Adoption Behavior of Privately Owned Autonomous Vehicles

BY

RAMIN SHABANPOUR ANBARANI
B.S., Sharif University of Technology, 2010
M.S., Sharif University of Technology, 2013

DISSERTATION

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Defense Committee:

Professor Abolfazl Mohammadian, Chair and Advisor
Professor Jane Lin
Professor Sybil Derrible
Professor Bo Zou
Professor Kazuya Kawamura, Urban Planning and Policy

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RSA

CONTRIBUTION OF AUTHORS

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SUMMARY

The research detailed in this dissertation provides a comprehensive analysis of market penetration of privately owned autonomous vehicles (AVs) and elaborates on several dimensions of people's adoption behavior. Research in the area of autonomous mobility is advancing at a fast pace, heavily centered around estimating the potential impacts of the technology on travel behavior, network operation, and the environment. While highly informative, most of these studies inevitably suffer from the absence of a sound estimation of AVs' market penetration and establish their assessments based on the speculations regarding people's adoption behavior.

Current research is conducted to address such a gap by focusing on multiple dimensions of people's AV adoption behavior such as sensitivity of their adoption decision to the vehicle attributes, their willingness to pay, their preferred AV adoption timing, and the potential variance in adoption behavior of people from different generations. The research is designed to thoroughly investigate how individual- and household-level demographics, travel preferences, social factors, and built-environment characteristics affect each dimension of people's adoption behavior. To collect the required data for the study, a comprehensive web-based stated preference (SP) survey has been designed and conducted in the Chicago metropolitan area. All results presented in this dissertation are based on the data derived from the implemented survey.

Various behavioral theories from the well-known utility maximization theory to the innovation diffusion theory have been adopted to improve the behavioral realism of the models. Further, several advanced methodological approaches have been employed to address the limitations of the traditional models. Estimating a heterogeneity-in-means

random parameters best-worst model as an advanced alternative of the select-one-choice models, developing a random parameters random thresholds hierarchical ordered probit model for estimating people's willingness-to-pay for AVs, and developing a joint model of vehicle fuel choice and automation choice to capture the potential correlation between the two decisions and account for the shared unobserved factors that might affect them are amongst the methodological contributions of the current research.

1 INTRODUCTION

1.1 Background

Autonomous mobility is one of the rapidly evolving megatrends in the transportation industry, which if combined with sharing mobility and vehicle electrification, will reshape not only people's travel behavior but also their lifestyle. Autonomous driving technology, as one of the leading players in the development of smart cities, has taken huge strides forward and is expected to be available on the market, probably not in a far future. Since 2011 that Nevada–as the first state in the U.S.–authorized the operation of autonomous vehicles (AVs, also known as self-driving or driverless vehicles), 20 other states have either allowed their testing on public roads or passed legislation related to them (NCSL, 2018). As of November 2017, Waymo's driverless cars have been driven more than 4 million miles on public roads. It becomes more interesting when we realize that while it took about 8 years to reach 3 million miles, they needed only 6 months to hit the fourth million miles (Waymo Safety Report, 2018). These trends, and many others, drive public opinion to the fact that autonomous mobility, if well implemented, would dominate the auto market in the next decades.

It will bring essential changes to all types of travel from personal travel to freight transport and from short-distance travel to long-distance commuting. As the drivers – who should probably be referred to as the "passengers" in AVs – are no longer required to pay full attention to the surroundings, they can engage in many other activities which might significantly reduce the disutility of traveling. This is a critical factor that governments, policymakers, and regulator should take into account, because the increasing ease of travel provided by AVs, if not controlled by effective policies, will most probably lead to more personal travel, higher congestion, and larger energy consumption. Therefore, predicting the potential impacts of autonomous mobility has turned into one the main research themes in transportation academia.

There is a huge body of literature focusing on predicting and simulating the effects of AVs, ranging from short-term effects such as changes in individuals' daily activity-travel behavior and network operation to long-term effects such as changes in households' residential location choice behavior. Analysis of potential impacts of automated driving on travel safety (Harper, Hendrickson, & Samaras, 2016; Kockelman et al., 2016), network operation and congestion (Hayat, Park, & Smith, 2016; Kamalanathsharma & Rakha, 2016; Le Vine, Adamou, & Polak, 2014), shared mobility (Dias et al., 2017; Fagnant & Kockelman, 2014; Krueger, Rashidi, & Rose, 2016), and energy and fuel consumptions (Chandra & Camal, 2016; Kamalanathsharma & Rakha, 2016) are some examples of this stream of research.

However, a key point which has been mostly ignored (or simplistically treated) in these studies is to understand how and to what extent people will embrace this technology. Of course, successful implementation of the AV technology is conditioned to the widespread adoption by different segments of the society. Without having a clear vision of the market penetration of AVs, all the studies aiming at predicting the implications of autonomous mobility will be biased toward the underlying assumptions about their market penetration.

1.2 Research Gaps & Objectives

There exist only a few studies focusing on the adoption behavior of AVs (a detailed review of these studies can be found in "Literature review" chapter). Most of these studies have only conducted simplistic descriptive analyses to investigate the associations between individuals' opinions about AVs and their demographic characteristics (Kyriakidis, Happee, & de Winter, 2015; Payre, Cestac, & Delhomme, 2014; Schoettle & Sivak, 2014). Few other studies have gone further and attempted to specify how demographic characteristics and travel habits, social factors, and built-environment attributes affect people's adoption behavior (Bansal, Kockelman, & Singh, 2016; Daziano, Sarrias, & Leard, 2017; Haboucha, Ishaq, & Shiftan, 2017; Shin, Bhat, You, Garikapati, & Pendyala, 2015). Evidently, the literature on people's AV adoption behavior is still limited, leaving major gaps for further study in this area. This dissertation provides a comprehensive research to fill such a gap in the literature by addressing questions such as:

- What are the main factors influencing people's AV adoption decision?
- How can different incentive policies affect peoples' adoption decision?
- How much are they willing to pay for AVs?
- How soon will they adopt AVs? What are the characteristics of innovators and imitators?
- Will heterogenous generational cohorts respond differently to the emergence of AVs?
- Is there any correlation between people's vehicle advanced fuel choice and their AV adoption behavior?

1.3 Terminology

Several definitions have been proposed in the literature and press to conceptualize the vehicle automation technology and the automation levels. Here, we follow the definitions provided by NHTSA (National Highway Traffic Safety Administration) and SAE International (Society of Automotive Engineers) which map the vehicle automation onto a six-level continuum from "no automation" to "full automation", as follows:

- Level 0 (No Automation): The driver performs all operating tasks and is in full control of the vehicle at all times.
- Level 1 (Driver Assistance): An automated module is provided to assist the driver in performing some specific parts of the operating task. However, the driver still has full responsibility for driving and performs all other driving tasks.
- Level 2 (Partial Automation): Multiple automated modules can conduct some parts of the driving task. Most automakers are currently producing vehicles at this level. The driver is still required to carefully monitor the environment and is responsible for performing all other driving tasks.
- Level 3 (Conditional Automation): At this level, an automated control system is provided to perform some parts of the driving task as well as to partially monitor the driving environment. However, the human driver is required to be ready to take back the vehicle control when requested.
- Level 4 (High Automation): At this level, the automated control system is able to fully conduct the driving task and monitor the driving environment, only under certain conditions and in certain environments defined by factors such as road type or geographic area.
- Level 5 (Full Automation): The vehicle control system can completely perform the driving tasks, even without the presence of a human driver.

As many people might not have a clear perception about the specifications of the middle levels of vehicle automation, most of the studies presented in this dissertation are centered on the adoption behavior of fully autonomous vehicles. Further, the terms “autonomous vehicles”, "automated vehicles", "self-driving vehicles", and "driverless vehicles" have been used interchangeably in this research.

1.4 Thesis Organization

Since the vehicle automation technology is not yet available on the real market, a web-based stated preference (SP) choice survey (*presented in chapter 3*) is designed to collect consumer preferences towards AVs and to explore the factors influencing their adoption process. All results presented in this study are based on this survey which is conducted by Qualtrics online platform in Chicago, US. It should also be noted that due to keep the duration and complexity of the survey within manageable bounds, I limit my focus to adoption behavior of privately-owned AVs and leave the analysis of market penetration of shared autonomous vehicles (SAVs) for future research.

In the first model (*presented in chapter 4*), I aim to scrutinize the adoption behavior of AVs by exploring peoples' expectations about the most and least attractive features of AVs and the impact of these expectations on their adoption decision. This approach allows us to focus on the direct influence of attributes on the adoption decision, which requires further analysis such as estimating marginal effects in traditional discrete choice experiments. To this end, I adopt the profile-case best-worst (B-W) modeling approach, in which participants are presented with a series of different AV profiles to be evaluated one at a time. In addition, I aim to investigate the sensitivity of respondents' adoption decision to the vehicle attribute levels. Therefore, a binary question at the end of the choice task was added to indicate whether the respondent is willing to buy the described vehicle or not. To account for the shared unobserved factors that might affect the two decisions (B-W and adoption), they are estimated via a joint model. In addition, the model accounts for both observed and unobserved heterogeneities to provide more accurate sensitivity analyses.

In the second model (*presented in chapter 5*), I aim to comprehensively analyze consumers' willingness-to-pay (WTP) as a critical aspect of adoption behavior of AVs. WTP plays a pivotal role in the pricing decisions of this technology, which can highly affect the penetration rate of AVs in the market. To that end, an advanced structure of ordered models called random parameters and random thresholds hierarchical ordered probit (RPRT_HOPIT) is developed. This model is ideally suited for estimating consumers' WTP due to its great capability in capturing both observed and unobserved heterogeneity in people's preferences towards AVs – which is likely to be prevalent in this context.

The third model (*presented in chapter 6*) focuses on predicting the market penetration of autonomous vehicles and consumers' adoption timing decision. This is also a critical aspect of consumers' AV adoption behavior, which is believed to play a significant role in marketing efforts and policy evaluations. To that end, I adopt an extension of the innovation diffusion model to predict people's technology adoption behavior based on two behavioral aspects: level of innovation and level of following norms of the society (level of imitation). The applied extended model enables us to associate individual-level innovation and imitation desires with various socio-demographic and land-use variables as well as individuals' attitudes and preferences towards AVs.

The fourth analysis (*presented in chapter 7*) is designed to address two major questions regarding the market penetration of AVs. First, I aim to explore how different generational cohorts will adopt autonomous vehicles and identify the fundamental determinants of their adoption decision. Second, I aim to investigate whether people's interest in autonomous vehicles is associated with their vehicle fuel choice decision. In the analysis, the three age cohorts, namely Baby Boomers, Generation Xers, and Millennials are compared in terms of their adoption behavior.

To that end, three generation-specific joint models of vehicle fuel type choice and control system choice are developed.

The remainder of this manuscript is organized as follows. Chapter 2 reviews the limited literature on the adoption behavior of autonomous vehicles. In Chapter 3, the survey design, data collection process, and summary statistics of the sample are discussed. Chapter 4 presents the best-worst analysis and Chapter 5 discusses the willingness-to-pay analysis. The innovation diffusion model is presented in chapter 6 and the cross-generational analysis of vehicle fuel type choice and control system choice is elaborated in Chapter 7. Finally, Chapter 8 summarizes the major findings of the dissertation, reviews the limitations of the studies, and provides recommendations for future research.

2 LITERATURE REVIEW

Over the past decades, various theoretical models, primarily rooted in psychological and sociological theories, have been proposed to explain how individuals adopt and use new technologies (Stathopoulos et al., 2017). Theory of reasoned action (Fishbein & Ajzen, 1975), social cognitive theory (Bandura, 1986), technology acceptance model (Davis, Bagozzi, & Warshaw, 1989), theory of planned behaviour (Ajzen, 1991), motivation model (Davis, Bagozzi, & Warshaw, 1992), and innovative diffusion theory (Rogers, 1995) are some example of the most popular technology acceptance models. While these methods have been extensively used to forecast adoption behavior of various disruptive technologies, their potential in investigating adoption behavior of autonomous mobility has not yet been exploited.

As AV technology is not yet available for public use, most of the studies focusing on their adoption behavior have used stated preference data to explore the factors affecting their public acceptance. The small but fast-growing literature in this area can be classified as those based on descriptive analysis of public awareness, concerns, and expected benefits of AVs such as Schoettle and Sivak (2014), Payre et al. (2014), and Kyriakidis et al. (2015); or based on behavioral analysis such as Shin et al. (2015), Bansal et al. (2016), Daziano et al. (2017), Haboucha et al. (2017), and Wadud (2017). The latter group, specifically, attempted to specify how respondents' demographic characteristics, technology awareness, travel habits, and built-environment factors affect different dimensions of their adoption behavior such as willingness-to-pay (WTP), adoption timing, vehicle type preference, etc. In the rest of this section, we review the key findings of some of the studies in both streams.

As one of the first studies in this area, Schoettle and Sivak (2014) investigated public opinion about autonomous vehicles through a web-based survey in the U.S., U.K., and Australia.

They reported that in comparison to the respondents in the U.K. and Australia, Americans have greater concern about system and equipment failure, data privacy, and interacting with human-driven vehicles. The survey results showed diverse WTP levels for adding self-driving technology. In the Australia, 10% of respondents were willing to pay more than $9,400 for adding this technology to their current vehicle, while the corresponding amounts in the U.S. and U.K. were $5,800 and $5,130, respectively.

In a similar study, Payre et al. (2014) investigated the opinion of 421 French travelers on fully autonomous vehicles through an online survey. Overall, 78% of the sample indicated they are willing to buy a fully automated vehicle and they were ready to spend on average 1624€ in addition to the price of a regular car. The survey results showed that the most preferred situations for using an automated vehicle were monotonous driving situations such as in highways, or stressful driving conditions such as in highly congested areas.

Following that, Kyriakidis et al. (2015) conducted an internet-based survey and collected 5000 responses from 109 countries. They found diverse opinions about automated driving. While 20% of respondents were not inclined to pay more than $0 for this technology, 5% reported that they would be ready to pay more than $30,000 to buy a fully autonomous vehicle. The authors also observed strong correlation between individuals' income level, vehicle miles traveled (VMT), and driving frequency, on the one hand, and their willingness to pay on the other hand. Among those surveyed, 69% believed that automated vehicles will reach a 50% market share by 2050.

Later on, in a comprehensive study, Bansal et al. (2016) investigated some of the major aspects related to AVs adoptions including WTP for and adoption timing of AVs. They conducted an internet-based survey (N = 347) in Austin, Texas from October to December 2014. The survey results showed that at a cost of $5000, 24% and 57% of respondents would be inclined to add limited and full automation[1] to their next vehicle. Using a bivariate ordered probit model, they estimated respondents' WTP for adding limited and full automation technologies and found the average WTP for these levels as $3300 and $7253, respectively. Their results indicate that a wide of range of factors including number of children in the household, living in high-income areas, and prior accident experience affect the willingness to pay for adding both limited and full automation.

In a more recent study, Daziano et al. (2017) explored vehicle-purchase behavior of 1260 individuals in the U.S., focusing on energy efficiency and autonomous features. They conducted a nationwide online survey and collected responses among adults with a driving license, in which respondents answered vehicle-purchase discrete choice experiments. They found that respondents' preferences for AVs is subject to heterogeneity. They reported that while a significant portion of the respondents were willing to pay more than $10,000 for adopting the full automation, some others were not inclined to pay any extra amount for adding this technology. They also estimated WTP for vehicle attributes as the ratio of the marginal utility of each vehicle attribute to the marginal utility of vehicle purchase price.

In another study, Haboucha et al. (2017) investigated preferences for privately-owned and shared AVs based on a stated preference survey completed by 721 individuals in Israel and in North America. A series of six stated preference questions were presented to the respondents, each contained three choice alternatives of: (1) continue to commute using your current car, (2) buy and shift to commuting using a privately-owned AV, and (3) shift to using a shared autonomous vehicle (SAV) for your commute. They estimated kernel logit with nested structure to account for the correlation of error terms among choice alternatives or among observations related to the same

[1] In limited autonomous vehicles, the driver can "cede full control of safety-critical functions under certain traffic or environmental conditions" but needs to be available to take back control if required. However, fully autonomous vehicles are designed to take full control of all operations for the entire trip and the driver is not required to be available to take over control (NHTSA, 2013).

individual. As compared to Americans, Israelis were estimated to be more willing to accept AVs, care more about marginal costs and less about capital costs. Interestingly, 25% of respondents indicated they would refuse to use SAVs even if completely free.

Apparently, the literature on adoption behavior of automated vehicles is limited and there is a need for further study in this area. Following the reviewed studies, current research aims to fill in such a gap by focusing on some of the major aspects of market penetration of autonomous vehicles, including 1) exploring peoples' expectations about the most and least attractive features of AVs and the impact of these expectations on their adoption decision, 2) estimating consumers' willingness-to-pay for adoption of partial and full AVs, 3) predicting market penetration of AVs using innovation diffusion approach, and 4) investigating whether people's interest in autonomous vehicles is associated with their vehicle fuel choice decision.

3 SURVEY DESIGN AND DATA ANALYSIS

3.1 Overview

As autonomous vehicles are not yet available on the market, a web-based stated preference (SP) survey was designed and dedicated to Qualtrics online platform to implemet in the Chicago metropolitan area in December 2016, which resulted in a sample of 1,253 individuals. A few introductory slides were presented at the beginning of the survey to familiarize respondents with the concept of autonomous mobility. The slides were designed to exhibit some general information about autonomous vehicles and the features offered by different automation levels, mostly through images and graphical visualizations. The introductory slides were carefully designed to convey a neutral message to the respondents.

Following that, in order to investigate respondents' preferences towards AVs, several opinion-based questions were asked about their expectations about benefits of and concerns with vehicle automation. Most of these questions were presented in Likert-scale format and respondents were asked to indicate the level of their opinions (in terms of agreement or likelihood perception) about each item. An inclusive set of individual-level and household-level demographic variables, built-environment factors, travel pattern indicators (e.g., number of long-distance trips, regular commute mode), and current use of advanced technologies (e.g., possession of alternative fuel vehicles) is also collected in the survey.

Furthermore, in order to improve the quality of the data, a number of quality checks were included to recognize the respondents who have not paid sufficient attention to the survey. I filtered those who failed to correctly answer the quality checks, overly fast responses (less than 15 minutes), and responses with multiple missing values. In the end, 1013 responses remained eligible for further analysis.

3.2 Sample Composition

While the collected sample comprises people with diverse demographic characteristics, some of the demographic groups were under-represented or over-represented compared to the census database. Therefore, to achieve an unbiased sample in terms of the main demographic characteristics, person-level and household-level weights were calculated based on the 2016 U.S. Census Bureau's American Community Survey (ACS) for Chicago region. Person-level weights were calculated for 37 clusters[1] (gender: 2 groups, age: 4 groups, and education level: 5 groups). These proportions result in 40 categories ($2 \times 4 \times 5 = 40$); however, three categories of "Men under 24 years old with graduate degree", "Women under 24 years old with graduate degree", and "Men over 64 years old without high school degree" were missing in the sample data. Therefore, they were merged with their adjacent education levels (with the same gender and age group). Similarly, household-level weights were calculated for 24 clusters (household size: 4 groups, vehicle ownership: 2 groups, and income level: 3 groups). Table 3-1 reports the summary statistics of the respondent characteristics in the unweighted and weighted sample.

[1] The sample underrepresented "Men under 24 years old without high school degree" and "Women under 24 years old without high school degree". Thus, these two categories required highest scaling factors, as 5.63 and 4.72, respectively. On the other hand, the sample overrepresented "Women between the ages of 44 and 64 with bachelor's degree" and "Women between the ages of 24 and 44 with associate or technical degree". These two categories required lowest scaling factors, as 0.55 and 0.61, respectively

Table 3-1. Summary Statistics of the Respondents' Key Characteristics

Variable	Unweighted Sample	Weighted Sample	Population
Person: Gender			
Male	42.7%	49.1%	49.1%
Female	57.3%	50.9%	50.9%
Person: Age			
<= 24	15.8%	28.6%	28.6%
> 24 and <= 44	37.7%	28.5%	28.5%
> 44 and <= 64	29.4%	17.0%	17.0%
> 64	17.1%	15.9%	15.9%
Person: Education level			
Not a high school graduate	14.4%	12.7%	12.7%
High school graduate	27.7%	22.3%	22.3%
Associate or technical degree	29.4%	27.3%	27.3%
Bachelor's degree (BA, AB, BS)	21.7%	23.8%	23.8%
Graduate or Professional degree	6.8%	13.9%	13.9%
Household: Size			
1	32.7%	29.4%	29.4%
2	24.1%	30.3%	30.3%
3	16.5%	15.5%	15.5%
>= 4	26.7%	24.8%	24.8%
Household: Vehicle ownership			
Not own vehicle	9.8%	14.5%	14.5%
Own vehicle	90.2%	85.5%	85.5%
Household: Income			
<= $50,000	43.8%	38.2%	38.2%
> $50,000 and <= $100,000	34.3%	29.0%	29.0%
> $100,000	21.9%	32.8%	32.8%

3.3 Built Environment Factors

To understand the association between land-use and built-environment factors on the one side, and respondents' AV adoption behavior, on the other side, approximate locations of their homes and workplaces were asked in the survey. Due to privacy concerns, we did not ask their exact address. Moreover, those who felt uncomfortable responding these questions could skip them; for such cases, following Bansal and Kockelman (2017), we used respondents' internet protocol (IP) locations as proxies for their residence locations. Opensource shapefiles in ArcGIS were then used to calculate several land-use variables such as population and employment density, housing density, transit accessibility, and walkability of the neighborhood. Figure 3-1 shows respondents' approximate locations across the Chicago metropolitan area.

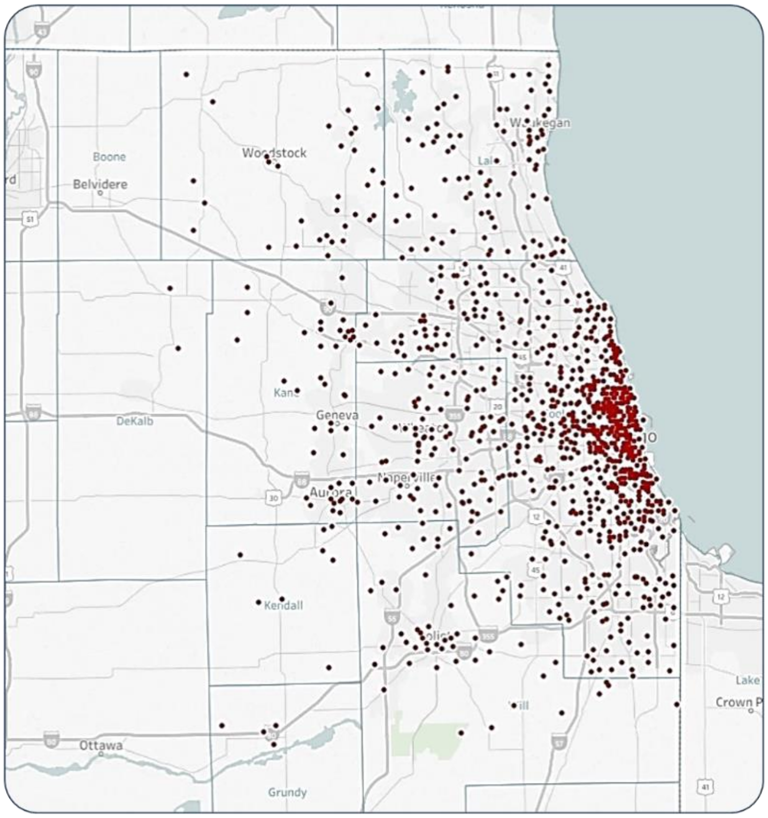


Figure 3-1. Graphical Representation of Respondents' IP Locations

3.4 Expectations about Pros and Cons of AVs

To have a clear vision about the diffusion of autonomous vehicles, it would be of great importance to understand respondents' current perceptions about potential pros and cons of AVs. Therefore, multiple potential benefits of and concerns about AVs were provided in Likert-scale format and respondents were asked to indicate 1) their expectations about these factors, and 2) the extent of importance of each factor in their future adoption decision. Figure 3-2 and Figure 3-3 present the expectations of respondents, and Figure 3-4 and Figure 3-5 illustrate the extent of importance of these factors in their adoption decision.

We found that more productive use of time in vehicle and less stressful driving experience are the most likely expected benefits of driverless vehicles (Figure 3-2), and high anticipated price of AVs and disclosure of personal information are the most likely expected downsides of AVs (Figure 3-3). In addition, fewer crashes/increased safety and lower car insurance rates are the most important benefits of AVs; that is 61% and 52% of respondents indicated that these positive factors are very important in their adoption decision (Figure 3-4). On the other hand, high anticipated price and vehicle imperfect performance in unexpected traffic situations are the most important concerns of respondents about AVs; that is 66% and 58% of respondents indicated that these negative factors are very significant in their adoption decision (Figure 3-5). Multiple dummy indicators are constructed to incorporate respondents' expectations about pros and cons of AVs into the estimated models.

