A STATED PREFERENCE STUDY FOR ASSESSING PUBLIC ACCEPTANCE TOWARDS AUTONOMOUS VEHICLES

by

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To the people that make my

roller coaster trips less bumpy

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ABSTRACT

Technology is rapidly transforming both vehicles and transportation systems. The nature of this transformation will depend on how fast the technology resulting from three related revolutions, those in automated, electric, and shared vehicles, will diffuse. At the same time, the 'sharing' economy is growing and affecting mobility in urban areas that includes additional travel alternatives, such as car-sharing services, ride-hailing services, bike-sharing services, and other micro-transit services. It is evident that to prepare for these large-scale operations involving autonomous vehicles (AVs), researchers and transportation professionals need the useful insights on people's attitudes toward and on acceptance of AVs that can be gained through behavioral experiments. In addition to this, it is also important to understand how the deployment of AVs will impact vehicle ownership and mode choice decisions.

The goal of this dissertation is to assess the public acceptance of AVs and shared autonomous vehicles (SAVs) via a behavioral experiment (stated preference survey) and offer insights on the potential implications of AVs and SAVs on mode choices. The following four overarching research objectives were formulated: (a) identifying the factors influencing the behavioral intention to ride in AVs; (b) identifying the characteristics of the AV market segments; (c) evaluating the attributes impacting personal vehicle ownership decisions (i.e., decisions to postpone the purchase of a non-AV due to the emergence of AVs); and (d) assessing the factors affecting mode choice decisions after the emergence of autonomous ride-sharing services operated through AVs, and evaluating the corresponding value of travel time savings. The results of each part of the research framework are integrated in the last chapter of the dissertation in order to provide the final conclusions and recommendations of the study.

To achieve these research objectives, a survey of the general population was distributed online in a major urban area with an advanced multimodal transportation system and captive users of ride-sharing users (Chicago, Illinois) and in an urban area with a more automobile-oriented culture (Indianapolis, Indiana). The survey sample included 400 responses of adults, representative of age and gender on each area.

One of the contributions of this dissertation is a theoretical model to assess the behavioral intention to ride in AVs that includes components of the theory of Planned Behavior, the theory of Diffusion of Innovation and additional factors derived from the literature while evaluating possible

interrelationships between these components. A more holistic approach along these lines can help explain whether the emerging AV technology can diffuse by identifying the factors and key determinants that influence the behavioral intention to ride in AVs. The market segmentation analysis can further provide knowledge of the socio-demographic characteristics of potential AV users and an accurate classification of these groups of potential users in terms of their willingness to ride in AVs. The findings can provide insights into perceptions of and attitudes toward AVs that can help transportation and urban planners, as well as original equipment manufacturers, to prepare for the deployment of AVs by designing marketing strategies to improve people's perceptions of AVs and increase market penetration.

Moreover, this dissertation provides a well-documented and easy-to-use framework that can support both planning and policy decisions in urban areas in an era of emergent automated transportation technologies. In urban areas with advanced multimodal transportation networks, the framework can be applied to identify the impact attributes affecting shared mobility in urban settings. In urban areas with a more car-oriented culture, the framework can be applied to explore the potential impacts of the emergence of AVs on personal vehicle ownership patterns. Finally, the survey that was designed to fulfill the goal of this dissertation can be replicated and distributed in metropolitan areas outside the US with more advanced multimodal transportation systems or areas within the US with traditionally higher rates of affinity to innovativeness and areas where AVs have been pilot-tested in real-world road conditions.

1. INTRODUCTION

1.1 Background

Technology is rapidly transforming both vehicles and transportation systems. According to Sperling, 2018), the nature of this transformation will depend on how fast the technology resulting from three related revolutions, those in automated, electric, and shared vehicles, will diffuse. Interest is growing in autonomous vehicles (AVs) especially, which have the potential to significantly transform current transportation systems. The different types or levels of AVs, as identified by NHTSA (2016), updated with SAE levels, are shown in Table 1.1 below.

Table 1.1: Definitions for different levels of AVs (NHTSA, 2016 update)

Level 0	• **No automation.**
Level 1	• **Function-specific automation.** • Automation of a specific control function, such as cruise control, lane guidance. Drivers are responsible for overall vehicle control.
Level 2	• **Combined function automation.** • Automation of multiple and integrated control functions such as adaptive cruise control with lane centering.
Level 3	• **Limited self-driving automation.** • Drivers can cede all safety-critical functions and rely on the vehicle for the transition back to driver control.
Level 4	• **Self-driving under specified conditions.** • Vehicles can perform all driving functions under specified conditions.
Level 5	• **Full automation.** • Vehicles can sustem performs all driving functions on all normal road types, speed ranges, and environmental conditions.

At the same time, the ‘sharing’ economy is growing, which is affecting mobility in urban areas. Specifically, in urban areas riders do not only rely on traditional modes of transportation (such as driving their private vehicles, using public transportation, walking, or biking) but also have access to additional travel alternatives, such as car-sharing services, ride-hailing services, specialized minibuses (i.e., shared riding services), bike-sharing services, and other micro-transit services for vehicles such as electric scooters. Therefore, shared transportation has grown significantly as a renewed interest in urbanism and growing environmental, energy, safety, and economic concerns have motivated the development of sustainable transportation alternatives. Shared autonomous vehicles (SAVs) have also begun to emerge as an alternative mode of transportation. Services that use these vehicles include features of both car-sharing and taxi services in an autonomous setting (Fagnant, Kockelman, & Bansal, 2015) and can provide flexible and affordable mobility on demand (Burns, Jordan, & Scarborough, 2013) in the form of driverless taxis. Studies project that by 2040, half of the market share of all vehicles in the US will consist of AVs (Litman, 2019). Furthermore, vehicle ownership is expected to decline, with each SAV potentially replacing seven traditional vehicles (non-AVs) and cutting into their market share (Fagnant et al., 2015). Under these projections, four operational models for AVs, which are summarized in Table 1.2, may exist on road networks by 2030.

Table 1.2: AV operational models (Litman, 2019, Krueger, Rashidi, & Rose, 2016)

Traditional non-autonomous vehicles	• Non-AVs are intended for personal and/or work use.
Personal autonomous vehicles	• Personal AVs owned by individuals and shared by a single family. • Appropriate for users that travel long distances, live in sprawled areas.
Shared autonomous vehicles	• Similar to existing ride-sharing services but without the driver; can also be defined as ‘taxi-robots’ (door-to-door service). • Appropriate for users with lower-than-average annual mileage.
Pooled shared autonomous vehicles/shared autonomous rides	• Similar to existing pooled ride-sharing services (micro-transit services). SAVs that can accommodate multiple riders at different points simultaneously (take people near destinations). • Appropriate for users with lower-than-average incomes.

1.1.1 Current and Emerging Trends

There were approximately 275 million registered vehicles in the US as of 2018 (Statista, 2019), which corresponds to roughly one vehicle for each citizen. According to the National Household Travel Survey (NHTS, 2017), it is estimated that on a daily basis an individual travels around 35 miles; this number includes all modes of transportation and trip purposes. Since 2006, there has been a slight downward trend in the number of annual vehicles miles traveled (VMT) while driving a personal vehicle (Traffic, 2015), a trend that is also evident in the findings of the most recent NHTS.

However, the emergence of AVs is one of the most significant developments for road networks in years, and current travel trends will need to be reconsidered. The diffusion of AVs, especially in urban areas with advanced multimodal transportation systems, could have multiple impacts, including on traffic safety, vehicle ownership and maintenance costs, fuel costs, the environment, the legal system, productivity, and public opinion on AVs, and the transportation system overall will need to be reevaluated and reshaped to accommodate these changes. Importantly, the impacts of AVs are no longer speculative; according to Gartner's technology hype cycle (Panetta, 2017), AVs have reportedly passed the 'peak of inflated expectations' and can achieve mainstream adoption in more than ten years.

As indicated in the technical report (Traffic, 2015) by 2045 the number of Americans over 65 years old will increase by 77% and the income inequality gap is expected to increase. At the same time, pooled SAVs are expected to become more affordable and provide mobility to people who cannot drive, such as the elderly and people with disabilities. Moreover, in the US there are approximately 76 million Millennials, people aged 18 to 34 years old, who currently outnumber the Baby Boomers, aged 50 to 68 years old. Millennials are the first generation to grow up with access to the Internet, they drive less (some of them do not even seek a driver's license), and they frequently use alternative modes of transportation (which are mostly available in urban areas) for their trips. In fact, people in this age range drove around 20% fewer miles by the end of 2000s than at the start of the decade (Traffic, 2015). The alternative modes of transportation that Millennials use for their trips include car-sharing and on-demand ride-hailing services using online applications and, to a lesser extent, public transportation. In contrast, older individuals are more likely to own private vehicles and travel using their vehicles regardless of the trip purpose (Shaheen, Totte, & Stocker, 2018).

In related research, a survey conducted by Feigon and Murphy (2016) found that the more that people are willing to use shared modes for their trips in urban areas, the more likely they are to be captive users of public transit, own fewer personal vehicles, and enjoy lower transportation costs, a finding that is also discussed in the report by Shaheen et al. (2018). Additionally, the respondents of that survey indicated that shared modes (such as ride-hailing and car-sharing services) complement public transit by similarly substituting for personal vehicle trips in urban areas, thereby enhancing urban mobility.

1.1.2 Potential Implications from the Emergence of Autonomous Vehicles

The new era of AVs has the potential to satisfy the demand for new services and can offer an opportunity to provide more mobility choices, address the first- and last-mile problems, reduce traffic congestion, mitigate various forms of pollution, ultimately reduce transportation costs and fossil fuel consumption, reduce the stress of finding a parking space, improve efficiency, and provide transportation alternatives to those who cannot afford to buy a personal vehicle or who choose to share rather than own one (Fagnant & Kockelman, 2014; Fagnant et al., 2015; Wadud, MacKenzie, & Leiby, 2016; Zmud, Sener, & Wagner, 2016). Various studies have explored the potential benefits of AVs in terms of mobility (less traffic congestion, less travel time, and increased mobility for elderly and transportation-disadvantaged people), safety (fewer accidents), costs (improved fuel economy), parking (easier and faster parking), increased productivity (the ability to multi-task while traveling), and emotional well-being (lower stress levels while riding in an AV compared to driving a personal vehicle) (Bansal & Kockelman, 2017; Begg, 2014; Howard & Dai, 2014; König & Neumayr, 2017; Schoettle & Sivak, 2014a; Shabanpour, Mousavi, Golshani, Auld, & Mohammadian, 2017; Silberg et al., 2013; Zmud et al., 2016).

In contrast, some studies have explored potential barriers to and concerns about the diffusion of AVs. For example, some studies have indicated that the emergence of AVs may increase travel demand, thereby increasing overall VMT and the resulting emissions (Fagnant & Kockelman, 2015). Additionally, it has been suggested that VMT and fuel consumption could increase if automation reduces the value of drivers' time and thereby negates the potential energy efficiency benefits of AVs (Wadud et al., 2016). Furthermore, studies have explored the potential for failures of AV technology, legal liability issues, cybersecurity issues (i.e., the potential for hacking), the disclosure of private trip data, and safety and environmental concerns (Bansal, Kockelman, & Singh, 2016; Brown, Ajzen, & Hrubes, 2003; Casley, Jardim, & Quartulli, 2013; Hulse, Xie, & Galea, 2018; Liljamo, Liimatainen, & Pöllänen, 2018; Penmetsa, Adanu, Wood, Wang, & Jones, 2019; Seapine Software, 2014; R. Shabanpour et al., 2017).

Another set of studies has explored opportunities for AV deployment and outlined practical policy suggestions to address potential difficulties caused by the diffusion of AVs. Silberg et al. (2013) suggested new business models for car manufacturers to account for new trends in vehicle ownership. Underwood, Marshall, and Niles (2014) suggested that incentives could be provided from government and car manufacturers to potential vehicle buyers in order to promote the use of vehicles with automated safety features. Krueger et al. (2016) noted that AV adoption rates are expected to be different among various demographic groups and that modality can be a defining characteristic for each group. Having a better idea of the demand for AVs among different groups can ultimately lead to more accurate and customized supply schemes, ensuring the smooth deployment of AVs. Begg (2014) described an innovative road pricing scheme involving AVs that can also lead to improved conditions for pedestrians, cyclists, and users of public transportation. Haboucha, Ishaq, and Shiftan (2017) suggested that parking costs for non-AVs should be increased as a way to encourage the use of AVs and that greater investment in public transportation could reduce the rate of private vehicle ownership; both suggestions are proposed as proactive measures to offset the negative impacts of new travel patterns resulting from widespread AV adoption. Bansal et al. (2016) suggested congestion pricing and credit-based congestion pricing schemes as remedies for the increased travel demand and emissions that may be caused by the anticipated land use changes resulting from large-scale AV deployment. Shabanpour, Golshani, and Mohammadian, 2019 and Shabanpour, Shamshiripour, and Mohammadian, 2018) found that the purchase price of AVs, exclusive lanes for AVs, and whether AV drivers/riders are liable for AV accidents would have direct impacts on the extent to which AVs are adopted.

AVs can raise new and unforeseen questions and problems for the public, and therefore advances in automated vehicle technology need to be communicated to the public in such a way as to increase the public's understanding of the issues surrounding AVs.

1.1.3 Identified Research Gaps

Based on the timeline of AV planning requirements established by Litman (2019), during the 2010s several test beds were designed to collect data on AVs. At a later stage, AVs will be operated on public roadways and be tested on-site in real-world conditions; the beginnings of this stage are already evident in the widespread operation of AVs on public roadways today. For instance, pilot projects involving Level 4 AVs, such as the campaigns announced by Waymo and Uber for driverless taxi services (Bergen, 2017; Lee, 2014), are currently being implemented. Similarly, according to the leaderboard rankings by Navigant Research Leaderboard (2019), the top three companies developing Level 5 AVs - Waymo, General Motors Cruise, and Ford Autonomous Vehicles - have all launched several pilot studies. Additionally, it is projected that during the 2020s AVs will be tested on a larger scale in order to assess their potential benefits and costs under real-world operating conditions.

It is evident that to prepare for these large-scale operations involving AVs, researchers and transportation professionals need the useful insights on people's attitudes toward and acceptance of AVs that can be gained through behavioral experiments. The nature of these behavioral experiments must be shaped by the fact that the revolution in automated transportation will soon be combined with another of the three revolutions described by Sperling (2018), that of shared transportation. It is projected that in the next decade the ability of AVs to support particular services, such as car-sharing and on-demand ride-hailing, will be tested. Consequently, behavioral experiments could be especially useful if conducted using well-structured hypothetical scenarios and stated-preference surveys, which propose several what-if scenarios to test responses to new ideas that do not currently exist. Through these types of behavioral experiments, policy makers can gain valuable insight on public perceptions of AVs that can facilitate their decision-making.

