood at convergence = -12,600.877

5.3.3.1. Vehicle attributes

The first vehicle attribute is **ownership type**, which is significant in two forms of leased and company vehicles. The estimation results show that households are interested in trading or adding a leased vehicle with an overall more tendency towards trade alternative. Among fuel types, their highest interest is in trading their leased vehicles with PHEVs and BEVs, which may be due to the related higher ownership cost, especially depreciation cost, than other alternatives (American Automobile Association, 2017; Guo and Zhou, 2019). This can also be verified by the observed share of leased BEVs in the dataset which has the largest share of leased vehicles with respect to fuel type (section 4.2.3). In addition, company vehicles are added to the households and their fuel type is more likely HEV than other fuel types and other transaction options.

The other vehicle attribute determines whether **a household uses its vehicle to gain a part of income**. The estimation results show that the households with positive answer to this question more probably buy a vehicle. Moreover, their preferred fuel type for the added vehicle is BEV, HEV, and CV, in a descending order. This finding shows the positive utility of BEVs and HEVs, especially BEVs, among the households who use their vehicles for-hire transport of passengers or goods.

5.3.3.2. Change in household socio-economic characteristics over the past 10 years

The choice model signifies three groups of variables, which describe dynamics of household socio-economic characteristics. The first group reflects changes of **household structure**. The first variable is the number of times a household had move in with spouse or partner over the past 10 years. The estimation results show that the larger number of this variable increases the probability of selling a vehicle. This factor also has a positive impact on adding a vehicle, especially non-CVs. Moreover, larger values of moving in increases the probability of trading a vehicle with a PHEV. The next variable is the number of children that joined the households. As the number of children in a household increases, the probability of adding a HEV increases as well. The second preferred alternative of the households with more children is trading one vehicle with a CV.

The second group of dynamic explanatory variables shows changes of **household income** over the past 10 years. According to the estimation results, increasing the income level leads to more interest in adding a vehicle compared to other transaction options. In addition, increasing the income level also has a positive impact on the utility of trading alternatives. In contrast, decreasing the income level leads to higher probability of selling a vehicle of the households.

The last group of dynamic variables captures changes of household **residential status** over the past 10 years. The findings highlight that moving to a house in suburbs more likely leads to purchase of a vehicle regardless of fuel type. This factor also causes positive tendency towards trading a vehicle with a CV. In contrast, moving to a house in downtown areas causes selling one of existing vehicles of the household. Interestingly, this factor likely leads to adding a BEV to the household. The last factor that describes dynamics of residential status is the number of times that a household member changes work or school location. The estimation results show that this factor increases the probability of adding a CV or trading a vehicle with a CV. In addition, this factor adds chance of adding a PHEV and selling an existing vehicle.

5.3.3.3. Latent constructs

The first latent construct describes perception of **vehicle specifications** at vehicle purchase time. The estimation results show that higher perception of this latent construct increases the probability of adding or trading CVs as well as adding BEVs. It means that persons who perceive vehicle specifications as an important factor at purchase time, more likely choose CVs regardless of adding it as another household vehicle or trading one of vehicles with it. These persons also have a positive tendency towards adding BEVs.

The second perceptual latent construct reflects the role of **social influence** in vehicle purchase decision. I found that persons who are more affected by society more probably add a vehicle to their households and interestingly they prefer PEVs, with more tendency towards BEVs. This group of people are also interested in trading a vehicle with HEVs, however, with a lower tendency compared to add alternative.

The latent **environmental consciousness** construct appears in the utility equations of trading hybrid vehicle (HEVs and PHEVs) and adding HEVs. Moreover, environmental conscious persons are interested in selling their vehicle, though with a lower interest than holding hybrid vehicles.

As expected, the latent construct explaining technology savviness increases the probability of trading a vehicle with a PEV, especially a BEV. Furthermore, tech-savvy persons have tendency towards adding a PHEV to their existing vehicles, however, with a lower tendency than trading a PEV.

5.3.4. Sensitivity Analysis

To further analyze the ICLV model, I computed the direct elasticities of the choice alternatives with respect to the exogenous variables. The direct elasticity of an alternative with respect to an exogenous variable is defined as the percentage change in the choice probability of the alternative caused by a percentage change in the desired exogenous variable while keeping all other exogenous variables constant. The direct elasticities of the alternatives with respect to the observed and the latent variables are calculated according to equations (5.12) and (5.13) (Wen and Koppelman, 2001).

$$(1 - f_{3i})\ \alpha_{1i} x_i \tag{5.12}$$

$$(1 - f_{3i})\ \alpha_{2i} x^* \tag{5.13}$$

The calculated values of direct elasticity (presented in Table 5.6) reveal that the alternatives are inelastic with respect to the all significant explanatory variables. Among the vehicle attributes, the largest elasticity is caused by the factor leasing vehicles. Moreover, the change of socio-economic characteristics that causes the largest elasticity is increasing income level and moving to suburban areas. Finally, the latent constructs with the largest changes to the probability of choosing alternatives are social influence and environmental consciousness. For instance, if social influence increases by 1%, the probability of adding a PHEV and BEV increases by 0.235% and 0.240%, respectively.

Table 5.6. Elasticity of explanatory variables of the choice model

Explanatory variables	Buy				Sell	Trade			
	CV	HEV	PHEV	BEV	Sell	CV	HEV	PHEV	BEV
Vehicle attributes									
Ownership									
Leased = 1	0.052	0.107	—	0.112	—	0.072	0.099	0.214	0.197
Company vehicle = 1	—	0.013	—	—	—	-0.018	—	—	—
Part of income is gained by vehicle									
Yes = 1	0.044	0.127	—	0.143	—	—	—	—	—
Changes in household socio-economic characteristics over the past 10 years									
# change in household structure									
Moving in	—	0.049	0.052	0.044	0.065	—	—	0.088	—
Joining children	—	0.190	—	—	—	0.072	—	—	—
# change in income level									
Increasing income	0.080	—	0.192	0.146	—	0.108	—	—	0.112
Decreasing income	—	—	—	—	0.049	—	—	—	—
# change in residential status									
House in suburban area	0.039	0.049	0.259	0.130	—	0.054	—	—	0.091
House in downtown area	—	—	—	0.097	0.033	-0.017	—	—	—
Change of work/school	0.025	—	0.061	—	0.030	—	0.055	—	—
Latent constructs									
Vehicle specification	0.104	—	—	0.143	—	0.067	—	—	—
Social influence	0.021	0.121	0.235	0.240	—	—	0.040	—	0.103
Environmental consciousness	—	0.194	—	—	0.049	—	0.208	0.223	—
Technology savviness	—	—	0.088	—	—	—	—	0.111	0.123