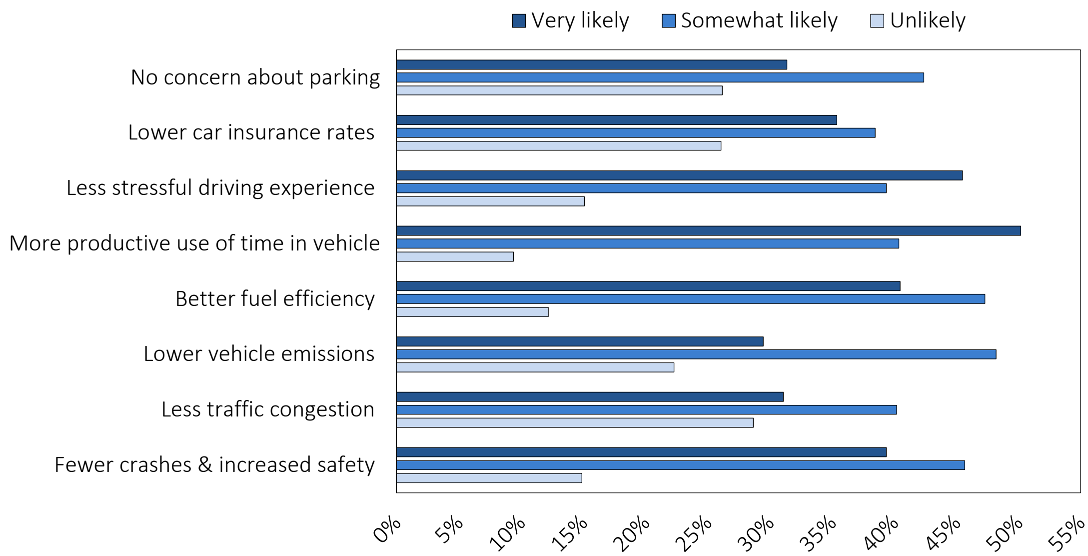


Figure 3-2. Distribution of Respondents' Expectations of Potential Benefits of AVs

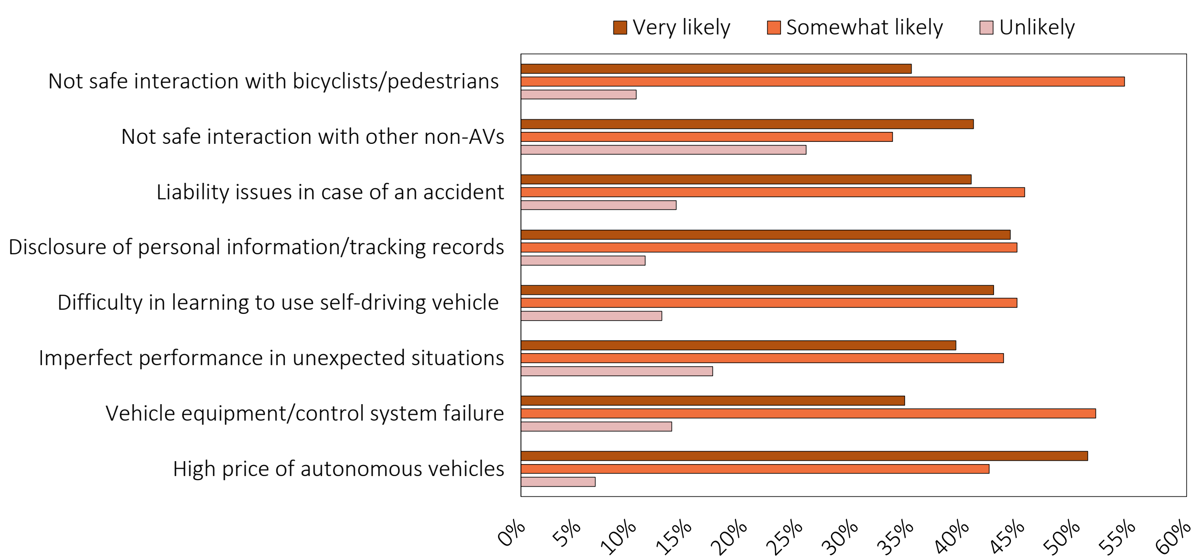


Figure 3-3. Distribution of Respondents' Expectations of Potential Concerns about AVs

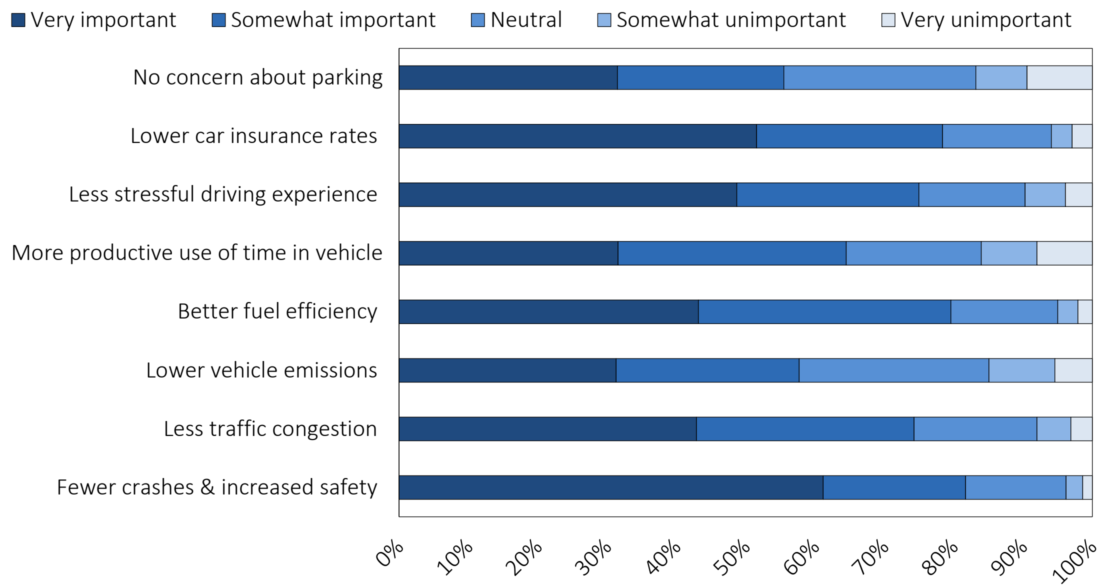


Figure 3-4. Distribution of Importance of Potential Benefits of AVs

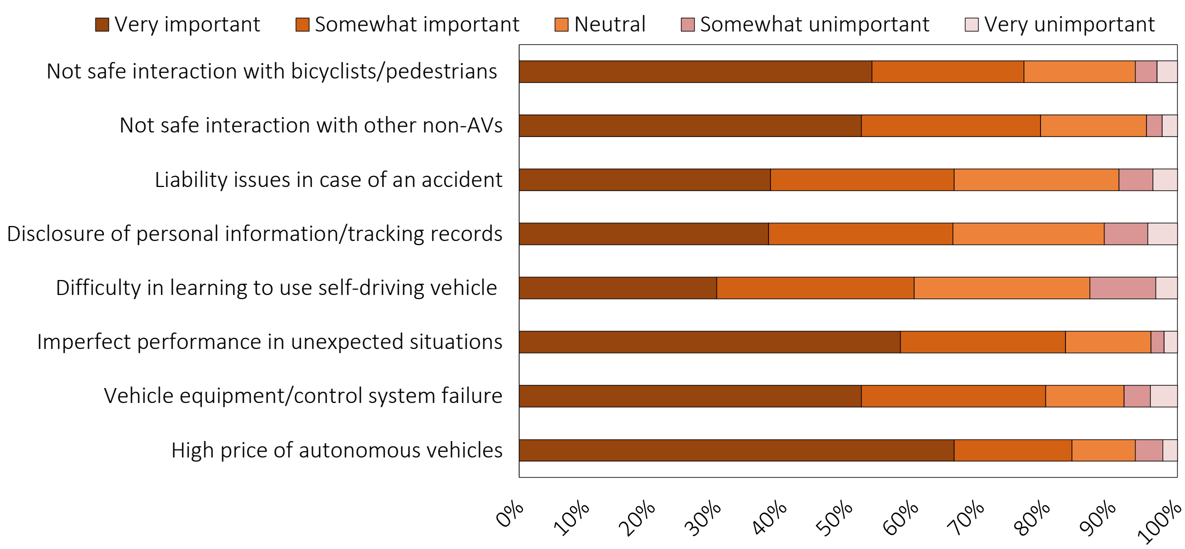


Figure 3-5. Distribution of Importance of Potential Concerns about AVs

3.5 Attitudinal Variables

A series of 26 statements was included in the survey to reflect general travel preferences of respondents and their technology awareness. The statements were designed in a way to incorporate attitudes towards new mobility services (e.g., electric vehicles, ride-sourcing, and car sharing services), private and public travel modes, and technology use. Some other statements were also extracted from related literature (Bansal et al., 2016; Haboucha et al., 2017; Jensen, Cherchi, & de Dios Ortúzar, 2014). Factor analysis is performed to reduce the number of these attitudinal variables and remove the potential correlation between them. We applied varimax rotation method, a type of orthogonal rotation, with Kaiser Normalization to transform the statements to uncorrelated latent factors. The factors were taken from the correlation matrix and were normalized to give values between -1 and 1.

Table 3-2 reports the final transformation which retains six factors. The factor loadings of each statement onto each of the factors are also summarized in the table. All the eigenvalues for the calculated factors are greater than one. The Chi-square of the factor analysis is 6645.25 with 325 degrees of freedom and the extracted factors explain 56.38% of the observed variance. The latent factors are labeled with respect to inference drawn from the statements as: advanced mobility user (AMU), thrilled to drive (TD), interest in AV (IAV), public transit enthusiast (PTE), tech-savvy (TS), concerned about environment (CE). These factors are then used as attitudinal latent variables in the model structure.

Table 3-2. Factor Analysis of General Travel Preferences and Technology Awareness

Statements	Factor loadings					
	AMU[1]	TD	IAV	PTE	TS	CE
S1: I was familiar with driverless vehicles before taking this survey	0.72[2]					
S2: I am familiar with Electric and Hybrid Electric vehicles	0.68				0.41	
S3: I frequently use ride-sourcing services such as Uber or Lyft	0.49	-0.37				
S4: I frequently use car-sharing services such as Zipcar	0.36					
S5: I feel safe when using Uber and Lyft	0.62					
S6: I tolerate extra travel time when using Uberpool	0.55					
S7: I dislike it that I do not have any control of how the vehicle drives		0.50	-0.31			
S8: I like it if I can recover control from the automated system when I want to drive myself		0.41				
S9: Driving a car is enjoyable for me		0.78				
S10: I sometimes enjoy driving around without a specific destination		0.47				
S11: Sometimes, driving is stressful for me		-0.59				
S12: I like it that I can engage in other tasks and be more productive when driving an AV			0.68			
S13: I am concerned about the malfunction of the autonomous vehicle			-0.40			
S14: I trust the automated pilot in controlling the car with no assistance from me			0.64			
S15: I believe that a computer-operated vehicle drives better than an average human driver			0.61			
S16: I like it that I can use AV when I am tired, or my BAC is over the legal limit			0.49			
S17: I like to use public transport because I would be able make better use of my time		-0.33		0.51		
S18: When using public transit, my privacy is restricted in an unpleasant way				-0.42		
S19: I like to use public transport because I do not need to pay attention to traffic				0.59		
S20: I like to use public transport because I do not need to be concerned about parking				0.49		
S21: I have a particular interest in being one of the first people to own an AV			0.38		0.57	
S22: I frequently use my smartphone apps (such as Google map) for travel information					0.62	
S23: I am actively engaged in social networks such as Facebook, Twitter, etc.					0.37	
S24: I am generally interested in innovative technologies					0.43	
S25: I like the fact that the electric cars do not directly produce pollutant emissions						0.32
S26: I like biking because it is good for my health and the environment						0.37

[1] AMU: advanced mobility user; TD: thrilled to drive; IAV: interest in AV; PTE: public transit enthusiast (PTE); TS: tech-savvy; CE: concerned about environment.
[2] Factor loadings with magnitudes below 0.30 are suppressed for ease of interpretation.

4 SENSITIVITY OF ADOPTION DECISION TO VEHICLE ATTRIBUTES[1]

4.1 Introduction

Similar to other emerging technologies, people's adoption behavior of autonomous vehicles (AVs) is expected to be subject to a considerable degree of heterogeneity. In other words, people would have different sensitivity towards various attributes of AVs. Some customers who are more concerned about driving safety might be interested in this technology because of its highly expected safety benefits (Kockelman et al., 2016). Those who are limited by affordability considerations would be highly concerned about the purchase price. Some customers might be driven by policies such as taking liability away from "driver" in case of AV accidents, while others might care for more efficient energy consumptions or provision of an exclusive lane for AVs. The investigation of consumers' sensitivity to various AV attributes is a critical step towards their successful implementation. However, the literature lacks specific research to address the question of how sensitive consumers are to AV attributes and how different levels of these attributes affect their adoption decision.

Such questions are important to answer, not only from the perspective of adoption behavior analysis (and predicting adoption rate), but also with regards to marketing applications (Lynch Jr, 1985). Automakers usually offer varied models of each vehicle to target different segments of the market. In order to determine the right service to be offered to each segment, however, it is critical

[1] The materials of the current chapter are previously published as: "Shabanpour R, Golshani N, Shamshiripour A, Mohammadian A (2018) Eliciting Preferences for Adoption of Fully Automated Vehicles using Best-Worst Analysis. Transportation Research Part C: Emerging Technologies, 93, 463-478". As indicated in Elsevier permission guidelines (provided in appendix and available online at https://www.elsevier.com/about/policies/copyright/permissions), the author of the article has retained the right to include the journal article, in full or in part, in a dissertation.

to first find out the preferences of each segment. This becomes even more important in case of autonomous vehicles since the technology would come with a wide range of benefits (costs) each of which attracting (repelling) specific groups of the society. Thus, knowing the individuals' preferences and sensitivities toward different features of AVs would help policymakers and marketing agencies determine benefit segments more accurately.

The current study aims to contribute to the literature on adoption behavior of AVs from two aspects: (1) exploring peoples' expectations about the most and least attractive AV attributes, and (2) analyzing how the final adoption decision is a function of those expectations in addition to other predictors. To understand respondents' attitudes towards the most and least attractive features of AVs, the best-worst modeling approach is applied. Further, a binary choice model is established to understand how these attitudes influence the decision of whether to purchase the vehicle or not. The two models are jointly estimated to account for the shared unobserved factors that might affect their outcomes. In addition, the models account for both observed and unobserved heterogeneities to provide more accurate sensitivity analyses.

Stated preference (SP) choice experiments are used in this study since the vehicle automation technology is not yet available on the real market. There are two general types of SP choice experiments: single-alternative selection and rating/ranking of alternatives. The most prevalent type is single-alternative selection when the respondent is asked to choose the most preferred alternative among a choice set (Flynn, Louviere, Peters, & Coast, 2007). Such an experiment, however, fails to elicit the respondent's preferences towards other alternatives. Rating and ranking tasks are proposed to bridge this gap (Hausman & Ruud, 1987). However, these experiments may complicate the choice experiment and/or induce behaviour in respondents which may bias the model outcomes (Ben-Akiva, Morikawa, & Shiroishi, 1992).

As a variant of single-alternative selection and rating/ranking tasks, best–worst (B-W) choice experiments provide a middle ground. That is, instead of selecting the best option or ranking all the options in a choice set, respondents are asked to indicate which alternative they consider to be the best (most attractive) and which to be the worst (least attractive) within the choice task. In other words, respondents opt for the pair that "they feel exhibit the largest perceptual difference on an underlying continuum of interest" (Finn & Louviere, 1992). Three types of B-W choice experiments are proposed in the literature, named as object case, profile case, and multi-profile case (see section 4.2 for a more detailed discussion).

With a focus on evaluating the impact of AV attributes on peoples' adoption decision, the current study adopts the profile case best-worst method in which the survey participant is presented with a single AV profile and is asked to select the most and the least attractive attributes. We chose this method as it particularly allows the impact of attributes to be measured meaningfully on a common scale. We find this property desirable given the need to directly focus on the influence of attributes, which requires further sensitivity analysis in other methods.

In order to collect information on consumers' preferences toward autonomous vehicles, we designed and launched a stated preference survey using an online platform in December 2016 in Chicago, US. One main section of the survey is dedicated to the best-worst choice experiment. In this experiment, we identified seven key attributes of AVs which can have significant impact on people's adoption behavior. The attributes are: purchase price, fuel cost, driving range, safety, emission rate, driver liability, and exclusive lane provision. Various combinations of attribute levels were designed, and respondents were asked to indicate their most and least preferred attributes in each choice card. In addition to the B-W choice task, a binary question was added at the end of the experiment to indicate whether the respondent is willing to buy the described vehicle or not. To account for the shared unobserved factors that might affect the two decisions (B-W and adoption), we set out to model them in a joint structure. To the best of our knowledge, this study is the first to apply B-W modeling approach to investigate consumers' preferences towards autonomous vehicles.

The remainder of this chapter is structured as follows: In the next section, we briefly discuss the design of the choice experiments. Following that, we describe the structure of the B-W model applied in this study. Subsequently, detailed estimation results, interpretation of model parameters, and policy implications are presented. The chapter concludes with a summary of the major findings and recommendations for future studies.

4.2 Experimental Design

As previously discussed, we adopt best-worst analysis to investigate peoples' expectations about the most and least attractive AV features. There are three types of B-W choice experiments in the literature as the object case, the profile case, and the multi-profile case (Louviere, Flynn, & Marley, 2015). In the object case, the relative values associated with a list of objects (e.g., different brands of a product) are questioned. In this case, the objects are not specified in terms of their attributes. In the profile case, a single profile (alternative) in terms of its attributes and their associated levels is presented and the respondent is asked to select the most and the least attractive attributes. In the multi-profile case, the respondent faces multiple alternatives, each described in terms of multiple attributes and their associated levels and are asked to indicate their most and least attractive alternative. As the focus of this study is on evaluating the impact of AV attributes on peoples' adoption decision, we adopt the profile case best-worst method.

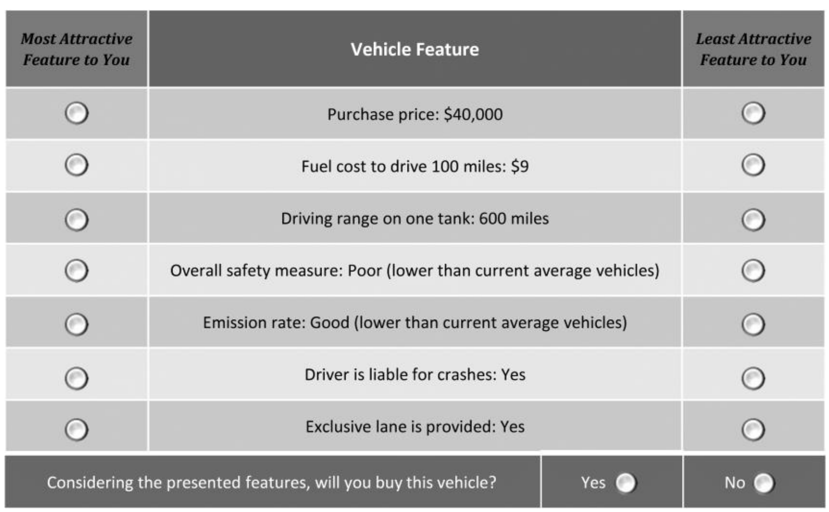
Through a comprehensive review of literature and reports from car companies, we identified seven attributes that may influence the likelihood of adopting AVs: purchase price, fuel cost[1] (to drive 100 miles), driving range (on one tank), overall safety measure, emission rate, driver liability (in case of accidents), and policy incentive (here, in the form of provision of exclusive lane). The first three attributes are presented in three levels and the rest have two levels. The attribute levels are determined in a way to cover a wide range of possible AV profiles. As previously mentioned, in each choice task, respondents were asked to select the most attractive (best) attribute, the least attractive (worst) attribute, and a binary question asking if they would consider buying the AV described in the choice card. It should be noted that prior to asking these questions, respondents were informed about average attribute levels of current vehicles in the market.

The attributes, their levels, and the coding system adopted in the experiment are summarized in Table 4-1. The variables are effects coded with the highest level as +1 and the lowest level as –1. This type of variable coding facilitates the interpretation of the results as it allows the intercept of the attribute to represent the mean among the attribute levels (Balbontin, Ortúzar, & Swait, 2015). Because a full factorial design generating all possible attribute-level combinations was not feasible, a fractional factorial design was applied to reduce the number of choice scenarios. As a result, 16 choice cards were generated and randomly assigned to the respondents, each card describing an autonomous vehicle on the basis of the seven attributes. Figure 4-1 illustrates an example of the choice cards in the experiment. Moreover, Table 4-2 summarizes the descriptive statistics of the variables used in the final models.

[1] The experiment in this study is designed to merely investigate the adoption of gasoline autonomous vehicles and analysis of adoption behavior of electric (or any alternative fuel) autonomous vehicles has left for future research.

Table 4-1. Definition, Levels, and Coding of Attributes Used in the Choice Tasks

Attribute	Level	Code
Purchase price	US$ 40,000	–1
	US$ 50,000	0
	US$ 60,000	+1
Fuel cost to drive 100 miles	US$ 9	–1
	US$ 11	0
	US$ 13	+1
Driving range on one tank	400 miles	–1
	500 miles	0
	600 miles	+1
Overall safety measure	Lower than current average vehicle	–1
	Higher than current average vehicle	+1
Emission rate	Lower than current average vehicle	–1
	Higher than current average vehicle	+1
Driver liability	No: driver is not liable for crashes	–1
	Yes: driver is liable for crashes	+1
Exclusive lane	No: exclusive lane is not provided	–1
	Yes: exclusive lane is provided	+1



Most Attractive Feature to You	Vehicle Feature	*Least Attractive Feature to You*
	Purchase price: $40,000	
	Fuel cost to drive 100 miles: $9	
	Driving range on one tank: 600 miles	
	Overall safety measure: Poor (lower than current average vehicles)	
	Emission rate: Good (lower than current average vehicles)	
	Driver is liable for crashes: Yes	
	Exclusive lane is provided: Yes	
Considering the presented features, will you buy this vehicle?	Yes	No

Figure 4-1. Example of Vehicle Profile Shown in Each Choice Task in the Survey

Table 4-2. Key Variables of the Best-Worst and Adoption Models

Variable	Description	Mean	Std. Dev.
Millennial	1: if respondent is aged between 22 and 37; 0: o/w	0.36	0.48
Senior	1: if respondent is aged 65 years or older; 0: o/w	0.16	0.37
Gender: male	1: if respondent is male; 0: o/w	0.49	0.50
Income: low	1: if household annual income is lower than $50k; 0: o/w	0.38	0.49
Income: high	1: if household annual income is greater than $100k; 0: o/w	0.33	0.47
Education: high	1: if respondent has a graduate or professional degree; 0: o/w	0.14	0.35
Disability	1: if respondent has disability which affects his/her mobility; 0: o/w	0.08	0.27
HH size ≥ 3	Number of household members	2.58	1.72
Home location: downtown	1: if respondent lives in downtown area; 0: o/w	0.11	0.31
Home location: suburb	1: if respondent lives in suburban area; 0: o/w	0.59	0.49
Home-work distance: high	1: if distance between home and work is higher than 20 miles; 0: o/w	0.51	0.50
Frequent telecommuter	1: if respondent telecommutes at least once a week; 0: o/w	0.08	0.27
Accident experience	1: if respondent has experienced accident in his/her lifetime; 0: o/w	0.61	0.49
Frequent long-distance traveler	1: if respondent makes 50+ miles travels, 5+ times per month; 0: o/w	0.71	0.45
Ln (VMT)	Natural logarithm of annual vehicle miles traveled, divided by 100	6.84	3.62
Work parking cost	Monthly parking cost at work (in dollars)	18.3	69.9
Shared ride to work	1: if respondent frequently shares his work trips with other family members; 0: o/w	0.05	0.22
Not safe interactions with pedestrians/bicyclists	1: if respondent expects that AVs will likely have “unsafe interactions with pedestrians/bicyclists” and this factor is important in his adoption decision; 0: o/w	0.72	0.45

4.3 Modeling Approach

Best–worst choice experiments, proposed by Finn and Louviere (1992), aim to "differentiate between the intrinsic impact of an attribute and that associated with its levels of variation" (Balbontin et al., 2015). As previously discussed, there exist three types of B-W choice experiments in the literature as the object case, the profile case, and the multi-profile case. In this study, we applied the profile case, in which a single vehicle profile in terms of its attributes and their associated levels is presented and the respondent is asked to select the most and the least attractive attributes. We also included a binary adoption question at the end of the choice task to inquire if the respondent is willing to purchase the described AV. We specifically aim to investigate the direct impact of participants' sensitivity to attribute level variations in adopting the AV technology.

Respondents' decision on selecting the most and the least attractive attributes in a given profile, can be modeled by means of utility maximization theory. In doing so, we adopt the multinomial logit model (MNL) to estimate respondents' choice regarding the pair of the best and worst attributes. The utility function of selecting attribute pair a by observation i is defined as shown in equations (4-1) and (4-2). As explained below, this formulation accounts for the heterogeneity in means of the parameters by incorporating individuals' characteristics into the formulation (Balbontin et al., 2015; Hynes, Hanley, & Scarpa, 2008).

$$U_{ai} = V_{ai} + \varepsilon_{ai} \tag{4-1}$$

$$V_{ai} = \beta_a^o + (\gamma_a Z_i) X_{ai} \tag{4-2}$$

Equation (4-2) is composed of two terms. The first term, β_a^o, is the intercept capturing the intrinsic impact of the attribute pair a (Balbontin et al., 2015) regardless of the attributes levels.