In addition to understanding attitudes toward and acceptance of AVs, it is important to understand how the deployment of AVs will impact vehicle ownership and mode choice decisions. The fleet of AVs is projected to represent 20% of the market share of all vehicles in the US in 2030 (Litman, 2019), a development that will be more obvious in urban areas. Some research on mode choice decisions has been conducted in the US to validate the need for public transportation systems (mostly for traditional modes of transportation). However, few studies have investigated the effects of different modes of transportation, whether traditional (public transportation systems, taxis, and private vehicles) or emergent (car-sharing and on-demand ride-hailing services, private AVs, SAVs, and pooled AVs), affect vehicle purchasing trends. Therefore, the perceived impacts of the emergence of AVs on people's decisions to postpone the purchase of non-AVs is not well understood. Providing such information is essential for determining which factors influence these decisions and ultimately identifying how many private non-AVs can be substituted by each AV. In a similar vein, the literature on mode choice decisions has focused mainly on private vehicles, and little information is available on the factors that influence travelers' decisions to switch from some modes, such as public transportation, to emerging shared modes, such as ride-sharing services operated through AVs.

Certainly, behavioral experiments have been conducted over the last few years exploring people's perceptions of AVs in an attempt to predict the market penetration rate and ascertain people's willingness to use AVs. However, little information is available regarding the public acceptance of AVs that can help facilitate the smooth deployment of AVs. A market segmentation analysis is needed to provide knowledge of the socio-demographic characteristics of potential AV users and an accurate classification of these groups of potential users in terms of their willingness to adopt AVs. The results of such an analysis can further inform planning and policy decisions.

To be useful, the data generated by stated-preference surveys and market segmentation analysis must be modeled carefully. The majority of studies that have focused on examining the behavioral characteristics of potential AV users and the public perceptions of and attitudes towards AVs have used descriptive analysis or some sort of econometric analysis. Methodologies that rely on the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the theory of the Diffusion of Innovation (DoI) (Rogers, 1995), the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 1996), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003) have only recently received attention for their ability to assess the behavioral intention to purchase or ride in AVs. However, studies based on these methodologies have not taken into consideration the synergistic effects between these theories, which can increase the explanatory power of models designed to predict the behavioral intention to ride in AVs. Studies (such as Bansal & Kockelman, 2017, 2018; Kolarova, Steck, & Bahamonde-Birke, 2019; Krueger et al., 2016; Wadud et al., 2016; Zhang et al., 2019) have conducted stated-preference choice experiments to assess the factors that affect mode choice decisions.

By evaluating existing studies according to components that may affect people's opinions of and attitudes toward AVs, which in turn influence the behavioral intention to ride in AVs, synergies between well-established theories can be used to identify different factors that can affect behavioral intention, thereby elucidating what drives the behavioral intention to use and ultimately adopt AVs. Similarly, while existing studies have included one or more components and tested whether each of these components independently influences behavioral intention to ride in AVs, possible interrelationships between these components and behavioral intention (direct and indirect effects) have not been explored to date. Such an approach could explain how, why, and to what extent an emerging technology like AVs can diffuse.

1.2 Research Objectives and Framework

This dissertation will answer the following research questions:

1) Which factors affect the behavioral intention to ride in AVs when the synergistic effects between the decomposed Theory of Planned Behavior, the Diffusion of Innovation theory and additional components identified from the literature review are considered?
2) Regarding the market's adoption of AVs, what are the characteristics of the respective market segments?
3) How will the emergence of AVs affect personal vehicle ownership decisions? Specifically, which attributes influence travelers' decisions to postpone the purchase of a non-AV, keep their current non-AV, or give up private ownership of their non-AV following the emergence of AVs in the short and long terms?
4) How will the emergence of autonomous ride-sharing services operated through AVs affect public transit use and, ultimately, mode choice decisions in the short and long terms? What would be the corresponding effect on the value of travel time savings?

To achieve the research objectives and address the research questions, a comprehensive research framework was developed. Figure 1.1Figure 1.1 illustrates the proposed research framework and the fundamental research parts involved. The following four overarching research objectives were formulated in line with the four research questions: (a) identifying the factors influencing the behavioral intention to ride in AVs; (b) identifying the characteristics of the AV market segments; (c) evaluating the attributes impacting personal vehicle ownership decisions (i.e., decisions to postpone the purchase of a non-AV due to the emergence of AVs); and (d) assessing the factors affecting mode choice decisions after the emergence of autonomous ride-sharing services operated through AVs and evaluating the corresponding value of travel time savings. The results of each part of the research framework are integrated in the last chapter of the dissertation in order to provide the final conclusions and recommendations of the study.

A detailed literature review was conducted in order to understand the current state of the research, identify key research gaps, and determine the appropriate modeling techniques to answer the aforementioned research questions. In particular, using the supporting literature and making educated assumptions, a questionnaire was designed consisting of different sections. This survey instrument was used to gather the main dataset used in the analysis. To help shape the survey, a proposed theoretical model was designed utilizing the synergistic effects between TPB, DoI and additional components identified from the literature review that was intended to identify the factors influencing the behavioral intention to ride in AVs. In addition to questions designed to identify these factors, the survey included questions to identify the attributes that affect private vehicle ownership and thereby, gain information on whether people would postpone the purchase of non-AVs due to the emergence of AVs. Moreover, questions were included that were designed to elicit the factors influencing the intention to switch from public transportation to SAVs, and more specifically, to ride-hailing services operated through AVs. Additionally, a separate section was designed to facilitate the stated-preference choice experiment that was used to assess how specific attributes, such as travel time and cost, would affect mode choice decisions. Lastly, sections were included in the questionnaire regarding people's awareness of AVs, their travel characteristics, and socio-demographic information. These sections were used to develop the potential AV user profiles of the distinct market segments resulting from the market segmentation analysis. Subsection 3.3 discusses in more detail the different sections included in the questionnaire, and Subsection 3.4 presents the different sampling methods and the remedies for hypothetical bias that were adopted in the survey.

The survey was distributed in Chicago, Illinois, and Indianapolis, Indiana. The metropolitan area of Chicago was selected because it represents an urban area with an advanced multimodal transportation system. Specifically, in Chicago only 49.2% of commuters drive alone to work, 28.2% use public transportation, and 7.9% carpool to get to work. In contrast, the metropolitan area of Indianapolis represents an urban area with a more automobile-oriented culture, where 82.2% of commuters drive alone to get to work, 2.0% use public transportation, and 9.3% carpool to get to work. The cities are also different from each other in their willingness to use emerging means of transportation. For instance, the 2017 NHTS revealed that 17.5% of

Chicago's residents had used a ride-sharing service in the 30 days prior to the survey, in comparison with 7.3% of residents in Indianapolis (NHTS, 2017).

Following the behavioral experiment and respective data collection, structural equations and econometric models were estimated as shown in Figure 1.1.

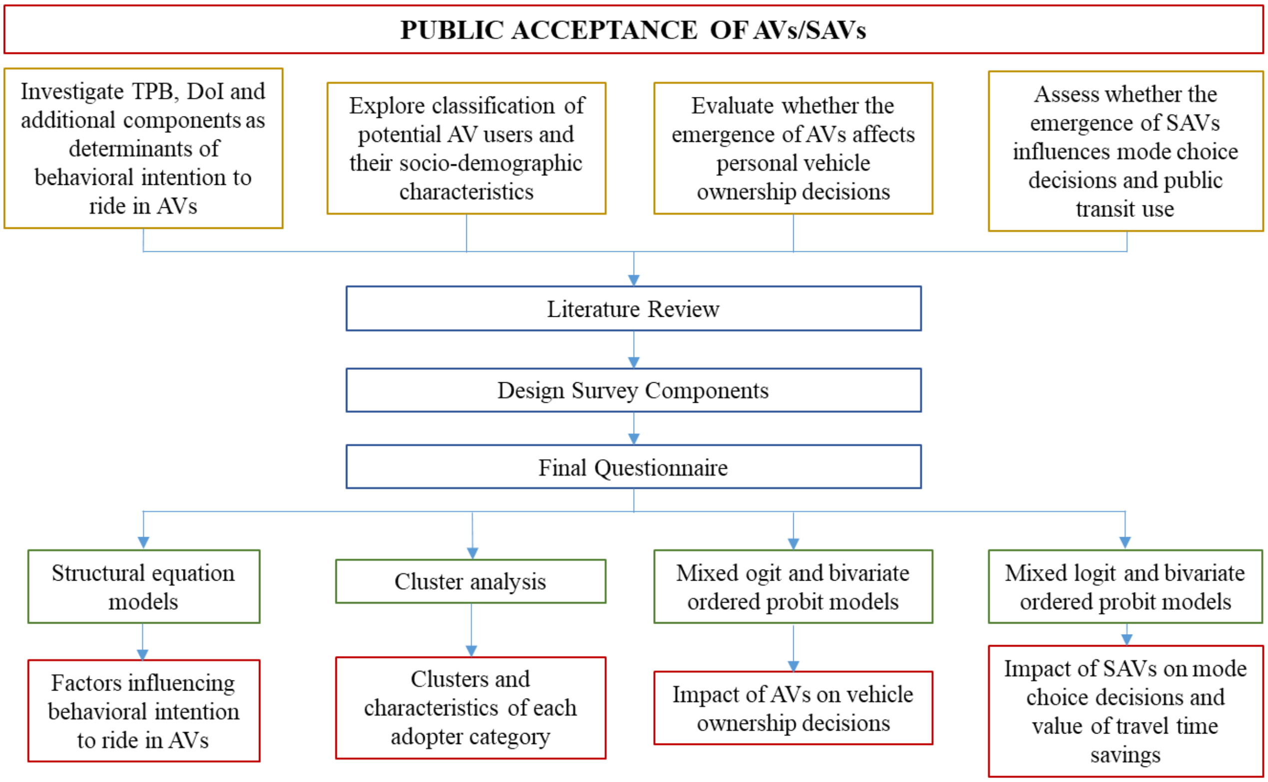

Figure 1.1: Research Framework

1.3 Anticipated Benefits and Contribution

Interest in AVs has been increasing significantly in recent years, especially regarding whether SAVs can enhance mobility in urban areas. This dissertation addresses this topic primarily by exploring people's attitudes towards AVs and SAVs, specifically in terms of the attributes that affect the behavioral intention to ride in AVs and identifying the characteristics of the AV market segments, using behavioral experiments. Additionally, the attributes influencing private vehicle ownership are explored to gain information on whether people plan to postpone the purchase of non-AVs due to the emergence of AVs. Lastly, the factors affecting mode choice decisions of SAVs and the corresponding value of travel time savings are also investigated.

In terms of methodological contributions, this study aims to address shortcomings in the literature by exploring how the synergistic effects between TPB and DoI can better assess the behavioral intention to ride in AVs. Additionally, because several factors that influence behavioral intention were identified in an extensive literature review, the models developed in this dissertation can be extended to evaluate possible interrelationships between these factors. A more holistic approach along these lines can help explain whether the emerging AV technology can diffuse by identifying the factors and key determinants that influence the behavioral intention to ride in AVs.

In terms of practical implications, this dissertation aims to provide a well-documented and easy-to-use framework that can support both planning and policy decisions in urban areas in an era of emergent automated transportation technologies. Both researchers and transportation professionals can benefit from the results of this dissertation. Researchers can build on this research framework and address new issues that may arise due to the emergent and rapidly changing nature of AVs. The developed research framework is applicable to urban areas with various characteristics. In urban areas with advanced multimodal transportation networks, the framework can be applied to identify the impact of attributes affecting shared mobility in urban settings. In urban areas with a more car-oriented culture, the framework can be applied to explore the potential impacts of the emergence of AVs on personal vehicle ownership patterns.

Transportation professionals working in different areas can benefit from this research in several ways. Transportation and urban planners, as well as original equipment manufacturers, can use the findings of this dissertation to prepare for the deployment of AVs by designing marketing strategies to improve people's perceptions of AVs and increase market penetration. The marketing of the relative advantages of AVs compared to non-AVs (benefits for society, mobility, and environment) to specific user groups or to broader audiences through educational or informational sessions can be effective approaches to encourage people to embrace the concept of AVs. This information can also be useful not only to vehicle original equipment manufacturers, but also for other categories of stakeholders such as fleets/financing/maintenance (i.e. vehicle rental services), internet/software players, and traditional/new suppliers (i.e. companies that are supplying with equipment the internet). Transportation planners may also find value in identifying which factors negatively influence the behavioral intention to ride in AVs (e.g., such as trust in the technology, safety concerns, or purchase cost). Identifying these factors can reinforce the need for wider testing of the technology or targeted marketing campaigns. Moreover, the analysis in this dissertation can aid public transit owners by identifying strategies such as deploying AVs for traditional transit services or providing premium on-demand services. Lastly, public entities such as transit agencies, transportation departments, and other local or regional agencies can utilize the key findings of the dissertation to promote cooperation between public and private mobility providers by maintaining accessibility and social equity as central mandates for urban mobility.

1.4 Dissertation Organization

Figure 1.2 presents a map of the dissertation. Chapter 1 summarizes the background information, study's motivation, research objectives, and anticipated benefits and contributions of this study. Chapter 2 presents a literature review of surveys on AVs and SAVs and a review of the related theories and methodologies. Chapter 3 describes the research framework, empirical setting, survey design, sampling methods, and data collection. Chapters 4-7 present the methodologies adopted for the behavioral experiments conducted for each part of the research framework. Chapter 8 provides the conclusions and limitations of this study and recommendations for future research.

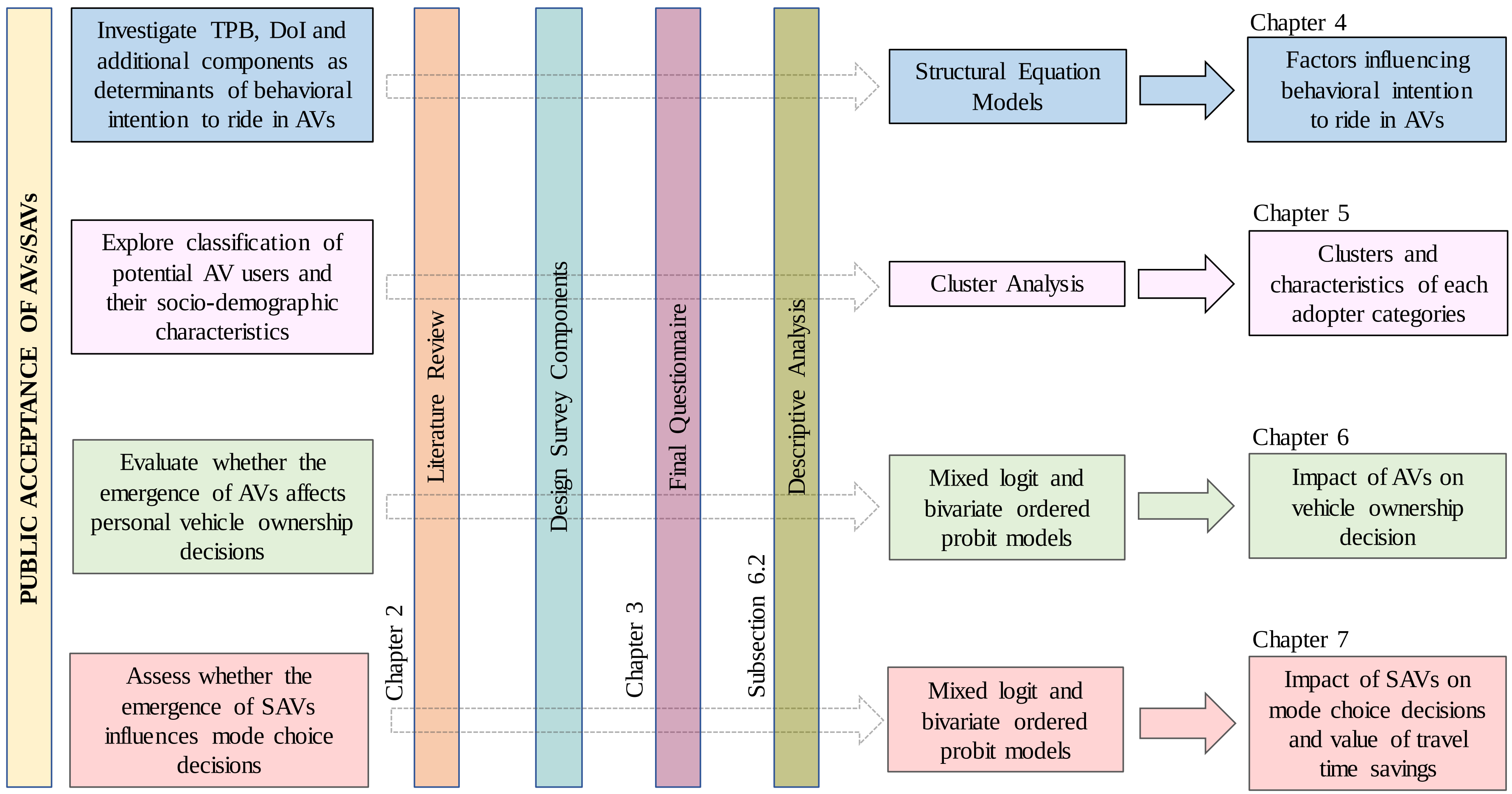

Figure 1.2: Dissertation map

2. LITERATURE REVIEW

This Chapter critically reviews the current literature on surveys conducted for AVs; every publication of such behavioral experimental studies published between January 2012 and July 2019 has been considered. The selection criteria are discussed in Section 2.1.2 and include studies that conducted a survey, a behavioral experiment, or a stated-preference experiment. Furthermore, words such as autonomous, automated, self-driving, and driverless were included in the queries. Furthermore, studies focusing only on Level 4 and 5 were included in the review. Additionally, this Chapter reviews studies on SAVs exploring this alternative mode of transportation to enhance shared mobility mostly in urban areas and investigating the economic feasibility, various implications (energy, environmental, economic, etc.) that may derive from its use and optimizing its fleet by implementing different pricing schemes. Lastly, this Chapter reviews studies on theoretical models of adoption and diffusion of new emerging technologies.