6. Conclusions and Future Research Directions

6.1. Autonomous vehicles

Autonomous/automated vehicles (AVs) might hit the roads in the near future. Besides, shared mobility services have been surging in recent years and show significant prospect for reducing private car ownership levels. Merged together, shared AVs (SAVs) could render shared mobility services ubiquitous by providing low-cost, convenient, and door-to-door travel modes comparable to private cars. In light of this, it may be hypothesized that future urban mobility will likely be a public utility and AV private ownership in unnecessary. The second chapter of this dissertation examines the impacts of the various observable and latent factors on public interest in private AV ownership and different SAV services (comprising carsharing, ridesourcing, ridesharing, and access/egress mode) by *jointly* modeling these (S)AV types. Multivariate and bivariate ordered probit models with latent variables are estimated, which accommodate the correlations across the (S)AV types and explicitly treat the latent attitudes/preferences explaining safety concern about AV, green travel pattern, and mobility-on-demand (MOD) savviness.

Drawing from a stated preference survey in the State of Washington (Puget Sound travel survey program, 2017), I find that the common unobserved factors of the (S)AV types are highly positively correlated. The correlation between the two AV-taxi types (i.e., AV-taxi with and without a backup driver) are relatively larger than those found by Nair et al. (2017) who used a different model setting on the same dataset. Results indicate that safety concern hinders public acceptance of (S)AVs, whereas green travel pattern and MOD savviness promote interest in (S)AVs, as expected. It is noteworthy that the marginal effects of safety concern are greater than those of green travel pattern and MOD savviness, which also suggest increasing returns to investments in policies aimed at reducing public safety concern about AVs. Important insights are also gained into the potential market segments interested in (S)AVs based on the underlying socio-economic, built environment, and daily/commute travel behavior characteristics. Everything else equal, young men who are accustomed to private car use and live in multi-member households and in monofunctional neighborhoods are likely interested in private AVs. While those with longer commute times embrace (S)AVs for *commuting*, persons associated with higher daily vehicle-miles traveled (VMT) disfavor (S)AVs for (all-purpose) *daily* trips. The opposing opinions about (S)AVs vis-à-vis daily and commute travel distance/time can be explained by noting that people likely enjoy productive use of their commute time conducting work-related activities (e.g., preparing for a business meeting), yet do not similarly value time saving for doing less urgent/important activities in other trip purposes. Such a trip purpose-based heterogeneity in time valuation becomes more evident by noting that commuters consider both uncongested and congested travel times, while merely travel distance (regardless of congestion) was shown to describe public interest in AV for (all-purpose) daily trips. Besides total daily VMT, which is ascribed to one or multiple trips, it is also revealed that individuals with larger inter-trip VMT variations are more inclined towards SAVs.

The noticeable role of safety concern in AV adoption behavior is an important finding of the first chapter and forms a hypothesis for the second chapter; AV adoption is controlled by, among various factors, the safety concern of travelers, which is itself a function of exogenous factors. For instance, persons who are more familiar with new technologies, especially vehicle technology, could be expected to have lower concerns about AV safety and thus be more interested in AV adoption. In light of this, the second chapter simultaneously models AV adoption and safety concern while considering the endogeneity of safety concern to AV adoption. To do so, I estimate a recursive bivariate ordered probit (RBOP) model. In addition to treating endogeneity, the model captures the cross-equation error correlation between the two dependent variables. Drawing from a stated preference survey in the state of California, I find a significant negative association between safety concern and AV adoption. Important insights are also obtained into the impact on shaping travelers' behavior of several socioeconomic and demographic characteristics, current travel behavior factors, and vehicle decision factors and attributes.

While the travel behavior research on (S)AVs is still in its infancy and numerous avenues are open to future studies (e.g., see Fagnant and Kockelman (2015)), I herein suggest four specific topics to complement this dissertation. *First*, ongoing research efforts should address the limitations of the data used in this dissertation by providing the respondents with detailed information about the (S)AV types and attributes thereof. More importantly, it is more realistic to model interest in (S)AVs considering the costs involved in each (S)AV type (a comprehensive cost-based analysis could be found in a recent study by Bösch et al. (2017)). *Second*, it would be appealing to consider an exhaustive choice set where travelers can express their opinions about the current human-driven private cars and public transit, in addition to the futuristic (S)AV types considered in this dissertation, given that such a mixed human/autonomous driving car choice situation seems more likely at least in the next few decades (Litman, 2018). *Third*, it is important to consider the impact on vehicle/mode decisions of both electric and gasoline (S)AVs, given that vehicle electrification is known as one of the three pillars of future urban mobility complementing vehicle automation and sharing economy (Chen et al., 2016; Nazari et al., 2018b). The *last* suggestion relates to improving the methodology used in this dissertation, which is a two-stage estimation of a multivariate ordered probit model with continuous latent constructs. In particular, a simultaneous estimation method as in Bhat (2015) and Lavieri et al. (2017) could be employed to integrate a multivariate ordered probit model with latent variables while the ordinal indicators of the latent constructs are treated as ordinal outcomes.

6.2. Electric vehicles

Advanced vehicle technologies such as electric vehicles (EVs), which include hybrid EVs (HEVs), plug-in HEVs (PHEVs), and battery EVs (BEVs), offer potential economic, environmental, and health benefits, but realization of these benefits requires considerable public EV adoption. However, the small market share of EVs in the U.S. calls for research on EV adoption behavior in order to identify current EV users based on their characteristics and attitudinal factors while also considering the competing alternatives, i.e., gasoline and diesel vehicles grouped as conventional vehicles (CVs). In light of this need, a retrospective vehicle survey (RVS) collects information on attributes of American households and their vehicles as well as their historical changes over the past 10 years from 2008 to 2017. Using the RVS database, then an integrated choice with latent variables (ICLV) model investigates households' vehicle fuel type choice considering their historical vehicle transaction decisions. The ICLV model further considers four latent constructs describing perception of vehicle specification and social influence at vehicle purchase time as well as lifestyle preference for environmental consciousness and technology savviness. The results verify the positive role of latent construct describing social influence, environmental consciousness, and technology savviness on adoption of EVs types compared to latent vehicle specification construct.

In this dissertation, I focused on vehicle fuel and transaction choice of households who hold (own/lease) vehicles. One suggestion for extending this line of research is to include households without vehicle in the modeling framework by jointly estimating decisions of vehicle ownership (whether a household holds a vehicle or not) and vehicle fuel type. The joint model therefore could yield findings on the impact of households' historical changes and latent construct, specially travel attitude and lifestyle preference, on the interest in holding a vehicle as well as choosing vehicle fuel and transaction type.