The second term, $\gamma_a Z_i$ (hereafter, the slope parameter), represents the effect of the attributes levels on the utility of the best-worst pair. The slope is further characterized into two parts as $\gamma_a^p + \gamma_a^q Z_i$. In this notation, Z_i is the vector of respondents' demographic characteristics, γ_a^p is the base slope parameter capturing the effects of the attributes in the absence of the interactors Z_i's, and γ_a^q is the vector of estimable parameters for interactions of demographic variables, Z_i, and the attributes levels, X_{ai}. Finally, ε_{ai} is the random error term that is assumed to have an identically and independently distributed (IID) Extreme Value Type-1 distribution. Assuming the utility maximization behavior by decision makers, individual i selects the attribute pair a if the following criteria is met (L. F. Lee, 1983):

$$\begin{aligned} BW_i = a \quad & \text{if and only if} \quad U_{ai} > \left\{ \max_{j=1,\dots A, a\neq j} U_{ji} \right\} \\ & \text{or equivalently} \quad V_{ai} > \left\{ \max_{j=1,\dots A, a\neq j} U_{ji} \right\} - \varepsilon_{ai} \end{aligned} \tag{4-3}$$

where BW_i denotes the best-worst pair selected by individual i, and A is the total number of best-worst pairs. The unique property of Extreme Value Type-1 distribution is that the maximum over an IID Extreme-Value random variable also follows an Extreme-Value distribution. Accordingly, the probability that individual i selects alternative a can be written as:

$$P(BW_i = a\,) = P\big(V_{ai} > \big(V_{ji} + \varepsilon_{ji}\big) - \varepsilon_{ai}\big) = P\left(V_{ji} < V_{ai} + \big(\varepsilon_{ai} - \varepsilon_{ji}\big)\right) \tag{4-4}$$

Since the difference of two IID Extreme-Value random variables is logistically distributed, the probability of selecting best-worst pair a by decision-maker i can be summarized as (McFadden, 1974):

$$F(\varepsilon_{ai}) = \frac{exp(\beta_a^o + (\gamma_a Z_i) X_{ai})}{\sum_{j=1}^{A} exp\big(\beta_j^o + (\gamma_j Z_i) X_{ji}\big)} \tag{4-5}$$

As previously discussed, determination of the best-worst attributes is also accompanied by investigating the final adoption decision. This is done by joint estimation of the two discrete choices, which in more details, could be described as: (1) the relative attractiveness of vehicle attributes as projected by the B-W model shown in equation (4-5), and (2) an adoption model as discussed in the following. The latter is estimated based on the responses to the question where participants indicated whether they would buy the AV described in the scenario. This choice is modeled using the binary logit formulation which is defined by the following notation: y_{ai} is the binary choice of AV adoption given the best-worst pair a is chosen by individual i, and y_{ai}^* is the unobserved latent utility (Greene & Hensher, 2010a).

$$y_{ai}^* = \lambda_a R_{ai} + \nu_{ai} \rightarrow \begin{cases} y_{ai} = 1 & \text{if} \quad y_{ai}^* > 0 \\ y_{ai} = 0 & \text{o/w} \end{cases} \tag{4-6}$$

here, y_{ai} is the binary choice of AV adoption on best-worst alternative a for individual i, λ_a is the vector of estimable coefficients, R_{ai} is the vector of explanatory variables, and ν_{ai} is the random error term corresponding to the unobserved factors. The probability of adopting AV technology in case of best-worst alternative a by individual i can be written as:

$$P(y_{ai} = 1) = P(\lambda_a R_{ai} + \nu_{ai} > 0) = P(\nu_{ai} > -\lambda_a R_{ai}) = P(\nu_{ai} \leq \lambda_a R_{ai}) \tag{4-7}$$

In this model, the error term follows a standard logistic distribution which forms the cumulative distribution function as (Greene & Hensher, 2010a):

$$F(\nu_{ai}) = \frac{exp(\lambda_a R_{ai})}{1 + exp(\lambda_a R_{ai})} \tag{4-8}$$

Linking the two decision variables of best-worst attributes and AV adoption can be done by forming a bivariate distribution of their error terms. As the error terms are not normally distributed Lee (1983) proposed to first transform the error terms into normally-distributed random variables and then, form a bivariate normal distribution with the transformed variables. The marginal distributions of the transformed random variables are as (L. F. Lee, 1983; Nurul Habib, Day, & Miller, 2009):

$$\varepsilon_{ai}^{*} = J_1(\varepsilon_{ai}) = \Phi^{-1}[F(\varepsilon_{ai})] = \Phi^{-1}\left(\frac{exp(\beta_a^o + (\gamma_a Z_i)X_{ai})}{\sum_{k=1}^{A} exp\left(\beta_j^o + (\gamma_j Z_i)X_{ji}\right)}\right)$$

$$\nu_{ai}^{*} = J_2(\nu_{ai}) = \Phi^{-1}[F(\nu_{ai})] = \Phi^{-1}\left(\frac{exp(\lambda_a R_{ai})}{1 + exp(\lambda_a R_{ai})}\right) \tag{4-9}$$

here, ε_{ai}^{*} and ν_{ai}^{*} are transformed standard normal variables of the corresponding random variables ε_{ai} and ν_{ai}, $J_1(.)$ and $J_2(.)$ are the transformation functions, and $\Phi^{-1}(.)$ is the inverse of the cumulative standard normal distribution. Imposing a bivariate normal distribution with the correlation coefficient ρ on the transformed error terms can capture the effects of the shared unobserved factors on the two dependent variables and therefore, the joint probability that individual i selects best-worst alternative a and adopts AV technology can be formulated as (L. F. Lee, 1983):

$$P(BW_i = a \cap y_i = 1) = F(\nu_{ai})\Phi\left(\frac{J_1(\varepsilon_{ai}) - \rho_{(BW=a,y=1)} J_2(\nu_{ai})}{\sqrt{1 - \rho_{(BW=a,y=1)}^2}}\right) \tag{4-10}$$

Considering δ_{ai} as a binary indicator that only takes the value of 1 when best-worst alternative a is selected by individual i, the likelihood function can be written as:

$$L = \prod_{i=1}^{I}\prod_{a=1}^{A}\left[\left(P(BW_i = a \cap y_i = 1)\right)^{y_i}\left(1 - P(BW_i = a \cap y_i = 1)\right)^{(1-y_i)}\right]^{\delta_{ai}} \tag{4-11}$$

To account for the unobserved heterogeneity in the decision variables, this study adopts the random parameters approach that allows the estimable parameters to vary across observation as follows (Washington, Karlaftis, & Mannering, 2010):

$$\gamma_{ai} = \gamma_a + \eta_{ia} \tag{4-12}$$

$$\lambda_{ia} = \lambda_a + \mu_{ia} \tag{4-13}$$

where γ_{ia} and λ_{ia} are randomly distributed coefficients with means γ_a and λ_a, respectively. Also, η_{ia} and μ_{ia} are random variables with mean zero and variance δ^2 and σ^2, respectively.

4.4 Model Estimation Results & Discussions

In terms of identifying the model, the log-likelihood function is coded in the Mata language of the Stata SE software package, and the model is estimated using simulated maximum likelihood. In this process, different number of Halton draws (Halton, 1960) were tested and we found that 750 draws provide stable parameter estimates for our data. To make sure the model is theoretically identifiable, the intercept parameter in the utility function of selecting purchase price as the best attribute, as well as all the intercepts in utilities of the worst attributes are set to zero. However, such normalization is not required in case of the base slopes (i.e. constant terms in the slopes), since they act as coefficients of the attribute values in the absence of other interacting regressors.

The estimated parameters of B-W and adoption components of the joint model are respectively outlined in Table 4-3 and Table 4-4, and are elaborated throughout this section. The discussions are organized such that slopes and utility scales estimated by the B-W model are presented first, followed by the discussions on the adoption component. As mentioned earlier, to capture the observable heterogeneous behavior, estimated parameters of attribute levels (i.e., slopes) are characterized by different components, namely a constant term and a set of other predictors. To facilitate obtaining an overall sense, slopes are calculated for all observations, and mean and standard deviations are reported in Figure 4-2. According to this figure, the steepest slope of losing interest towards AV attributes corresponds to its purchase price. On the other hand, providing exclusive lanes for AVs leads to the highest slope of gaining interest in these vehicles. Furthermore, the lowest slope is associated with emission rate, which according to the intercept results, is also recognized to have the least likelihood of being selected as the best attribute. To add further details, individual-specific slope components are discussed in the following.

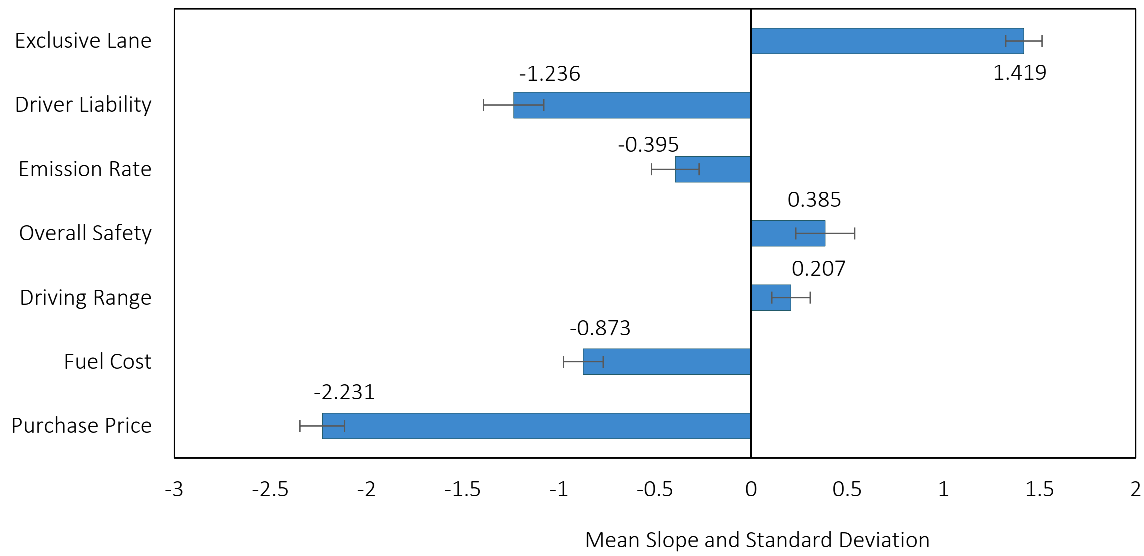


Figure 4-2. Utility Slopes (Mean and Standard Deviation) for the Best Alternative

Turning to the B-W estimation results (Table 4-3), we found that the majority of people with disabilities are less sensitive to higher AV purchase price. This is possibly because of their higher interests in the vehicle automation technology which can greatly facilitate their mobility (Harper, Hendrickson, Mangones, & Samaras, 2016; Milakis, van Arem, & van Wee, 2017). This effect, however, is not found to hold for all the society under consideration. Indeed, having disability is found to escalate people's sensitivity to purchase price, for about 27 percent of the cases. This randomness might be associated with different sources. For instance, such individuals might have disabilities that do not keep them from driving.

Table 4-3. Estimation Results of the Best-Worst Model

Variable	Best-worst Model [1,2]		Best-only Model	
	Coefficient	t-stat	Coefficient	t-stat
Intercept				
Fuel cost to drive 100 miles	0.93	6.04	0.88	6.08
Driving range on one tank	1.44	2.76	0.57	2.25
Overall safety	0.87	5.59	0.28	5.09
Emission rate	-0.21	-3.37	-0.10	-3.23
Driver is liable for crashes	0.16	1.68	0.40	1.54
Exclusive lane is provided	-0.36	-0.97	-0.03	-0.21
Slope				
Purchase price				
Base slope	-2.32	-7.30	-2.15	-4.16
Income: high	0.85	3.66	1.18	3.92
Disability	0.36	2.14	0.53	2.18
Standard deviation of parameter distribution	0.59	1.89	—	—
Fuel cost to drive 100 miles				
Base slope	-0.64	-1.83	-0.59	-1.71
Income: high	0.58	3.04	0.62	3.16
Ln (VMT)	-0.04	-2.91	—	—
Home location: suburb	—	—	-0.80	-5.29
Driving range on one tank				
Base slope	0.25	1.78	0.18	1.65
Frequent telecommuter	-0.74	-2.36	—	—
Frequent long-distance traveler	0.26	1.95	0.37	2.14
Overall safety				
Base slope	0.82	3.77	0.66	3.58
Accident experience	0.19	3.06	0.38	4.09
Ln (VMT)	-0.08	-1.95	-0.46	-1.85
Standard deviation of parameter distribution	—	—	0.91	2.07
Emission rate				
Base slope	-0.29	-3.48	-0.22	-2.05
Senior	0.13	2.01	0.16	3.17
Standard deviation of parameter distribution	0.32	1.76	—	—
Education: high	-0.61	-2.99	-0.72	-3.04
Driver liability				
Base slope	-0.90	-3.23	-0.74	-1.92
Frequent long-distance traveler	-1.02	-1.97	-0.96	-1.72
Accident experience	-0.48	-1.85	-0.58	-2.14
Exclusive lane				
Base slope	1.33	2.42	1.16	2.89
Home-work distance: high	0.49	3.66	0.66	4.75

[1] Only coefficients of the best utilities are reported in this table (worst values have the opposite sign).
[2] The correlation coefficients range from -0.22 to 0.14.

Intuitively, coefficients of income indicators in the utility functions of purchase price and fuel cost are in opposite direction to the corresponding constant values. The opposite effects suggest that although increasing the purchase price or fuel cost raises the probability that people consider them as the worst attributes, higher household income dampens such loss of interest. This is in line with Shabanpour et al. (2018) where the authors showed that higher income is associated with more willingness to be an early adopter of the technology. It is also argued in the literature that highly educated people are more likely to be early AV adopters (Lavieri et al., 2017). Our results add that these people are less enthusiastic towards AVs with higher emission levels.

The results also indicate significant associations of annual VMT and accident experience, to the perceptions towards safety of AVs. It is found that travelers with higher annual VMT are less likely to see safety as the best feature of an AV. This is in fact consistent with the literature arguing that people tend to account less for safety concerns as they gain more driving experience (Golshani, 2015). According to our results, however, the pattern is disrupted as accidents occur. Per the results, those travelers who have experienced an accident before would perceive safety of an AV as its best attribute if the vehicle is known to be safer than an average human-driven vehicle in the market. Such individuals are more likely to gain interest toward an AV if the car company would be liable for possible accidents.

Also, long distance travelers are found to consider liability or driving range as the best features of an AV. Per the results, those who live farther from their work location are more likely to appreciate exclusive AV lanes. Home-work trips are daily routine travels; in this sense, a worker can save plenty of time in the long run by saving even small portions a day. Driving through exclusive lanes can save the AV users travel time given that vehicle-to-vehicle communications provide the opportunity to move smoother and faster than usual traffic.

To gain further insight on how an average individual perceives different AV attributes, we depict the estimated utility scales in Figure 4-3. This figure is constructed out of three vertical lines. The marks on the left (right) line depict utility values assuming all attribute levels are at their lowest (highest) possible level. The three-level variables are represented by square marks and the binary ones are shown by circle marks. This figure provides a graphical tool for comparing the effect of different attributes through a unified system. According to Figure 4-3, purchase price has the greatest potential in surpassing other continuous attributes (i.e., fuel cost and driving range), both in being the best incentive when it is the lowest and in being the strongest disincentive when it is in the highest state. The difference between utility levels associated with the highest and lowest states of this attribute is almost 4.46. Among binary attributes, exclusive lane has the highest utility scale variation with relative difference of 2.84. Driver liability for crashes, emission rate, and overall safety take the 2nd to 4th positions with the difference scale of 2.47, 0.79, and 0.77, respectively.

The results mentioned above are important in the sense of segmenting the market to different groups based on their perspective towards different attributes of AVs. In fact, policy-makers can use such information to offer more efficient incentives and better promote adoption of AVs. The adoption component of the model further facilitates investigation of the interrelationships between participants' sensitivity to attribute level variations and adoption of the AV technology. This component is a random parameters binary logit model incorporating results of the B-W analysis as endogenous variables as well as individual-specific and AV-specific exogenous variables. It should also be noted that the coefficients of the adoption model are assumed to be constant across B-W pairs. The estimated parameters are summarized in Table 4-4.

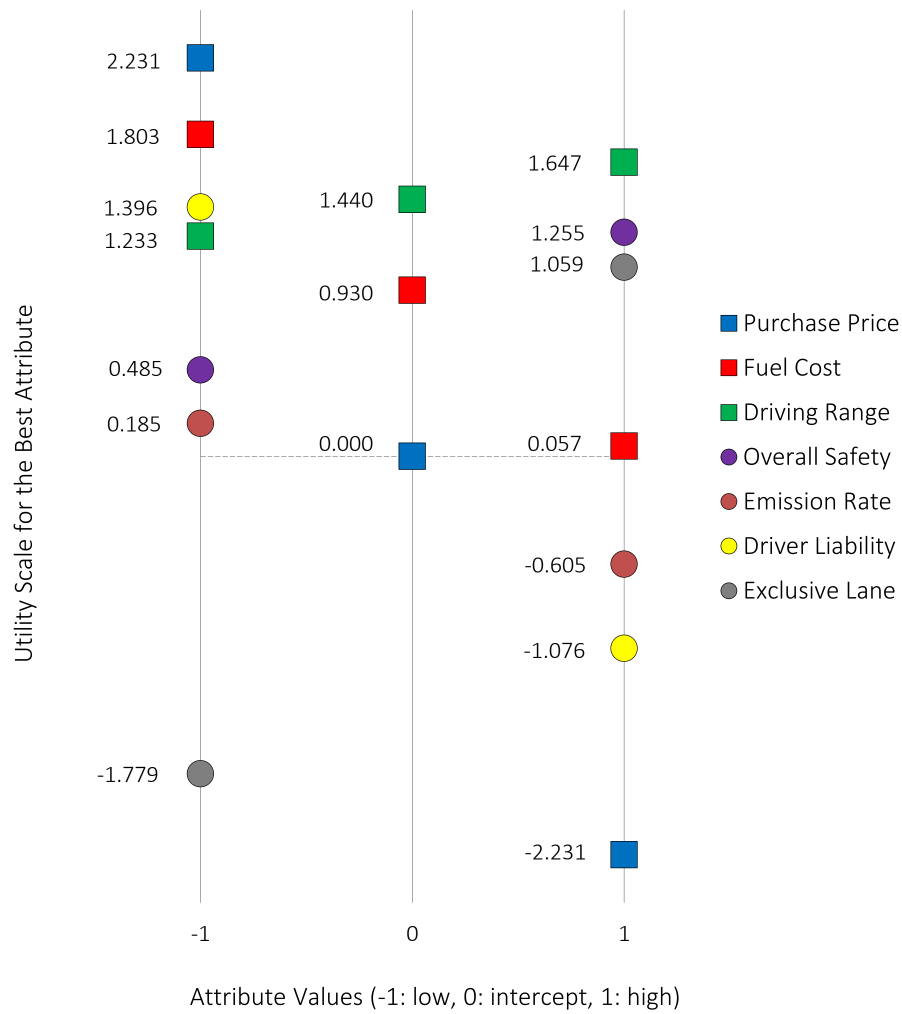


Figure 4-3. Utility Scales for the Best Alternative

In terms of individuals' attributes, we found that age, income level, home location, annual VMT, and accident experience significantly influence the AV adoption decision. Per the results, millennials, defined as those in the 22-37 age group (Pew Research Center, 2018b), are more interested in AV adoption than others; that is probably because such individuals are more tech-savvy and highly reliant on technology in their everyday life (Circella et al., 2017). Intuitively, low-income participants are less willing to adopt AV technology, possibly due to their high anticipated purchase price.

Table 4-4. Estimation Results of the Adoption Model

Variable	Best-worst Model		Best-only Model	
	Coefficient	t-stat	Coefficient	t-stat
Attributes of Individual				
Constant	-1.83	-7.24	-1.69	-4.10
Millennial	0.36	2.16	0.23	2.75
Gender: male	—	—	1.92	1.36
Standard deviation of parameter distribution	—	—	2.86	4.25
Income: low	-0.52	-2.98	-0.67	-3.10
HH Size ≥ 3	0.29	1.75	—	—
Ln (VMT)	0.13	3.29	0.26	3.38
Work parking cost	0.02	2.66	0.11	2.74
Shared ride to work	0.84	3.57	0.70	3.56
Home location: downtown	0.61	1.87	—	—
Accident experience	0.43	1.82	0.20	1.01
Standard deviation of parameter distribution	0.62	1.99	0.53	1.84
Not safe interactions with pedestrians/bicyclists	-0.59	-3.73	—	—
Attributes of AV				
Purchase price				
Base slope	-1.08	-4.21	-1.45	-3.09
Income: high	0.43	2.50	—	—
Driver liability	-0.36	-2.11	-0.17	-2.00
Exclusive lane	0.39	2.63	0.22	2.53
B–W Alternatives				
Exclusive lane – Purchase price	-0.85	-2.92	—	—
Standard deviation of parameter distribution	2.34	4.57	—	—
Driving range – Purchase price	-0.37	-1.78	—	—
Fuel cost – Driver liability	-0.26	-1.85	—	—
Exclusive lane – Emission rate	0.32	2.40	—	—
B-only Alternatives				
Purchase price	—	—	0.76	4.94
Driver liability	—	—	0.17	1.89
Exclusive lane	—	—	0.26	2.50
Log-likelihood at convergence	-3471.08		-2268.54	
Restricted log-likelihood	-4329.66		-2670.91	

Moreover, members of larger households and those who frequently share their work trips with other family members are more likely to buy AVs; this could be because AVs can relax the constraints associated with mandatory joint trips (such as dropping-off or picking-up children at/from school) and save time for the travelers. Saving travel time along with the expected productive use of time in AVs could also be the rationale behind the positive association between traveler's annual VMT and his/her willingness to adopt an AV.

We also found that raising parking cost increases the probability of AV adoption, possibly due to the general perception that they can drop the passengers off and return home (or somewhere cheaper to park). Furthermore, the majority of people who have experienced an accident in the past are more likely to buy AVs in future. This is possibly because such individuals expect that using this technology will increase driving safety (Bansal et al., 2016; Shabanpour, Golshani, Auld, & Mohammadian, 2017). In line with past studies, our analysis also shows that those who expect AVs will likely fail to have safe interactions with pedestrians and bicyclists and this factor highly affects their adoption decision, are less likely to purchase an AV (Bansal et al., 2016; Kyriakidis et al., 2015; Schoettle & Sivak, 2014).

Turning to the attributes of AVs, interestingly, the results confirm the B-W component in that the adoption decision is significantly influenced by purchase price, provision of exclusive lanes, and driver liability. Supported also by the intuition, we found that people lose interest in adopting an AV as the vehicle price increases. Slope of losing interest, however, drops by 39.8% (i.e., from -1.08 to -0.65) for those who are from higher income households. Also, having the travelers be liable for crashes negatively affects their adoption decision while provision of exclusive lanes encourages them to adopt.

With respect to the endogenous variables, we found that the majority of people (65%) who have selected exclusive lane as the best feature and purchase price as the worst attribute are less likely to adopt AVs. However, the remaining 35% are more inclined towards AV adoption, which indicates that providing exclusive lanes significantly compensates the disutility of purchase price for them. On the contrary, driving range is not expected to play the same role as exclusive lane, supporting the negative association found between *driving range – purchase price* pair and AV adoption. Similar results are observed for the pairs of *fuel cost – driver liability* and *exclusive lane – emission rate* in the sense that driver liability and exclusive lane (as two important AV attributes per Figure 4-2) are key determinants of the adoption decision.

4.5 Policy Implications

The presented results can offer useful insights for policymakers to better understand people's attitudes towards adoption of automated vehicles which is vital in implementing incentive policies to boost the use of this technology. This section analyzes the potential market penetration of AVs under different possible scenarios based on the presented estimation results. The results of the adoption model indicate that both considered policy options in the choice scenarios, namely liability in the case of an accident and having exclusive lanes have significant effects on people's adoption decision. Table 4-5 summarizes all possible scenarios derived from various combinations of these policy-oriented variables.

Table 4-5. Possible policy incentive scenarios based on the three options.

Scenario no.	Policy options	
	Is driver liable for AV accidents?	Is exclusive lane provided for AVs?
1	YES	NO
2	YES	YES
3	NO	NO
4	NO	YES

As vehicle purchase price has a predominant influence on people's adoption decision, we investigate the impact of the policy-related variables in three different cases varying in terms of the price (Figure 4-4). In this figure, the green profile represents the 4 scenarios corresponding to the low purchase price (illustrated as $40k in the choice scenarios), blue profile corresponds to the medium purchase price (illustrated as $50k in the choice scenarios), and red profile corresponds to the high purchase price (illustrated as $60k in the choice scenarios). Some of the key conclusions derived from this analysis are discussed below.