2.1 Stated Preference and Choice Studies on AVs

The work has been published in Gkartzonikas & Gkritza (2019) and it is reprinted here with the permission from Gkartzonikas, C., and Gkritza, K. '*What Have we Learned?: A Review of Stated Preference and Choice Studies on Autonomous Vehicles*.' Transportation Research Part C: Emerging Technologies, 98, pp. 323-337, 2019. https://doi.org/10.1016/j.trc.2018.12.003.

2.1.1 Introduction

Previous studies explored five different methods that are utilized to investigate the implications of AVs on travel-related behaviors. These five methods are stated preference surveys, field experiments, agent-based models and travel demand models, testbeds and driving simulators including virtual reality. The first three methods are related to attitudes and perceptions towards AVs, which is the focus of this dissertation, while the last two are related to human factors and safety. Testbeds are used when the objective is to make certain that the technology works as it was designed and is evaluated whether it is safe to integrate AVs with the real-world conditions. Driving simulators (Buckley et al., 2018, Jamson et al., 2013, Vollrath et al., 2011) and virtual reality (Pillai, 2017) are used when the objective is to diminish the risk on people. Agent-based models and travel demand models are used for simulating large-scale disaggregated networks to evaluate the effect of AVs with the transportation system (see subsection 2.2 for a list of studies). Field experiments are conducted involving people in not necessarily controlled environments and it is usually one of the last steps before the technology such as AVs, will be commercially available (e.g., field experiments of AVs in several cities such as San Francisco, Phoenix). Lastly, stated preference surveys are used to assess several hypothetical scenarios and evaluate people's attitudes, preferences and choices (Ben-Akiva, et al., 2019), which cannot be accomplished with revealed preference surveys. The rest of this section provides detailed information about the stated preference and choice study literature on AVs that this dissertation builds on.

Various research studies are currently being undertaken that examine the potential impacts of the widespread implementation of AVs on the transportation system. Stated preference/choice studies which follow an experimental design to examine potential user preferences/behaviors have examined the general acceptance of these technological advances and have explored which factors, and the extent to which these factors, influence people's decisions regarding AVs.

The objective of this chapter is a comprehensive review of the literature on stated preference/choice studies examining potential user preferences/behaviors regarding AVs. The surveys are categorized based on their respective methodologies, target populations, categories of questions, and results. The rationale for the selected categorization of the literature is provided in the methodology section and is followed by a few examples of the studies in each category. This chapter aims to categorize questions pertaining to behavioral intention to ride in AVs into different components and will suggest that each of these components could be a factor that can potentially influence the public acceptance and adoption of AVs. Additionally, this chapter summarizes the results of the reviewed studies regarding the benefits, barriers/concerns, and opportunities related to the deployment of AVs while highlighting the commonalities and differences across the reported findings. Lastly, research gaps are identified and discussed in the conclusions section.

Note that during the preparation of this chapter, unlike the Becker and Axhausen (2017) paper, this chapter identifies different components that may affect the behavioral intention to ride in AVs and focuses on the potential benefits, barriers/concerns, and opportunities related to the deployment of AVs. At the same time, it places less emphasis on comparing the corresponding results of the studies based on socio-demographic variables, attitudinal variables, travel behavior, and trip characteristics; rather, this analysis evaluated the existing work and identified common themes such as attitudinal components that affect the behavioral intention to ride in AVs.

2.1.2 Review Methodology

This section critically reviews the current literature on surveys about AVs, with a focus on studies that have conducted stated preference/choice experiments to examine potential user preferences/behaviors towards AVs. Different publication types were considered in the review, such as scientific papers, academic reports, and private sector reports published between January 2012 and July 2019. The review included studies written and in English and published in English language journals; as such, language bias may exist herein (Higgins, Green, & Cochrane Collaboration, 2008). The literature search was conducted using various queries in scientific databases, such as ScienceDirect, Web of Science and Google Scholar. The inclusion criteria include studies that conducted a survey, a behavioral experiment, or a stated-preference experiment. Additionally, words such as autonomous, automated, self-driving, and driverless were included in the queries. Furthermore, studies focusing only on Level 4 and 5 (defined by NHTSA and SAE) were included in the review.

The questions in the majority of studies were related to Level 5 AVs, or full self-driving automated vehicles, defined by NHTSA-SAE (NHTSA, 2016). Additionally, the questions in some studies were related to Level 4 AVs, or limited self-driving automated vehicles, defined by NHTSA.

‘Level 5 AVs are designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles.’ Level 4 AVs are vehicles that ‘enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time.’

Table 2.1 provides an overview of the AV studies that were reviewed as part of this chapter. For each study, information is provided about the study period (year of data collection) and the publication year. The review covered studies published in 2012 and onward. Additionally, for each study information is included about the location where the survey was distributed. To capture people's opinions worldwide about AVs, the reviewed studies included surveys that were distributed in the US, Europe, Asia, and Australia. The target population of the surveys varied; some surveys focused on a specific group of people (e.g. transportation experts, vehicle owners, students), and some surveys were distributed to the general population. In addition, information is provided about the number of responses to each survey; this number ranged from 32 people who participated in focus groups to 23,000 people who responded to a survey distributed in 19 countries. The distribution method and sampling strategy of each survey are also included in Table 2.1; almost all of the surveys were distributed online, and only a couple of the surveys were paper-based. As Table 2.1 shows, some surveys targeted the general population of a region, a country, or even multiple countries, other surveys targeted a specific group of people (such as drivers), while other studies involved focus groups of transportation experts. Table 2.1 also provides a summary of the AV surveys' objectives and the methodology adopted. More than half of the reviewed studies only reported a descriptive analysis of the survey results. The remaining studies involved some sort of econometric analysis, such as multivariate ordered probit and multinomial logit models for assessing respondents' willingness to pay for different levels of vehicle automation, identifying the characteristics of different uses for AVs, and exploring consumer preferences regarding advanced vehicle technologies or structural equation models to assess opinions on AVs.

Table 2.1. Summary of selected studies from literature on surveys for AVs according to their objective and methodology

Study	Study Year	Study Area	Target Population	Sampling Strategy	Distribution Method	Number of Responses	Study Objective(s)	Methodology
(Power, 2012)	2012	US	vehicle owners	random sample	online	17,400	Estimate willingness-to-pay for AVs.	Descriptive analysis.
(Casley et al., 2013)	2013	Worcester, MA	Students and people older than 60 years old	convenience sample	online	107	Identify the key influences that might impact the desirability of AVs (related to cost, safety, legislation, productivity, efficiency, and environment).	Descriptive analysis. Factor analysis to test six research hypotheses.
(Power, 2013)	2013	US	vehicle owners	random sample	online	>15,000	Estimate willingness-to-pay for AVs.	Descriptive analysis.
(Silberg et al., 2013)	2012 - 2013	CA, IL, NJ	vehicle owners	stratified random sample	10 focus groups	32	Investigate the decision to purchase AVs.	Descriptive analysis.
(Vallet, 2013)	2013	US	vehicle owners	random sample	online	2000	Investigate the willingness to purchase AVs.	Descriptive analysis.
(Begg, 2014)	2012	London, UK	transportation experts	convenience sample	online	3500	Understand expectations and concerns on advanced vehicle technologies in London, UK.	Descriptive analysis.
(Brown et al., 2014)	2014	19 countries	general population	stratified random sample	online	23,000	Estimate people's preferences on AVs in different markets around the world.	Descriptive analysis.
(Howard & Dai, 2014)	2013	Berkeley, CA	general population	convenience sample	paper based (survey & video)	107	Investigate people's attitudes towards AVs.	Descriptive analysis.
(Ipsos MORI, 2014)	2014	UK	general population	random sample	online	1,000	Investigate awareness and attitudes on AVs. Explore perceptions of potential concerns and benefits.	Descriptive analysis.

Table 2.1. continued

(Payre, Cestac, & Delhomme, 2014)	2013	France	general population	stratified random sample	interview, paper based, online	421	Explore to what extent drivers are willing to accept the use of AVs. Investigate and link attitudes to the intention to use AVs.	Confirmatory factor analysis. Hierarchical linear regression.
(Schoettle & Sivak, 2014a)	2014	US, UK, Canada	general population	random sample	online	1,596	Investigate public opinion towards emerging technologies in different countries.	Descriptive analysis.
(Schoettle & Sivak, 2014b)	2014	US, UK, Canada	general population	random sample	online	1,533	Understand the perceptions towards AVs in different countries. Estimate willingness-to-pay for AVs.	Descriptive analysis.
(Seapine Software, 2014)	2014	US	general population	random sample	online	2,038	Examine concerns towards the emergence of AVs.	Descriptive analysis.
(Underwood et al., 2014)	2014	US	transportation experts	convenience sample	online	217	Explore people's opinion on future emergence of AVs. Identify research and policy changes on AVs.	Descriptive analysis.
(Young, 2014)	2014	US	vehicle owners	convenience sample	online - follow up	15,171	Estimate willingness-to-pay for AVs.	Descriptive analysis.
(Continental, 2015)	2015	US, France, Germany, Japan, China	vehicle owners, transportation experts	random sample (veh. owners), convenience sample (tp. experts)	focus groups, online	4,100	Understand the acceptance of AVs in different countries and whether the technology is welcome.	Descriptive analysis.
(Kyriakidis, Happee, & de Winter, 2015)	2014	109 countries	general population	stratified random sample	online	4,886	Examine user acceptance, risks, and willingness-to-pay towards fully and partial automated vehicles in different countries.	Descriptive analysis.

Table 2.1: continued

(Shin, Bhat, Garikapati, & Pendyala, 2015)	2012	South Korea	general population	random sample	online	675	Explore consumer preferences for alternative fuel types of advanced vehicle technologies.	Multiple discrete-continuous probit model of vehicle type choice. Multinomial probit model of smart vehicle choice and option valuation.
(Abraham et al., 2016)	2016	US	general population	convenience sample	online	3,034	Assess whether respondents are willing to use automated features in their vehicles. Evaluate if older adults (over 55 years old) are willing to use AVs increasing their mobility.	Descriptive analysis.
(Bansal et al., 2016)	2014	Austin, TX	general population	convenience sample (weighted after data collection)	online	347	Estimate the average willingness-to-pay for fully and partial automated vehicles. Estimate adoption rates of shared AVs using different pricing scenarios.	Multivariate ordered probit models.
(Bansal & Kockelman, 2017a)	2016	US	general population	convenience sample (weighted after data collection)	online	2,167	Develop a framework to forecast long term adoption levels of connected and AVs. Estimate adoption rates of shared AVs using different pricing scenarios.	Multinomial logit models: determine the probabilities of annual decisions: buy, sell or replace a vehicle. Different simulation scenarios for long term adoption.

Table 2.1: continued

(Hohenberger, Spörrle, & Welpe, 2016)	2014	Germany	general population	stratified random sample	online	1,603	Estimate the willingness to use AVs. Identify potential differences among gender or age groups.	Conceptual moderated mediation model. Ordinary least squares.
(Krueger et al., 2016)	2015	Australia	general population	random sample	online	435	Identify characteristics of potential users of shared AVs. Elicit willingness-to-pay measures for service attributes (travel time, waiting time, and fares).	Mixed logit model.
(Zmud et al., 2016)	2015	Austin, TX	general population	stratified random sample	online	556	Investigate the intention to use AVs and the factors that are associated with it. Explore potential benefits and concerns towards AVs.	Descriptive analysis.
(Daziano, Sarrias, & Leard, 2017)	2014	US	general population	random sample	online	1,260	Estimate the willingness-to-pay for fully and partial automated vehicles.	Conditional logit models. Parametric and semi-parametric logit models.
(Haboucha et al., 2017)	2014	Israel, USA, Canada	general population	random sample	online	721	Understand what motivates the intention to use AVs. Estimate long term decision mode choices.	Confirmatory factor analysis. Logit Kernel model with panel effects.
(König & Neumayr, 2017)	2015	33 countries	general population	random sample	online	489	Investigate barriers and concerns on AVs. Examine people’s attitudes towards AVs.	Descriptive analysis.

Table 2.1: continued

(Shabanpour et al., 2017)	2016	US	general population	random sample	online	1,253	Evaluate people's perception on benefits and concerns of AVs. Examine most preferable vehicle option to purchase.	Random parameter logit model.
(Hulse et al., 2018)	2016	UK	general population	convenience sample (weighted after data collection)	online	1,048	Assess people's perception towards acceptance of AVs and regards to safety.	Factor analysis. Multinomial logistic for non-weighted data.
(Jiang, Zhang, Wang, & Wang, 2019)	2016	Japan	vehicle owners	random sample	online	1,002	Explore ownership behaviors due to the emergence of AVs.	Mixed logit model.
(Kaur & Rampersad, 2018)	2017	Australia	students and university staff	convenience sample	online	101	Identify the factors that affect AV adoption.	Descriptive analysis and structural equation model.
(Liljamo et al., 2018)	2017	Finland	general population	random sample	online	2,036	Investigate people's attitudes towards AVs.	Descriptive analysis.
(Liu et al., 2018)	2017	China	general population	random sample	interview	452	Assess the acceptance, willingness-to-pay and intention to use AVs.	Structural equation model.
(Nielsen & Haustein, 2018)	2016	Denmark	general population	random sample	online	3,040	Market segmentation analysis to explore people's expectations for AVs.	Principal Component Analysis. Cluster Analysis.
(Nordhoff, de Winter, Kyriakidis, van Arem, & Happee, 2018)	2015	116 countries	general population	random sample	online	7,755	Examine the factors driving acceptance of driverless shuttles.	Descriptive analysis. Principal Component Analysis.