References

1. Achtnicht, M., Bühler, G., Hermeling, C., 2012. The impact of fuel availability on demand for alternative-fuel vehicles. Transportation Research Part D: Transport and Environment 17(3), 262-269.
2. Agatz, N., Erera, A., Savelsbergh, M., Wang, X., 2012. Optimization for dynamic ride-sharing: A review. European Journal of Operational Research 223(2), 295-303.
3. American Automobile Association, 2017. Your driving costs: How much are you really paying to drive? (Accessed 21 Feb. 2019), Available at: http://exchange.aaa.com/wp-content/uploads/2017/08/17-0013_Your-Driving-Costs-Brochure-2017-FNL-CX-1.pdf.
4. Astroza, S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Lavieri, P.S., Dias, F.F., 2017. Analysis of the impact of technology use on multimodality and activity travel characteristics. Transportation Research Record: Journal of the Transportation Research Board 2666, 19-28.
5. Auto Alliance, D.I., 2018. U.S. light-duty advanced technology vehicle (ATV) sales (2011-2018). (Accessed 13 Nov. 2018), Available at: https://autoalliance.org/energy-environment/advanced-technology-vehicle-sales-dashboard/.
6. Axsen, J., TyreeHageman, J., Lentz, A., 2012. Lifestyle practices and pro-environmental technology. Ecological Economics 82, 64-74.
7. Bahamonde-Birke, F.J., Ortúzar, J.D., 2014. Is sequential estimation a suitable second best for estimation of hybrid choice models? Transportation Research Record: Journal of the Transportation Research Board 2429, 51-58.
8. Bahamonde-Birke, F.J., Ortúzar, J.D., 2017. Analyzing the continuity of attitudinal and perceptual indicators in hybrid choice models. Journal of Choice Modelling 25, 28-39.
9. Bansal, P., Kockelman, K.M., 2017. Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. Transportation Research Part A: Policy and Practice 95, 49-63.
10. Bansal, P., Kockelman, K.M., Singh, A., 2016. Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. Transportation Research Part C: Emerging Technologies 67, 1-14.
11. Barter, G.E., Reichmuth, D., West, T.H., Manley, D.K., 2013. The future adoption and benefit of electric vehicles: a parametric assessment. SAE International Journal of Alternative Powertrains 2(1), 82-95.
12. Beaumais, O., Giannoni, S., 2018. Insiders vs. outsiders in the hotel sector. Applied Economics, 1-14.
13. Beck, M.J., Fifer, S., Rose, J.M., 2016. Can you ever be certain? Reducing hypothetical bias in stated choice experiments via respondent reported choice certainty. Transportation Research Part B: Methodological 89, 149-167.
14. Becker, F., Axhausen, K.W., 2017. Literature review on surveys investigating the acceptance of automated vehicles. Transportation 44 (6), 1293-1306.
15. Ben-Akiva, M., Boccara, B., 1995. Discrete choice models with latent choice sets. International journal of Research in Marketing 12(1), 9-24.
16. Ben-Akiva, M., Walker, J., Bernardino, A.T., Gopinath, D.A., Morikawa, T., Polydoropoulou, A., 2002. Integration of choice and latent variable models. Perpetual Motion: Travel Behaviour Research Opportunities and Application Challenges, 431-470.
17. Bhat, C.R., 2015. A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. Transportation Research Part B: Methodological 79, 50-77.
18. Bhat, C.R., Dubey, S.K., 2014. A new estimation approach to integrate latent psychological constructs in choice modeling. Transportation Research Part B: Methodological 67, 68-85.
19. 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.

20. Bhat, C.R., Srinivasan, S., 2005. A multidimensional mixed ordered-response model for analyzing weekend activity participation. Transportation Research Part B: Methodological 39(3), 255-278.
21. Bösch, P.M., Becker, F., Becker, H., Axhausen, K.W., 2017. Cost-based analysis of autonomous mobility services. Transport Policy 64, 76-91.
22. Browne, M.W., Cudeck, R., 1992. Alternative ways of assessing model fit. Sociological Methods & Research 21(2), 230-258.
23. Brunette, M., Foncel, J., Kéré, E.N., 2017. Attitude towards risk and production decision: an empirical analysis on French private forest owners. Environmental Modeling & Assessment 22 (6), 563-576.
24. Burnett, N.J., 1997. Gender economics courses in liberal arts colleges. The Journal of Economic Education 28 (4), 369-376.
25. Byrne, B.M., 2016. Structural equation modeling with AMOS: Basic concepts, applications, and programming. Routledge, New York.
26. California Energy Commission, 2016. California Vehicle Survey. Available at: http://www.energy.ca.gov/assessments/vehiclesurvey/.
27. Centrone, F., Goia, A., Salinelli, E., 2007. Demographic processes in a model of innovation diffusion with dynamic market. Technological Forecasting and Social Change 74(3), 247-266.
28. Chen, T.D., Kockelman, K.M., Hanna, J.P., 2016. Operations of a shared, autonomous, electric vehicle fleet: implications of vehicle & charging infrastructure decisions. Transportation Research Part A: Policy and Practice 94, 243-254.
29. Chen, Z., He, F., Yin, Y., Du, Y., 2017. Optimal design of autonomous vehicle zones in transportation networks. Transportation Research Part B: Methodological 99, 44-61.
30. Chen, Z., He, F., Zhang, L., Yin, Y., 2016. Optimal deployment of autonomous vehicle lanes with endogenous market penetration. Transportation Research Part C: Emerging Technologies 72, 143-156.
31. Cherchi, E., Ortúzar, D.J., 2006. On fitting mode specific constants in the presence of new options in RP/SP models. Transportation Research Part A: Policy and Practice 40(1), 1-18.
32. Cirillo, C., Liu, Y., Maness, M., 2017. A time-dependent stated preference approach to measuring vehicle type preferences and market elasticity of conventional and green vehicles. Transportation Research Part A: Policy and Practice 100, 294-310.
33. Clewlow, R.R., 2016. Carsharing and sustainable travel behavior: Results from the San Francisco Bay Area. Transport Policy 51, 158-164.
34. Correia, G., Silva, J., Viegas, J.M., 2013. Using latent attitudinal variables estimated through a structural equations model for understanding carpooling propensity. Transportation Planning and Technology 36(6), 499-519.
35. Correia, G., van Arem, B., 2016. Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. Transportation Research Part B: Methodological 87, 64-88.
36. Correia, G., van Cranenburgh, S., Snelder, M., van Arem, B., 2018. Potential changes in value of travel time as a result of vehicle automation: A case study in the Netherlands. Available at: https://www.researchgate.net/publication/322274535_Potential_changes_in_value_of_travel_time_as_a_result_of_vehicle_automation_a_case-study_in_the_Netherlands.
37. Davis, S.C., Williams, S.E., Boundy, R.G., 2018. Transportation energy data book, Edition 36.2 of ORNL-5198. Oak Ridge National Laboratory, Oak Ridge, TN, USA., Available at: https://cta.ornl.gov/data/tedbfiles/Edition36_Full_Doc.pdf.
38. Daziano, R.A., Achtnicht, M., 2013. Forecasting adoption of ultra-low-emission vehicles using Bayes estimates of a multinomial probit model and the GHK simulator. Transportation Science 48(4), 671-683.
39. Daziano, R.A., Sarrias, M., Leard, B., 2017. Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. Transportation Research Part C: Emerging Technologies 78, 150-164.
40. Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation 44(6), 1307-1323.