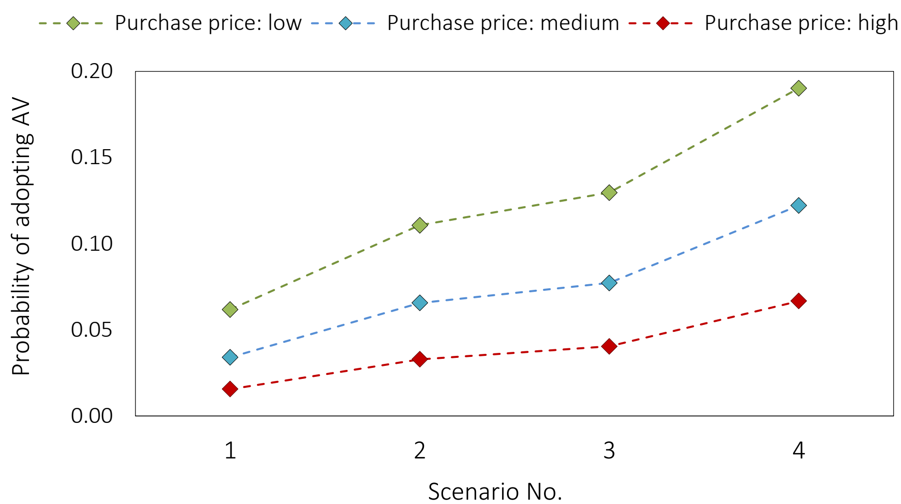


Figure 4-4. Average Probability of Adopting AVs in Different Policy Scenarios

We found that taking liability away from "driver" in case of accidents is an important policy lever in the adoption of AVs. The debates on the regulation protocols to determine whether the auto-maker or the driver is responsible for the accidents are still inconclusive. Our analysis indicates that in the scenarios where the driver is not liable for crashes, with all other factors remaining constant, the adoption likelihood increases up to 8.0% for the case of low purchase price, up to 5.7% for the case of medium purchase price, and up to 3.4% for the case of high purchase price. Furthermore, it is found that in the scenarios where exclusive lanes are provided for AVs, the probability of adopting AVs increases up to 6.1% for the case of low purchase price, up to 4.5% for the case of medium purchase price, and up to 2.6% for the case of high purchase price.

4.6 Conclusions

This chapter presented the results of a profile case best-worst scaling analysis to evaluate the impact of AV attributes on people's adoption decision. The adopted modeling approach allows us to differentiate between the intrinsic impacts of the vehicle attributes and the impact of the attribute levels. In the B-W choice experiment, a single AV profile is presented to each respondent and he/she is asked to select the most and the least attractive attributes. We found that people are much more sensitive to purchase price and policies regarding liability of the driver in the case AV accidents and provision of exclusive lanes for AVs compared to other vehicle attributes. Also, a binary adoption question was asked to inquire if the respondent is willing to purchase the described AV. We found age, income level, household size, residence area, accident experience, annual VMT, and parking cost at work location to be influential in the adoption choice of an AV. Interestingly, results of the adoption analysis confirm findings of B-W scaling model in that people are far more sensitive to purchase price of AVs, compared to other attributes of the vehicle.

This study has several potentials for future research directions. First, other possible incentive policies such as tax rebate and congestion charge exemptions can be considered in the adoption scenarios to obtain a more comprehensive understanding of the influence of incentive policies on people's AV adoption behavior. Second, other types of best-worst analysis such as multi-profile case (where respondents face multiple vehicle profiles) can be adopted in future studies to expand the assessment of people's preferences and their adoption decision sensitivity to vehicle features. Lastly, representations of vehicle attributes in the choice tasks can be improved. For example, people might have more clear perceptions of annual fuel cost rather than fuel cost over a specific mileage. Also, other costs such as maintenance and insurance costs should be considered.

5 WILLINGNESS-TO-PAY FOR AUTONOMOUS VEHICLES

5.1 Introduction

Customers' willingness-to-pay (WTP) for autonomous vehicles is a critical aspect of their adoption behavior, which plays a pivotal role in pricing decisions of this technology. Indeed, the penetration rate of AVs in the market highly depends on the amount that consumers are willing to pay to adopt them. A review of the literature dealing with the AVs adoption behavior highlights the insufficiency of studies focusing on consumers' WTP and affirms the need for an in-depth understanding of involved factors in consumers' decisions. This chapter aims to disclose the factors associated with consumers' WTP for partial and full AVs.

As one of the very few studies focusing on WTP for AV technology, Bansal, Kockelman, and Singh (2016) presented an ordered probit model to estimate WTP for partial and full vehicle automation technologies. They specifically asked the respondents to indicate how much extra they are willing to pay to add partial and full automation to their next vehicle. Their results show that respondents, on average, are willing to pay $3300 and $7253 for adding partial and full vehicle automation, respectively. While this study offers valuable insights about the relationships between demographics and built-environment factors on WTP, it suffers from some limitations mainly regarding the capability of accounting for the heterogeneity of car buyers' preferences.

In such ordered models, the same set of explanatory variables affects the probability of all outcomes. Also, the thresholds of the choice categories are assumed to be the same for all individuals in the sample. To account for the heterogeneity in the ordered models, past studies developed generalized ordered models (Williams, 2006) and mixed generalized ordered models (Eluru, Bhat, & Hensher, 2008). However, these extended models cannot ensure that the estimated probabilities are always positive. The hierarchical ordered probit (HOPIT) model proposed by Greene & Hensher (2010b) addresses this issue and ensures that the thresholds are always increasingly ordered. The HOPIT model also captures the observed threshold heterogeneity by incorporating explanatory variables in the thresholds' formulation. However, this model cannot account for the unobserved heterogeneity that commonly exists in SP survey data (King, Murray, Salomon, & Tandon, 2009).

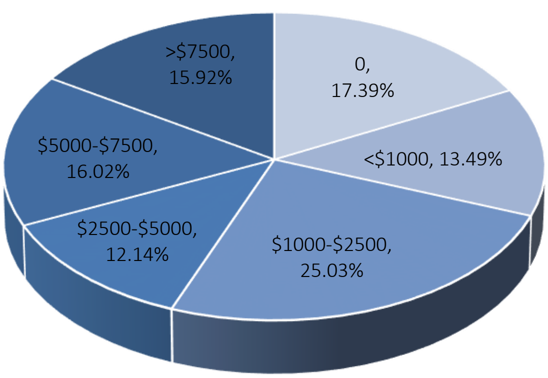
To account for the unobserved threshold heterogeneity, we extend the HOPIT model and consider the constant term of the thresholds to vary across the observations (using random parameters approach), so that it captures both observed and unobserved threshold heterogeneity. Furthermore, to account for the systematic unobserved heterogeneity, we also employ the random parameters approach through which the estimable parameters in the latent utility function of the choice categories vary across individuals following a specific distribution.

The presented model called random parameters and random thresholds hierarchical ordered probit (RPRT_HOPIT) model is ideally suited for estimating consumers' WTP due to its great capability in capturing heterogeneity in people's preferences towards AVs which is likely to be prevalent. The RPRT_HOPIT model is able to (1) account for the unobserved heterogeneity that generally exists in stated preference surveys by incorporating the random parameters approach, (2) ensure that the thresholds are ordinally arranged and probabilities are always positive, (3) account for the observed individuals' heterogeneous behavior that may affect the choice outcomes by incorporating explanatory variables in the thresholds' formulation, and (4) account for the unobserved heterogeneity in the thresholds' formulation by allowing the constant terms to vary across the observations.

The remainder of this chapter is structured as follows: the following section presents the descriptive statistics of the dependent variables of this study. Section 5.3 elaborates on the empirical models and section 5.4 discusses the estimation results. Key findings and conclusions of the study are presented in the last section.

5.2 Dependent Variables

In a specific section of the survey, respondents were asked to indicate their willingness-to-pay to add partial and full automation to their next vehicle purchase. Based on the distribution of reported WTP, 6 categories are considered for the analysis. These categories are defined as: (1) zero; (2) between zero and $1k; (3) between $1k and $2.5k; (4) between $2.5k and $5k; (5) between $5k and $7.5k; and (6) greater than $7.5k. Frequency distribution of these categories are illustrated in Figure 5-1. Furthermore, Table 5-1 presents descriptive statistics of all variables and latent factor used in the final models.



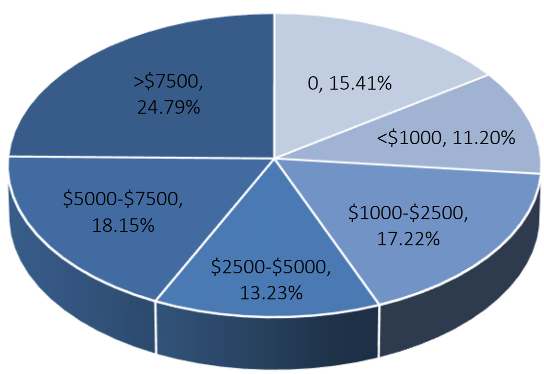


Figure 5-1. Willingness-to-Pay for Adding Partial Automation (a) and Full Automation (b)

Table 5-1. Key Variables of the Willingness-to-Pay Models

Variable	Description	Mean	Std. Dev.
Demographic & built environment			
Education: low degree	1: if participant does not have a university degree; 0: o/w	0.62	0.49
Job type: administrative	1: if individual works in Clerical/administrative support services; 0: o/w	0.08	0.26
Income: high	1: if household income is greater than $100,000; 0: o/w	0.33	0.47
HH size: high	1: if household size is greater than 5; 0: o/w	0.09	0.29
Telecommute: never	1: if participant never telecommutes; 0: o/w	0.18	0.41
Access to vehicle	1: if participant has access to a vehicle in his/her household (as a driver); 0: o/w	0.83	0.32
Home to work distance: high	1: if distance between home and workplace is greater than 15 miles; 0: o/w	0.62	0.37
Ln (VMT)	Natural logarithm of annual vehicle miles traveled (VMT)	6.84	3.62
Long time driver	1: if participant have had a valid driver's license for more than 20 years; 0: o/w	0.57	0.50
Long distance trip	1: if participant makes more than 10 trips longer than 20 miles per month; 0: o/w	0.45	0.50
Major accident	1: if participant have had a major accident in his/her lifetime; 0: o/w	0.22	0.39
AV to work	1: if participant regularly drives to work & would like to use AV for work trips; 0: o/w	0.30	0.46
Employment density: high	1: if employment density of workplace census tract is greater than 5000 workers per sq. miles	0.11	0.31
Transit accessible	1: if walking time from home to the closest public transit station is less than 10 minutes	0.56	0.50
Expectations about AVs			
Better fuel efficiency: unlikely & important	1: if participant expects that using AVs is unlikely to lead to “better fuel efficiency” and this factor is important in his/her adoption decision; 0: o/w	0.11	0.31
Less stressful: likely	1: if participant expects that driving AVs is likely to result in less “stressful” driving; 0: o/w	0.45	0.50
Increased safety: likely & important	1: if participant expects that using AVs is likely to lead to “fewer crashes and increased safety” and this factor is important in his/her adoption decision; 0: o/w	0.09	0.28
Imperfect performance: unlikely & important	1: if participant expects that it is unlikely for AVs to have “imperfect performance in unexpected traffic situations” and this factor is important in his/her adoption decision; 0: o/w	0.07	0.25
Control system failure: unlikely & important	1: if participant expects that “control system failure” is unlikely to happen when using AVs and this factor is important in his/her adoption decision; 0: o/w	0.07	0.26
High price: unlikely & important	1: if participant expects that it is unlikely for AVs to have “high price” and this factor is important in his/her adoption decision; 0: o/w	0.05	0.22
Privacy breach: important	1: if privacy of travel information is highly important for the participant; 0: o/w	0.63	0.48
Latent factors			
Factor: advanced mobility user	Latent variable reflecting participant’s familiarity with advanced mobility services	0.03	1.70
Factor: thrilled to drive	Latent variable reflecting that participant enjoys driving	-0.10	0.86
Factor: public transit enthusiast	Latent variable reflecting participant’s inclination to use public transit	0.29	1.65
Factor: interest in AV	Latent variable reflecting participant’s interest in vehicle automation technology	0.06	1.39
Factor: concerned about environment	Latent variable reflecting that participant is concerned about environment	-0.20	2.23

5.3 Modeling Approach

This section elaborates on the applied modeling approach to estimate individuals' WTP for AVs. The model is an advanced extension of the ordered probit (OP) model. The OP model, originally proposed by McKelvey and Zavoina (1975), accounts for the ordinal nature of the alternatives while assuming that the same set of variables affect their selection probabilities. The formulation for such model can be written as (Greene & Hensher, 2010a):

$$z_i^* = \beta x_i + \varepsilon_i \,,$$
$$y_i = j \quad \text{if and only if} \quad \mu_{j-1} < z_i^* \le \mu_j \,, \quad j = 0, 1, \ldots, J. \quad (\mu_{-1} = -\infty, \mu_J = +\infty) \tag{5-1}$$

here, z_i^* corresponds to the unobserved continuous latent utility for person i that represents his/her propensity to pay more for adoption of an AV, β is the vector of estimable parameters, x_i is the vector of explanatory variables, ε_i is the stochastic error term assumed to be normally distributed with zero mean and variance equal to one, j is the label of WTP categories (here, ranges from 0 to J=5) corresponding to the observed discrete outcomes in the dataset (i.e., y_i), and μ_j is the threshold that separates categories j and $j + 1$. The latent propensity z_i^* is mapped to the observed WTP level y_i by the μ thresholds. The probability of outcome j and the likelihood function for such ordered model can be formulated as follows:

$$\text{Prob}(y_i = j | x_i) = \left[F\left(\mu_j - \beta x_i\right) - F\left(\mu_{j-1} - \beta x_i\right)\right] \tag{5-2}$$

$$L = \prod_{i=1}^{N} \prod_{j=0}^{J} \left[F\left(\mu_j - \beta x_i\right) - F\left(\mu_{j-1} - \beta x_i\right)\right]^{m_{ij}} \tag{5-3}$$

where $F(.)$ is the cumulative distribution function of the standard normal distribution, N is the total number of observations, and m_{ij} is a binary indicator, which is equal to one if observation i belongs to category j, and zero if this condition is not met.

There are restrictive assumptions in the development of traditional OP models. For example, in such models, the same set of determinants influence the probability of all outcomes and the thresholds are assumed to be the identical for all decision-makers. To relax these assumptions, Williams (2006) proposed the generalized ordered probit (GOP) model. GOP models allow a different parameter vector for each outcome, but as stated by Greene and Hensher (2010a), they cannot guarantee that the outcomes probabilities are always positive. To address this issue, Greene and Hensher (2010a) proposed a hierarchical ordered probit (HOPIT) model, in which the thresholds functions are structured in a way that the thresholds would be ordinally arranged and consequently, the probabilities would be always positive. Further, as shown in Equation (5-4), this model allows for systematic variations in the thresholds across decision-makers:

$$\mu_{i,j} = \mu_{i,j-1} + exp\left(\theta_j + \alpha_j t_i\right) \tag{5-4}$$

here, $\mu_{i,j}$ is the threshold between outcomes j and $j+1$ for observation i, $\mu_{i,j-1}$ is the previous threshold, θ_j is a constant term for $\mu_{i,j}$, t_i is a set of explanatory variables that influence the thresholds, and α_j is the set of their corresponding weight. In this formulation, $\mu_{i,-1} = -\infty$, $\mu_{i,0} = 0$, and $\mu_{i,J} = +\infty$.

While the HOPIT model captures the observed threshold heterogeneity by incorporating explanatory variables in the thresholds' formulation, it cannot account for the unobserved heterogeneity that commonly exists in SP survey data (King et al., 2009). To account for the unobserved threshold heterogeneity, we consider the constant term of the thresholds (θ) to vary across the observations (using random parameters approach), so that they would be able to capture both observed and unobserved heterogeneity in thresholds' configurations. Furthermore, to account for the systematic unobserved heterogeneity, we also employ the random parameters approach through which the estimable parameters of the latent utility function vary across individuals following a specific distribution. The formulation for these parameters is as follows (Greene & Hensher, 2010a; Washington et al., 2010):

$$\theta_{i,j} = \theta_j + w_{i,j} \tag{5-5}$$

$$\beta_i = \beta + u_i \tag{5-6}$$

where $\theta_{i,j}$ is the randomly distributed intercept for the threshold j, θ_j is the mean of the random intercept, $w_{i,j}$ is a random variable with mean zero and variance σ^2, β_i is the randomly distributed coefficients in the utility function with mean β, and u_i is a random variable with mean zero and variance δ^2.

5.4 Model Estimation Results & Discussions

In addition to the proposed random parameters random thresholds hierarchical ordered probit (RPRT_HOPIT) model, we have estimated ordered probit (OP) and hierarchical ordered probit (HOPIT) models to facilitate the evaluation of their estimation performance. To better differentiate individuals' perceptions toward partially and fully automated vehicles, we estimated two sets of WTP models for both partial and full vehicle automation. Table 5-2 and Table 5-3 present the results of the best estimated models obtained from each approach.

Table 5-2. WTP Model Estimation Results for Partially Automated Vehicles

Variables	RPRT_HOPIT[1]		HOPIT[2]		OP[3]	
	Param.	t-stat	Param.	t-stat	Param.	t-stat
Model Parameters:						
Constant	2.30***	4.04	0.79***	6.73	0.84***	7.44
Standard deviation of parameter distribution	1.50***	3.78	—	—	—	—
Education: low degree	—	—	-0.17**	-2.33	-0.15**	-2.07
Job type: administrative	-0.64*	-1.81	—	—	—	—
Standard deviation of parameter distribution	0.80*	1.67	—	—	—	—
Income: high	—	—	—	—	0.28***	2.62
Access to vehicle	-1.86***	-3.33	-0.37**	-2.27	-0.36**	-2.23
Standard deviation of parameter distribution	3.75***	4.76	—	—	—	—
Long distance trip	0.43***	3.59	—	—	0.14*	1.95
Standard deviation of parameter distribution	1.40***	4.40	—	—	—	—
Major accident	1.20***	3.33	0.24***	3.02	0.24***	2.97
Standard deviation of parameter distribution	1.90***	4.32	—	—	—	—
Telecommute: never	-0.96***	-3.12	-0.19**	-2.41	-0.18**	-2.32
Standard deviation of parameter distribution	0.47*	1.91	—	—	—	—
HH size: high	—	—	0.29**	2.02	0.27*	1.82
Better fuel efficiency: unlikely & important	-1.78***	-3.45	-0.25**	-2.23	-0.26**	-2.19
Standard deviation of parameter distribution	1.45***	2.58	—	—	—	—
Less stressful: likely	0.85***	3.02	0.21***	2.78	0.20***	2.82
Standard deviation of parameter distribution	0.90**	2.49	—	—	—	—
Imperfect performance: unlikely & important	1.97**	2.45	0.51***	2.84	0.48***	3.01
Control system failure: unlikely & important	—	—	0.31**	2.14	0.28**	2.02
High price: unlikely & important	1.51***	3.50	0.19**	2.24	0.19**	2.22
Standard deviation of parameter distribution	2.33***	3.58	—	—	—	—

(*continued on next page*)

Table 5-2. WTP Model Estimation Results for Partially Automated Vehicles (*continued*)

Variables	RPRT_HOPIT[1]		HOPIT[2]		OP[3]	
	Param.	t-stat	Param.	t-stat	Param.	t-stat
Privacy breach: important	—	—	—	—	-0.13*	-1.85
Employment density: high	—	—	1.16**	2.58	0.22*	1.74
Transit accessible	-0.18**	-2.01	-0.13*	-1.85	-0.11**	-2.56
Ln (VMT)	0.19***	3.32	0.05***	2.79	0.04***	2.59
Standard deviation of parameter distribution	0.06*	1.67	—	—	—	—
AV to work	1.65***	3.90	0.24***	2.59	0.21**	2.48
Standard deviation of parameter distribution	1.25***	3.28	—	—	—	—
Factor: advanced mobility user	1.78***	4.91	0.38***	7.12	0.36***	7.29
Standard deviation of parameter distribution	1.31***	4.56	—	—	—	—
Factor: thrilled to drive	-0.21*	-1.78	-0.08**	-2.04	-0.08**	-2.06
Standard deviation of parameter distribution	0.43***	3.15	—	—	—	—
Factor: public transit enthusiast	0.11*	1.74	—	—	—	—
Standard deviation of parameter distribution	0.43***	2.74	—	—	—	—
Factor: concerned about environment	0.28**	1.99	0.14***	3.02	0.12***	2.66
Standard deviation of parameter distribution	0.41***	3.27	—	—	—	—
Threshold Parameters:						
μ_1	—	—	—	—	0.54***	15.54
μ_2	—	—	—	—	1.33***	33.17
μ_3	—	—	—	—	1.70***	39.47
μ_4	—	—	—	—	2.48***	41.85
θ_1	0.37*	1.68	-0.53***	-6.25	—	—
Standard deviation of parameter distribution	1.16***	5.63	—	—	—	—
θ_2	0.54**	2.42	0.37***	6.86	—	—
Standard deviation of parameter distribution	1.55***	5.86	—	—	—	—

(*continued on next page*)

Table 5-2. WTP Model Estimation Results for Partially Automated Vehicles (*continued*)

Variables	RPRT_HOPIT[1]		HOPIT[2]		OP[3]	
	Param.	t-stat	Param.	t-stat	Param.	t-stat
θ_2	0.54**	2.42	0.37***	6.86	—	—
Standard deviation of parameter distribution	1.55***	5.86	—	—	—	—
θ_3	0.19*	1.89	0.62***	12.56	—	—
Standard deviation of parameter distribution	0.74***	2.96	—	—	—	—
θ_4	1.36***	6.68	1.00***	21.86	—	—
Standard deviation of parameter distribution	0.31*	1.69	—	—	—	—
Income: high	-0.45***	-3.49	-0.28***	-4.13	—	—
Increased safety	-0.15***	-3.01	-0.12***	-2.72	—	—
Long time driver	—	—	-0.09**	-2.10	—	—
Model Specification:						
Log-likelihood at convergence	-1522.38		-1607.43		-1615.43	
Restricted log-likelihood	-1743.62		-1743.62		-1743.62	
AIC	3128.76		3264.86		3280.86	
BIC	3335.43		3387.88		3403.88	

Note: * Significant at 90%, ** significant at 95%, *** significant at 99%

[1] RPRT_HOPIT: Random parameters and random thresholds hierarchical ordered probit.

[2] HOPIT: Hierarchical ordered probit.

[3] OP: Ordered probit.

Table 5-3. WTP Model Estimation Results for Fully Automated Vehicles

Variables	RPRT_HOPIT[1]		HOPIT[2]		OP[3]	
	Param.	t-stat	Param.	t-stat	Param.	t-stat
Model Parameters:						
Constant	2.47***	3.94	0.88***	9.20	0.96***	9.91
Standard deviation of parameter distribution	1.88***	4.06	—	—	—	—
Education: low degree	-0.21*	-1.79	-0.15**	-2.08	-0.16**	-2.31
Standard deviation of parameter distribution	0.52*	1.65	—	—	—	—
Income: high	1.35***	3.04	0.37***	3.71	0.36***	3.37
Standard deviation of parameter distribution	1.41***	3.26	—	—	—	—
Access to vehicle	-0.41**	-2.21	—	—	—	—
Standard deviation of parameter distribution	1.52***	4.16	—	—	—	—
Long distance trip	0.67***	2.65	0.16**	2.14	0.17**	2.41
Standard deviation of parameter distribution	0.84***	3.19	—	—	—	—
Major accident	0.55*	1.85	0.24***	2.93	0.24***	2.95
Standard deviation of parameter distribution	0.73*	1.79	—	—	—	—
Telecommute: never	-0.58**	-2.22	—	—	-0.15*	-1.95
Standard deviation of parameter distribution	0.61**	2.11	—	—	—	—
HH size: high	1.93**	2.22	0.29**	2.04	0.30*	1.96
Standard deviation of parameter distribution	2.33***	2.59	—	—	—	—
Better fuel efficiency: unlikely & important	-0.29*	-1.78	-0.21*	-1.79	-0.23*	-1.89
Standard deviation of parameter distribution	1.32***	2.95	—	—	—	—
Increased safety: likely & important	1.66**	2.07	1.37**	2.13	—	—
Less stressful: likely	1.24***	3.82	0.21***	2.74	0.21***	2.85
Imperfect performance: unlikely & important	1.58**	2.53	0.53***	2.79	0.52***	3.21
Control system failure: unlikely & important	2.39**	2.51	0.24*	1.65	0.25*	1.78
Standard deviation of parameter distribution	3.61***	2.98	—	—	—	—

(*continued on next page*)

Table 5-3. WTP Model Estimation Results for Fully Automated Vehicles (*continued*)

Variables	RPRT_HOPIT[1]		HOPIT[2]		OP[3]	
	Param.	t-stat	Param.	t-stat	Param.	t-stat
High price: unlikely & important	0.62**	1.97	0.25***	2.82	0.23***	2.76
Standard deviation of parameter distribution	0.99**	2.46	—	—	—	—
Privacy breach: important	-0.56**	-2.24	-0.16**	-2.01	-0.16**	-2.21
Standard deviation of parameter distribution	0.95***	3.36	—	—	—	—
AV to work	0.68**	2.16	—	—	0.15*	1.79
Employment density: high	—	—	—	—	0.02*	1.69
Factor: advanced mobility user	1.70***	3.60	0.49***	10.51	0.46***	10.43
Factor: interest in AV	0.38***	2.27	0.08*	1.79	—	—
Standard deviation of parameter distribution	0.30**	2.16	—	—	—	—
Factor: public transit enthusiast	0.21*	1.89	0.09**	2.10	—	—
Standard deviation of parameter distribution	0.39***	2.83	—	—	—	—
Factor: concerned about environment	0.33**	2.19	0.13***	2.81	0.12***	2.72
Standard deviation of parameter distribution	0.38**	2.05	—	—	—	—
Threshold Parameters:						
μ_1	—	—	—	—	0.45***	13.59
μ_2	—	—	—	—	1.03***	26.85
μ_3	—	—	—	—	1.41***	3467
μ_4	—	—	—	—	2.00***	40.43
θ_1	0.74**	2.34	-0.65***	-6.65	—	—
Standard deviation of parameter distribution	1.31***	3.82	—	—	—	—
θ_2	0.85***	3.58	0.19***	2.78	—	—
Standard deviation of parameter distribution	1.78***	5.87	—	—	—	—
θ_3	0.53***	3.03	0.50***	8.35	—	—
Standard deviation of parameter distribution	1.28***	3.52	—	—	—	—

(*continued on next page*)

Table 5-3. WTP Model Estimation Results for Fully Automated Vehicles (*continued*)

Variables	RPRT_HOPIT[1]		HOPIT[2]		OP[3]	
	Param.	t-stat	Param.	t-stat	Param.	t-stat
θ_4	1.39***	5.18	0.86***	15.58	—	—
Standard deviation of parameter distribution	1.71***	4.48	—	—	—	—
Ln (VMT)	-0.05***	-2.85	-0.02***	-3.14	—	—
Home to work distance: high	-0.49***	-4.87	-0.11**	-2.33	—	—
Model Specification:						
Log-likelihood at convergence	-1554.38		-1639.45		-1654.18	
Restricted log-likelihood	-1778.06		-1778.06		-1778.06	
AIC	3198.76		3322.90		3350.36	
BIC	3420.19		3431.16		3453.69	

Note: * Significant at 90%, ** significant at 95%, *** significant at 99%

[1] RPRT_HOPIT: Random parameters and random thresholds hierarchical ordered probit.