Table 2.1: continued

(Pakusch, Stevens, Boden, & Bossauer, 2018)	2017	Germany	general population	random sample	online	302	Analyze the impact of AV driving on mobility behavior and resulting user preferences.	Using utility scale values to suggest a ranking for different modes and descriptive statistics.
(Panagiotopoulos & Dimitrakopoulos, 2018)	2017	-	general population	random sample	online	483	Predict consumer's attitudes towards AVs.	Structural equation model using modified technology acceptance model.
(Sanbonmatsu, Strayer, Yu, Biondi, & Cooper, 2018)	2017	US	general population	random sample	online	114	Examine beliefs and how confident people think about AV technology.	Descriptive and correlation analysis.
(Ramin Shabanpour et al., 2018)	2016	US	general population	random sample	online	1,253	Explore adoption decisions related to attributes of AVs.	Multinomial logit model using best-worst analysis.
(Talebian & Mishra, 2018)	2018	US	university employers	convenience sample	online	327	Examine how willingness-to-pay of connected AVs changes due to peer-to-peer communication.	Descriptive analysis and sensitivity analysis.
(Hegner, Beldad, & Brunswick, 2019)	2018	Germany	general population	random sample	online	369	Evaluate the impact of trust as a motivator that influences the public acceptance of AVs.	Structural equation model.
(Sweet & Laidlaw, 2019)	2016	Canada	general population	random sample	online	3,201	Examine consumers' interest on owning AVs.	Structural equation model.
(Asgari & Jin, 2019)	2017	US	general population	random sample	online	1,198	Assess whether attitudinal factors influence the willingness-to-pay decisions for AVs.	Structural equation model.

Table 2.1. continued

(Moody, Bailey, & Zhao, 2019)	2016-2017	51 countries	general population	random sample	online	41,932	Evaluate whether safety perceptions of AVs are different across various countries.	Structural equation model.
(Jiang et al., 2019)	2018	China	general population	random sample	online	216	Assess the influence of trust and perceived risk in people's acceptance of AVs.	Structural equation model.
(Hassan, Ferguson, Razavi, & Vrkljan, 2019)	2018	Canada	general population	stratified random sample	online	18,727	Evaluate attitudinal factors influencing the use of AVs for older population.	Structural equation model.
(Jing, Huang, Ran, Zhan, & Shi, 2019)	2018	China	general population	random sample	online	906	Evaluate whether factors of theory of planned behavior and knowledge and perceived risk affect the intention to use AVs.	Structural equation model.
(Acheampong & Cugurullo, 2019)	-	Ireland	general population	random sample	online	507	Developing different conceptual models and measurement models to evaluate the behavioral determinants of AV adoption.	Confirmatory factor analysis.
(Sener, Zmud, & Williams, 2019)	2015, 2016	US	general population	random sample	online	3,653	Assessing factors that affect AV intention to use.	Multivariate analysis.
(Nordhoff et al., 2019)	2017	Germany	users of automated shuttle	convenience sample	interview	30	Understand users revealed preference opinions' of automated shuttles opinions.	Descriptive statistics.
(Penmetsa et al., 2019)	2017	US	general population	combination of convenience sample and random sample	online	321 (convenience sample) and 798 responses (random sample)	Evaluate perceptions and expectations on AVs from vulnerable road users perspective.	Descriptive statistics.

Table 2.1. continued

(Wang & Zhao, 2019)	2017	Singapore	general population	random sample	online	1,142	Assess the relationship between risk preference and AV adoption.	Linear regression and mixed logit model.
(Zoellick, Kuhlmey, Schenk, Schindel, & Blüher, 2019)	2017	Germany	participants who experienced AV ride with level 4 automation	convenience sample	online	125	Evaluate the role of gender and age and differences between attitudes on AVs.	Exploratory factor analysis, correlation analysis, analysis of variance.

2.1.3 Key Findings

This section presents the key takeaways from the reviewed studies on surveys about AVs in terms of study objective (Section 2.1.3.1); comparison of reviewed studies according to study population (Section 2.1.3.2); components that affect opinions and attitudes towards the behavioral intention to ride in AVs including more information on specific hypotheses that were set in the reviewed papers and a brief remark whether those hypotheses hold or not (Section 2.1.3.3); respective benefits, barriers to and concerns about AVs, as well as opportunities for AV deployment (Section 2.1.3.4). Note that the discussion does not mean to be exhaustive but rather it presents a synthesis of main takeaways by identifying common themes that emerge from the reviewed studies from each category.

2.1.3.1 *Comparison of reviewed studies on surveys about AVs according to the study objective*

Each study on AVs had a different objective and included different categories of questions targeting different samples (general population or transportation experts) in different countries. As such, the studies were classified into categories based on their objectives. Different common themes have emerged and hence, the studies were divided into the following categories: a) the process of the adoption of AVs, b) the likelihood of AV adoption, c) the perceptions of various aspects of the technology and operation of AVs, d) the level of awareness of and general attitudes toward AVs, e) the preferred modes of operation for AVs, f) behavioral characteristics and perceptions related to AVs, g) the willingness to pay for fully AVs, and h) the perceived benefits of AVs. Table 2.2 shows how each study was classified into these categories according to the study's objective.

Table 2.2: Classification of reviewed studies according to the study objective

Study	Process of adoption of AVs	Likelihood of adoption of AVs	Perception of technology and operations	Level of awareness and attitudes on AVs	Preferred modes of AVs operation	Behavioral characteristics and perceptions	Willingness-to-pay for AVs	Perceived benefits/concerns of AVs
Power, 2012				x	x	x	x	
Casley et al., 2013			x			x		x
Power, 2013				x	x	x	x	
Silberg et al., 2013	x	x						
Vallet, 2013	x	x						x
Begg, 2014	x	x						
Brown et al., 2014						x		
Howard & Dai, 2014			x			x	x	x
Ipsos MORI, 2014						x		
Payre et al., 2014				x	x	x	x	
Schoettle & Sivak, 2014(a)			x	x		x	x	x
Schoettle & Sivak, 2014(b)			x	x		x	x	x
Seapine Software, 2014			x					x
Underwood et al., 2014	x	x						
Young, 2014				x	x	x	x	
Continental, 2015	x	x						x
Kyriakidis et al., 2015			x	x		x	x	
Shin et al., 2015			x				x	
Abraham et al., 2016				x	x			
Bansal et al., 2016			x			x	x	x

Table 2.2: continued

Bansal & Kockelman, 2016			x			x	x	
Hohenberger et al., 2016				x		x		
Krueger et al., 2016				x	x	x		
Zmud et al., 2016				x		x		x
Daziano et al., 2017							x	x
Haboucha et al., 2017				x	x	x		
König and Neumayr, 2017				x				x
Shabanpour et al., 2017					x		x	x
Hulse et al., 2018				x		x		x
Jiang et al., 2018							x	
Kaur & Rampersad, 2018				x		x		
Liljamo et al., 2018				x		x		x
Liu et al., 2018				x		x	x	
Nielsen & Haustein, 2018				x		x		
Nordhoff et al., 2018				x		x		
Panagiotopoulos & Dimitrakopoulos, 2018				x		x		
Pakusch et al., 2018					x			
Sanbonmatsu et al., 2018				x		x		
Shabanpour et al., 2018				x		x		x
Talebian and Mishra, 2018							x	
Hegner et al, 2019				x		x		
Sweet and Laidlaw, 2019		x			x	x		
Asgari and Jin, 2019						x	x	
Moody et al., 2019				x		x		
Zhang et al., 2019				x		x		
Hassan et al., 2019				x	x	x		
Jing et al., 2019				x		x		
Acheampong and Cugurullo, 2019				x		x		
Sener et al., 2019				x	x	x		

Table 2.2: continued

Nordhoff et al., 2019				x		x		
Penmetsa et al., 2019					x	x		
Wang and Zhao, 2019				x	x	x		
Zoellick et al., 2019				x		x		

The first category includes studies about the process of the adoption of AVs; in these studies, the common theme is the inclusion of different scenarios of market adoption and penetration that were introduced to the survey participants. For example, Silberg et al. (2013) designed a survey that asked focus groups in California, New Jersey, and Illinois for their opinion on AVs in light of different scenarios and business models for the diffusion of AVs in transportation systems. A key determinant about the process of the adoption of AVs derived from this study is the inclusion of incentives to the users. In other words, it was found in this study that the respondents were more interested in adopting AVs when they were provided incentives like designated lanes for AVs. Additionally, people over 60 years old and people between 18 and 25 years old were found to be the most willing to pay to use AVs. Furthermore, according to Vallet (2013), more than half of the respondents to surveys in this category were interested in purchasing an AV, and approximately 25% of the respondents would allow their children to ride in one.

The second category included studies related to the likelihood of AV adoption under different scenarios. Begg (2014) developed a survey targeting a cross-section of transportation experts in London, UK, to ascertain their perceptions on whether and how soon the respondents would expect AVs to become a reality. In that survey, 35% of respondents stated that Level 4 AVs would be on public roads in the UK by 2025, around 28% stated that Level 5 AVs would be on public roads by 2040, and almost 25% stated that road safety would improve with the implementation of AVs.

The third category concerns the perceptions of various aspects of the technology and operation of AVs. Schoettle and Sivak (2014) distributed an online survey in three countries – UK, US, and Australia – getting 1,533 responses including questions on different aspects of AV technology. This study investigated respondents' level of familiarity with AVs, their attitudes toward the benefits of and their concerns about the emergence of AVs, their interest in owning one, and their willingness to pay for one. It was found that 66% of respondents were aware of AVs before the survey, 72% expected increases in fuel economy, 43% expected travel time savings, and more than half did not want to pay more for advanced technologies and features installed on AVs. Additionally, a study conducted by Seapine Software (2014) included questions on similar aspects of the technology and it was found that approximately 88% of the respondents were concerned about riding in AVs, 79% were worried about equipment failures, 59% were concerned about liability issues, and 52% were concerned about hacking issues.

Turning to the fourth category, the level of awareness of and general attitudes toward AVs, a representative study is Kyriakidis et al. (2015), who conducted an online survey of 4,886 people in 109 countries using software crowdsourcing service to make the responses more consistent. This study investigated respondents' acceptance of AVs, their concerns, and their willingness to pay for all level of AVs. It was concluded that respondents who reported higher vehicle miles traveled (VMT) and who used cruise control in their personal vehicles were more likely to express a willingness to pay more for an AV. Also, 20% of respondents stated that they would be willing to pay $7,000 more for a Level 5 fully AV and 69% stated that AVs could gain around a 50% market share by 2050.

Under the fifth category, which concerns the preferred modes of operation for AVs, a similar survey was developed using an online tool in France. A scoring system was used to ask 421 drivers about their attitudes towards AVs, as well as their intention to use an AV; the survey focused on Level 5 fully AVs (Payre et al., 2014). It was found that 68% of respondents were concerned regarding the acceptance of AVs and that older people were less likely to pay for such technologies; though these respondents did express acceptance towards them. As found in Haboucha et al. (2017), older people tend to have a preference towards private conventional vehicles and are indifferent between shared and privately-owned AVs. It was found that men in Israel tend to prefer SAVs over private vehicles or privately-owned AVs. Similarly, people with higher levels of education showed a greater tendency towards preferring AVs over private vehicles.

The sixth category includes studies on behavioral characteristics and perceptions related to AVs. An interview-format survey targeting students was developed; for older participants, an online tool was used to gather respondents' opinions on AVs (Casley et al., 2013). A total of 467 responses were obtained regarding the factors that most influence the desirability of AVs; it was found that safety influenced 82% of people's attitudes toward AVs, legal/regulatory issues influenced 12%, and cost influenced 7%. Interestingly, 58% of respondents were unfamiliar with current laws regarding the testing and operation of AVs. The report by Ipsos MORI (2014) found that younger people and people living in densely populated areas such as metropolitan areas are more likely to express a willingness to adopt these emergent technologies. According to Hohenberger et al. (2016) concluded that, emotional and affective reactions towards AVs, in terms of willingness to use AVs, differ by gender. Specifically, it was found that men were more likely to anticipate pleasure and not anxiety when using AVs, which can influence the willingness to use AVs.

The seventh category includes studies on respondents' willingness to pay for AVs. In a key study in this category, Bansal et al. (2016) conducted a survey in Austin, TX, and found that people indicated that they were willing to pay around $7,000 more on average for a Level 5 fully AV and around $3,300 more for a Level 4 AV. Moreover, as stated in Daziano et al. (2017), the average US household has been found to be willing to pay $3,500 for partial automation and approximately $4,900 for full automation.

In the last category, which includes studies on the perceived benefits of AVs, Schoettle & Sivak (2014b) developed an online survey in the UK, US, and Australia that included questions about respondents' opinions regarding connected-vehicle technologies. A total of 1,596 responses were received. It was found that only 25% of respondents were aware of AVs prior to the survey, 86% expected AVs to be involved in fewer accidents, 61% expected less distraction for the driver, and 84% thought that safety was the most important benefit. Likewise, the study by Continental (2015) found that 60% of respondents expected to use AVs in stressful driving scenarios and more than half believed that crashes may be prevented due to the widespread adoption of AVs. In a survey conducted by Howard and Dai (2014), 75% of respondents stated that safety was the most attractive feature of AVs. However, in the same survey around 70% and 69% of respondents indicated that liability issues and purchasing cost, respectively, were the least attractive features of AVs.

2.1.3.2 *Comparison of reviewed studies according to study population (general population, vehicle owners, and transportation experts)*

The majority of the reviewed studies as it can be observed in Table 2.1 targeted the general public as their audience (Abraham et al., 2016; Bansal & Kockelman, 2017; Bansal et al., 2016;

Brown et al., 2014; Daziano et al., 2017; Haboucha et al., 2017; Hohenberger et al., 2016; Howard & Dai, 2014; Hulse et al., 2018; Ipsos MORI, 2014; König & Neumayr, 2017; Krueger et al., 2016; Kyriakidis et al., 2015; Payre et al., 2014; Schoettle & Sivak, 2014b, 2014a; Seapine Software, 2014; Shabanpour et al., 2017; Zmud et al., 2016), whereas few studies targeted only vehicle owners (Continental, 2015, Power, 2012, 2013; Silberg et al., 2013; Vallet, 2013; Young, 2014), and only a handful studies engaged transportation experts (Begg, 2014; Continental, 2015; Underwood et al., 2014). In addition, a synthesis of the key takeaways that emerged for each group of studies is provided followed by a comparison of the findings.

a) General population: A study conducted by Brown et al. (2014) concluded that Baby Boomers, Generation X, and Generation Y consumers have different mobility needs and habits. For example, Generation Y consumers are more willing to abandon vehicle ownership compared to the other generations. In addition, US respondents were more concerned about legal liability and data privacy, whereas UK respondents were less concerned about vehicle and system security (Schoettle & Sivak, 2014b)). Moreover, Kyriakidis et al. (2015) concluded that men were less worried about fully AVs than women, and people with higher household income were willing to pay more for AV technology.

b) Vehicle owners: The study by Continental (2015) found that vehicle ownership plays a key role in the mobility of automation regardless of age. Additionally, incidents such as stop-and-go traffic and traffic jams are found to be key factors of stress according to vehicle drivers. The surveys conducted by (Power, 2012, 2013) and (Vallet, 2013) included questions on primary technologies installed in vehicles. Approximately one third of the respondents were willing to buy a fully AV initially, but this percentage dropped to 25% and 14% for male and female, respectively, when they were asked to pay around $1,500 more for the full automation (Power, 2012). Male drivers were more interested in low-speed collision avoidance and emergency braking, whereas Millennials were interested in emerging driving technologies (Power, 2013). Moreover, it was found that around 20% of the respondents were willing to purchase an AV and the percentage increased to 34% when the respondents were asked about an 80% reduction in their insurance.

c) Transportation experts: Approximately 80% of the transportation experts indicated that by 2030, UK drivers would be able to switch to level 4 AVs (Begg, 2014), whereas only around 30% mentioned that a switch to fully AVs will not take a place at all on UK roads. This study also discussed potential implications for traffic congestion, parking issues, and road pricing schemes from an agency perspective. Underwood et al. (2014) also reported 2030 as a median forecast year for the deployment of full automation.