41. Digital Trends. Available at: Https://Www.Digitaltrends.Com/Cool-Tech/most-Significant-Self-Driving-Car-Crashes/.
42. El Zarwi, F., Vij, A., Walker, J.L., 2017. A discrete choice framework for modeling and forecasting the adoption and diffusion of new transportation services. Transportation Research Part C: Emerging Technologies 79, 207-223.
43. Eppstein, M.J., Grover, D.K., Marshall, J.S., Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy 39(6), 3789-3802.
44. European Alternative Fuels Observatory, 2018. EV market share in 2018 YTD. (Accessed 13 Nov. 2018), Available at: https://www.eafo.eu/top-5.
45. Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transportation Research Part C: Emerging Technologies 40, 1-13.
46. Fagnant, D.J., Kockelman, K.M., 2015. Preparing a nation for autonomous vehicles: Opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice 77, 167-181.
47. Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of shared autonomous vehicle fleet for Austin, Texas, market. Transportation Research Record: Journal of the Transportation Research Board 2536, 98-106.
48. Farhan, J., Chen, T.D., 2018. Impact of ridesharing on operational efficiency of shared autonomous electric vehicle fleet. Transportation Research Part C: Emerging Technologies 93, 310-321.
49. Ferdous, N., Eluru, N., Bhat, C.R., Meloni, I., 2010. A multivariate ordered-response model system for adults' weekday activity episode generation by activity purpose and social context. Transportation Research Part B: Methodological 44(8), 922-943.
50. Gao, Y., Rasouli, S., Timmermans, H., Wang, Y., 2017. Understanding the relationship between travel satisfaction and subjective well-being considering the role of personality traits: A structural equation model. Transportation Research Part F: Traffic Psychology and Behaviour 49, 110-123.
51. Garikapati, V.M., Pendyala, R.M., Morris, E.A., Mokhtarian, P.L., McDonald, N., 2016. Activity patterns, time use, and travel of millennials: A generation in transition? Transport Reviews 36(5), 558-584.
52. Gates, K.M., Molenaar, P.C., Hillary, F.G., Slobounov, S., 2011. Extended unified SEM approach for modeling event-related fMRI data. NeuroImage 54(2), 1151-1158.
53. Gnann, T., Stephens, T.S., Lin, Z., Plötz, P., Liu, C., Brokate, J., 2018. What drives the market for plug-in electric vehicles? A review of international PEV market diffusion models. Renewable and Sustainable Energy Reviews 93, 158-164.
54. Golob, T.F., 2003. Structural equation modeling for travel behavior research. Transportation Research Part B: Methodological 37(1), 1-25.
55. Gray, D., 2014. Financial Concerns and overall Life Satisfaction: A Joint Modelling Approach.
56. Greenblatt, J.B., Shaheen, S., 2015. Automated vehicles, on-demand mobility, and environmental impacts. Current Sustainable/Renewable Energy Reports 2(3), 74-81.
57. Greene, W.H., 2000. Econometric analysis. Prentice-Hall, New Jersey.
58. Greene, W.H., Hensher, D.A., 2010. Modeling ordered choices: A primer. Cambridge University Press, Cambridge.
59. Guo, J., Bhat, C.R., Copperman, R., 2007. Effect of the built environment on motorized and nonmotorized trip making: Substitutive, complementary, or synergistic? Transportation Research Record: Journal of the Transportation Research Board 2010, 1-11.
60. Guo, Z., Zhou, Y., 2019. Residual value analysis of plug-in vehicles in the United States. Energy Policy 125, 445-455.
61. Haboucha, C.J., Ishaq, R., Shiftan, Y., 2017. User preferences regarding autonomous vehicles. Transportation Research Part C: Emerging Technologies 78, 37-49.
62. Hackbarth, A., Madlener, R., 2013. Consumer preferences for alternative fuel vehicles: A discrete choice analysis. Transportation Research Part D: Transport and Environment 25, 5-17.

63. Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles–A review of the evidence. Renewable and Sustainable Energy Reviews 80, 1100-1111.
64. Harper, C. D., Hendrickson, C.T., Samaras, C., 2016. Cost and benefit estimates of partially-automated vehicle collision avoidance technologies. Accident Analysis & Prevention 95, 104-115.
65. Helveston, J.P., Liu, Y., Feit, E.M., Fuchs, E., Klampfl, E., Michalek, J.J., 2015. Will subsidies drive electric vehicle adoption? Measuring consumer preferences in the US and China. Transportation Research Part A: Policy and Practice 73, 96-112.
66. Hess, S., Fowler, M., Adler, T., Bahreinian, A., 2012. A joint model for vehicle type and fuel type choice: evidence from a cross-nested logit study. Transportation 39(3), 593-625.
67. Hidrue, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. Resource and Energy Economics 33(3), 686-705.
68. Higgins, C.D., Mohamed, M., Ferguson, M.R., 2017. Size matters: How vehicle body type affects consumer preferences for electric vehicles. Transportation Research Part A: Policy and Practice 100, 182-201.
69. Hoen, A., Koetse, M.J., 2014. A choice experiment on alternative fuel vehicle preferences of private car owners in the Netherlands. Transportation Research Part A: Policy and Practice 61, 199-215.
70. Hoshino, T., Bentler, P.M., 2011. Bias in factor score regression and a simple solution. Department of Statistics papers, University of California, Los Angeles.
71. Hyland, M., Mahmassani, H.S., 2018. Dynamic autonomous vehicle fleet operations: Optimization-based strategies to assign AVs to immediate traveler demand requests. Transportation Research Part C: Emerging Technologies 92, 278-297.
72. Javid, R.J., Nejat, A., 2017. A comprehensive model of regional electric vehicle adoption and penetration. Transport Policy 54, 30-42.
73. Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before and after experiencing an electric vehicle. Transportation Research Part D: Transport and Environment 25, 24-32.
74. Jin, L., Searle, S., Lutsey, N., 2014. Evaluation of state-level U.S. electric vehicle incentives. The International Council on Clean Transportation. Available at: https://www.theicct.org/sites/default/files/publications/ICCT_state-EV-incentives_20141030.pdf.
75. Johansson, M.V., Heldt, T., Johansson, P., 2006. The effects of attitudes and personality traits on mode choice. Transportation Research Part A: Policy and Practice 40(6), 507-525.
76. Jöreskog, K.G., 1977. Factor analysis by least squares and maximum likelihood methods. Statistical Methods for Digital Computers, Wiley, New York.
77. Kalra, N., Paddock, S.M., 2016. Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? Transportation Research Part A: Policy and Practice 94, 182-193.
78. Kim, J., Rasouli, S., Timmermans, H., 2014. Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars. Transportation Research Part A: Policy and Practice 69, 71-85.
79. Koppelman, F.S., Hauser, J.R., 1978. Destination choice behavior for non-grocery-shopping trips. Transportation Research Record(673).
80. Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transportation Research Part C: Emerging Technologies 69, 343-355.
81. Kyriakidis, M., Happee, R., de Winter, J.C.F., 2015. Public opinion on automated driving: results of an international questionnaire among 5000 respondents. Transportation Research Part F: Traffic Psychology and Behaviour 32, 127-140.
82. Laurent, J., Katz, A., 2013. Joint workshop report for the workshop held on April 10-11, 2013, California Public Utilities Commission, San Francisco.

83. Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., Dias, F.F., 2017. Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. Transportation Research Record: Journal of the Transportation Research Board 2665, 1-10.
84. Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. Computers, Environment and Urban Systems 64, 373-383.
85. Liao, F., Molin, E., van Wee, B., 2017. Consumer preferences for electric vehicles: A literature review. Transport Reviews 37(3), 252-275.
86. Lin, Z., Greene, D.L., 2011. Promoting the market for plug-in hybrid and battery electric vehicles: Role of recharge availability. Transportation Research Record 2252(1), 49-56.
87. Litman, T., 2018. Autonomous vehicle implementation predictions: Implications for transport planning. Victoria Transport Policy Institute. Available at: https://www.vtpi.org/avip.pdf.
88. Liu, W., 2018. An equilibrium analysis of commuter parking in the era of autonomous vehicles. Transportation Research Part C: Emerging Technologies 92, 191-207.
89. Lokhandwala, M., Cai, H., 2018. Dynamic ride sharing using traditional taxis and shared autonomous taxis: A case study of NYC. Transportation Research Part C: Emerging Technologies 97, 45-60.
90. Mabit, S.L., Fosgerau, M., 2011. Demand for alternative-fuel vehicles when registration taxes are high. Transportation Research Part D: Transport and Environment 16(3), 225-231.
91. Mamdoohi, A., Nazari, F., Noruzoliaee, M., 2014. An investigation of human factors impact on Tehran urban crash severity. Journal of Traffic and Logistics Engineering 2(2), 100-103.
92. McFadden, D., 1986. The choice theory approach to market research. Marketing science 5(4), 275-297.
93. McManus, W., Senter, R., 2009. Market models for predicting PHEV adoption and diffusion, UMTRI-2009-37. University of Michigan Transportation Research Institute., Available at: https://pdfs.semanticscholar.org/070e/fad67466ac48b8bf2ea7f998e182c1bab5cd.pdf.
94. Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. Transportation Research Part A: Policy and Practice 83, 14-29.
95. Moons, I., De Pelsmacker, P., 2012. Emotions as determinants of electric car usage intention. Journal of Marketing Management 28(3-4), 195-237.
96. Musti, S., Kockelman, K.M., 2011. Evolution of the household vehicle fleet: Anticipating fleet composition, PHEV adoption and GHG emissions in Austin, Texas. Transportation Research Part A: Policy and Practice 45(8), 707-720.
97. Nair, G.S., Astroza, S., Bhat, C.R., Khoeini, S., Pendyala, R., 2017. An application of a rank-ordered probit modeling approach to understanding level of interest in autonomous vehicles. In: Proceedings in the 96th Annual Meeting of the Transportation Research Board, Washington, D.C.
98. Nazari, F., Noruzoliaee, M., Mohammadian, A., 2018a. Shared mobility versus private car ownership: A multivariate analysis of public interest in autonomous vehicles. In: Proceedings of the 97th Annual Meeting of the Transportation Research Board, Washington, D.C.
99. Nazari, F., Mohammadian, A., Stephens, T., 2018b. Dynamic household vehicle decision modeling considering plug-In electric vehicles. Transportation Research Record: Journal of the Transportation Research Board, 1-10.
100. Nazari, F., Seyedabrishami, S., Mamdoohi, A., 2015. A direct demand model of departure time and mode for intercity passenger trips. International Journal of Transportation Engineering 3(2), 125-141.
101. Nie, Y., 2017. How can the taxi industry survive the tide of ridesourcing? Evidence from Shenzhen, China. Transportation Research Part C: Emerging Technologies 79, 242-256.
102. Nieuwenhuijsen, J., Correia, G., Milakis, D., van Arem, B., van Daalen, E., 2018. Towards a quantitative method to analyze the long-term innovation diffusion of automated vehicles technology using system dynamics. Transportation Research Part C: Emerging Technologies 86, 300-327.
103. Noruzoliaee, M., Zou, B., Yang, L., 2018. Roads in transition: Integrated modeling of a manufacturer-traveler-infrastructure system in a mixed autonomous/human driving environment. Transportation Research Part C: Emerging Technologies 90, 307-333.