[2] HOPIT: Hierarchical ordered probit.

[3] OP: Ordered probit.

A full set of variables and their relevant interactions were tested and only the significant ones with 90%, 95%, and 99% confidence levels are presented in the result tables. Further, to determine the best modeling approach in terms of the statistical fit, we calculated Akaike Information criteria (AIC) and Bayesian Information Criteria (BIC) as follows:

$$AIC = -2LL(C) + 2K \quad (5\text{-}7)$$

$$BIC = -2LL(C) + K\ln(N) \quad (5\text{-}8)$$

here, $LL(C)$ is the log-likelihood at convergence, K is the total number of estimated parameters for each model, and N is the number of observations in the dataset. The best statistical fit is achieved from the proposed RPRT_HOPIT model with AIC of 3128.8 and BIC of 3335.4 for the automation level 3 model and AIC of 3198.8 and BIC of 3420.2 for the automation level 5 model.

As presented in Table 5-2 and Table 5-3, demographic characteristics (e.g., household size, education level, income level, job category), driving patterns and experiences (e.g., number of long-distance trips, number of accidents in the past), and respondents' general opinions about AVs (e.g., potential effects on safety, fuel consumption, and congestion mitigation) significantly affect their WTP. The results indicate that individuals with income higher than $100k are willing to pay more to add automation technology to their vehicles. Those who have clerical or administrative jobs have ambivalent responses to adopt automation level 3; they are normally distributed with the mean of -0.64 and the standard deviation of 0.80, which means only 21.2% of these participants are willing to pay more for automation level 3. We did not find job type as a significant determinant of WTP for full AVs. We also found that household size has a mixed effect on individuals' WTP for AV adoption. Table 5-3 indicates that 79.6% of individuals in households larger than five are willing to pay more to adopt full AVs whereas the remaining 20.4% are willing to pay less to adopt them. This can probably be explained by the heterogeneity in respondents' demographics, specifically income, where large households may be either underprivileged or wealthy and only those with higher income are willing to pay more than $7500.

The results also show that participants with higher annual VMT are willing to pay more to adopt partial or full AVs. Furthermore, those who commute long distances to work (more than 15 miles) are willing to pay more for full automation, which is likely because they can effectively make use of commute time for other tasks rather than driving. Similarly, those who regularly drive to work and reported that they intend to use AVs for their work trips are more likely to pay more than $7500 for adopting full automated vehicles whereas 90.7% of these participants (normally distributed with a mean of 1.65 and standard deviation of 1.25) are willing to pay more to adopt partial AVs. Interestingly, about 62.1% of the respondents who make more than 10 long distance trips per month are willing to pay more to adopt level 3 automation (hence, 37.9% are willing to pay less) whereas 78.8% are willing to pay more to adopt level 5 of automation (hence, 21.2% are willing to pay less). Overall, these findings indicate that participants with longer and more frequent trips are willing to pay more to adopt AVs, which is substantially in line with findings of previous studies (see, for example, Bansal et al., 2016; Haboucha et al., 2017).

We also found that respondents' accident history significantly affects their WTP for AVs. Specifically, 74% and 77% of participants who have had experienced at least one major accident (resulting in major property damage and/or injury) in their lifetime are willing to pay more to add automation level 3 and level 5 to their next vehicle purchase, respectively. Perhaps these participants may expect that automated vehicles will have safer operations compared to traditional vehicles.

Past studies showed that variables representing concerns about and benefits of driverless vehicles directly affect individuals' adoption behavior. The results presented in this study indicate that not only the public opinions about pros and cons of AVs (i.e., expectations) significantly affect their adoption behavior, but also the importance of these factors (i.e., importance measures) for individuals affects their WTP decision. We have developed and tested numerous forms of interactions between expectations and importance measures, and the role of the significant interactions are discussed as follow.

As NHTSA (2013) reported that more than 90% of crashes in the US are attributed to human driver errors, increasing travel safety and reducing number of crashes is one the foremost anticipated benefits of automated driving systems (Bansal et al., 2016; Fraedrich & Lenz, 2014; Milakis et al., 2017). However, control system vulnerabilities, cyberattacks, and human limitation in taking control when necessary might compromise traffic safety benefits of AVs (Bansal et al., 2016; Fraedrich & Lenz, 2014; Kyriakidis et al., 2015; Schoettle & Sivak, 2014). On the same note, we found that participants who expect that emergence of AVs will likely reduce the number of crashes, and safety is a highly important factor in their adoption decision are more willing to pay a higher price to add automation to their next vehicles. We also found that participants who expect that it is unlikely for AVs to have imperfect performance in unexpected traffic situations, and this factor is important in their adoption decision are willing to pay more to adopt automation technology.

However, we found mixed results for the expectations about privacy breach, control system failure, and fuel efficiency of AVs. About 72.2% of those who indicated that privacy breach is an important concern for them are willing to pay less to adopt full automated vehicles. Moreover, 74.6% of participants who expect that control system failure is unlikely to happen when using AVs and this factor is important in their adoption decision are willing to pay more for full automation. We also found that 89.0% and 58.7% of those who consider fuel efficiency as an important factor in their vehicle purchase decision and do not expect that automation technology will increase the fuel efficiency of vehicles are less likely to pay more than $7500 to adopt partial and full AVs, respectively.

Moving to latent factors, the estimation results indicate that 91.3% of "advanced mobility users" are willing to pay more to add automation level 3 to their vehicles whereas this variable has a positive fixed effect on adoption of automation level 5. This latent factor reflects participants' familiarity with advanced mobility services such as driverless vehicles, electric and hybrid electric vehicles, ride-sharing, and car-sharing services. Therefore, it is reasonable to expect that they tend to pay more to adopt automated vehicles. Furthermore, about 60.1% and 70.5% of "public transit enthusiasts" are willing to pay more to adopt partially and fully automated vehicles, respectively. This factor represents participants' inclination to use public transit. As shown in section 3.4, this propensity originates from some advantages of transit services such as travel time productivity and lack of concern about traffic and parking, which are also known as potential expected benefits of AVs. Thus, most of these people are inclined to pay more to adopt driverless vehicles. However, some of them, most probably those who prefer transit services because of their lower travel costs, are willing to pay less for AVs.

We also found that 68.7% of participants who are "thrilled to drive" are less likely to pay more to adopt automation level 3. These people enjoy driving and dislike the situation that they do not have any control over the vehicle operations. Also, over 89.7% of those who are "interested in AV" technologies are willing to pay more to adopt fully automated vehicles. These findings are in line with recent studies on AV adoption (see for example, Haboucha et al., 2017). Finally, 75.3% and 80.1% of participants who are "concerned about environment" are willing to pay more to add partial and full automation driving technology to their next vehicle purchase, respectively.

5.5 Conclusions

Focusing on the adoption behavior of autonomous driving technology, this chapter has presented a random parameters and random thresholds hierarchical ordered probit model to estimate consumers' WTP for partially and fully automated vehicles. The presented model is well-suited for this purpose due to its ability to account for both observed and unobserved heterogeneity in consumers' preferences. The findings of this study are based on my recent web-based stated preference survey which collected consumers' potential WTP for adding partial and full automation to their next vehicle purchase.

The analysis of estimation results reveals that the proposed RPRT_HOPIT model is statistically superior to its counterparts in terms of goodness-of-fit measures. It is found that a broad range of variables including demographic attributes (e.g., education and income level), driving experiences (e.g., number of long-distance trips, number of accidents in the past), and respondents' general opinions about AVs (e.g., importance of safety, fuel consumption, and congestion mitigation) significantly affect the WTP decision. I also found that consumers' WTP decision behavior is subject to notable degrees of heterogeneity.

The results of our analysis indicate that people, on average, are willing to pay $3,225 for adding partial automation and $5,475 for adding full automation to their next vehicle purchase. Respondents with higher income, those who regularly drive to workplace, those who anticipate higher safety and better fuel efficiency from AVs, and long-distance commuters have greater interest in and higher WTP for this new vehicle technology. The results of this analysis offer valuable insights about people's AV adoption behavior, which would be of great interest for policymakers to plan for future transportation systems.

6 ADOPTION TIMING OF AUTONOMOUS VEHICLES

6.1 Introduction

With the rapid advancement of technology in recent years, the idea of autonomous driving is no longer a dream and if regulations allow, autonomous vehicles (AVs) are expected to be introduced to the market as early as 2025–2030 (Langheim, 2014; Manyika et al., 2013; Silberg & Wallace, 2012). AVs are expected to act as an economically disruptive transportation technology, offering several benefits to the society and causing significant changes in travel behavior and network performance (Fagnant & Kockelman, 2015; Langheim, 2014; Manyika et al., 2013; Milakis et al., 2017). However, one of the critical issues that policymakers are facing is the potentially slow market penetration rate estimated for AVs.

Despite all appealing attributes of AVs, it is argued that several barriers lie in the way of their immediate adoption (Fagnant & Kockelman, 2015). Affordability would be one of the most challenging issues. Given the high costs associated with advanced equipment that is needed for automated communication and guidance, high purchase prices are anticipated in the first few years after their public release (Fagnant & Kockelman, 2015; Shchetko, 2014). However, it is estimated that the additional prices will considerably drop following further technological advances and large-scale productions (Dellenback, 2013). Another concern would arise from potentials of tracking data disclosures. Other barriers include software security threats from computer hackers (Fagnant & Kockelman, 2015), legislation inconsistencies among different countries and even states, and difficulty of learning how to operate them (Kyriakidis et al., 2015).

To this complexity, individual-level heterogeneity in overall desires to innovate or follow society's norms should also be added. This overwhelming conflict between various expected benefits and costs of the technology on one hand, and inter-personal perspective variations, on the other hand bring up the question of how to predict the market penetration of this technology.

To address this critical question, the current chapter focuses on predicting the market penetration of fully autonomous vehicles and consumers' adoption timing decision, which I believe play a pivotal role in marketing efforts and policy evaluations. In this vein, I adopt an extension of the innovation diffusion model proposed by Bass (1969). The model has been widely accepted in the literature (see, for example, (Islam, 2014; Islam & Meade, 2012; Tsai, Li, & Lee, 2010)), offering a novel opportunity to map the adoption profile into two behavioral aspects: level of innovation and level of following norms of the society (i.e., level of imitation).

Many extensions of the Bass model are proposed in the literature (refer to Meade & Islam (2006) for a comprehensive review), among which I use the structure suggested by Schmittlein & Mahajan (1982). This structure enables us to estimate a heterogeneous-in-mean model to associate individual-level innovation/imitation desires with various socio-demographic and land-use variables as well as individuals' attitudes and preferences towards AVs.

The remainder of this chapter is structured as follows: In the next section, I briefly describe the design of the choice experiments embedded in the survey to collect required data for this analysis. Following that, the structure of the adopted innovation diffusion model is presented. Subsequently, detailed discussions on model estimation results and policy implications are presented. The major findings are summarized in the conclusion section.

6.2 Data Analysis

In a specific section of the survey, respondents were presented with six time options from 2025 to 2050 (every 5 years) and asked to assign each with a cumulative probability of adopting their first <u>fully autonomous vehicle</u>. Each time option corresponded to an average estimate of the additional AV price (compared to a regular human-driven vehicle) at that time. It is assumed that the additional price drops every 5 years and the assumption was revealed to the respondents. The additional purchase prices are determined based on a comprehensive review of literature and reports from automakers and tech companies, starting from $20,000 at 2025 and dropping to $15,000 and $10,000 by 2030 and 2035, respectively. The additional price was assumed to the fixed amount of $5,000 for the following time options. The question was asked from every respondent, regardless whether they intend to eventually adopt or not. Self-reported probabilities are oftentimes used as a proxy for actual adoption timing probabilities, during the very first years that a product is introduced to the market or beforehand (Silk & Urban, 1978; Van Ittersum & Feinberg, 2010).

6.3 Innovation Diffusion Model

First solid studies on the innovation diffusion phenomenon date back to 1940s, triggered by the work of Ryan & Gross (1943). However, the theory of “diffusion of innovations” was proposed by Rogers (1962). He defines the term diffusion as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 1962). He further argues that individuals are heterogeneous in their propensities to have innovation in adopting a new technology. He defines five levels of innovation: innovators (first 2.5% of adopters), early adopters (following 13.5%), early majority (next 34%), late majority (next 34%), and laggards (last 16%). In addition, based on solid evidence on an S-shaped nature of the diffusion distribution, Rogers assumes normally-distributed adoption thresholds at the aggregate level (Rogers, 1962).

The assumption of an S-shaped diffusion curve has also been proven legitimate (Meade & Islam, 2006) and adopted by several recognized research afterward. Instances include the lognormal distribution proposed by Bain (1963), the logistic distribution proposed by Gregg, Hossell, & Richardson (1966), and the exponential distribution by McCarthy & Ryan (1976). A novel distribution is proposed by Bass (1969). Despite many attractions of the Bass model, the estimation technique which was originally proposed by the author was later criticized for not being accurate enough (Heeler & Hustad, 1980; Meade & Islam, 2006; Schmittlein & Mahajan, 1982). Later, Schmittlein & Mahajan (1982) suggested an extension to address the issues, which also opened up the possibility of applying the model to individual-level data instead of aggregate information. That version makes it possible to capture various individual-level sources of heterogeneity. The basic model of Bass (1969) and the extension proposed by Schmittlein & Mahajan (1982) are discussed in the following sub-sections.

6.3.1 The Bass Diffusion Model

Bass (1969) argues that individuals' propensities to adopt a new product takes influence from a desire to innovate (quantified by the parameter p) and a need to imitate the rest of the society (quantified by the parameter q). The imitation effect is also known as word of mouth (WOM). He defines the hazard function corresponding to the likelihood of a purchase at the time t given no purchases prior to t as shown in Equation (6-1):

$$\frac{f(t)}{1-F(t)} = p + qF(t) \tag{6-1}$$

where, $f(t)$ and $F(t)$ are the probability distribution function (PDF) and the cumulative distribution function (CDF) associated with adopting a new technology at time t.

The unconditional adoption probability function, consequently, can be written as $f(t) = (p + qF(t))(1 - F(t))$. Also, let S_t denote total sales at time t (also known as adoption rate), Y_t denote cumulative sales up to time t, and m be the total number of potential purchases (i.e., potential market size) during the analysis period T. Given that $S_t = mf(t)$ and that $Y_t = mF(t)$, then, sales at time t can be expressed as in Equation (6-2):

$$S_t = \frac{dY_t}{dt} = m(p + qF(t))(1 - F(t)) \; = (p + \frac{q}{m}Y_t)(m - Y_t) \qquad (6\text{-}2)$$

Furthermore, the adoption timing CDF is derived as shown in Equation (6-3), solving the differential equation shown in Equation (6-2) by integration. Immediately following Equation (6-3), cumulative sales at time t is derived as shown in Equation (6-4):

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \qquad (6\text{-}3)$$

$$Y_t = m\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \qquad (6\text{-}4)$$

6.3.2 The Individual-level Extension

Schmittlein & Mahajan (1982) proposed an individual-level extension of the Bass model. The extension adopts the same theory but presents a new perspective. In the new context, in fact, Equation (6-3) should be interpreted as the adoption timing CDF corresponding to a consumer given that he/she will eventually adopt the new product (Schmittlein & Mahajan, 1982). The authors, further, suggest Equation (6-5) as the unconditional adoption timing CDF (denoted as ${Y'}_t$), where m' denotes likelihood of the technology being eventually adopted. Equation (6-5) is similar to Equation (6-4), but it defers in one aspect: ${Y'}_t$ is the cumulative probability of adoption at time t for a particular consumer, while Y_t is the total number of observed adoptions in the society.

$$Y'_t = m' \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}} \tag{6-5}$$

On the model specification side, efforts have been focused on incorporating external influence variables such as cost (Lavasani, Jin, & Du, 2016; Tsai et al., 2010) and different sources of interpersonal variations such as socio-demographics and attitudes (Islam, 2014; Islam & Meade, 2012). These studies can be categorized into two groups, depending on how the effects are incorporated. While the first group assumes that every incorporated variable equally affects p, q, and m (or m') (Lavasani et al., 2016), The second group tries to characterize p, q, and m to a different set of variables (Islam, 2014; Islam & Meade, 2012; Tsai et al., 2010). In the present study, we stick to the second approach, since it seems to be more theoretically sound.

6.4 Model Estimation Results & Discussions

In order to capture the heterogeneity in mean values of p and q, following the literature (Islam, 2014; Islam & Meade, 2012), I characterized the parameters to different variables. The functions assumed for p and q are referred to as p and q functions henceforth. Both functions are assumed to be linear in parameters following the literature. The functions encompass a constant term (referred to as the base effect) and a set of explanatory variables. The estimation results are outlined in Table 6-1 and discussed in this section in details.

While disaggregate results provide unique opportunities for policy analysis, aggregate results are useful to draw an image of overall behavioral patterns. In this regard, we first present the aggregate-level results. The overall adoption likelihood is estimated to be 0.713. This value indicates that an average resident of the Chicago metropolitan area is 71.3% likely to eventually adopt an AV. The average values of innovation and imitation parameters could be calculated as $\overline{p}$ = 0.108 and $\overline{q}$ = 0.957, indicating an S-shaped adoption pattern on the aggregate level.

To gain a general sense of the inter-personal variations, the frequency distribution of different components of the model are depicted in Figure 6-1. Figure 6-1(a) and (b) depict the distribution of the estimated values for p and q, respectively. As seen, neither p nor q take negative values in the estimation sample. If confirmed by future studies and larger samples, this would indicate that AV sales are anticipated not to fall over the first 25 years.

Validity of this conclusion as a hypothesis can also be statistically assessed using the information available to us in the present study; that is, the parameters' deviation from 0 can be tested using the t-test. The t-test results indicate that for the innovation parameter, the median (0.097) is significantly far from 0 at a 90% level of confidence. Further, regarding the imitation parameter, even the minimum value (0.409) is recognized to be far at a 95% level of confidence. Thus, the aforementioned conclusion is expected be statistically valid for at least half of the sample.

Furthermore, Figure 6-1(c) shows the distribution of q/p values. This figure provides insights on two behavioral aspects. The first aspect is the assumption of an S-shaped adoption curve. To test this assumption, we first filtered the values above 17.1 out to achieve a bell-shaped distribution which is consistent with the assumptions of a t-test. Then, the test is run on the new sample. Results indicate that, at a 95% confidence, the ratio associated with only half of observations (median and above) are far from 1. This sheds light on the fact that although AV adoption follows an S-shaped CDF at aggregate-level, this might not be the case for every individual of the society.

The second aspect corresponds to the level of social contagion in the data. The fact that the 10^{th} percentile value of q/p is 4.02 and the median is 9.94 reveals a more or less "collectivism" nature for the AV adoption in Chicago. Collectivism is the term used to refer to societies in which people are less immune to social contagion (Schmittlein & Mahajan, 1982). For more information, the reader may refer to Van den Bulte and Stremersch (2004), where the authors conduct a meta-analysis on 746 applications of the Bass model.

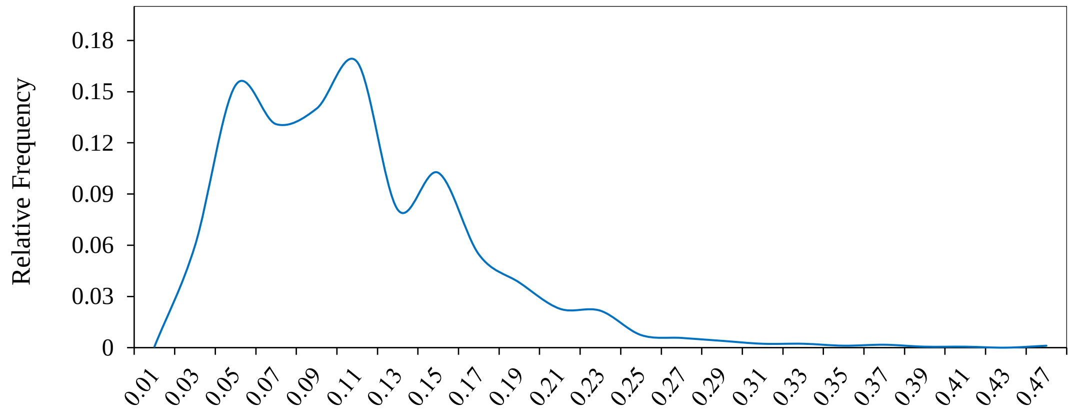
Rest of the discussions in this section are devoted to the individual-level results. A subtle but critical point on the interpretation of the estimation results is that it is not the sign of the coefficients themselves that matters, but their sign and value relative to the so-called "base effect" parameter. For instance, negative coefficient of an explanatory variable within the q function should be interpreted as damping the positive base effect, rather than having a negative effect. The overall effect would remain positive until the variable's value times its effect exceeds the base effect.

Accepted additional purchase price is one of the explanatory variables incorporated into the p and q functions. The reason for including the term "accepted additional" is to underline the specific way the experiment was designed. As mentioned, I provided different time-options to the respondents, each of the periods being assigned a hypothetical value as the average additional price of purchasing an AV at that time. In this sense, the variable should not be interpreted as the actual additional price of purchasing an AV (as determined in a market of different brands and players), but as a representative of the overall pattern of price reduction. In other words, a positive correlation is expected between the variable and level of innovation, since higher accepted prices are associated with earlier adoptions. Furthermore, the coefficient of the accepted purchase price is itself assumed to be a function of a constant term (to capture the pure effect of the variable) and other variables (to capture interactions).

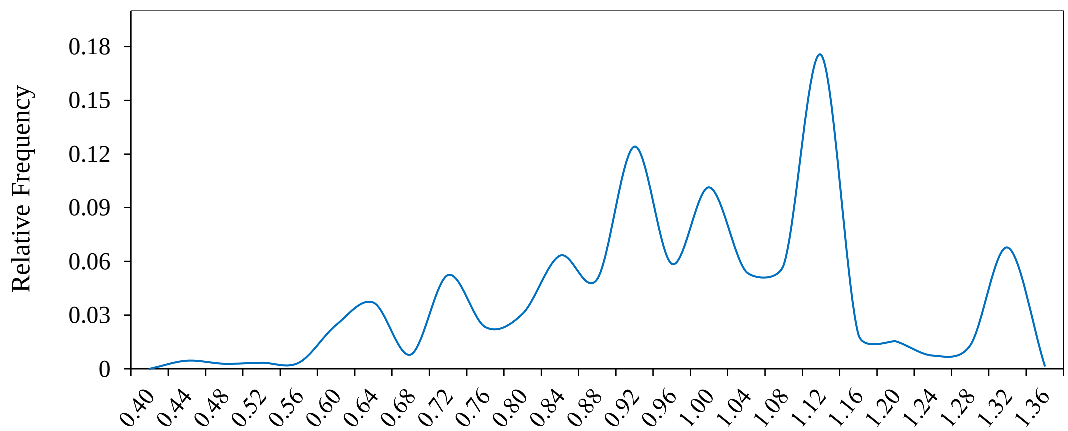
Table 6-1. Estimation Results of the Innovation Diffusion Model

Variable	**Coefficient** †	**t-statistic**
Coefficient of Innovation		
Base Effect	0.019 **	2.01
High Education: *if respondent has obtained a university degree*	0.005 ***	2.65
Couple: *if respondent lives with a partner*	0.040 ***	2.53
High Freq. Long Dist. Travel: *if respondent goes to travels of 50+ miles, 5+ times per month*	0.039 **	1.69
High Transit Acc. × Senior: *if transit station is available within a quarter-mile walking distance & age>65*	-0.024 **	-1.81
Driving AV Would be Stressful: *if respondent expects that driving an AV will be stressful*	-0.011 **	-1.82
Parking Cost at Work [$1k]: *Monthly parking cost at work location, divided by 1000*	0.363 ***	4.07
Accepted Purchase Price [$10k]: *Accepted* additional *cost of adopting an AV instead on a regular vehicle, div. by 10k*		
Base Effect	0.324 ***	3.55
Income [$100k]: *Household annual income of the respondent, divided by 100,000*	0.071 **	1.84
Heard of Internet of Things: *if respondent has heard of Internet of Things before the survey*	0.061 **	2.05
Coefficient of Imitation		
Base Effect	1.276 ***	8.99
Couple: *if respondent lives with a partner*	-0.193 **	-1.81
Accident Experience: *if respondent has been involved in an accident before*	0.172 ***	3.70
High Freq. Long Dist. Travel: *if respondent goes to travels of 50+ miles, 5+ times per month*	-0.283 **	-2.08
Accepted Purchase Price [$10k]: *Accepted additional cost of adopting an AV instead on a regular vehicle, div. by 10k*	-1.114 **	-1.94
Market Potential (m)		
Base Effect	0.713 *	1.33
Number of Observations	1013	
R-squared	0.852	

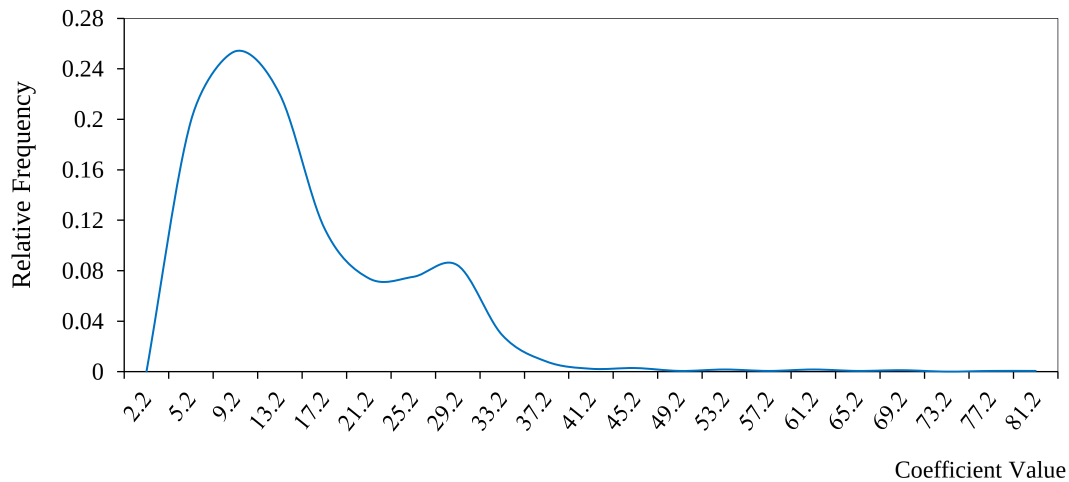
† ***, **, * indicate significance at 1%, 5%, and 10% level.