In conclusion, the studies targeting the general public included attitudinal characteristics and preferences of various user groups classified based on socio-demographic and travel characteristics. On the other hand, the studies focused on vehicle owners attempted to identify different level of adopters by classifying vehicle owners in various categories. Particularly, the survey instruments included questions for the willingness to pay or preferences for specific vehicle features in order to get a better understanding on which each group of vehicle owners is interested in. The studies targeting transportation experts focused on planning and policy topics on AVs from an agency perspective, thereby providing frameworks on pathway deployment. The methodology adopted in these studies was mainly descriptive analysis illustrating the key trends emerging from each respective survey. In general, transportation experts were found to be more optimistic on the likelihood of AV adoption compared to the general public and vehicle owners.

2.1.3.3 *Comparison of reviewed studies according to components affecting opinions and attitudes towards the behavioral intention to ride in AVs*

Within a large number of the reviewed studies that included surveys about AVs, nine concepts were identified that can potentially impact an individual's intention to ride in an AV by evaluating the reviewed studies for common themes: a) level of awareness of AVs; b) consumer innovativeness; c) safety; d) trust of strangers; e) environmental concerns; f) relative advantage, compatibility, complexity; g) subjective norms, which reflect external social pressures; h) self-efficacy, or whether a person considers him/herself capable of doing a specific task; and i) driving-related seeking scale, which is defined as an individual's need for complex sensations and his/her willingness to take risks for a target experience and is linked to an individual's physiological factors and his/her personality when driving.

The motivation for classifying the questions included in the reviewed studies according to the nine concepts listed above stems from existing theories and models widely adopted in the social sciences and psychology, used to get a better understanding on the factors influencing a particular behavior. One of these, from the perspective of the individual, is the Theory of Reasoned Action (TRA), which evaluates what people are considering and the implications of their behaviors before they perform an action (Fishbein & Ajzen, 1975). A subsequent theory, the Theory of Planned

Behavior (TPB), includes the component of perceived behavioral control to account for non-intended behaviors (Ajzen, 1991).

On a similar note, the Diffusion of Innovation (DoI) theory uses the concepts of relative advantage, compatibility, and complexity to investigate the potential adoption of a new idea/innovation by a population (Rogers, 1995). The theory classifies people into five adopter categories: a) innovators (first group of people to adopt the innovation); b) early adopters (second group of people to adopt the new idea, or 'cosmopolites'); c) early majority (the group of people that adopts the new idea before the average member of a population does); d) late majority (the group of people that adopts the new idea immediately after the average member of the population does); and e) laggards (last group of people to adopt the innovation, or 'near isolates'). The DoI theory considers an individual's perception of the new idea, which, in the present study, can be determined by analyzing the reviewed studies. The first aspect of an individual's perception of a new idea is the new idea's relative advantage, which describes whether an individual believes that the new idea is better/worse than the idea being replaced. An individual is more likely to adopt a new idea with a greater relative advantage. Secondly, compatibility describes whether the new idea is compatible with an individual's values and needs. The higher the compatibility, the more likely and faster an individual will be to adopt the innovation. Thirdly, complexity describes an individual's concerns regarding the ease with which the new idea can be used. The higher the complexity, the less likely and slower an individual will be to adopt the new idea, because he/she must develop new skills. The final theory motivating the classification of questions into the eight components used in this study is decomposed TPB, developed by Taylor and Todd (1995). This theory aims to provide a better understanding of behavioral intention by decomposing behavioral beliefs. Table 2.3 indicates the components that are included in each study, and a discussion of each component is provided below.

Table 2.3: Classification of reviewed studies according to components affecting opinions and attitudes towards the behavioral intention to ride in AVs

Study	Level of Awareness	Consumer Innovativeness	Safety	Trust of Strangers	Environmental Concerns	Relative Advantage, Compatibility, Complexity	Subjective Norms	Self-efficacy	Driving-related Seeking Scale
Casley et al., 2013			x		x				
Silberg et al., 2013		x							x
Brown et al., 2014					x	x	x		
Howard & Dai, 2014			x			x		x	x
Ipsos MORI, 2014									x
Payre et al., 2014						x	x	x	x
Schoettle & Sivak, 2014(b)	x	x							
Continental, 2015					x	x			x
Kyriakidis et al., 2015			x	x					
Shin et al., 2015		x				x			
Abraham et al., 2016	x					x			
Bansal et al., 2016	x			x	x				
Bansal & Kockelman, 2016		x	x						
Krueger et al., 2016					x				
Zmud et al., 2016		x	x	x		x			
Daziano et al., 2017						x			
Haboucha et al., 2017		x	x	x	x	x		x	x
König and Neumayr, 2017	x					x			
Shabanpour et al., 2017		x	x		x	x			
Hulse et al., 2018			x			x			

Table 2.3: continued

Kaur & Rampersad, 2018				x		x	x	x	
Liu et al., 2018			x	x		x	x		
Nielsen & Haustein, 2018						x			
Nordhoff et al., 2018	x			x		x	x		x
Panagiotopoulos and Dimitrakopoulos, 2018			x			x	x		
Sanbonmatsu et al., 2018	x					x		x	
Shabanpour et al., 2018			x		x				
Hegner et al., 2019		x		x		x	x		
Sweet and Laidlaw, 2019		x				x	x		x
Asgari and Jin, 2019		x		x		x			x
Moody et al., 2019			x	x		x			
Zhang et al., 2019				x		x	x		
Hassan et al., 2019		x	x			x	x		
Jing et al., 2019				x		x	x		
Acheampong and Cugurullo, 2019	x	x				x	x	x	
Sener et al, 2019	x					x			
Nordhoff et al., 2019				x		x			
Penmetsa et al., 2019		x	x			x	x		
Wang and Zhao, 2019				x		x			
Zoellick et al., 2019		x	x	x		x	x		

a) *Level of awareness of AVs*: The surveys by Bansal et al. (2016) and Schoettle and Sivak (2014b) included questions on technology-based predictors, such as respondents' level of awareness of Google's driverless car, whether ABS is considered a form of automation, and respondents' familiarity with ride-hailing and car-sharing services. Schoettle and Sivak (2014b) and Silberg et al, 2013) indicated that respondents with a higher level of awareness of AVs were more likely to have a stronger intention to adopt them.

b) *Consumer innovativeness*: Haboucha et al. (2017) included attitudinal questions asking about respondents' technology-related interests, which can be related to respondents' comfort with innovation, such as their tendency to try new products before friends and family or buy new technologies despite the fact that such products are expensive, which Shin et al., (2015) found that older respondents were less comfortable adopting emerging vehicular options than other respondents'. In a different survey, Bansal and Kockelman, (2017) found that around 55% of the respondents indicated that the emergence of AVs is a useful advancement in transportation, whereas around 60% indicated that they have some apprehension. Additionally, more than three-quarters of the respondents to this survey indicated that they enjoy driving a car and that they tend to wait before adopting certain technologies (Bansal & Kockelman, 2017a).

c) *Safety*: A survey by Bansal and Kockelman (2017) related to respondents' perceptions about AVs and safety showed mixed results. While around one out of five respondents indicated that they would be liable if an accident were to occur, some participants agreed that automation has great potential to decrease the occurrence of accidents. In a different survey, more than four out of five respondents ranked safety as the most important concern resulting from the emergence of AVs (Casley et al., 2013). Howard and Dai (2014) concluded that safety and liability concerns play a critical role in the adoption of AVs. Kyriakidis et al. (2015) suggested that an individual's attitudes toward safety, such as a rider's level of comfort with surrounding vehicles, a rider's comfort with not being behind a wheel, and privacy concerns, might be related to their perceptions regarding automation. Hulse et al. (2018) included questions pertaining to the perceived risk associated with different transportation modes, defining perceived risk as the potential for an accident to occur that has a negative influence with the intention to ride in AVs.

d) *Trust of strangers*: Bansal et al., (2016) included questions asking about respondents' comfort with ride-sharing services in different settings, such as riding a shared vehicle with a stranger, with social media friends, with regular friends, and with family members. Haboucha et al. (2017) included attitudinal questions about public transportation that covered topics such as safety concerns when riding on public transit with strangers.

e) *Environmental concerns*: Haboucha et al. (2017) included attitudinal questions about the environment that solicited respondent's concerns about global warming and the effects of pollution and respondents' intention to purchase environmentally friendly products. Approximately six out of ten respondents stated that they would consider purchasing an AV if it were to emit fewer pollutants than conventional (non-autonomous) vehicles. It was found that the component of environmental concerns influences the decision on using shared vehicles positively. In the study by Continental (2015), more than 80% of respondents answered that low fuel consumption is important to them. In a different survey, respondents indicated their concerns about environmental sustainability, emphasized the need to improve fuel efficiency, and acknowledged the establishment of environmental targets and expectations by governments and organizations (Brown et al., 2014). Krueger et al. (2016) concluded that pro-environmental attitudes are common characteristics of users of car-sharing programs and may impact people's attitudes toward the adoption of automated features in their own vehicles.

f) *Relative advantage, compatibility, and complexity*: Respondents to a survey conducted by Brown et al. (2014) indicated that innovations in the vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) connectivity technologies installed in AVs are transforming the automotive industry Brown et al. (2014). In addition, the same survey found that lifestyle needs are one of the key determinants in mode choice decisions, in that respondents make mode choice decisions that are compatible with their lifestyles. Haboucha et al. (2017) included attitudinal questions about the relative advantages of AVs, such as their potential for solving parking and mobility issues, and whether it is more fun to ride in an AV than drive a conventional vehicle. It was found that an increase in parking costs has the potential to encourage the use of AVs, but respondents who stated that they enjoy driving were less likely to switch to AVs. It was also found that the relative advantages of AVs influence the choice of AVs positively. At least one out of three respondents to the report by Continental (2015) stated that automated driving is a feature that drivers want and that this feature indicates a potential relative advantage of AVs compared to conventional vehicles. Additionally, at least 70% of the respondents indicated that driving a private vehicle is compatible with their lifestyle Continental (2015). Daziano et al., 2017) stated that determinants that influence people's perceptions of AVs are current vehicle ownership, higher education levels, and driving long distances which can be related to compatibility an individual's lifestyle.

Howard and Dai (2014) found that safety and amenities, such as multitasking and convenience, were the most attractive features of AVs. Furthermore, a significant minority of respondents to the same survey indicated concerns about the loss of control when riding in AVs, which may be related to complexity (Howard & Dai, 2014). Shin et al. (2015) included questions related to those aspects of respondents' lifestyles that may impact their opinions on advanced vehicle technology options, such as preferences regarding wireless internet, autonomous driving features, and real-time information applications. It was found that respondents who prefer these advanced vehicle technology options available in their vehicles are more likely to purchase an AV. Hulse et al. (2018) included questions regarding the general attitudes of respondents towards the emergence of AVs, such as hacking concerns, operation of AVs on public roads, and the road safety capabilities of AVs.

g) *Subjective norms*: Results from a survey conducted by Brown et al. (2014)indicate that more than half of generation Y consumers are influenced by friends and family (a key determinant) during the purchasing process of vehicles.

h) *Self-efficacy*: Payre et al. (2014) included questions related to the concept of ‘locus of control’, which describes the extent to which an individual believes that he/she can control events affecting him/her; this personality trait may impact a person’s intention to ride in AVs. The study examined the hypothesis that people with external locus of control would intend to use AVs more often than those with internal locus of control.

i) *Driving-related seeking scale*: In the study by Continental (2015), more than 60% of respondents answered that if AVs become widely available, driving private vehicles will remain an enjoyable experience. Haboucha et al. (2017) included attitudinal questions about public transportation, such as preferences regarding being the driver rather than being the passenger in a vehicle. Respondents who usually drove alone for the majority of their trips were more likely to prefer greater control of the vehicle and were less likely to indicate a willingness to purchase an AV (Howard & Dai, 2014). Payre et al. (2014) concluded that questions related to sensation seeking are related to the intention to use AVs. It was assumed that people with higher driving-related sensation seeking scale use the AV technology more frequent than the ones with lower scale. A survey conducted by Ipsos MORI (2014) suggested that respondents who preferred driving their personal vehicles have a weaker intention to adopt emerging technologies such as AVs.

2.1.3.4 *Benefits, barriers/concerns, and opportunities for AV deployment*

This subsection explores different concepts related to the wider deployment of AVs that were documented in the reviewed studies. Table 2.4 summarizes the benefits of AVs, barriers to and concerns about AVs, and opportunities for AV deployment that were included in the aforementioned studies. Specifically, the surveys conducted for the reviewed studies included questions on the potential benefits of AVs with regards to safety (fewer accidents), mobility (less traffic congestion, less travel time, and increased mobility for elderly and transportation disadvantaged people), the environment (lower vehicle emissions), costs (better fuel economy), parking (easier and faster parking), emotional well-being (less stress while traveling), and increased productivity due to multi-tasking in AVs. Furthermore, the respective surveys conducted for the reviewed studies included questions regarding the barriers to and concerns about the diffusion of AVs, such as the potential for failures of equipment and the AV system, legal liability, cybersecurity issues (i.e., hacking), the disclosure of private trip data, and environmental concerns. Lastly, a few studies outlined opportunities for AV deployment and offered policy suggestions.