104. Payre, W., Cestac, J., Delhomme, P., 2014. Intention to use a fully automated car: Attitudes and a priori acceptability. Transportation Research Part F: Traffic Psychology and Behaviour 27, 252-263.
105. Potoglou, D., Kanaroglou, P.S., 2007. Household demand and willingness to pay for clean vehicles. Transportation Research Part D: Transport and Environment 12(4), 264-274.
106. Puget Sound travel survey program, 2017. Available at: https://Www.Psrc.Org/Household-Travel-Survey-Program.
107. Qian, L., Soopramanien, D., 2011. Heterogeneous consumer preferences for alternative fuel cars in China. Transportation Research Part D: Transport and Environment 16(8), 607-613.
108. Querini, F., Benetto, E., 2014. Agent-based modelling for assessing hybrid and electric cars deployment policies in Luxembourg and Lorraine. Transportation Research Part A: Policy and Practice 70, 149-161.
109. Rasouli, S., Timmermans, H., 2016. Influence of social networks on latent choice of electric cars: a mixed logit specification using experimental design data. Networks and Spatial Economics 16(1), 99-130.
110. Raveau, S., Álvarez-Daziano, R., Yáñez, M., Bolduc, D., Ortúzar, J.D., 2010. Sequential and simultaneous estimation of hybrid discrete choice models: Some new findings. Transportation Research Record: Journal of the Transportation Research Board 2156, 131-139.
111. Rezvani, Z., Jansson, J., Bodin, J., 2015. Advances in consumer electric vehicle adoption research: A review and research agenda. Transportation Research Part D: Transport and Environment 34, 122-136.
112. Saeed, T.U., Qiao, Y., Chen, S., Gkritza, K., Labi, S., 2017. Methodology for probabilistic modeling of highway bridge infrastructure condition: Accounting for improvement effectiveness and incorporating random effects. Journal of Infrastructure Systems 23(4), 04017030.
113. Sajaia, Z., 2008. Maximum likelihood estimation of a bivariate ordered probit model: Implementation and Monte Carlo simulations. The Stata Journal 4 (2), pp. 1-18.
114. SAS, 2013. SAS/STAT 13.1 user's guide: The CALIS procedure. Available at: https://support.sas.com/documentation/onlinedoc/stat/131/calis.pdf.
115. SAS, 2014. SAS/ETS 13.2 user's guide: The QLIM procedure. Available at: https://support.sas.com/documentation/onlinedoc/ets/132/qlim.pdf.
116. Satorra, A., Bentler, P.M., 1994. Corrections to test statistics and standard errors in covariance structure analysis. In A. von Eye & C. C. Clogg (Eds.), Latent variable analysis: Applications for developmental research, 399-419, Thousand Oaks, CA, US: Sage Publications, Inc.
117. Schaefers, T., 2013. Exploring carsharing usage motives: A hierarchical means-end chain analysis. Transportation Research Part A: Policy and Practice 47, 69-77.
118. Schuitema, G., Anable, J., Skippon, S., Kinnear, N., 2013. The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles. Transportation Research Part A: Policy and Practice 48, 39-49.
119. Seraj, S., Sidharthan, R., Bhat, C.R., Pendyala, R., Goulias, K., 2012. Parental attitudes toward children walking and bicycling to school. Transportation Research Record: Journal of the Transportation Research Board 2323, 46-55.
120. Shaheen, S., Cohen, A., Chung, M., 2009. North American carsharing: 10-year retrospective. Transportation Research Record: Journal of the Transportation Research Board 2110, 35-44.
121. Silva, J.A., Goulias, K.G., 2007. Using structural equations modeling to unravel the influence of land use pattern on travel behavior of urban adult workers of Puget Sound Region. In: Proceedings of the European Transport Conference 2007, 17–19 October, The Netherlands.
122. Steiger, J.H., 1990. Structural model evaluation and modification: An interval estimation approach. Multivariate behavioral research 25(2), 173-180.
123. Stephens, T., Zhou, Y., Burnham, A., Wang, M., 2018. Incentivizing adoption of plug-in electric vehicles: A review of global policies and markets. U.S. Department of Energy (US DOE), Argonne National Laboratory, ANL/ESD-18/7, Available at: https://publications.anl.gov/anlpubs/2018/08/145318.pdf.

124. Stuart, E.A., 2010. Matching methods for causal inference: A review and a look forward. Statistical Science: A Review Journal of the Institute of Mathematical Statistics 25(1), 1-21.
125. Tal, G., Nicholas, M., 2016. Exploring the impact of the federal tax credit on the plug-in vehicle market. Transportation Research Record: Journal of the Transportation Research Board(2572), 95-102.
126. Talebian, A., Mishra, S., 2018. Predicting the adoption of connected autonomous vehicles: A new approach based on the theory of diffusion of innovations. Transportation Research Part C: Emerging Technologies 95, 363-380.
127. Tanaka, M., Ida, T., Murakami, K., Friedman, L., 2014. Consumers' willingness to pay for alternative fuel vehicles: A comparative discrete choice analysis between the US and Japan. Transportation Research Part A: Policy and Practice 70, 194-209.
128. The Statistics Portal, 2018. Number of motor vehicles registered in the United States from 1990 to 2017. (Accessed 9 Apr. 2019), https://www.statista.com/statistics/183505/number-of-vehicles-in-the-united-states-since-1990/.
129. Train, K.E., McFadden, D.L., Goett, A.A., 1987. Consumer attitudes and voluntary rate schedules for public utilities. The Review of Economics and Statistics 69(3), 383-391.
130. U.S. Department of Energy (US DOE), Energy Information Administration, 2018. Use of energy in the United States explained: How the United States uses energy. (Accessed 13 Nov. 2018), Available at: https://www.eia.gov/energyexplained/index.php?page=us_energy_use.
131. U.S. Department of Energy (US DOE), Office of Energy Efficiency & Renewable Energy, 2018a. Vehicle technologies office, FOTW #1057, November 26, 2018: One million plug-in vehicles have been sold in the United States. (Accessed 29 Nov. 2018), Available at: https://www.energy.gov/eere/vehicles/articles/fotw-1057-november-26-2018-one-million-plug-vehicles-have-been-sold-united.
132. U.S. Department of Energy (US DOE), Office of Energy Efficiency & Renewable Energy, 2018b. Electric vehicles, charging at home. (Accessed 26 Jul. 2018), Available at: https://www.energy.gov/eere/electricvehicles/charging-home.
133. U.S. Department of Energy (US DOE), Office of Energy Efficiency & Renewable Energy, 2018c. U.S. HEV sales by model. (Accessed 9 Apr. 2019), https://afdc.energy.gov/data/10301.
134. U.S. Environmental Protection Agency (US EPA), 2018. Fast facts: U.S. transportation sector greenhouse gas emissions 1990-2016. Available at: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100USI5.pdf.
135. U.S. Census Bureau, 2018. American Community Survey 2013-2017 5-year data release. (Accessed 15 Mar. 2018), Available at https://www.census.gov/newsroom/press-kits/2018/acs-5year.html.
136. U.S. Census Bureau, 2016. Income and poverty in the United States: 2015. Available at: https://www.census.gov/content/dam/Census/library/publications/2016/demo/p60-256.pdf.
137. Valeri, E., Danielis, R., 2015. Simulating the market penetration of cars with alternative fuel powertrain technologies in Italy. Transport Policy 37, 44-56.
138. van den Berg, V.A.C., Verhoef, E.T., 2016. Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity. Transportation Research Part B: Methodological 94, 43-60.
139. Washington, S.P., Karlaftis, M.G., Mannering, F., 2010. Statistical and econometric methods for transportation data analysis. Chapman & Hall/CRC press, Florida.
140. Yáñez, M.F., Raveau, S., Ortúzar, J.D., 2010. Inclusion of latent variables in mixed logit models: Modelling and forecasting. Transportation Research Part A: Policy and Practice 44(9), 744-753.
141. Yap, M.D., Correia, G., van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. Transportation Research Part A: Policy and Practice 94, 1-16.
142. Yeager, D.S., Krosnick, J.A., Chang, L., Javitz, H.S., Levendusky, M.S., Simpser, A., 2011. Comparing the accuracy of RDD telephone surveys and internet surveys conducted with probability and non-probability samples. Public opinion quarterly 75(4), 709-747.