(a) Innovation Parameter, p



(b) Imitation Parameter, q



(c) Imitation Parameter over Innovation Parameter, q/p

Figure 6-1. Distribution of Innovation and Imitation Parameters

As shown in Table 6-1, individuals who have experienced an accident in their lifetime are more influenced by word of mouth. However, we could not find a significant association to the coefficient of innovation. This is understandable given the fact that such individuals care more about safety of their ride and would probably wait a few years to make sure AVs are safer than human-driven vehicles. In addition, more frequent long-distance travelers are found to be less influenced by word of mouth and more influenced by their desire to innovate. However, the overall effect on adoption timing is not directly clear from the raw results, since the two effects operate in different directions. In this regard, the reader may refer to the next section where further sensitivity analyses are provided. Further, a significant and positive association is found between parking cost at work location and level of innovation of workers in adopting an AV. In the next section, further sensitivity analyses are provided for this parameter as well.

Regarding effects of other economic variables, in accordance with the literature (Islam, 2014), our results indicate that individuals whose accepted purchase price is higher make the adoption decision more innovatively. A similar result is also achieved in case of household annual income, which is in line with findings of Rogers (2010). Also, the dummy variable “Heard of Internet of Things” is introduced to the function forming coefficient of purchase price in the p function, as a proxy for being well-informed about new technological terms and notions. Per the results, such individuals are also more likely to behave innovatively with regards to the AV adoption. This finding is in line with the results of Lavieri et al. (2017), where the authors report a positive association between being tech-savvy and being an early adopter of AVs.

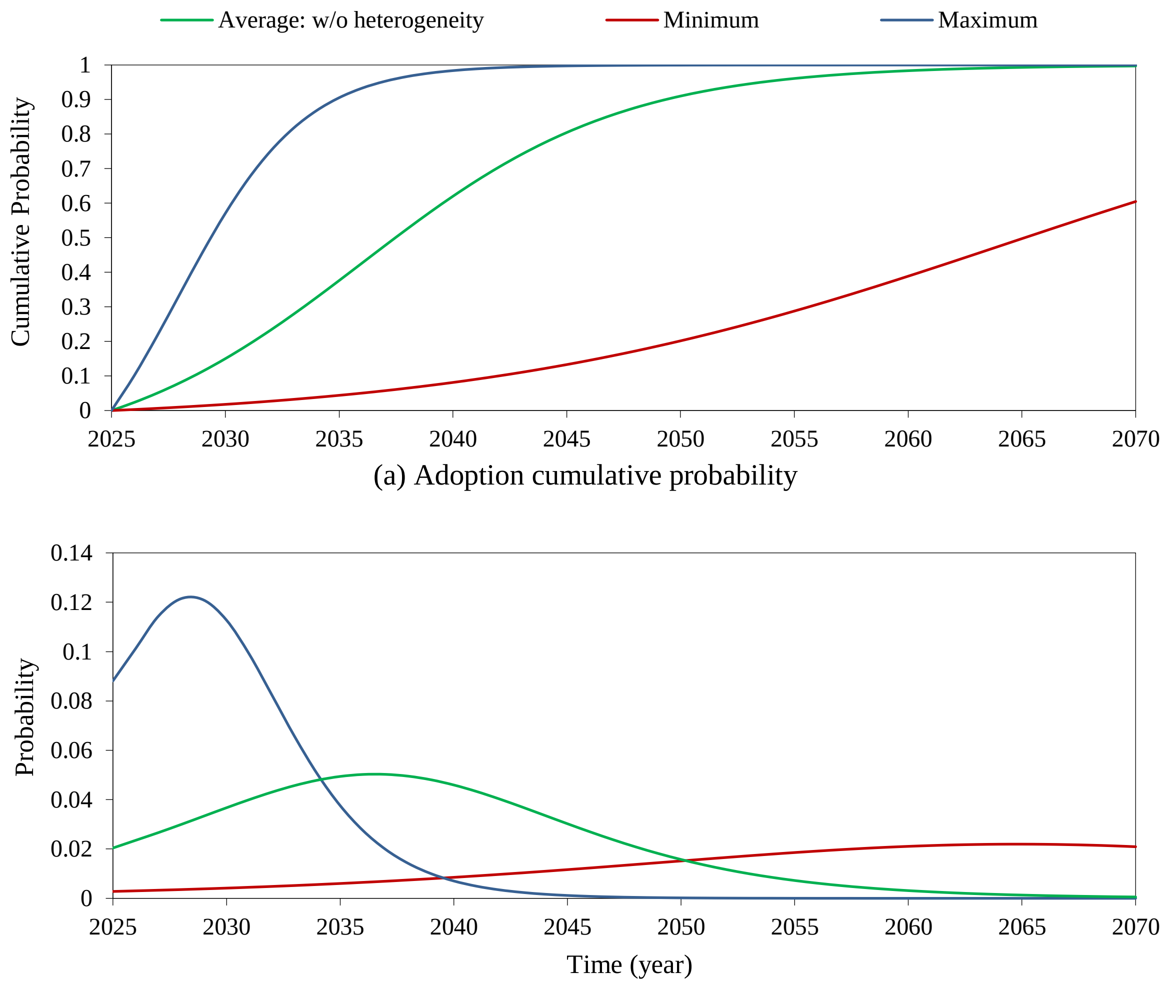
The results further indicate that couples are more under influence of innovation rather than word of mouth, which makes sense given the fact that couples have more complex daily travel chains. Furthermore, such individuals usually try to maximize the household’s overall utility rather than individual utilities (Zhang, Kuwano, Lee, & Fujiwara, 2009), which requires more immunity to social contagion than a person who lives alone or with roommates. The results also conform to the literature (Lavieri et al., 2017) in that higher education level is found to be positively associated with the level of innovation. This relationship is also argued to hold in other contexts (see, for example, (Islam, 2014; Rogers, 2010)).

Conforming to the intuition, the results further indicate that those who believe that driving AVs would be stressful are less likely to purchase one during the very first years of introduction. We also found that senior citizens who are within a quarter-mile proximity to a transit station are less likely to adopt AVs in an innovative manner. This is in line with previous studies which showed that senior citizens who are no longer able to personally drive, usually opt for having someone give them a ride or for switching to public transit services (Mattson, 2012; Shabanpour, Golshani, Derrible, Mohammadian, & Miralinaghi, 2017).

6.5 Sensitivity Analysis

In the previous section, population heterogeneity corresponding to the coefficients of innovation and imitation functions were discussed. In this section, the discussions are extended to cover how sensitive the innovation diffusion curves are to different sources of heterogeneity. For this purpose, two main types of experiments are designed to: (1) obtain a range within which the innovation diffusion curve of a potential adopter lie, and (2) analyze the average sensitivity of the curve to particular explanatory variables.

As the first experiment, p and q values are calculated for each observation, and two different CDF and PDF curves are plotted in Figure 6-2(a) and Figure 6-2(b), based on the minimum and maximum values of the parameters. For example, the "Minimum" curve utilizes the minimum values of both p and q. This experiment, in fact, is inspired by an intuitive property of the Bass model. The property is that, if both p and q are higher for a person, he/she would have higher cumulative adoption probabilities, for all t. In this sense, the "Minimum" and "Maximum" curves, respectively, act as lower and upper bounds of the adoption timing CDF for individuals in our sample. Figure 6-2 also embodies the curve associated with a constant-only model that does not take into account any population heterogeneity (shown as "Average: w/o heterogeneity"). As can be seen, the differences are not negligible. Per Figure 6-2(a), a model disregarding the population heterogeneity is prone to underestimating cumulative adoption probabilities for up to 54.1% or overestimating them for up to 70.8%.



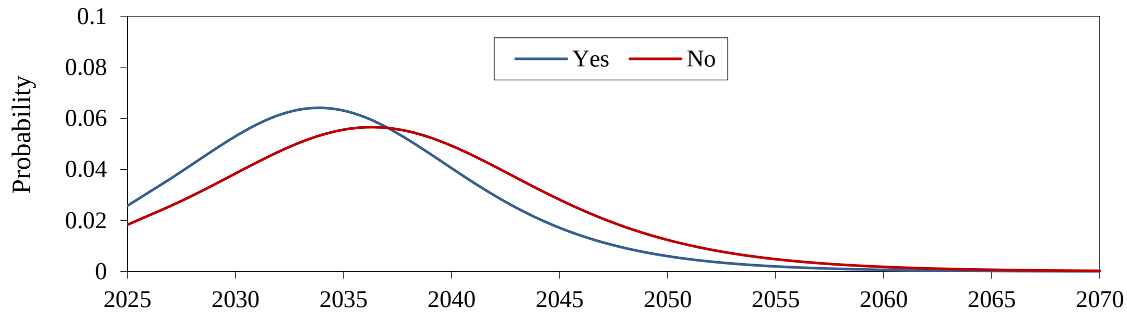
(b) Adoption probability density

Figure 6-2. Innovation Diffusion Curves Associated with Different Values of p and q

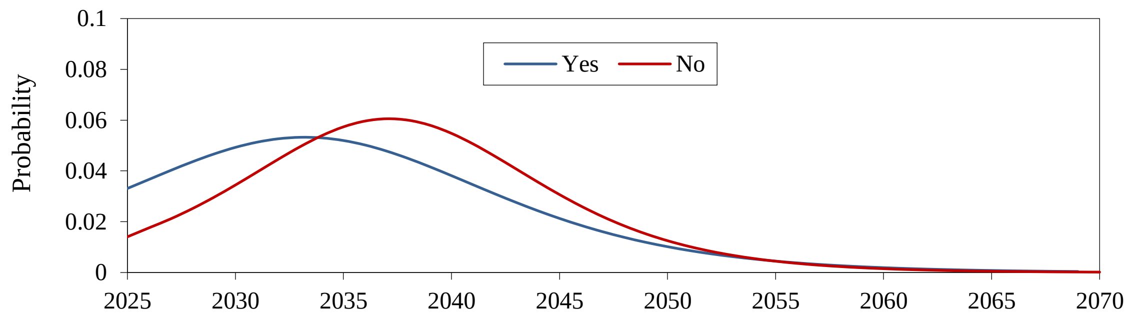
Another interesting finding is that the market of individuals whose CDF is close to the Minimum is expected to be less than 60% saturated by 2070. In addition, Figure 6-2(b) can be used to draw inferences on the peak point of the adoption rate distributions (the PDFs). As shown, the occurrence of the peak point might be underestimated for 7 years or overestimated for up to 28 years as a result of disregarding the intra-population heterogeneity.

The second experiment is designed to analyze the sensitivity of the innovation diffusion curves to effects of different explanatory variables. The variables of interest are accident experience, frequent long-distance travel, accepted additional purchase price, and income level. To analyze each variable, its value is set to different fixed points, and the corresponding adoption probability distributions are plotted while other variables are set to their mean in case of continuous variables, or their mode in case of dummies or ordinals. The results are presented in Figure 6-3.

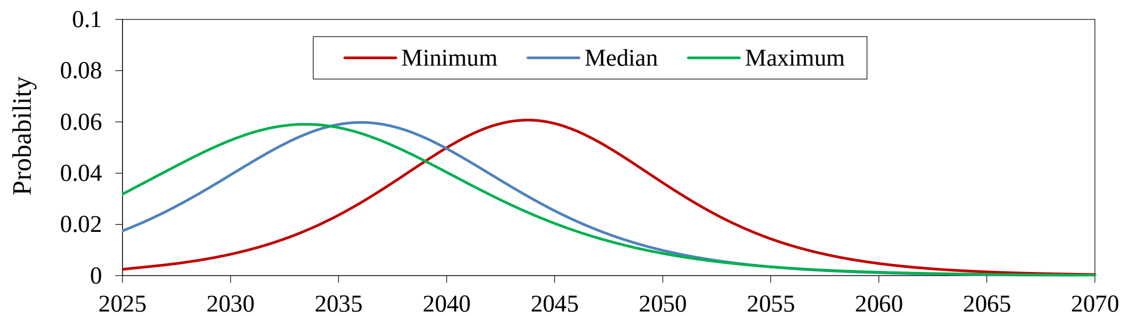
Results depicted in Figure 6-3(a), confirming the results outlined in Table 6-1, indicate that those individuals who have experienced an accident in their lifetime are more likely to be early adopters of AVs. Moreover, per Figure 6-3(b), peak point of the adoption rate of frequent long-distance travelers occurs 4 years earlier than others. According to Figure 6-3(c)-(d), in addition, accepted additional purchase price and income level could also result in considerable deviations on the adoption rate’s peak point.



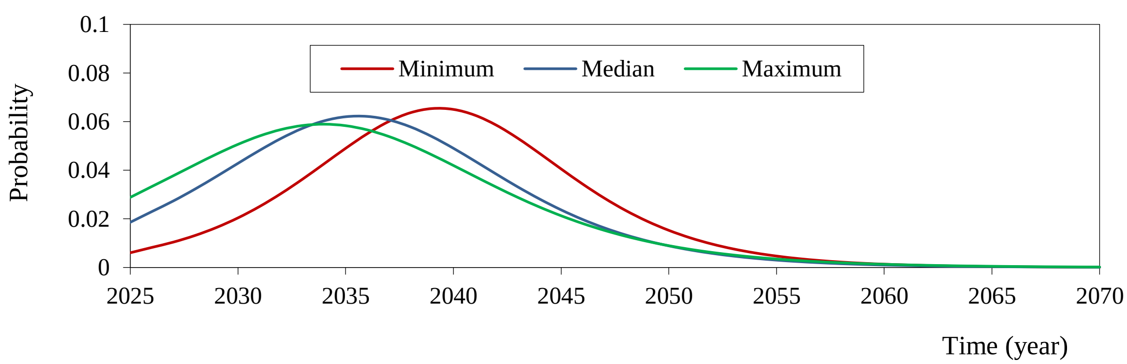
(a) Accident experience



(b) Frequent long-distant traveler



(c) Accepted additional purchase price



(d) Income level

Figure 6-3. Sensitivity of the Diffusion Curves to Different Sources of Heterogeneity

6.6 Conclusions

In this chapter, I developed an innovation diffusion model based on a recently collected data in the Chicago metropolitan area. The adopted method not only enables us to distinguish between individuals' desires to innovate and their propensities to follow words of mouth, but also allows for capturing various sources of heterogeneity for each effect. Per the results, individuals with an accident experience are found to be more inclined towards imitating the society, while frequent long-distance travelers and those who pay more for parking at their work are more likely to act in an innovative manner. Also, those who have already heard of new technological terms, those from higher-income households, and highly educated people tend to be innovators. We have found that the market penetration of AVs in the Chicago metropolitan area would be eventually 71.3%. We have also found that the adoption timing behavior is subject to notable degrees of heterogeneity, ignoring which could cause up to 54.1% underestimation or 70.8% overestimation of the cumulative adoption timing probabilities.

The results reveal that increasing parking cost in urban areas with higher job opportunities would encourage people who work in those areas to adopt an AV. It is also found that individuals with an accident experience are more sensitive to word of mouth. It is widely argued that AVs are expected to be much safer than regular vehicles. However, not much is known about marketing consequences of the first few major accidents of AVs after being introduced to the market. This finding, if supported by future studies (especially from the psychological point of view), indicates that individuals with previous accident experiences are among the first who would reconsider riding an AV. Yet, much more is to be discovered about the word of mouth regarding possible technological failures of AVs, which could be pursued in future studies.

As another policy implication, the results also suggest that short-term marketing policies could focus more on long-distance travelers (e.g., those who live suburbs and work in CBD or vice versa). Such individuals are more likely to become early adopters. Also, they are found to be more immune to word of mouth, causing them to be less influenced by potential oppositions to the technology (e.g., oppositions triggered by a technology failure).

The present study also has certain drawbacks which need to be addressed in the future efforts. One direction for future studies would be capturing potential marketing dynamics in the adoption timing decision. The applicability of the applied modeling approach should be tested using larger databases and in other geographical contexts. Future studies might also discover the effect of population aging on the AV adoption behavior.

7 VEHICLE FUEL AND AUTOMATION CHOICE ACROSS GENERATIONS

7.1 Introduction

While research in the area of autonomous vehicles is advancing at a fast pace, it is heavily centered around the technology implementation aspects such as design of sensors and control processors. However, little is known about the demand for this technology. One of the main research questions in this area which needs to be carefully addressed is how people will react to emergence of these vehicles. Focusing on the adoption behavior of AVs, only a few studies have attempted to investigate how individual- and household-level demographics, travel preferences, social factors, and built-environment characteristics affect people's adoption behavior. The literature on people's AV adoption behavior is still limited, leaving major gaps for further study. A critical aspect of people's AV adoption behavior which has not received enough attention in the literature is its investigation from a cross-generational perspective.

People of different generations have diverse perceptions, values, and preferences that significantly influence their technology adoption behavior. Older generations often shy away from adopting new technologies mainly because of physical challenges, lack of familiarity, lack of trust in the technology, or low self-confidence in their ability to learn how to use new technologies (Czaja et al., 2006). This general technology aversion behavior is one of the main reasons that despite the explosive growth of the internet in recent years, about one-third of seniors ages 65 and older have never used internet and their smartphone ownership rate is about 46% (Pew Research Center, 2018a). However, as the emergence of autonomous mobility brings back the opportunity of independently traveling to these population segments, there could be a potential interest in this technology among such people.

Younger generations, on the other hand, are more tech-savvy and highly reliant on technology in their everyday life. Indeed, 94% of young Millennials who have grown up in a technology-driven world, own a smartphone (Pew Research Center, 2018a). Further, as supporters of sharing economy (Entrepreneur, 2016), Millennials are more interested in adoption of shared mobility services and ICT enabled mobility options such as telecommuting, and online shopping (Godelnik, 2017; Hong & McArthur, 2017; Lissitsa & Kol, 2016).

It has been found in previous studies that age is a key factor in shaping individuals' travel preferences. However, as people's personal values and perceptions are associated with long-term factors such as economic changes, cultural trends, and technological advances, age as a single variable may not be a reliable representative of heterogeneous behavior of various generational cohorts (Brey & Lehto, 2007; Kim, Fidgeon, & Kim, 2015; Lyons & Kuron, 2014). Thus far, quite a few studies have explored the differences between travel behavior of people from different generations (see, for example, Huang and Petrick (2010), Lee et al. (2018), Moscardo and Benckendorff (2010), and Wang et al. (2018)). They have generally found that generation is a significant predictor of people's travel decisions. It is also observed that individuals within a specific generation exhibit similar travel patterns compared to those from unalike generations. Nonetheless, such a cross-generational analysis in the context of adoption behavior of advanced vehicle technologies such as autonomous vehicles has not yet been conducted.

Thus, the first major objective of the current study is to investigate how different generational cohorts will respond to the emergence of fully autonomous vehicles and compare the fundamental drivers of their adoption decisions. Such questions are of great importance to address, not only from the behavioral perspective of AVs public adoption but also with regards to the marketing applications. It is evident that autonomous driving technology will emerge with a broad range of benefits (drawbacks) each of which attracting (repelling) specific segments of the society. Having a clear understanding of the preferences of people from various generations towards AVs would help auto companies devise differentiated and effective marketing approaches in targeting customers from all generations.

In this study, we compare three major generational cohorts in the US, namely Baby Boomers, Generation X, and Millennials, in terms of their AV adoption behavior. There are minor variations in the birth years of these generations, depending on the source. In this study, we follow the definitions proposed by the Pew Research Center (2018b) which identifies Baby Boomers as the individuals born between 1946 and 1964, Generation Xers as those born between 1965 and 1980, and Millennials as the individuals born between 1981 and 1996. Figure 7-1 illustrates the definition of the targeted generations in this study.

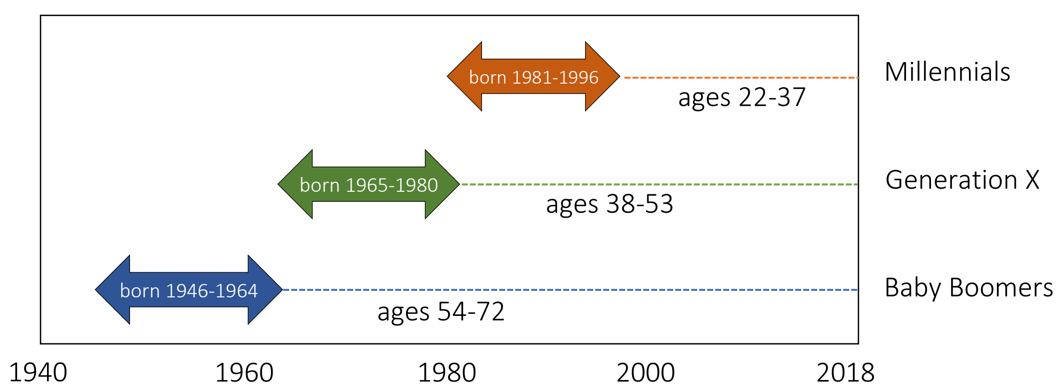


Figure 7-1. Definition of Three Major US Generations Considered in this Study

The second major objective of this study is to investigate whether people's interest in autonomous vehicles is associated with their vehicle fuel choice. This is a significant research question because both autonomous vehicles and electric vehicles are rapidly advancing, and future vehicles will most likely take advantage of both autonomous control systems and electric fuel sources. The intuitive idea is that as electric vehicle (EV) users are mainly among highly educated tech-savvy individuals who have higher willingness-to-pay and have more environmental concerns (Beck, Rose, & Greaves, 2017; Smith, Olaru, Jabeen, & Greaves, 2017; S. Wang, Li, & Zhao, 2017; White & Sintov, 2017), they will be also among early adopters of autonomous vehicles. However, there is not yet any empirical evidence to support or refute this hypothesis. Therefore, the current study aims to address this need, offering a detailed analysis of consumers preferences towards vehicles with electric fuel sources and autonomous control systems in a joint modeling structure.

The collected data includes 365 Millennials, 228 Generation Xers, and 246 Baby Boomers. Related to the direction of this study, respondents were presented with two choice tasks. In the first experiment, they were asked to select their most preferred choice among three options of a gasoline vehicle, a hybrid vehicle, and a plug-in electric vehicle. These options were described in terms of purchase price, operating cost, driving range, refueling time, environmental efficiency, and policy incentives. In the second experiment, they were asked to indicate their preferred choice between two options of a traditional human-driven vehicle and an autonomous vehicle, which were characterized in terms of purchase price, operating cost, environmental efficiency, safety level, and policy incentives. Complete details about the data description and design of the choice experiments are provided in the next section.

The remainder of this chapter is structured as follows: In the next section, the choice experiments and summary statistics of the collected data are discussed. Following that, we describe the structure of the model applied in this study. Subsequently, detailed estimation results and interpretation of model parameters are presented. The chapter concludes with a summary of the major findings.

7.2 Data Analysis

As detailed in 3the third chapter of the manuscript (Survey design and data analysis), a comprehensive web-based survey was designed and implemented to collect the required data for the multi-dimensional analysis in this research effort. Descriptive analysis of the collected data reveals that the sample encompasses 365 Millennials, 228 Generation Xers, and 246 Baby Boomers. Table 7-1 reports the cross-generational summary statistics of the respondents' characteristics in the sample.