Table 2.4: Summary of benefits, barriers/concerns, and opportunities for AV deployment

Study	**Benefits**	**Barriers/Concerns**	**Opportunities**
Casley et al., 2013	Increased fuel efficiency Decreased needs for right-of-way Reduced travel times that leads to social benefits such as more leisure trips	Increased cost of the system Increased safety concerns Legal issues to protect users and civilians	
Silberg et al., 2013	Fewer crashes Reduced needs for new infrastructure Shorter travel times Increased productivity Better energy efficiency	Data challenges – issues to personal privacy	New models for vehicle ownership New business models
Begg, 2014	Reduction of stress levels while traveling Independent mobility for non-drivers Reduction in parking costs and accidents Energy conservation and emission reductions	Problem of driver ‘underload’ – whether drivers of AVs be engaged Liability issues AVs may potentially compete with bus services and public transportation Cyber security issues Ethical issues on privacy and use of data and testing	Innovative road pricing Improvement of conditions for walking, cycling and public transportation
Brown et al., 2014	Improvement in safety (reduction in accidents) Increased fuel efficiency	High cost of the system Lifestyle needs can be met by walking and public transportation instead	

Table 2.4: continued

Howard & Dai, 2014	Increased productivity – multitasking Reduction in time spent finding parking More environmentally friendly Increased mobility Improvement in safety (reduction in accidents)	Lack of control Increased ownership or other costs Issues with equity – who will and who will not afford to use AVs Privacy concerns Safety concerns	Demand responsive routing of AVs to choose a route that minimizes delays may lead to strategies to avoid potential bottlenecks in congestion-prone areas
Schoettle & Sivak, 2014(b)	Better fuel economy Shorter travel times Fewer crashes and reduction in severity of crashes Less traffic congestion Lower insurance rates	Safety issues due to equipment or system failure Legal liability for drivers/owners Cyber security of vehicles Data privacy (location and destination tracking) Learning curve to use AVs	
Seapine Software, 2014		Liability issues Cyber security Data privacy issues	
Underwood et al., 2014			Remove cell restrictions on AVs as an incentive Provide incentives to use a vehicle with automated safety features Provide flexibility and incentives of insurance companies to AV owners
Abraham et al., 2016			Learning strategies such as training methods may provide the opportunity to educate drivers to become more familiar and comfortable with AVs and lead to higher adoption rates

Table 2.4: continued

Bansal et al., 2016	Fewer crashes Less traffic congestion Lower vehicle emissions Better fuel economy Decrease in need for parking in higher rent locations Lower private vehicle ownership	Equipment or system failure Legal liability for drivers or owners Hacking computer systems of vehicle Privacy disclosure of travelers Interactions with conventional vehicles Learning curve to use AVs Affordability of AVs Adoption rates can modify development projects in commercial and residential areas along roadways	Congestion pricing and credit-based congestion pricing to manage travel demand and emissions. More proactive land-use transportation planning and policy
Bansal & Kockelman, 2016	Less traffic congestion Increased mobility independence Easier and quicker parking Increased productivity due to multitasking Increased safety		
Krueger et al., 2016			Adoption rates may differ between sub-groups and modality may be a discriminator of sub-groups memberships
Zmud et al., 2016	AVs are safer compared to conventional vehicles Less stress levels while riding in AVs Increased productivity and mobility	Possibility of feeling nervous while riding in AVs	
Haboucha et al., 2017		Environmental concerns Longer commuting distances that may lead to increased urban sprawl and vehicle miles traveled	Increase in parking prices to discourage use of conventional vehicles Investment in public transportation may reduce private vehicle ownership trends Pre-emptive measures to prevent negative impacts on land use and travel patterns

Table 2.4: continued

König and Neumayr, 2017	Increased mobility for elderly and disabled people Increased productivity – multitasking	Legal issues Cyber security of vehicles Lack of control Safety concerns	
Shabanpour et al., 2017	Fuel efficiency	Safety concerns Existence of exclusive lane	Residential location plays critical role on adoption strategies Vehicle price affects purchase and adoption decisions
Brell et al., 2018	Level of experience on automated features can reduce the risk perceptions for AVs	Risk perceptions were found higher in AVs compared to conventional vehicles Cyber security of vehicles	
Hulse et al., 2018		Lack of knowledge of intrinsic road safety capabilities of AVs Privacy concerns Cyber security of vehicles	
Liljamo et al., 2018		Traffic safety Morality and ethical considerations	Increased adoption due to the emergence of AVs if potential ethical issues are not significant.
Shabanpour et al., 2018	Productivity and lower stress levels can be anticipated benefits of AVs Fewer crashes/increased safety Lower insurance rates	High expected purchase price of AVs Imperfect performance under non-anticipated traffic conditions	Increased adoption if the liability of AV accidents is not on drivers Exclusive lanes for AVs enhances adoption of AVs

2.2 Published Studies about SAVs

Table 2.5 provides a summary of the objectives and the methodologies adopted in each study about SAVs. A large proportion of these studies consist of case studies of shared autonomous taxi systems mainly implemented in the US. More than half of the reviewed studies conducted various simulation scenarios using agent-based models to achieve the study objective. Furthermore, some studies used optimization modeling techniques with an objective to maximize the profit, optimize the fleet or minimize the vehicle miles traveled by the users of such services.

Table 2.5: Summary of SAV studies according to their objective and methodology

Authors	Year	Study Objective	Methodology
(Agatz, Erera, Savelsbergh, & Wang, 2011)	2011	Exploration of smartphone technology and whether it can enhance dynamic ride-sharing in Atlanta, Georgia	Simulation model using travel demand data Optimization model to minimize the total VMT by system users
(Anderson et al., 2014)	2014	Understanding the current practices for autonomous and SAVs in the US and provide guidance for policymakers	Discussion on potential mechanisms and benefits of emerging technologies
(Burns et al., 2013)	2013	Evaluation on whether SAVs can provide better mobility at a lower cost in Ann Arbor, Michigan	Simulation scenarios using data from the 2009 NHTS Comparison of cost estimates between SAVs and private vehicles
(Chan & Shaheen, 2012)	2012	Understanding ride-sharing impacts on infrastructure, congestion and energy and environment	Discussion paper on determining best practices
(Chen, Kockelman, & Hanna, 2016)	2016	Exploration of implications on shared autonomous electric vehicles fleet	Simulation scenarios using agent-based model to examine the performance and profitability of fleet using different price schemes
(CityMobil2, 2016)	2016	Key findings from a large-scale project demonstrating automated road transport systems in 7 European Cities and future recommendations	Technical report discussing on how the automated road transport system can be integrated on urban streets

Table 2.5: continued

(Fagnant & Kockelman, 2015)	2013	Recommendations on present and future opportunities, barriers and policy issues on autonomous and SAVs	Discussion paper on providing recommendations for opportunities and barriers
(Fagnant & Kockelman, 2014)	2014	Estimation of travel and environmental implications using SAV fleet in Austin, TX	Simulation scenarios using agent-based model to determine SAVs fleet Calculated environmental implications using EPA's MOBILE6 model
(Fagnant et al., 2015)	2015	Understand potential of SAVs in US urban areas using Austin, TX as a case study	Simulation scenarios using agent-based model to evaluate dynamic ride-sharing system Optimize the fleet size of SAVs
(Ford, 2012)	2012	Evaluation of performance of a shared autonomous taxi system Assessment of benefits derived from using shared autonomous taxi system based on students' weekday travel patterns in New Jersey	Review of current developments for AV technologies Calculate travel demand and allocated trips to shared autonomous taxi system using weekday travel patterns and Census data
(Hayes, 2011)	2011	Exploration of benefits using autonomous and SAVs	Discussion article on future benefits of emerging technologies

Table 2.5: continued

(Kang, Feinberg, & Papalambros, 2017)	2016	System design optimization framework for shared autonomous electric vehicles Examine the feasibility of shared autonomous electric vehicles and SAVs in Ann Arbor, Michigan	Optimization framework maximizing service profit by integrating fleet size, number of charging stations, vehicle powertrain requirements and service fees Economic feasibility of SAEV and SAV using different market scenarios
(Martinez & Viegas, 2017)	2012	Assessment of market potential for implementing shared taxi service in Lisbon, Portugal	Simulation scenarios using agent-based model Evaluation of different pricing schemes of shared taxi service and comparison between traditional taxi services and shared taxi service
(Zachariah, Gao, Kornhauser, & Mufti, 2014)	2013	Feasibility study of assembling fleet of autonomous taxis in New Jersey	Simulation scenarios using spatiotemporal dataset to examine whether such a fleet is feasible
(Zhang, Guhathakurta, Fang, & Zhang, 2015)	2015	Investigation on whether SAVs can reshape urban forms and the demand for parking	Simulation scenarios using agent-based model to test the penetration rate of SAVs

Regarding the reviewed studies for SAVs, some studies conducted simulation scenarios for a better understanding of travel behaviors and therefore, evaluate the economic feasibility of such systems. For example, using different pricing schemes, it was found that the implementation of shared autonomous electric vehicles can approximately replace 7.3 private vehicles (Chen et al., 2016). A study that was conducted in Lisbon, Portugal found that by implementing a shared-taxi service the fleet can be reduced to 2,000 compared to the 3,100 current traditional taxis (Martinez & Viegas, 2017). Similarly, it was concluded that dynamic ride-sharing has the potential to reduce total service times and travel costs by incorporating extra passenger pick-ups, drop-offs and non-direct routes (Fagnant et al., 2015). Zhang et al. (2015) found that the demand for parking significantly reduces even when the penetration rate of SAVs as low as 2%. Additionally, it was found that SAVs can provide more flexible service than car-sharing and cheaper than existing non-autonomous ride-sharing services (Zhang et al., 2015). Additionally, Zachariah et al. (2014) indicated that SAVs can enhance travel behaviors towards ride-sharing systems especially in dense locations during peak hours by achieving better mobility and reduced energy and environmental consequences. A study that was conducted in Ann Arbor, Michigan. Burns et al. (2013) concluded that a pricing scheme of $0.32-$0.39 per mile depending on the fleet size is economic feasible for SAVs. Fagnant et al. (2015) found that when the market share of SAVs of Austin, Texas reaches 5%, it can lead to significant benefits on energy consumption, greenhouse gas emissions and other air pollutants.

2.3 Theoretical Models of Adoption and Diffusion of New Technologies

This section reviews the most widely used theoretical models of adoption and diffusion of new technologies. These include the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Diffusion of Innovation (DoI) and lastly, the Decomposed Theory of Planned Behavior (DTPB), which can link the Theory of Planned Behavior and the Diffusion of Innovation theory.

2.3.1 Theory of Reasoned Action

TRA was introduced by Fishbein in 1967. TRA assesses what people are considering and the implications of their behaviors before the action is performed. According to TRA, attitudes can result from a combination of beliefs about the characteristics of specific attitudes and evaluation of these characteristics. As it was identified in Fishbein and Ajzen (1975), intention is critical in this theoretical model and can predict whether an individual will perform or not a particular behavior.

TRA established by in Fishbein and Ajzen, (1975) is a fundamental theory in order to predict human behavior (Venkatesh et al., 2003). According to TRA, human attitude toward behavior and subjective norms toward this behavior are depended on the individual's behavioral intention (Fishbein & Ajzen, 1975). Therefore, the behavioral intention can directly influence human behavior. The theoretical model of TRA does not take into account variables of perceived behavioral control. This is considered in the TPB, which is an extension of TRA and it can assess whether human behavior can be altered (Ajzen, 1991), as discussed next.

2.3.2 Theory of Planned Behavior

Behavioral intention is an indicator of a person's inclination to perform a given behavior and it is considered to be the direct antecedent of behavior (Ajzen, 1991). According to Wicker (2005), it was revealed that a non-considerable behavior relationship exists in studies that use the intention to predict behavior. On the other hand, Ajzen (1991) found that the relationship between intention and behavior is positive and can be significant if the research purpose is properly established.

Brown et al. (2003) also found that the intention can poorly predict the behavior in cases of: a) the attitude and intention alter after they have been measured, b) the length between the measurement of behavior and intention is very long, and c) the target behavior is formulated in a vague way. In order to predict the behavior from intention in a reliable way the time aspect, target behavior and the situation (in which the behavior is achieved) need to be formulated specifically (Ajzen, 1991).

The intention as a predictor of behavior can be extensively used in product development, medical research and acceptance of Information Technology and it is not limited to studies focused on behavior changing (Davis, 1989; Venkatesh et al., 2003).

The variable of perceived behavioral control was included into TRA by Ajzen (1991) in order to account for non-intended behaviors. It is assumed that by implementing this variable into a model, it will help predict behavior more accurate than other models (Ajzen, 1991). Based on TPB, variables of attitude toward behavior, subjective norms and perceived behavioral control guide the behavioral intention and behavior (Ajzen, 1991). The variable of attitude toward behavior explains the evaluation of positive and negative perceived consequences of performing the behavior under consideration by each individual (Fishbein & Ajzen, 1975). Subjective norms can describe the perception of an individual whether people who are close to him/her believe that the individual should adopt the target behavior or not (Fishbein & Ajzen, 1975). Furthermore, the variable of perceived behavioral control evaluates the difficulty or easiness that the target behavior will be performed for each individual by considering non-intended behaviors (Ajzen, 1991). Whereas, the behavioral intention can measure the individual's relative power of intention to perform the behavior under consideration (Fishbein & Ajzen, 1975) and the variable of behavior is the observed outcome related to a given situation and a target (Fishbein & Ajzen, 1975).

$$AAct_{wi} + SN_{wi} + PBC_{wi} = BI \quad (Eq. 2.1)$$

,where AAct refers to the attitudes towards behavior, SN to subjective norms, PBC to perceived behavioral control, and BI to behavioral intention (note: wi = weights which are based on multiple regression analyses).

The utility of TPB is replicated in a plethora of social scientific disciplines. Studies include health-related behavior (Ajzen & Fishbein, 2004) and related to technology and Internet-related behavior. For example, George (2002) found 'general support' for the model when the relationship between privacy and online purchasing was examined. Robinson and Doverspike (2006) used TPB to evaluate which factors can predict the decisions of students to take an online course instead of a face-to-face one. TPB in general received research support from scholars. One of its advantages is the fact that it can be applied to various behaviors in different contexts including environmental concerns, risk communication, mass transit use and technology adoption. On a similar note, a theory weakens when external variables are influenced which is not the case for TPB. The model does not depend on external variables such as affection or emotion related ones. Another reason that the model does not include emotional variables although it was criticized on this decision (Conner & Armitage, 1998) is the fact that TPB assumes all behavior is rational. A meta-analysis study conducted by Armitage et al. (2004) studied 185 different studies. It found that the perceived behavioral control variables accounted for a significant amount of variance in behavior and intention.

2.3.3 Diffusion of Innovation Theory

DoI theory was introduced in Rogers (1995) and it used to evaluate potential adoption. The theory is based on how various ideas and/or products spread and adopted by different categories of population.

Diffusion is based on four main products of the diffusion model; innovation, communication channels, time and social system. Innovation represents the new idea that is presented to a group of people (Rogers, 2003). Communication is the procedure where individuals or groups of individuals distribute the information of the ‘new idea’, which can result to convergence or divergence of ideas. Communication channels can be mass media centers (i.e. television), interpersonal channels or interactive media (i.e. internet). Social system represents a system with a joint problem to accomplish a goal and time represents the innovation process timeframe (Rogers, 2003).

According to DoI (Rogers, 1995), there are five stages of diffusion process which are: a) knowledge (exposure on the new idea), b) persuasion (attitude towards the new idea), c) decision (commitment to the adoption), d) implementation (putting the new idea into use), and e) confirmation (reinforcement based on positive outcomes from the new idea). According to Rogers, innovativeness can be categorized into five adopter categories.

Innovators (2.5%): The first group of people to adopt the innovation, even though a high degree of uncertainty exists. Their interest in new ideas leads them out of local circles and into more cosmopolite social relationships.

Early Adopters (13.5%): The second group to adopt the new idea. They are considered as ‘localites’ instead of ‘cosmopolites’, since they are respected by their peers in a form of a role model in their social system.

Early Majority (34%): The early majority group of people adopts the new idea before the average member of a system. They often interact with their social peers but they are not leading their social groups.