143. Zambrano-Gutiérrez, J.C., Nicholson-Crotty, S., Carley, S., Siddiki, S., 2018. The role of public policy in technology diffusion: The case of plug-in electric vehicles. Environmental Science & Technology 52(19), 10914-10922.
144. Zha, L., Yin, Y., Yang, H., 2016. Economic analysis of ride-sourcing markets. Transportation Research Part C: Emerging Technologies 71, 249-266.
145. Zhang, W., Guhathakurta, S., Khalil, E.B., 2018. The impact of private autonomous vehicles on vehicle ownership and unoccupied VMT generation. Transportation Research Part C: Emerging Technologies 90, 156-165.
146. Ziegler, A., 2012. Individual characteristics and stated preferences for alternative energy sources and propulsion technologies in vehicles: A discrete choice analysis for Germany. Transportation Research Part A: Policy and Practice 46(8), 1372-1385.
147. Zmud, J., Sener, I.N., Wagner, J., 2016. Consumer acceptance and travel behavior: Impacts of automated vehicles. Final Report, Texas A&M Transportation Institute. Available at: https://rosap.ntl.bts.gov/view/dot/32687.

Appendix A. Permission for reuse of the previously published materials

5/18/2019 Rightslink® by Copyright Clearance Center

Copyright Clearance Center RightsLink

Home | Create Account | Help

Title: Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes

Author: Fatemeh Nazari,Mohamadhossein Noruzoliaee,Abolfazl (Kouros) Mohammadian

Publication: Transportation Research Part C: Emerging Technologies

Publisher: Elsevier

Date: December 2018

© 2018 Elsevier Ltd. All rights reserved.

LOGIN

If you're a copyright.com user, you can login to RightsLink using your copyright.com credentials.

Already **a RightsLink user** or want to learn more?

Please note that, as the author of this Elsevier article, you retain the right to include it in a thesis or dissertation, provided it is not published commercially. Permission is not required, but please ensure that you reference the journal as the original source. For more information on this and on your other retained rights, please visit: https://www.elsevier.com/about/our-business/policies/copyright#Author-rights

BACK | CLOSE WINDOW

Appendix B. Permission for reuse of the previously published materials

5/18/2019 Rightslink® by Copyright Clearance Center

Copyright Clearance Center RightsLink®

Home | Create Account | Help

Title: Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure

Author: Fatemeh Nazari,Abolfazl (Kouros) Mohammadian,Thomas Stephens

Publication: Transportation Research Part D: Transport and Environment

Publisher: Elsevier

Date: July 2019

LOGIN

If you're a copyright.com user, you can login to RightsLink using your copyright.com credentials.

Already **a RightsLink user** or want to learn more?

Please note that, as the author of this Elsevier article, you retain the right to include it in a thesis or dissertation, provided it is not published commercially. Permission is not required, but please ensure that you reference the journal as the original source. For more information on this and on your other retained rights, please visit: https://www.elsevier.com/about/our-business/policies/copyright#Author-rights

BACK | CLOSE WINDOW

VITA

Fatemeh Nazari

University of Illinois at Chicago (UIC)
Email: fnazar2@uic.edu | Cell: (714) 718-0671 | Address: 2095 ERF, 842 W. Taylor St., Chicago, IL 60607

EDUCATION

Aug 2015-July 2019 Chicago, IL — **University of Illinois at Chicago**
- Ph.D., Civil (Transportation) Engineering
- Dissertation: Modeling travel behavior with the advent of electric and autonomous vehicle technologies (Advisor: Prof. Abolfazl (Kouros) Mohammadian)
- GPA: 4.00 out of 4.00

Sep 2011-Sep 2013 Tehran, Iran — **Tarbiat Modares University**
- M.Sc., Civil (Transportation) Engineering
- GPA: 18.22 out of 20 (Top student)

Jan 2006-Sep 2010 Zanjan, Iran — **University of Zanjan**
- B.Sc., Civil Engineering
- GPA: 14.82 out of 20

RESEARCH INTERESTS

- Automated, electric, and shared mobility
- Smart urban goods delivery systems
- Advanced travel behavior/demand modeling
- Integrated transportation and energy modeling
- Econometrics/statistics, big data analytics, and optimization

---

RESEARCH PROJECTS & APPOINTMENTS

Jan 2017-Aug 2019 Chicago, IL — **University of Illinois at Chicago**
- Market Dynamics Modeling – Household-level Vehicle Decision Modeling
  Role: Graduate research assistant
  Sponsor: **U.S. Department of Energy** through Argonne National Laboratory
  Description: Assessing the potential changes in transportation energy use with adoption of advanced-technology vehicles

Jan 2012-Aug 2013 Tehran, Iran — **Tarbiat Modares University**
- Updating Mashad Transportation Master Plan
  Role: Graduate research assistant
  Sponsor: Mashad municipality

Description: Updating Mashad transportation master plan considering the new and future developments of the city

- Planning Iran Intercity Road Network in Case of Disaster with Emphasis on Road Capacity
  Role: Graduate research assistant
  Sponsor: Iran Department of Transportation
  Description: Developing a decision support tool to assess the impact of pre-disaster and post-disaster scenarios on intercity road networks