Table 7-1. Summary Statistics of the Respondents' Demographics

Variable	Baby Boomers	Generation X	Millennials
Number of respondents	246	228	365
Age range	54–72	38–53	22–37
Gender			
Male	47.9%	52.3%	49.4%
Female	52.1%	47.7%	50.6%
Household size			
1	30.7%	24.3%	28.0%
2	38.2%	21.9%	29.9%
3	20.3%	16.5%	17.8%
>= 4	10.8%	37.3%	24.3%
HH vehicle ownership			
Not own vehicle	12.5%	7.0%	15.6%
Own vehicle	87.5%	93.0%	84.4%
Education level			
Not a high school graduate	12.3%	10.8%	7.9%
High school graduate	24.1%	19.5%	18.1%
Associate or technical degree	29.3%	28.7%	33.3%
Bachelor's degree	21.6%	25.7%	30.5%
Graduate or Professional degree	12.7%	15.3%	10.2%

In accordance with the objective of the current research, respondents were presented with two choice tasks to indicate their preference towards vehicle fuel type and driving control system. They were asked to assume that they are going to buy a new vehicle in the next few years and fully autonomous vehicles are also available in the market. In the first experiment, they were asked to select their most preferred choice among three options of a gasoline vehicle, a hybrid gasoline vehicle, and a plug-in electric vehicle (PEV). In order to manage the complexity and required time for completing the choice task, other fuel types such as plug-in hybrid electric vehicle (PHEV), fuel cell electric vehicle (FCEV) are not included in the choice experiments. Based on a comprehensive review of related literature, six attributes were identified to describe the vehicle alternatives as purchase price, operating cost, driving range, refueling time, emission rate, and policy incentives.

In the choice experiments, vehicle purchase price was customized to the respondent's stated willingness to pay for purchasing a new vehicle. This approach facilitates the design of a more realistic and understandable choice experiment for each respondent. Furthermore, the operating cost was introduced to the respondent as the summation of fuel, insurance, and repair costs. Emission rate was described as the percentage of deviation from a current average gasoline vehicle. It was introduced as well-to-wheel emission which includes all emissions related to fuel production, processing, distribution, and use; therefore, it is not set as zero for EVs [1].

In addition, to investigate the potential effects of incentive policies on promoting the use of electric vehicles, four incentives were randomly included in some of the choice cards. The considered incentives include tax exemption, exclusive lane, toll exemption, and free parking. It

[1] The attribute levels are designed based on related literature, reports from automakers, and websites such as: https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle; https://www.afdc.energy.gov/vehicles/electric_emissions.php; https://www.fueleconomy.gov; https://automobiles.honda.com; https://newsroom.aaa.com/tag/driving-cost-per-mile.

was also mentioned that other unspecified attributes (such as vehicle size and comfort level) are assumed to be the same across alternatives. Applying the fractional factorial design, 16 choice cards were generated and randomly assigned to the respondents, each card describing three vehicle options which are characterized by the six attributes. The attribute levels for each alternative are described in Table 7-2.

Table 7-2. Attributes and Attribute Levels for the Vehicle Fuel Choice Experiment

Attribute	Attribute level
Purchase price [$]	Gasoline: 90% (low) – 100% (med) – 110% (high) of reference Hybrid: 100% (low) – 110% (med) – 120% (high) of reference Electric: 110% (low) – 130% (med) – 150% (high) of reference
Operating cost [$/month]	Gasoline: 300 (low) – 400 (high) Hybrid: 200 (low) – 300 (high) Electric: 150 (low) – 250 (high)
Driving range on one full tank/charge [miles]	Gasoline: 400 (low) – 500 (med) – 600 (high) Hybrid: 500 (low) – 600 (med) – 700 (high) Electric: 100 (low) – 150 (med) – 300 (high)
Refueling/recharging time	Gasoline, Hybrid: 5 min Electric: 2 (low) – 5 (med) – 8 hour (high)
Emission rate	Gasoline: 10% less (low) – 10% more (high) Hybrid: 30% less (low) – 10% less (high) Electric: 80% less (low) – 50% less (high)
Policy incentive	Electric: none, tax exemption, exclusive lane, toll exemption, free parking

In the second experiment, respondents were asked to indicate their preferred choice between two options of a traditional human-driven vehicle and a fully autonomous vehicle. To keep the experiment manageable, partial automation levels are not considered in this analysis. As summarized in Table 7-3, each vehicle option was characterized in terms of purchase price, operating cost, emission rate, safety level, and policy incentives. Vehicle purchase price, operating cost, and emission rate were described similar to the previous experiment with different variations. It was again highlighted that other unspecified attributes in the choice task such as fuel type are assumed to be the same for the two alternatives. Applying the fractional factorial design, 16 choice cards were generated and randomly assigned to the respondents, each card describing the two vehicle options characterized by the five attributes.

Table 7-3. Attributes and Attribute Levels for the Vehicle Control System Choice Experiment

Attribute	Attribute level
Purchase price [$]	Human-driven: 90% (low) – 100% (med) – 110% (high) of reference Autonomous: 105% (low) – 125% (med) – 145% (high) of reference
Operating cost [$/month]	Human-driven: 300 (low) – 400 (high) Autonomous: 200 (low) – 300 (high)
Safety level	Human-driven: 20% higher chance of crash (low) – base (med) - 20% lower chance of crash (high) Autonomous: base (low) - 20% lower chance of crash (med) - 50% lower chance of crash (high)
Emission rate	Human-driven: 10% less (low) – 10% more (high) Autonomous: 20% less (low) – 10% less (high)
Policy incentive	Autonomous: none, liability exemption, tax exemption, exclusive lane, toll exemption

Analysis of respondents' selected choices in the first experiment reveals that 19.68% of Millennials have preferred electric vehicles. This rate decreases to 15.75% among Gen Xers and 13.47% among Baby Boomers (Figure 7-2). A similar pattern is observed for hybrid vehicles. However, the share of gasoline vehicles in Baby Boomers is higher than other generations.

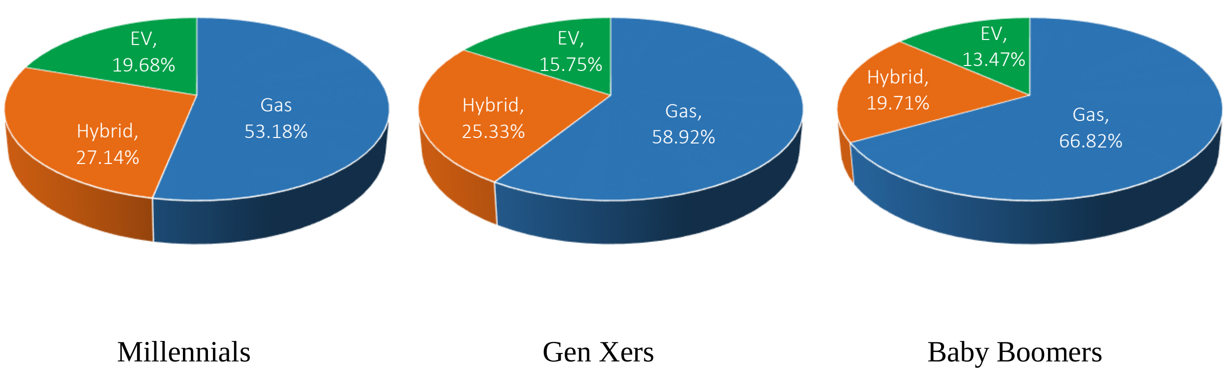


Figure 7-2. Frequency Distribution of Selected Fuel Types across Generations

Similarly, Figure 7-3 illustrates the distributions of respondents' selected choices in the second experiment. As shown in this figure, the share of autonomous vehicles among Millennials is 38.07% which decreases to 31.65% and 24.57% for Gen Xers and Baby Boomers, respectively.

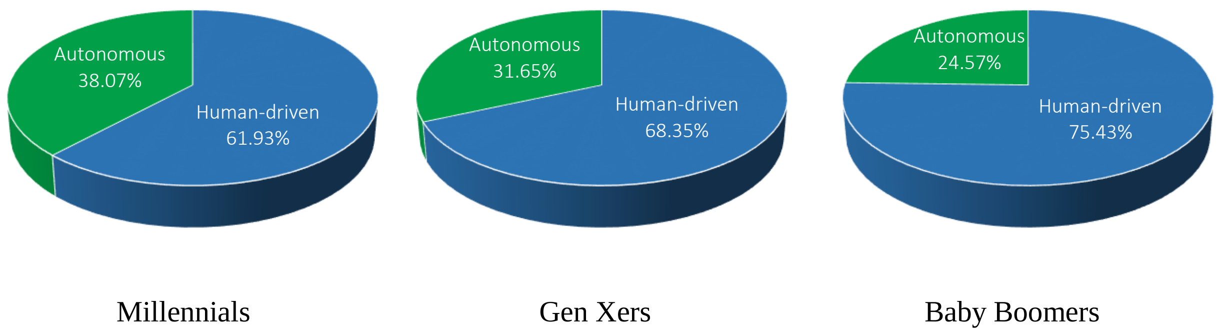


Figure 7-3. Frequency Distribution of Selected Driving Control System across Generations

7.3 Modeling Approach

As previously described, this study investigates individuals' preferences toward vehicle fuel type (among three options of gasoline, hybrid, and electric fuel sources) and vehicle control system (between two options of human-driven and autonomous systems). To account for the shared unobserved factors that might affect these decisions, we set out to model them in a joint structure. The first component of the joint model deals with the selection of vehicle fuel type which is modeled by the widely used multinomial logit formulation. The utility function of fuel type a for individual i can be written as:

$$U_{ai} = \beta_a X_{ai} + \varepsilon_{ai} \tag{7-1}$$

here, β_a is the vector of estimable parameters, X_{ai} are the explanatory variables, and ε_{ai} is the unobserved error term which is assumed to have an identically and independently distributed (iid) Extreme Value Type-1 distribution. The probability of selecting fuel type a by decision maker i can be summarized as (McFadden, 1974):

$$P(FT_i = a) = F(\varepsilon_{ai}) = \frac{exp(\beta_a X_{ai})}{\sum_{j=1}^{A} exp(\beta_j X_{ji})} \tag{7-2}$$

With regards to the second component of the joint model which deals with the decision on vehicle control system (between two options of human-driven and autonomous systems), a binary logit model is adopted. The binary choice (y_{ai}) can be modeled by an unobserved latent utility (y_{ai}^*) for individual i as:

$$y_{ai}^* = \gamma_a Z_{ai} + \nu_{ai} \quad , \quad y_{ai} = 1 \quad \text{if} \quad y_{ai}^* > 0 \tag{7-3}$$

here, y_{ai} is the binary choice of AV adoption conditional on fuel type a for individual i, γ_a is the vector of estimable coefficients, Z_{ai} is the vector of explanatory variables, and ν_{ai} is the random error term corresponding to the unobserved factors, which is assumed to have a logistic distribution. Therefore, the probability of adopting an autonomous vehicle with fuel type a by individual i can be written as:

$$P(y_{ai} = 1\,) = F(\nu_{ai}) = \frac{exp(\gamma Z_{ai})}{1 + exp(\gamma Z_{ai})} \tag{7-4}$$

As previously highlighted, to capture the potential correlation between two decisions of vehicle fuel type and control system, they are estimated in a joint framework. This can be done by forming a bivariate distribution of their error terms. As the error terms are not normally distributed, following the approach proposed by (L. F. Lee, 1983), we first transform the error terms into normally distributed random variables and then, form a bivariate normal distribution with the transformed variables. The marginal distributions of the transformed random error terms can be shown as (L. F. Lee, 1983; Nurul Habib et al., 2009):

$$\varepsilon_{ai}^* = J_1(\varepsilon_{ai}) = \Phi^{-1}[F(\varepsilon_{ai})] = \Phi^{-1}\left(\frac{exp(\beta_a X_{ai})}{\sum_{k=1}^{A} exp(\beta_k X_{ki})}\right)$$

$$\nu_{ai}^* = J_2(\nu_{ai}) = \Phi^{-1}[F(\nu_{ai})] = \Phi^{-1}\left(\frac{exp(\gamma Z_{ai})}{1 + exp(\gamma Z_{ai})}\right) \tag{7-5}$$

here, ε_{ai}^* and ν_{ai}^* are transformed standard normal variables of the corresponding random variables ε_{ai} and ν_{ai} , $J_1(.)$ and $J_2(.)$ represents the transformation functions, and $\Phi^{-1}(.)$ denotes the inverse of the cumulative standard normal distribution. The effects of the shared unobserved factors on the two dependent variables can be captured by imposing a bivariate normal distribution with the correlation coefficient ρ on the transformed error terms. Therefore, the joint probability that individual i selects fuel type a and adopts the vehicle automation, and the likelihood function can be formulated as (L. F. Lee, 1983):

$$P(FT_i = a \cap y_i = 1) = F(\nu_{ai})\Phi\left(\frac{J_1(\varepsilon_{ai}) - \rho_{(FT=a,y=1)} J_2(\nu_{ai})}{\sqrt{1 - \rho_{(FT=a,y=1)}^2}}\right) \tag{7-6}$$

$$L = \prod_{i=1}^{I} \prod_{a=1}^{A} \left[\left(P(FT_i = a \cap y_i = 1)\right)^{y_{ai}} \left(1 - P(FT_i = a \cap y_i = 1)\right)^{(1-y_{ai})}\right]^{\delta_{ai}} \tag{7-7}$$

here δ_{ai} is a binary indicator that takes the value of 1 when fuel type a is selected by individual i.

7.4 Model Estimation Results & Discussions

This section presents the results of the estimated joint models on individuals' preferences for vehicle fuel type and control system across generations. To facilitate the readability of the results, we start by presenting the generation-specific findings followed by a discussion on significant heterogeneities in individuals' decision behavior across different generations.

Estimated model parameters for Millennials, Gen Xers, and Baby Boomers are summarized in Table 7-4 through Table 7-6, respectively. Overall, the results indicate that a broad range of variables including demographic information, built-environment characteristics, travel habits, and vehicle attributes affect people's decision behavior toward vehicle fuel type and automated driving systems.

From the results presented in Table 7-4, it can be inferred that Millennials who are frequent telecommuters (defined as those who telecommute once a week or more) are less likely to purchase a gasoline vehicle and hence more likely to select hybrid and electric vehicles. Their propensity toward the more advanced fuel technologies could be an indication of their familiarity with modern technologies such as ICT-enabled remote working. In addition, as telecommuters generally have lower VMT (Shabanpour, Golshani, Tayarani, Auld, & Mohammadian, 2018), the negative impact of relatively low driving range of EVs, which is among the significant barriers to their widespread market penetration (Egbue & Long, 2012), will be dampened in their decision behavior.

One the same note, we found that Millennials who live in the city are more likely to purchase an electric vehicle, probably due to the (on average) shorter travel distances that they have compared to suburban people, which again diminishes the negative effect of EV's lower driving range. It is also observed that Millennials who frequently make long travels (more than 20 miles) prefer hybrid vehicles over gasoline vehicles, which might be associated with their higher fuel efficiency.

With regards to the alternative specific attributes, the results indicate that increasing the purchase price of a vehicle with any fuel type significantly decreases the probability of selecting that vehicle. To better understand the effect of vehicle attributes, Figure 7-4 illustrates the marginal effects of the significant vehicle attributes. In addition to the purchase price (which is a continuous variable and is not included in this figure), driving range, recharging time, and policy incentive are significant determinants of Millennials' preference toward EVs. As shown in the figure, providing exclusive lanes for electric vehicles, as one of the potential incentive policies to promote their market penetrations (Mersky & Samaras, 2016), can increase their selection probability by 6.4% among Millennials. In addition, a low driving range of an EV (described as 100 miles in the choice tasks) reduces its selection probability by 9.6%, and low recharging time (described as 2 hours in the choice tasks) raises the probability of selecting EVs by 8.7%.

Interestingly, Figure 7-4 reveals that reducing the emission rate of a gasoline vehicle (described as 10% less than an average gasoline in the choice tasks) increases its purchase probability by 15.0%, which can be attributed to the high environmental concerns of Millennials (Circella et al., 2017). Further, having a low operating cost for a hybrid vehicle (described as $200 per month in the choice tasks) increases the chance of their adoption by 12.5%.

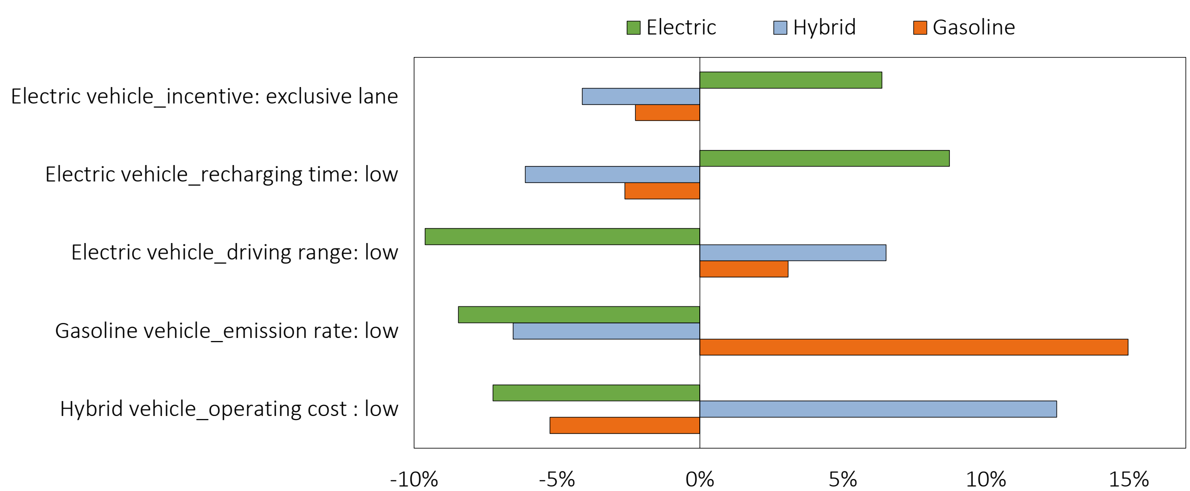


Figure 7-4. Marginal Effects of Vehicle Attributes on Millennials' Fuel Type Choice

Moving to the vehicle control system choice, we found a significant role of household income level in this decision for all vehicle fuel types. Accordingly, Millennials with higher household income (greater than $100K) are more willing to adopt automated control system while those with lower income (less than $50K) are less inclined to adopt this technology. This is intuitive because the market price of AVs is expected to be higher than human-driven vehicles which hinders their adoption by low-income people. In addition, Millennials who have experienced an accident in their lifetime are significantly more interested in autonomous vehicles where their safety level is higher than traditional vehicles (described as 50% lower chance of accidents in the choice tasks).

We also found that home to work distance positively affects the probability of adopting automated vehicles, which is possibly because of the more convenient commuting experience provided by AVs and/or the opportunity to perform in-vehicle activities (including their work-related tasks) while commuting. On the same note, those who expect that they will have a more productive use of time during their travels by AVs are more interested to adopt them. Another critical determinant of Millennials' decision to buy an AV is parking cost, where those who pay more than $300 a month for parking are more likely to adopt this technology because as the vehicle can autonomously move to cheaper places to park, they can avoid the parking fees.

As a land-use variable which is found to be significant in the AV adoption model, median income in residential census tract positively affects the probability of AV selection. This could be because AVs are expected to have higher purchase prices compared to traditional vehicles, and thereby those who live in more affluent neighborhoods are more likely to adopt them. We also found that providing exclusive lanes for automated vehicles where there is no interaction with human-driven vehicles significantly increases the probability of adopting these vehicles by Millennials.

Table 7-4. Estimation Results of the Models for Millennials

Variable	Gasoline vehicle		Hybrid vehicle		Electric vehicle	
	Param. †	t-stat	Param.	t-stat	Param.	t-stat
Fuel type choice:						
Constant	0.95**	2.13	–	–	-0.51***	-3.94
Gender: male	–	–	–	–	0.60**	2.25
Frequent telecommuting: once a week or more	-0.23**	-2.08	–	–	–	–
Home location: city	–	–	–	–	0.38*	1.79
Frequency of 20+ mile trips: 10+ per month	-0.21*	-1.73	0.40**	2.29	–	–
Purchase price [in $10K]	-0.18*	-1.82	-0.22**	-2.05	-0.30***	-2.77
Operating cost: low	–	–	0.13*	1.69	–	–
Driving range: low	–	–	–	–	-0.67***	-4.08
Refueling/recharging time: low	–	–	–	–	0.81***	3.55
Emission rate: low	0.23**	2.44	–	–	–	–
Incentive policy: exclusive lane	–	–	–	–	0.25**	2.34
Control system choice:						
Constant	-1.09**	-2.49	-0.85***	-4.66	-1.75**	-2.34
HH income > $100K	–	–	0.56**	2.11	0.81**	2.48
HH income ≤ $ 50K	-1.25***	-3.99	–	–	–	–
Education level: university degree	–	–	–	–	0.14*	1.68
Accident experience: yes × Safety level: high	0.35**	2.32	0.47*	1.73	0.21**	2.49
Ln (home to work distance) [mile]	0.17*	1.85	0.23**	1.98	–	–
Parking cost ≥ $300 per month	–	–	1.00**	2.04	–	–
Expected more productive use of time in AVs	0.88*	1.73	–	–	–	–
Median income in residential census tract [in $10K]	0.09**	2.41	–	–	–	–
Purchase price [in $10K]	-0.31***	-3.52	-0.46***	-4.17	-0.24**	-1.96
Incentive policy: exclusive lane	–	–	0.35**	2.22	0.43***	5.37
Model specifications:						
Correlation coefficient	0.37***	6.07	-0.29***	-8.23	-0.71***	-13.55
Log-likelihood at convergence			-311.93			

† ***, **, * indicate significance at 1%, 5%, and 10% level.

Finally, the significance of the estimated correlation coefficients confirms the hypothesis that there is a correlation between the unobserved factors affecting the two components of the joint structure (i.e., vehicle fuel type and control system choices). It should be noted that the interpretation of the correlation coefficients in this modeling approach is counter-intuitive in the sense that the negative value of the coefficient indicates a positive correlation between the unobserved factors of the two dependent variables (Nurul Habib et al., 2009). Therefore, the unobserved factors that increase the propensity to choose hybrid and electric fuel types are likely to increase the chance of adopting vehicle automation among Millennials.

Table 7-5 presents the estimation results of the models developed for Generation Xers. We found that highly educated members of this generation (bachelor's degree and higher) are more inclined towards electric vehicles compared to others. This can be attributed to their greater awareness of benefits of these technologies and/or their higher sense of responsibility toward the environment (Nayum, Klöckner, & Mehmetoglu, 2016; S. Wang, Fan, Zhao, Yang, & Fu, 2016). As another significant indicator, we found that as the ratio of the number of vehicles in the household to the number of individuals with a driving license in the household increases, the probability of purchasing a new gasoline vehicle decreases (hence, the chance of other fuel types increases). This important finding implies that people often prefer not to buy alternative fuel vehicles as their main vehicle (Rezvani, Jansson, & Bodin, 2015). Further, those who currently own a hybrid or electric vehicle are more likely to purchase a new electric vehicle.

We also found that long-distance travelers (who have more than 10 trips longer than 50 miles in a month) are less likely to choose electric vehicles, possibly because of the limited driving range of such vehicles compared to others. On the same note, those who live in downtown areas, where the limited driving range is a less critical issue (because of the high accessibility to the work locations, shopping centers, etc.), are more interested in electric vehicles.

With regards to the alternative specific attributes, as expected, the purchase price has a significant negative effect on selecting the corresponding alternative. Figure 7-5 presents the marginal effects of other vehicle attributes that are found to significantly affect the vehicle fuel choice of Gen Xers. According to the figure, providing exclusive lanes for electric vehicles increases the chance of their adoption by 7.4%. Furthermore, low recharging time (described as 2 hours in the choice tasks) increases the probability of selecting EVs by 6.0%. High driving range (described as 300 miles per one full charge in the choice tasks) also increases the probability of selecting EVs by 9.1%. Interestingly, the results reveal that lower driving range of a hybrid vehicle (described as 500 miles per full tank in the choice tasks) dramatically decreases the probability of purchasing such vehicle by 11.8%. In addition, reducing the emission rate of a gasoline vehicle (described as 10% less than an average gasoline in the choice tasks) significantly raises its selection probability by 13.9% and reduces the probability of selecting hybrid and electric vehicles accordingly.