Late Majority (34%): The late majority group adopts the new idea right after the average member of the system, possibly due to pressures from their peers.

Laggards (16%): The last group of people to adopt the innovation and they can be considered as ‘near isolates’ in their social network.

The DoI theory also considers individual’s perception towards the ‘new idea’ which are:

Relative advantage or disadvantage: Whether an individual believes that the new idea is better/worse than the one he/she replaces. An individual will more likely adopt the new idea if more relative advantages exist.

Compatibility: Whether the new idea is compatible towards individual's values and needs. The higher compatibility is, the more likely and faster an individual will adopt the innovation.

Complexity: Concerns on how easily the new idea is used. The higher complexity is, the less likely and slower an individual will adopt the new idea since he/she has to develop new skills.

Trialability: Whether the new idea can be experimented with. The higher trialability is, the individual has less concerns about the innovation.

Observability: Whether the new idea can be observed by others. The higher observability is, the more likely an individual will adopt the innovation.

Some of the aforementioned variables from DoI can be used to enhance TPB (Ajzen, 1991). For example, the variables of relative advantage/disadvantage, compatibility and complexity are beliefs on behavior, which can be structured in the TPB under the cognitive structure of attitudes. Trialability and observability of Rogers' DoI can be used under subjective norms.

2.3.4 Decomposed Theory of Planned Behavior

Taylor and Todd (1995) indicated that a better understanding can be achieved when the behavioral beliefs are decomposed. As mentioned (Taylor & Todd, 1995), the decomposition can be based on the DoI theory where the behavioral beliefs can be decomposed into relative advantage/disadvantage, compatibility and complexity. Furthermore, Taylor and Todd (1995) showed that the decomposed model has more explanatory power compared to TRA and TPB. Related to the normative beliefs given the fact that it was found that a decomposition of them can be supported, Taylor and Todd (1995) decided that there is no need for decomposition. On the other hand, perceived behavioral control can be decomposed into two categories (Ajzen, 1991); facilitating conditions, which reflects the needed resources in order to perform the target behavior and self-efficacy, which reflects the self-confidence of an individual to behave successfully.

2.4 Concluding Remarks

Stated preference/choice studies, which follow an experimental design to examine potential user preferences/behaviors, have been conducted over the last few years worldwide exploring people's perceptions of and attitudes towards AVs in attempt to predict the market penetration rate and ascertain people's willingness to pay for AVs. These studies have gauged not only the public's perspective on AVs but also the perspective of transportation experts, which can provide valuable insights for policy making.

This section discussed the objectives and methodologies of prior stated preference/choice studies about AVs, summarized their key findings, and categorized them. The reviewed studies were also categorized based on the study population (general population, vehicle owners, and transportation experts). Furthermore, the questions included in the reviewed studies were classified according to different components that may affect opinions and attitudes that influence behavioral intention to ride in AVs. Lastly, this chapter explored and summarized the benefits of AVs, barriers to and concerns about AVs, and opportunities for AV deployment.

The review of the stated preference/choice studies about AVs revealed that studies targeting the general public mainly focused on the socio-demographic and travel characteristics of respondents; whereas studies targeting vehicle owners further attempted to classify the respondents into different level of adopters. On the other hand, studies targeting transportation experts mainly tried to unravel policy-planning implications of AVs from an agency perspective. Furthermore, most studies have examined the behavioral characteristics, perceptions, and attitudes related to AVs using descriptive analysis or some sort of econometric analysis. Interestingly, models of intention to use AVs based on theories such as TRA (Fishbein & Ajzen, 1975) and TPB (Ajzen, 1991), which can relate behavior with attitudes, have not been estimated to date. While some studies have investigated the likelihood that AVs will be adopted and the process by which that might happen, the questions included in those studies' respective surveys have not been based on well-established theories. By evaluating herein the studies that have included surveys about AVs according to components affecting opinions and attitudes that influence behavioral intention to ride in AVs, this chapter has identified different factors that may affect behavioral intention to ride in AVs. These factors include the level of awareness of AVs; consumer innovativeness; safety; trust of strangers; environmental concerns; relative advantage, compatibility, and complexity; subjective norms; self-efficacy; and driving-related seeking scale. Some of the reviewed studies included one or more of the aforementioned components and examined whether that factor or set of factors influences behavioral intention. However, possible interrelations between these components and behavioral intention to ride in AVs have not been explored to date. Such an approach could explain how, why, and to what extent an emerging technology like AVs can diffuse.

This chapter also summarized the benefits and barriers to the widespread adoption of AVs that were perceived as most important in each study. As indicated by the majority of the reviewed studies, there is a consensus among researchers that the widespread diffusion of AVs on road networks leads to fewer crashes, lower vehicle emissions, better fuel economy, and improved productivity while riding in AVs. Most studies also agreed on the potential barriers to AV adoption, such as legal liability and ethical issues, privacy concerns (i.e., about the disclosure of trip data), cybersecurity, and hacking issues. However, there is no consensus on the mobility and travel demand benefits of AVs. Some studies concluded that AVs would enhance mobility independence for the elderly and transportation disadvantaged and reduce travel times, whereas other studies indicated that the diffusion of AVs may increase vehicle miles traveled and thus, result in longer commuting distances and greater urban sprawl. On a similar note, some studies suggested that the widespread adoption of AVs is expected to reduce the need for parking in higher rent locations and alter residential and commercial land use. Gaining a better understanding of the potential impacts of AV deployment on travel demand and land use could lead to better informed policy recommendations. For example, Haboucha et al. (2017) recommended preemptive measures to mitigate the impacts of AV deployment on land use and travel patterns. Other studies (Bansal et al., 2016; Begg, 2014) suggested the need for innovative road pricing to manage travel demand.

The reviewed studies for SAVs focused on studies attempting to evaluate the economic feasibility of SAVs by conducting simulation scenarios. Different approaches were used in the simulation scenarios, such as different pricing schemes, replacing traditional taxi fleet with shared-taxi fleet operated through AVs or applying different market share of SAVs, and implementing dynamic ride-sharing. In general, it was concluded that SAVs can provide more flexible service than car-sharing services and cheaper than existing non-autonomous ride-sharing services.

Both researchers and transportation professionals can benefit from this condensed review of the literature on public and expert perceptions of this emerging technology. Researchers can build on the existing work and address the research gaps identified, while transportation professionals contemplating the implementation of AVs can benefit from the important insights in the reviewed studies regarding AV adoption. Note that this section presents the current status quo on behavioral studies regarding AVs. Due to the emergent nature of this topic, the state of the art in this area is rapidly changing as several behavioral studies are currently being conducted both in the US and internationally.

3. EMPIRICAL SETTING AND DATA

This chapter provides information about the questionnaire and more specifically details are provided about the survey design, the sampling methods used and the data collection that led to the final sample.

3.1 Empirical Setting

The case study areas evaluated in this dissertation are the metropolitan areas of Chicago, Illinois, and Indianapolis, Indiana. Indianapolis is mainly an automobile-oriented city, where 82% of commuters drive alone to get to work, 2% of workers use public transportation, and 10% carpool to get to work and approximately 6% use other modes (e.g., walking or biking). On the other hand, Chicago has an advanced multimodal transportation system offering additional transportation modes alternatives. In particular, regarding to the 2017 NHTS, approximately 50% of people in Chicago use their private vehicles, around 8% carpool, approximately 28% use public transportation, and around 14% use other modes (e.g., walking or biking) for the commuting trips. Furthermore, more than 23% of the Chicago residents commute less than 5 minutes to work in comparison with 6.1% in Indianapolis. Indianapolis is also four times less densely populated than Chicago, and exhibits below-average transit coverage (42%) compared to Chicago (79%) (US Census Bureau, 2015).

The area of the metropolitan area of Chicago was used as a case study for the analysis of Chapter 4, where a theoretical model is developed to assess the behavioral intention to ride in AVs. One study area was selected for this analysis in order to evaluate and test the developed theoretical model. One study area was selected since one of the objectives was to validate the use of the theoretical model. The proposed theoretical model can be replicated and the developed survey instrument can be disseminated in other urban areas to compare the findings on AV adoption and corresponding impacts of deployment. Furthermore, for the analysis of Chapters 5 and Chapter 6 both areas were considered as case studies. This way, the results could provide feedback on whether the attributes vary among cities with different characteristics.

3.2 Survey Design

3.2.1 Overview

A survey instrument was created and presented in APPENDIX A to accomplish the research objectives. The questionnaire included five sections and it was based on the supporting literature.

1. Level of awareness:

Specifically, a section of questions was included regarding people's awareness towards AVs. Awareness may be used as a proxy to characterize an individual who follows the news on AVs and it is hypothesized that it indicates someone who uses multiple modes of transportation for his/her trips. Additionally, high level of awareness can indicate the innovators - first group of people to adopt the innovation, even though a high degree of uncertainty exists, their interest in new ideas leads them out of local circles and into more cosmopolite social relationships - or early adopters - second group to adopt the new idea who are considered as 'localites' instead of 'cosmopolites', since they are respected by their peers in a form of a role model in their social system - of Rogers' DoI.

2. Travel characteristics:

Additionally, a section of travel characteristics was included in the final questionnaire, where respondents are asked to fill out a mini travel diary regarding their mode of transportation related to each trip purpose. Additionally, some questions are included to determine if they are 'heavy', 'light' or 'not-at-all' users of private vehicles, car-sharing services and on demand ride-sharing services. This set of questions is expected to be used in the majority of analyses that will be conducted for the purposes of this dissertation. Furthermore, a table which includes different attributes that affect mode choice decisions is included in the final questionnaire. Respondents are asked to indicate the level of importance (rank) that each attribute has when they choose a transportation mode for a short distance work trip (a short distance work trip is defined as a trip commuting to work that is less than 50 miles). The attributes consist of cost, travel time, waiting time, reliability (not being late), convenience and comfort, safety, distractions (such as travel companions, scenery), flexibility of travel (being able to go wherever and whenever I want to go), and ease of traveling (minimized the required effort for travel). The aforementioned attributes were found from supporting literature and most specifically on surveys about traditional modes of transportation (mostly, private vehicles, walk and public transportation) and it was found that are valued highly regarding mode choice decisions.

3. Opinions on AVs:

Theoretical models such as the TRA (Fishbein & Ajzen, 1975), TPB (Ajzen, 1991), Theory of DoI (Rogers, 1995) and DTPB (Taylor & Todd, 1995) were thoroughly discussed in subsection 2.3 of the literature review. The proposed theoretical model that will assess the behavioral intention to ride in AVs. Specifically, it includes three components based on the DoI (relative advantage/disadvantage, compatibility and complexity), subjective and personal moral norms, two components that may affect the perceived behavioral control (self-efficacy, trust with strangers), the component of driving-related seeking scale which can be linked with psychological factors and people's personality, and the component of environmental concerns to capture potential habitual factors that are not based on rational decisions but it is formed through repeated performances (habit). For a more detailed discussion on each component included in the theoretical model refer to subsection 4.2.

4. Choice experiment

Choice experiment of stated preferences will be conducted in order to assess the attributes, which impact people's opinion as their preferred mode of transportation, if AVs fleet is implemented in different time periods. In other words, based on hypothetical scenarios in different time periods, the respondents will form their personal mobility portfolio. The design of the choice experiments is thoroughly discussed in subsection 6.2.1.

5. Socio-demographics

Lastly, typical socio-demographic questions were added in the final questionnaire in order to relate the respondents' characteristics of the previous sections to a specific socio-demographic profile. Particularly, questions were added about the gender, age group, employment situation, annual household income, highest level of education, race, ethnicity, people living in a household, children living in a household, holders or driver's license and brief crash history.

3.2.2 Remedies about Hypothetical Bias

In general, revealed preferences are preferred than stated preferences surveys since the former represents a real setting and the latter relies on hypotheses. However, in the case of AVs, it is difficult to conduct a revealed preferences survey, because the AVs are not widespread. Additionally, in stated preferences surveys several 'what-if' scenarios can be conducted which may provide useful insights for decision-making process by enabling the testing of new ideas or attribute levels that do not currently exist. On a similar note, stated preferences surveys are preferred than revealed ones under the domain of value of travel time savings (VTTS) or choice experiments, since the revealed ones are not strictly equivalent to real market data and the data forced on the respondent for non-chosen alternatives is controversial (concerns about lack of variance and measurement error) as discussed in Hensher, Rose, and Greene (2005). On the other hand, hypothetical bias is evident in the stated preferences surveys, as discussed next.

One of the main criticisms of stated preferences surveys is the fact that the choices are made in a hypothetical setting and do not equate to choices that would be made in real life settings (hypothetical bias). Potential remedies for the hypothetical bias are split into ex ante and ex post techniques. It was found that by including an opt-out or null alternative in the choice experiment, respondents are not forced to select a choice which improves the results (Alfnes & Steine, 2005; Lusk, Feldkamp, & Schroeder, 2004). Cheap talks (ex-ante technique) are one of the most successful attempts to reduce the influence of hypothetical bias (Cummings, Harrison, & Osborne, 1995; Cummings, Harrison, & Rutström, 1995). Cheap talks describe and discuss the tendency of the respondents to exaggerate and encourage respondents to avoid hypothetical bias (Brown et al., 2003; Cummings, Harrison, & Rutström, 1995). List, Sinha, and Taylor (2006) found that by including cheap talks in choice experiments can yield credible estimates of the purchase or use decision. Norwood (2005) indicated that when a scale of 1 to 10 (where 10 means very certain) was used and the completed responses of a value lower than 8 was coded as 'no' responses, the hypothetical bias was disappeared. This approach can also be explored by asking the respondents to swear to tell the truth (Jacquemet et al. 2013) by signing an oath and it can eliminate the hypothetical bias when it is combined with cheap talks. Moreover, it was found that pivoting the attribute levels of a choice experiment around a reference alternative which has already been experienced or there is substantial awareness (in this survey, the mode choices of driving a private vehicle or using the public transportation) can provide more accurate results. For this reason, the attribute levels of the choice experiment were pivoted (percentage decrease or increase of each attribute level corresponding to its reference value) to existing reference alternatives identified in the literature.

3.3 Sampling Methods

As it was mentioned previously, the surveys were distributed in a major urban area with a multimodal transportation system and captive users of ride-sharing users (Chicago) and a city with a car-oriented culture (Indianapolis). The metropolitan area of Chicago (Chicago-Naperville-Joliet, Illinois-Indiana-Wisconsin) was selected and has a population of 2,695,598 (US Census, 2010). The metropolitan area of Indianapolis (Indianapolis-Carmel-Anderson) was also selected with a population of 2,082,142 (US Census, 2010). The target population of the questionnaire were people who are currently living in Chicago and Indianapolis and they are over 18 years. The objective is to collect a representative sample of both study areas. The questionnaires were distributed online through LightspeedGMI which has a panel that resides in Chicago and Indianapolis.

Web-based surveys are preferred since they cost lower than face to face interviews and telephone surveys and the data can be obtained faster. Additionally, the web-based surveys are more interactive, visual and they have more flexibility and they can be taken any time, since the respondent does not need to be present at a specific time. It was found that people who often ignore participating in telephone surveys are more willing to participate in web-based surveys (Duffy, Smith, Terhanian, & Bremer, 2005; Kellner, 2004). However, often the sample is not representative and a current practice to make the sample representative is to weight variables in regards with socio-demographic characteristics and various attitudes (Lee & Valliant, 2009; Loosveldt & Sonck, 2008). Furthermore, some studies came to the conclusion that online panels attract a more knowledgeable sample than face-to-face surveys (Duffy et al., 2005).