PUBLICATIONS

Published / under review papers

1. **Nazari, F.**, Mohammadian, A., Stephens, T. (2019) Modeling electric vehicle adoption considering a latent travel pattern construct and charging infrastructure. *Transportation Research Part D: Transport and Environment* 72C, 65-82.
2. **Nazari, F.,** Noruzoliaee, M., Mohammadian, A. (2018) Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. *Transportation Research Part C: Emerging Technologies* 97, 456-477.
3. **Nazari, F.**, Mohammadian, A., Stephens, T. (2018) Dynamic household vehicle decision modeling with consideration of electric vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 1-10.
4. **Nazari, F.**, Taghipur, H., Mohammadian, A. (2018) How electric vehicles and mobility-on-demand services influence vehicle usage and shape latent lifestyle traits? *Transportation Research Part D: Transport and Environment*. Under review.
5. **Nazari, F.**, Rahimi, E., Mohammadian, A. (2018) Simultaneous estimation of battery electric vehicle adoption with endogenous willingness to pay. *eTransportation*. Under review (2nd round).
6. **Nazari, F.**, Noruzoliaee, M., Zou, B., Mohammadian, A. (2017) Optimal facility-specific inspection and maintenance decisions under measurement uncertainty: Unifying framework. *ASCE Journal of Infrastructure Systems* 23 (4), 04017036.
7. **Nazari, F.**, Seyedabrishami, S., Mamdoohi, A. (2015) A Direct demand model of departure time and mode for intercity passenger trips. *International Journal of Transportation Engineering* 3 (2), 125-141.
8. Mamdoohi, A., **Nazari, F.**, Noruzoliaee, M. (2014) An investigation of human factors impact on Tehran urban crash severity. *Journal of Traffic and Logistics Engineering* 2(2), 100-103.

Conference papers

9. **Nazari, F.,** Noruzoliaee, M., Mohammadian, A. (2019) Adoption of autonomous vehicles with endogenous safety concerns: A recursive bivariate ordered probit model. *Transportation Research Board (TRB) 98th Annual Meeting*, January 13-17, Washington, D.C., U.S.A.
10. **Nazari, F.**, Mohammadian, A., Derrible, S. (2018) Interaction between energy/water consumption and travel decisions in an activity-based framework. *15th International Conference on Travel Behavior Research (IATBR)*, July 15-20, Santa Barbara, California, U.S.A.

11. **Nazari, F.**, Mohammadian, A., Stephens, T. (2018) Investigating the impacts of mobility-on-demand services and green lifestyle on vehicle transaction decisions: a behavioral choice model with latent variables. *15th International Conference on Travel Behavior Research (IATBR)*, July 15-20, Santa Barbara, California, U.S.A.
12. **Nazari, F.**, Mohammadian, A., Stephens, T. (2018) Dynamic household vehicle decision modeling with consideration of electric vehicles. *Transportation Research Board (TRB) 97th Annual Meeting*, January 7-11, Washington, D.C., U.S.A.
13. **Nazari, F.**, Noruzoliaee, M., Mohammadian, A. (2018) Shared mobility versus private car ownership: A multivariate analysis of public interest in autonomous vehicles. *Transportation Research Board (TRB) 97th Annual Meeting*, January 7-11, Washington, D.C., U.S.A.
14. **Nazari, F.** and Mohammadian, A. (2016) An activity-based model of energy consumption. Accepted at *Behavior, Energy, and Climate Change Conference*, Baltimore, Maryland, U.S.A.
15. Karimi, B., **Nazari, F.**, Javanmardi, M., Mohammadian, A. (2015) Does using a different decision rule of discrete choice change the dependence structure between discrete decision and continuous outcome? *4th International Choice Modeling Conference (ICMC)*, May 10-13, Austin, Texas, USA.
16. Mamdoohi, A., **Nazari, F.**, Noruzoliaee, M. (2014) An investigation of human factors impacts on Tehran urban crash severity. *3rd International Conference on Traffic and Transportation Engineering (ICTTE)*. April 17-18, Lisbon, Portugal.
17. Mamdoohi, A., Noruzoliaee, M., **Nazari, F.** (2013) Modeling road network links effectiveness based on their systems role in case of disasters. *Australian Transportation Research Forum*, January, Brisbane, Australia.

Technical reports

18. Stephens, T., **Nazari, F.**, Mohammadian, A., Nealer, R., Market dynamics modeling—household-level vehicle decision modeling, analysis, 2017 annual progress report, U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, Vehicle Technologies Office
19. Stephens, T., **Nazari, F.**, Mohammadian, A., Nealer, R., Market dynamics modeling—household-level vehicle decision modeling, analysis, 2018 annual progress report, U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, Vehicle Technologies Office

Manuscripts in-preparation

20. **Nazari, F.**, Noruzoliaee, M., Mohammadian, A. Endogeneity of safety concern and vehicle usage to adoption of autonomous vehicles: A new joint recursive bivariate ordered probit and endogenous linear regression. To be (soon) submitted to Journal of *Transportation Research Part B: Methodological*.
21. **Nazari, F.**, Mohammadian, A., How attitudes and preferences shape electric vehicle adoption of Americans? Revelations from a national retrospective vehicle survey. To be (soon) submitted to Journal of *Transportation Research Part A: Policy and Practice*.
22. **Nazari, F.**, Mohammadian, A., Stephens, T. A joint model of vehicle transaction and fuel type decisions. To be (soon) submitted to Journal of *Transportation Research Part A: Policy and Practice*.

HONORS & AWARDS

- 2019 Bob Camillone Memorial Scholarship, presented by the Transportation & Development Institute of the Illinois Section of the American Society of Civil Engineers (IS-ASCE T&DI)
- Selected Doctoral Research Dissertation for Presenting at 2019 Workshop on Doctoral Research. Transportation Research Board: The National Academies of Sciences, Engineering, and Medicine
- Student Fellowship Award, the 15th International Conference on Travel Behavior Research (IATBR2018)
- 1st place: 2018 Christopher Burke and Susan Burke Ph.D. Poster Competition. Department of Civil and Materials Engineering, University of Illinois at Chicago
- 2nd place: 2017 George Krambles Transportation Scholarship Award. Urban Transportation Center, University of Illinois at Chicago
- 2016 David Boyce Graduate Award. Department of Civil and Materials Engineering, University of Illinois at Chicago
- 2013 Top Student Award in Master Program. Department of Civil and Environmental Engineering, Tarbiat Modares University, Tehran, Tehran, Iran

INVITED PRESENTATIONS (TALKS)

- Invited talk at Emerging Methods sub-committee in Transportation Research Board (TRB) Annual Meeting (January 2019)
- Invited lecturer for course of sustainable mobility at University of Illinois at Chicago, College of Liberal Arts and Science (Spring 2017)

PROFESSIONAL SERVICE

Journal review service

- Transportation Letters: The International Journal of Transportation Research (Publisher: Taylor & Francis)
- Transportation Research Board (TRB) Annual Meeting

Leadership

- Treasurer, Institute of Transportation Engineers (ITE) UIC student chapter

PROFESSIONAL MEMBERSHIP

- Student member: American Society of Engineers (ASCE)
- Student member: Institute of Transportation Engineers (ITE)
- Student member: Society of Women Engineers (SWE)