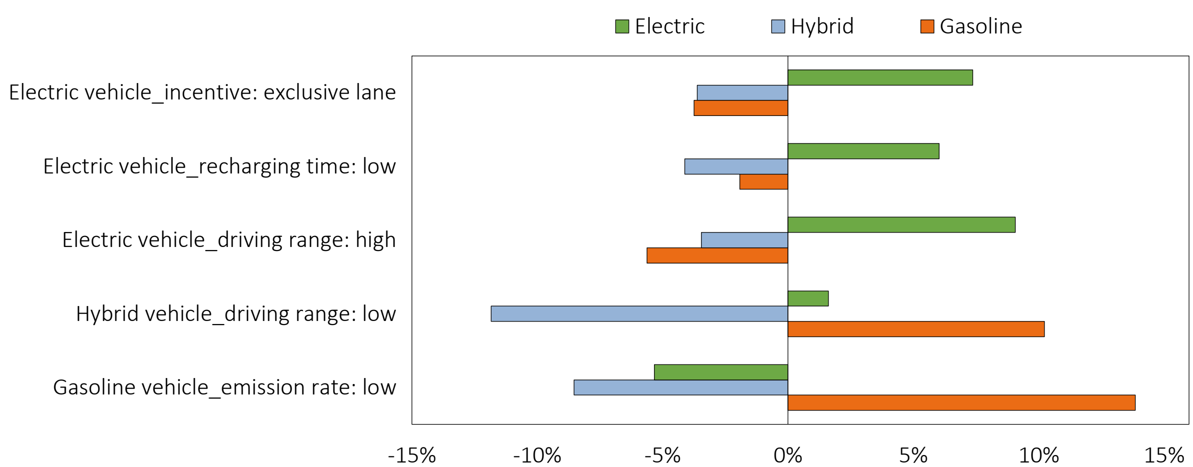


Figure 7-5. Marginal Effects of Vehicle Attributes on Generation Xers' Fuel Type Choice

Moving to the vehicle control system choice, Table 7-5 indicates that lower income levels are associated with a lower chance of adopting autonomous vehicles. On the other hand, frequent telecommuters are more likely to select the automated control system possibly because of their greater familiarity with new technologies. We also found that longer home-to-work distances and higher parking costs increase the chance of adopting autonomous vehicles, possibly because AVs provide the opportunity to engage in various in-vehicle activities during the travel and they have the capability to move to cheaper places to park by themselves.

Table 7-5. Estimation Results of the Models for Generation Xers

Variable	Gasoline vehicle		Hybrid vehicle		Electric vehicle	
	Param.†	t-stat	Param.	t-stat	Param.	t-stat
Fuel type choice:						
Constant	1.71***	4.85	–	–	-1.34***	-5.21
Education level: university degree	–	–	0.16*	1.93	0.21***	3.06
HH vehicle/HH license	-0.45**	-2.08	–	–	–	–
Non-gasoline vehicle ownership: yes	–	–	–	–	0.11**	2.16
Frequency of 50+ mile trips: 10+ per month	–	–	–	–	-0.53***	-4.49
Home location: CBD	–	–	–	–	0.08*	1.91
Purchase price [in $10K]	-0.33**	-1.99	-0.37**	-2.07	-0.48***	-3.75
Driving range: low	–	–	-0.45**	-1.98	–	–
Driving range: high	–	–	–	–	0.67***	2.66
Refueling/recharging time: low	–	–	–	–	0.51***	4.05
Emission rate: low	0.29***	3.07	–	–	–	–
Incentive policy: exclusive lane	–	–	–	–	0.27*	1.68
Control system choice:						
Constant	-1.35***	-3.16	-1.52***	-5.08	-1.74*	-1.84
HH income ≤ $ 50K	-0.66***	-2.85	-0.78**	-2.24	–	–
Frequent telecommuting: once a week or more	–	–	0.19*	1.73	0.26**	2.30
Ln (home to work distance) [mile]	0.32**	2.07	0.37***	2.96	–	–
Major accident experience: yes × Safety level: high	0.40***	4.18	0.29*	1.84	0.38***	2.94
Parking cost ≥ $300 per month	–	–	–	–	0.47**	2.17
Expected disclosure of tracking information by AVs	-0.27*	-1.69	-0.32**	-2.32	–	–
Purchase price [in $10K]	-0.40***	-3.06	-0.35**	-1.94	-0.22***	-4.55
Incentive policy: liability exemption	0.51*	1.77	0.19***	3.01	–	–
Incentive policy: exclusive lane	–	–	–	–	0.44***	2.88
Model specifications:						
Correlation coefficient	0.26**	2.09	-0.33**	-2.25	-0.66***	-8.07
Log-likelihood at convergence			-160.86			

† ***, **, * indicate significance at 1%, 5%, and 10% level.

Similar to the Millennials, members of Generation X have more propensity to adopt an AV if they have been involved in a major accident in their lifetime, and the autonomous control systems provide higher safety levels than the traditional ones (described as 50% lower chance of accidents in the choice tasks). Furthermore, respondents who expect that autonomous vehicles will face major challenges in terms of privacy protection are less likely to purchase such vehicles. As expected, the purchase price has a significant negative effect on the adoption of AVs. Provision of incentive policies for autonomous vehicles is also found to have a significant effect on the chance of their adoption. The results indicate that liability exemption in case of accidents and provision of exclusive lanes for AVs have a positive influence on Generation Xers' AV adoption decision. Finally, the estimated correlation coefficients reveal that the unobserved factors that increase the probability of selecting hybrid and electric fuel types enhance the chance of adopting autonomous vehicles by members of Generation X.

With respect to the decision behavior of Baby Boomers, Table 7-6 shows that household income level significantly affects the probability of selecting different fuel types. Per results, Boomers with medium household income levels (between $50K and $100K) are more likely to buy gasoline and hybrid vehicles whereas those with high income levels (greater than $100K) have more propensity to purchase electric vehicles. This is as expected because the market price of electric vehicles is generally higher than the price of their similar non-electric models. Further, retired respondents are more likely to buy gasoline vehicles probably because of their lower total expenses during the first years of usage (Wu, Inderbitzin, & Bening, 2015). The results also indicate that Baby Boomers who live in suburban areas and those with higher annual VMT have lower propensity to adopt electric vehicles most probably due to the relatively low driving range of such vehicles.

Regarding the vehicles' attributes, purchase price intuitively has a negative impact on the probability of selecting each alternative. Figure 7-6 illustrates the change in the probability of selecting an alternative with respect to a unit of change in the explanatory variable. According to the figure, providing incentives for electric vehicles significantly increases their market share. The results show that among all considered incentives, tax exemption has the highest effect on the market share of electric vehicles where it can increase the probability of adopting such vehicles by

7.0%. Providing free parking and exclusive lanes are also found to increase the probability of EV adoption by 3.4% and 2.5%, respectively.

Analysis of marginal effects also reveals high recharging time and operating cost of EVs (respectively described as 8 hours and $250 per month in the choice tasks) lowers their selection probability by 4.1% and 5.3%. In addition, a low operating cost of hybrid vehicles (described as $200 per month in the choice tasks) increases the chance of their adoption by 5.5%.

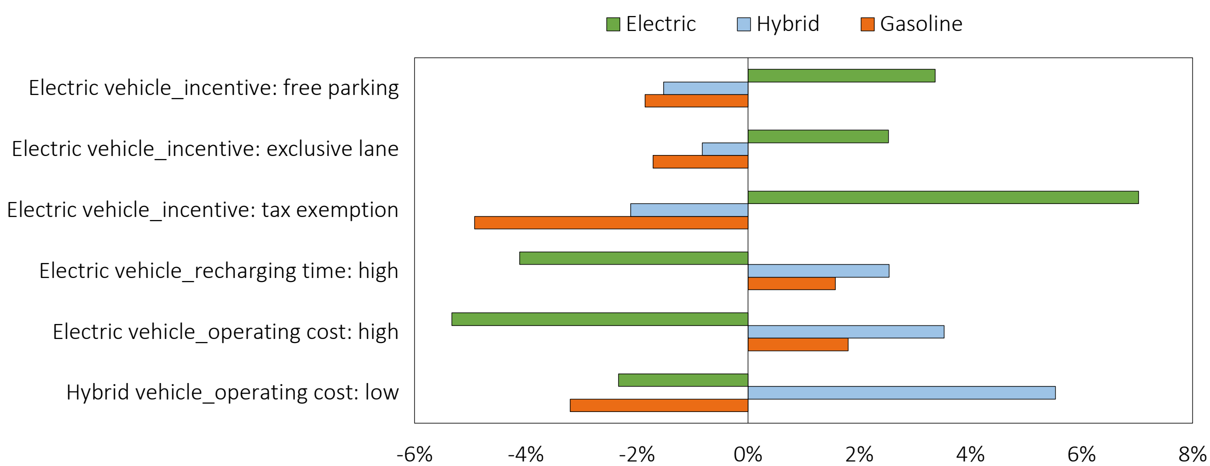


Figure 7-6. Marginal Effects of Vehicle Attributes on Baby Boomers' Fuel Type Choice

With regards to the adoption of the automated control system, Table 7-6 reveals that similar to other generations, highly educated and high-income Boomers are more likely to adopt AVs. We also found that frequent long-distance travelers have more propensity to adopt autonomous vehicles. The results indicate that those who pay more than $200 a month for parking are more likely to adopt this technology. Interestingly, the threshold parking cost for Millennials was found as 300$ per month, which indicates the higher sensitivity of Boomers to cost-related factors compared to other generations. Turning to the variables that represent respondents' perceptions about AVs, we found that those who expect that "driving" such vehicles will be less stressful than human-driven ones are more willing to adopt them.

Table 7-6. Estimation Results of the Models for Baby Boomers

Variable	Gasoline vehicle		Hybrid vehicle		Electric vehicle	
	Param.†	t-stat	Param.	t-stat	Param.	t-stat
Fuel type choice:						
Constant	1.86***	5.47	0.59**	2.26	–	–
HH income: $50 –100K	0.18*	1.91	0.23**	2.04	–	–
HH income > $100K	–	–	–	–	0.30***	2.71
Employment status: retired	0.34*	1.80	–	–	–	–
Home location: suburbs	0.29**	2.48	–	–	–	–
Ln (Annual VMT/1000)	–	–	0.26*	1.87	–	–
Use of ride-sharing services: never	–	–	–	–	-0.27**	-2.16
Purchase price [in $10K]	-0.31***	-4.19	-0.37**	-2.11	-0.52***	-3.67
operating cost: low	–	–	0.16**	2.34	0.28**	2.54
Refueling/recharging time: high	–	–	–	–	-0.31**	-2.37
Incentive: tax exemption	–	–	–	–	0.49***	3.60
Incentive policy: exclusive lane	–	–	–	–	0.12*	1.73
Incentive: free parking	–	–	–	–	0.17**	2.05
Control system choice:						
Constant	-1.63**	-2.34	-1.45***	-7.51	-1.21***	-6.40
HH income > $100K	0.42**	2.22	–	–	0.24***	2.89
HH income ≤ $50K	-1.03***	-4.07	-0.81***	-2.73	-0.50**	-1.91
Education level: Grad	–	–	–	–	0.14**	1.97
Frequency of 50+ mile trips: 5+ per month	0.26**	2.33	–	–	–	–
Parking cost ≥ $200 per month	–	–	0.64**	2.11	–	–
Expected less stressful driving in AVs	–	–	0.15*	1.80	–	–
Purchase price [in $10K]	-0.20***	-4.34	-0.36***	-4.53	-0.47***	-5.99
Safety level: high	0.34**	2.25	0.29***	4.52	0.58**	2.33
Incentive policy: tax exemption	0.38***	4.40	–	–	0.34**	2.19
Incentive policy: toll exemption	0.11**	2.05	–	–	–	–
Model specifications:						
Correlation coefficient	0.12	1.14	-0.08	-1.36	-0.16*	-1.75
Log-likelihood at convergence			-224.81			

† ***, **, * indicate significance at 1%, 5%, and 10% level.

The results also indicate that implementing monetary incentives for autonomous vehicles (i.e., providing tax exemption and toll exemption) positively influence their adoption probability by Baby Boomers. With respect to the estimated correlation coefficients, it is interesting to note that only one of the coefficients is found to be marginally significant and the others are not statistically significant. This can be attributed to the fact that the preference of Baby Boomers toward AVs is because of the opportunity to travel independently (as they mostly rely on others for traveling) rather than other common factors that jointly affect the fuel type choice and automation choice. Therefore, the choice of vehicle fuel type is not expected to be significantly correlated with their AV adoption decision.

Comparison of the generation-specific results suggests a complex association between individuals' vehicle fuel type and automation choice behavior on one hand, and their generational membership on the other hand. The estimation results summarized in Table 7-4 to Table 7-6 indicates that the determinants of individuals' preferences are largely heterogeneous across generations. Moreover, those variables that are found to be significant in multiple generations have heterogeneous influences on the decision outcomes. For instance, provision of exclusive lanes for electric vehicles is found to be the only incentive that significantly affects the vehicle fuel choice of Millennials and Gen Xers, while other incentives including toll and tax exemption have a higher influence on the decision behavior of Baby Boomers. These observations confirm the initial hypothesis that people's decision behavior towards vehicle fuel type and automation choice varies across generations.

Figure 7-7 illustrates the marginal effects of vehicle attributes on the fuel choice decision across different generations. According to the figure, low recharging time of electric vehicles and low emission rate of gasoline vehicles significantly increase the chance of adopting the corresponding fuel choice by Millennials and Gen Xers, whereas they have no significant effect on the fuel choice of Baby Boomers. On the other hand, low operating cost of a hybrid vehicle increases the probability of adopting this fuel type by Generation Xers and Baby Boomers, whereas it has no significant effect on Millennials' fuel choice decision.

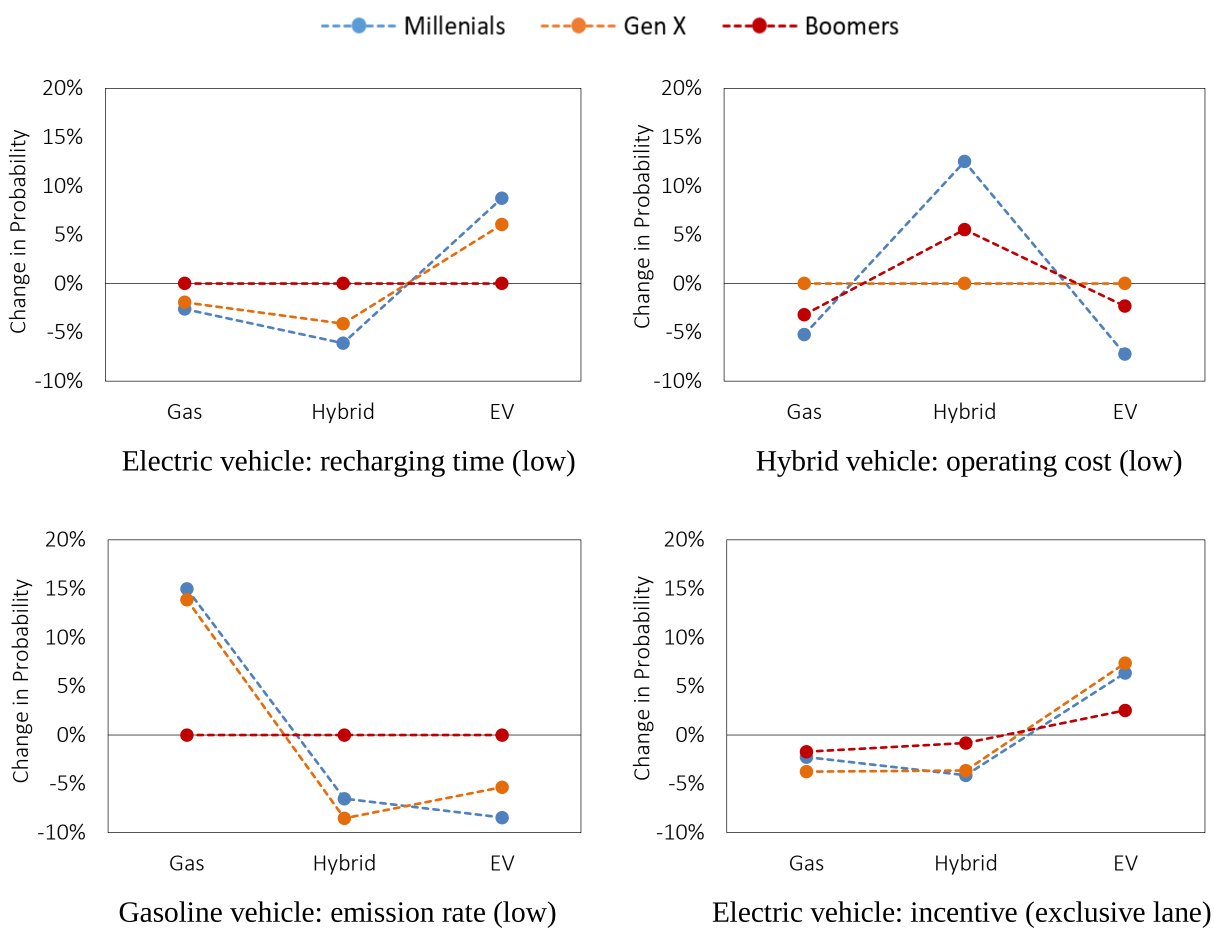


Figure 7-7. Comparison of Marginal Effects of Vehicle Attributes on Fuel Choice across Generations

With respect to the vehicle control system decision, the results indicate that all considered policy options in the choice scenarios, namely liability exemption in case of an accident, tax exemptions, provision of exclusive lanes, and toll exemptions have diverse impacts on AV adoption behavior of members of different generations. We found that provision of exclusive lane encourages Millennials to adopt AVs. This policy along with the exemption of liability in case of accidents is also found to motivate Gen Xers, and tax exemption and toll exemption are found to encourage Boomers to adopt AVs. Further, regarding the personal opinions about pros and cons of vehicle automation (introduced in Section 3.4), we found that Millennials who expect that they will have more productive use of time during travel by AVs have more propensity to adopt them. However, members of Generation X are found to be more concerned about privacy issues. Indeed, Gen Xers who anticipate that AVs cannot avoid disclosure of personal tracking information are less motivated to adopt them. Further, Baby Boomers who expect that they will experience less stressful travel by AVs are more willing to buy them.

7.5 Conclusions

This chapter attempts to address two major questions regarding consumers' adoption behavior of autonomous vehicles: 1) how different generational cohorts will respond to the emergence of AVs and what are the main determinants of their adoption decision, and 2) whether there is an association between people's interests in autonomous mobility and their vehicle fuel choice behavior. Related to the scope of this study, survey respondents were presented with two choice tasks in the survey. In the first task, they faced three options of a gasoline vehicle, a hybrid vehicle, and a plug-in electric vehicle and were asked to select their most preferred fuel choice. In the second experiment, they were asked to indicate their preferred choice between two options of a traditional human-driven vehicle and an autonomous vehicle. In addition to the general vehicle attributes, various incentive policies were also included in the choice tasks.

From the methodological perspective, since we are interested to investigate the potential associations between individuals' preferences towards autonomous vehicles and alternative fuel vehicle, the two dependent variables are modeled in a joint structure. As the collected dataset includes enough observations from three generations of Millennials, Generation X, and Baby Boomers, three different joint models are estimated. Comparison of the generation-specific results indicates that the determinants of individuals' preferences are largely different across generations. This is an important finding specifically with respect to the marketing applications in the sense that auto companies should devise differentiated marketing approaches in targeting customers from different generations.

Further, the significance of the estimated correlation coefficients confirms the hypothesis that there is a correlation between the unobserved factors affecting the two components of the joint structure (i.e., vehicle fuel type and control system choices). Overall, it is found that the unobserved factors that increase the propensity to choose non-gasoline fuel types are likely to increase the chance of adopting autonomous vehicles. This is also an informative finding helping policymakers to offer more effective incentives to develop sustainable and smart transportation systems.

There are, of course, some limitations in this study which can be addressed by the future research. For example, in order to manage the complexity and required time for completing the choice experiment, we have excluded other fuel types (such as PHEVs and FCEVs), other potential decision parameters (such as availability of charging stations for electric vehicles), and partial automation levels. Future research can broaden the scope of current results by including such dimensions in their analysis. Also, this study has not considered the use of ridesharing services (as an alternative to buying a private vehicle) which are gaining considerable acceptance particularly among younger generations.

8 CONCLUSIONS AND FUTURE WORK

8.1 Summary & Contributions

Autonomous vehicles (AVs) are expected to act as an economically-disruptive transportation technology causing significant changes in travel behavior and offering several benefits to the society. However, one of the critical issues that policymakers are facing is the wide range of uncertainties that can affect AVs' market penetration after their public release. One major source of these uncertainties is the heterogenous adoption behavior of people. Also, as the technology is not yet available in the market, there is no observed and revealed preference data regarding people's adoption preferences. Therefore, gaining access to a reliable assessment of people's adoption behavior and market penetration of AVs is of great significance for both policymakers and researchers who aim to evaluate the potential impacts of this technology.

The research presented in this dissertation aims to contribute to the limited but fast-growing literature on autonomous mobility by quantifying the effect of different drivers on people's adoption behavior towards this emerging technology. Multiple aspects of people's adoption behavior such as their sensitivity to the vehicle attributes, their willingness to pay for purchasing AVs, and their preferred adoption timing have been investigated in this study. As it is highly expected that people would have different sensitivity towards various attributes of AVs, we have devoted significant efforts to capture such potential heterogeneity in their behavior.

The research is designed to thoroughly investigate how individual- and household-level demographics, travel preferences, social factors, and built-environment characteristics affect each dimension of people's adoption behavior. All results presented in this dissertation are based on the data derived from the survey that we designed and dedicated to Qualtrics to implement in the Chicago metropolitan area.

In terms of the methodological contributions, we have applied various behavioral theories from utility maximization theory to the innovation diffusion theory to improve the behavioral realism of the analyses. Several advanced modeling approaches including heterogeneity-in-means random parameters best-worst model, random parameters random thresholds hierarchical ordered probit model, and joint model structures have been applied in this research.

The dissertation consists of four main studies. In the first study, we have adopted the best-worst modeling approach to explore peoples' expectations about the most and the least attractive features of AVs and the impact of these expectations on their adoption decision. We found people's adoption decision is highly sensitive to the vehicle market price and policies regarding liability of the driver in case of accidents and provision of exclusive lane for AVs compared to other vehicle attributes.

In the second study, we have analyzed consumers' willingness-to-pay as a critical factor in estimating penetration rate of AVs in the market. An advanced structure of ordered models called random parameters and random thresholds hierarchical ordered probit has been proposed to capture both observed and unobserved heterogeneity in people's preferences towards AVs. The study reveals that the respondents with higher income, those who regularly drive to workplace, those who anticipate higher safety and better fuel efficiency from AVs, and long-distance commuters have a greater interest in and higher WTP for this new vehicle technology.

The third model focuses on predicting the market penetration of autonomous vehicles and consumers' adoption timing decision – another important decision which can significantly affect the marketing strategies and policy evaluations regarding AVs. To that end, an extension of the innovation diffusion model has been used to predict people's technology adoption behavior based on two behavioral aspects: level of innovation and level of following norms of the society (level of imitation). The results of this study imply that those who have experienced an accident in their lifetime are more inclined towards imitating the society, while those who pay more for parking at their work and frequent long-distance travelers are more likely to act in an innovative manner. Also, highly educated people and those with higher income levels tend to be innovators. We have found that the market penetration of AVs in the Chicago metropolitan area would be 71.25% by 2050.

The fourth study addresses two major questions regarding the market penetration of AVs. It aims to first explore whether various generational cohorts will adopt autonomous vehicles based on different preferences and values, and second, whether people's interest in autonomous vehicles is associated with their vehicle fuel choice decision. Three major age cohorts (Baby Boomers, Generation Xers, and Millennials) have been considered in the study and generation-specific joint models of vehicle fuel type choice and control system choice have been developed. We found that the factors that affect individuals' adoption behavior towards AVs are largely different across generations. Further, the significance of the correlation coefficients confirms the hypothesis that there is a correlation between the unobserved factors affecting the two components of the joint structure. More specifically, it is found that the unobserved factors that increase the propensity to choose non-gasoline fuel types are likely to increase the chance of adopting vehicle automation.

The findings of this dissertation can shed light on people's complex adoption behavior towards autonomous vehicles which would be of great interest for planners and policymakers who aim to develop smart, efficient, and sustainable transportation systems. In addition, other researchers who are interested in assessing the potential impacts of vehicle automation technology on people's travel behavior and network operation can profit from the results of this research as they can gain more reliable perceptions regarding the market penetration of autonomous vehicles.

8.2 Future Research

The first and foremost limitation of this research is the limited sample size. Indeed, the low number of observations that were available for each study highlights the fact that the results need to be interpreted with caution. This limitation has also hindered the ability to validate the estimation results. Therefore, testing the developed models using larger databases and in other geographical contexts could be one of the future research directions.

The other significant direction for future research is to consider shared autonomous mobility, which has not been included here because of the limitations in collecting the required data for such analysis. The results of such study together with the findings of current research could provide a comprehensive assessment of market penetration of privately owned and shared autonomous vehicles.

There are also several other areas in which this research can be improved. For example, in the best-worst analysis, only one incentive policy has been included in the choice experiment. However, other possible incentive policies such as tax rebate and congestion charge exemptions should also be considered to obtain a more comprehensive understanding of the influence of incentive policies on people's AV adoption behavior. Representations of vehicle attributes in the choice tasks can also be improved. For example, people might have more clear perceptions of annual fuel cost rather than fuel cost over a specific mileage. In addition, in the cross-generational analysis, other vehicle fuel types and other parameters such as availability of charging stations for electric vehicles can also be considered.

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APPENDIX

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VITA

NAME: Ramin Shabanpour Anbarani

EDUCATION:
B.S., Civil Engineering, Sharif University of Technology, 2010
M.S., Civil Engineering, Sharif University of Technology, 2013
Ph.D., Civil & Materials Engineering, University of Illinois at Chicago, 2018

PROFESSIONAL MEMBERSHIP:
American Society of Civil Engineers
Institute of Transportation Engineers
World Conference on Transport Research Society
International Association of Travel Behavior research
Transportation Research Board - Standing Committee on Transportation and Sustainability

PUBLICATIONS:

Shabanpour R, Golshani N, Shamshiripour A, Mohammadian A (2018) Eliciting Preferences for Adoption of Fully Automated Vehicles using Best-Worst Analysis. *Transportation Research Part C: Emerging Technologies*, 93, 463-478.

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