One of the limitations of this study is the fact that the surveys were distributed online and hence the target populations were not a random probability sample which is almost identical with the sampled population. Instead, they were convenience samples, which is under-coverage since some people cannot be reached (either they do not have access to the internet or they are not included in the online panel) and some of them will refuse.

However, in order to minimize the limitation of the convenience sample and to have a representative sample, hard quotas were implemented related to the gender and the age groups to represent the ratios of each group according to the US Census data (2010). Specifically, for Chicago the sample consisted of almost equally with male and female and it will include 18.1% of respondents to be 18-24 years old, 25% to be 25-34 years old, 20.4% to be 35-44 years old, 15.5%

to be 45-54 years old, 10.1% to be 55-64 years old and 14% to be over 65 years old. Specifically, for Indianapolis the sample consisted of almost equally with male and female and it will include 17.6% of respondents to be 18-24 years old, 16.6% to be 25-34 years old, 16.6% to be 35-44 years old, 18.1% to be 45-54 years old, 14.9% to be 55-64 years old and 16.2% to be over 65 years old. Table 3.1 shows the panel counts of LightspeedGMI in Chicago and Indianapolis along age groups.

Table 3.1: Panel counts of survey distributor in Chicago and Indianapolis

Age groups	**Chicago**		**Indianapolis**	
	Male	**Female**	**Male**	**Female**
18-24 years old	412	941	271	436
25-34 years old	364	896	224	462
35-44 years old	323	837	283	509
45-54 years old	448	1082	365	583
55-64 years old	541	1147	397	567
65+ years old	637	1274	448	604

The sample size of the survey was decided based on the parameters of margin of error (MoE), confidence level and the population of Chicago and Indianapolis. The MoE reflects the confidence intervals and defined as positive or negative deviation that it is allowed on survey results of the sample. The parameter of confidence level explains the confidence of the sample and a confidence level of 95% is used and a 5% of MoE are adopted.

$$MoE = z\sqrt{\frac{p\,(1-p)}{n}} \quad (Eq. 3.1)$$

,where MoE is the margin of error (5%), z is the z-score for 95% confidence level (1.96), p is our initial estimate of p which is not known and hence a value of 0.5 is used as a conservative assumption and n is the desired sample size.

Therefore, it was found that at least a sample of 385 respondents is needed to meet the requirements of the parameters. Finally, it was decided that the sample sizes will be consisted of 400 current residents for each study area, older than 18 years old.

3.4 Data Collection and Final Sample

The surveys were distributed online using Qualtrics in October-November 2017 (IRB Protocol Number: 1701018708) in Chicago and May 2018 (IRB Protocol number 1801020160) in Indianapolis. The target population of the surveys were adults residing in the metropolitan areas soliciting a total of 400 completed responses in each area to ensure a confidence level of 95% and a 5% of margin of error. Additionally, the sample is considered representative in terms of age and gender because hard quotas were implemented for these groups (US Census data, 2010). The sample includes participants with higher level of education and income compared to the general population. Table 3.2 presents summary statistics of socio-economic and demographic variables.

Table 3.2: Summary statistics of selected socio-economic and demographic variables

		Chicago		Indianapolis	
Variable	Description	Freq. (sample)	*Freq. (Census)	Freq. (sample)	*Freq. (Census)
Gender	Male	47%	47%	46%	46%
	Female	53%	53%	54%	54%
Age	18-24 years old	14%	14%	18%	18%
	25-34 years old	25%	25%	17%	17%
	35-44 years old	18%	18%	17%	17%
	45-54 years old	16%	16%	18%	18%
	55-64 years old	14%	14%	15%	15%
	65 plus years old	13%	13%	16%	16%
Education	High school graduate	21%	33%	19%	38%
	Technical training after high school	5%	6%	5%	5%
	Some college	28%	18%	27%	25%
	College graduate	34%	28%	34%	20%
	Graduate school	12%	15%	14%	12%
Income	Less than $25K	16%	31%	18%	26%
	$25K-$50K	28%	23%	25%	26%
	$50K-$75K	22%	17%	23%	18%
	$75K-$100K	15%	11%	17%	11%

$100K-$150K	14%	10%	12%	11%
Over $150K	5%	8%	5%	8%

*U.S. Census 2010 data Chicago-MSA, Illinois Indianapolis-MSA, Indiana. The same data were used to accomplish representative age and gender brackets.

4. BEHAVIORAL INTENTION TO RIDE IN AUTONOMOUS VEHICLES

This Chapter describes the hypotheses leading to the theoretical model and the methodology used to evaluate the behavioral intention to ride in AVs. In particular, this chapter discusses the results of the measurement and structural model. Lastly, a summary on the evaluation of the initial hypotheses is included. Part of this work is under review in an academic journal and it is reprinted here with the authors' (Gkartzonikas, Losada-Rojas, Christ, Pyrialakou, Gkritza) permission.

4.1 Introduction

AVs have the potential to disrupt the transportation system, the automotive industry and the labor market as we know them (Anderson et al., 2014; Christensen, 1997; Milakis, Arem, & Wee, 2017; Nordhoff et al., 2019; Shaheen et al., 2018; Sprei, 2018). As such, understanding what drives the intention to use this technology and determining the corresponding implications of the diffusion of this emerging technology is critical. For example, some implications in the context of transportation system can be the potential equipment/system failures (Bansal et al., 2016; Howard & Dai, 2014), cybersecurity issues (Hulse et al., 2018; König & Neumayr, 2017; Schoettle & Sivak, 2014a), legal liability (Begg, 2014; König & Neumayr, 2017; Schoettle & Sivak, 2014a), among others.

A number of behavioral experimental studies in the form of stated-preference surveys and choice studies have been conducted to examine the general acceptance of technological advances for AVs. These surveys have covered topics such as user acceptance, risks, willingness to pay, and adoption rates (Bansal et al., 2016; Daziano et al., 2017; Kyriakidis et al., 2015) and have explored the factors that influence people's decisions regarding new technologies and the extent of influence of these factors (Bansal & Kockelman, 2017a; Hohenberger et al., 2016; Howard & Dai, 2014; Hulse et al., 2018). As mentioned in Gkartzonikas and Gkritza, (2019), previous studies that conducted surveys to associate behavioral characteristics of survey respondents with their perceptions of AVs (such as Bansal et al., 2016; Casley et al., 2013; Hohenberger et al., 2016; Kyriakidis et al., 2015; Payre et al., 2014) estimated econometric models, such as multivariate ordered probit and multinomial logit models or applied simple descriptive analysis of the survey findings.

Interestingly, research on AVs employing behavioral intention theories and models has only recently emerged. A number of studies have adopted the original TAM proposed by Davis et al. (1989) and Venkatesh and Davis (1996) (Buckley et al., 2018; Choi and Ji, 2015; Panagiotopoulos and Dimitrakopoulos, 2018; Ward et al., 2017; Wu et al. 2019, Zhang et al., 2019). Although these studies developed comparable models, they reported mixed results in terms of the association between the perceived ease of use, perceived usefulness, and the intention to ride in AVs. For example, Buckley et al. (2018) and Choi and Ji., (2015) did not find a statistically significant association between all the components of the original TAM and the behavioral intention to ride in AVs, whereas Panagiotopoulos and Dimitrakopoulos (2018) and Wu et al. (2019) reported such associations to be significant.

The TPB, proposed by Ajzen (1991), has also been explored, both as part of an extended TAM and standalone or combined with other theories. Moták et al. (2017) concluded that the constructs of TPB are influential predictors of the behavioral intention to ride in AVs; as influential as the constructs of TAM. Lee et al. (2019) further suggested extending the theoretical model of TAM with TPB as the TAM cannot capture the "distinctive properties of AVs". The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003), has also found some applications in road vehicle automation (Madigan et al, 2016) and driver support systems (Adell, 2010) and has been recently adopted in the domain of AVs. This model extends the constructs of the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975) and TAM. Madigan et al. (2017) explored the UTAUT and reported significant associations among the components of the social influence, facilitating conditions, and performance expectancy and the behavioral intention to ride in AVs.

While past studies have identified psychological and behavioral factors that can affect the intention to ride in AVs, the resulting findings of these studies did not yield a consensus, probably because of different underlying assumptions. Moreover, the most compelling theory of technology innovation diffusion, DoI proposed by Rogers (1995) has just recently received attention to forecast the market penetration and diffusion of AVs (see Lavasani et al., 2016; Luo et al., 2019; Shabanpour et al., 2018; Simpson et al. 2019; Talebian et al., 2018). However, the components of the DoI theory, such as relative advantage, complexity, and compatibility have not been examined in behavioral experiments, such as stated preference surveys. Exploring the DoI theory is important because, in addition to people's perceptions and attitudes on a specific technology or emerging idea, this theory can provide a better understanding of the characteristics of a population that help or hinder the adoption of the innovation (Mustonen-Ollila and Lyytinen, 2003).

In addition, the synergistic effects between DoI and TPB have not been explored in the context of AVs and stated preference survey-based studies. Weigel et al. (2014) reviewed more than fifty articles in the domain of information science and explored the synergies between the components of the DoI theory and the components of the original theoretical model of TPB. It was found that the synergies and associations among components were statistically significant. The reconstruction of the relationships of psychological factors and the synergistic effects between the TPB and the DoI theory could yield a better understanding regarding the behavioral intention to ride in AVs. Furthermore, as Nordhoff et al. (2018) concluded, it is important to not only evaluate the direct effects with the different constructs of the analyzed theoretical model but also to assess the interrelationships and hence, the indirect effects among the constructs. Since the current knowledge on these effects is scarce, a better understanding can lead to more accurate conclusions on the behavioral intention and thus, the public acceptance of AVs. In similar vein, behavioral experiments assessing people's attitudes toward AVs can help enhance our understanding of the potential impacts AV deployment can be achieved, which can, in turn, lead to more informed planning and policy-making.

In view of the above, this chapter proposes a theoretical model for assessing behavioral intention to use AVs based on the TPB (Ajzen, 1991) that is decomposed to include components of the theory of DoI (Rogers, 1995) to assess the development of and opportunities for AV adoption, and that is further extended to evaluate whether other attitudinal components, such as safety concerns, trust of strangers, environmental concerns, affinity to innovativeness, and driving-related sensation seeking, can also be determinants of the behavioral intention to ride in AVs. Specifically, the objectives of this chapter are a) to empirically validate the use of an extended decomposed form of the TPB that includes the aforementioned components (compatibility, complexity, relative advantage, attitudes towards use, subjective norms, personal moral norms, self-efficacy, trust of strangers, perceived behavioral control, safety concerns, driving-related sensation seeking, environmental concerns, early adopters, late adopters, and behavioral intention) by conducting a confirmatory factor analysis and b) to assess whether these components, among other factors, are key determinants of the behavioral intention to ride in AVs by estimating structural equation models. This approach can provide insights into consumer perceptions and preferences and obtaining an understanding of whether attitudinal and lifestyle factors influence the behavioral adoption of AVs.

The proposed model is demonstrated using the responses to the stated preference survey that was distributed in the Chicago, Illinois metropolitan area. One study area was selected since one of the objectives was to validate the use of the theoretical model. The proposed theoretical model can be replicated and the developed survey instrument can be disseminated in other urban areas to compare the findings on AV adoption and corresponding impacts of deployment. The transferability of the theoretical model by assessing the differences between the factors affecting the behavioral intention to ride in AVs between an area with an advanced multimodal transportation system (Chicago), an area that in terms of culture is car-oriented (Indianapolis) and an area with a greater exposure on AVs due to pilot testing and the reported first pedestrian fatality associated with AVs (Phoenix) is a next step that it is not presented in this chapter; however the reader can refer to the manuscript.

4.2 Methods

4.2.1 Theoretical Model and Hypotheses

The theoretical model is based on the TPB (Ajzen, 1991) that is discussed in subsection 2.3.2. Several attempts have been made to increase the strength of the TPB by decomposing it and adding components such as *personal moral norms* (Heath & Gifford, 2002; Kaiser & Scheuthle, 2003). Personal moral beliefs can be examined to determine whether they increase the explanatory power of the proposed model to predict the target behavior (Fagnant & Kockelman, 2015; Liu et al., 2018; Nordhoff et al., 2018; Petschnig, Heidenreich, & Spieth, 2014). *Personal moral norms* imply that an individual considers himself/herself morally responsible for adopting a behavior; this is different than *subjective norms,* which reflect external social pressures (Beck & Ajzen, 1991). Therefore, both components are included in the model. Two components related to the decomposition of the variable of *perceived behavioral control* can also be introduced: *self-efficacy* and facilitating conditions (Moons & Pelsmacker, 2015; Taylor & Todd, 1995). Although *self-efficacy* can be assessed in terms of AVs, the component of facilitating conditions is problematic.

Facilitating conditions reflect the resources needed to perform the target behavior in terms of time and money. Because such information is still being studied in the case of AVs, individuals do not have the information required to decide on the resources needed to perform the target behavior (Choi & Ji, 2015; Sanbonmatsu et al., 2018). Another component that is introduced with *perceived behavioral control* is *trust of strangers*, which can potentially influence *behavioral intention* (Azam & Qiang, 2012; Hawes, Mast, & Swan, 1989; Pavlou & Fygenson, 2006), also in the context of AVs (Acheampong & Cugurullo, 2019; Buckley et al., 2018; Choi & Ji, 2015; Liu et al., 2018). Buckley et al. (2018) and Choi and Ji (2015) found that the component of *perceived behavioral control* is only associated with the *behavioral intention* to use; whereas it can be extended by including the component of *self-efficacy*.

The model also includes three components based on the DoI theory: *relative advantage/disadvantage*, *compatibility*, and *complexity*. In related work, Moons and Pelsmacker (2015) designed a decomposed TPB to predict the usage intention of electric vehicles in Belgium. Specifically, Moons and Pelsmacker (2015) they decomposed the behavioral beliefs of respondents according to decomposed TPB by using the three innovation characteristics established by Rogers (1995): *complexity*, *compatibility*, and *relative advantage*. However, the authors did not use the other two innovation characteristics established by Rogers (1995), observability and triability, which can provide insight into *subjective norms*, because these characteristics could not be captured in terms of the adoption of electric vehicles at that time. Other studies came to similar conclusions (Petschnig et al., 2014). Because AVs have not been widely introduced to the public and are not available on the market, the components of observability and triability were left out of the present model as well. In other words, due to the limited availability of AVs, observability is relatively low and triability is challenging to assess.

The model is enriched and extended by implementing additional factors related to different habits because habits are not based on rational decisions, which are the basis of the TPB, but rather are formed through recurrent performances. According to Aarts, Paulussen, and Schaalma (1997), habitual factors play a critical role in travel mode decisions, and this finding is supported by other studies (Verplanken, Aarts, van Knippenberg, & Moonen, 1998; Verplanken, Aarts, Knippenberg, & Knippenberg, 1994; Wood, Tam, & Witt, 2005). In the proposed model, variables related to *environmental concerns* are the components that are used to assess habitual factors. Thogersen and Olander (2006) argued that behaviors towards the environment can be perceived as habitual behaviors. This assumption is also verified by other studies in different fields (Bamberg, 2003; Bamberg & Möser, 2007; Daziano et al., 2017; Heath & Gifford, 2002, 2002; Roy, Potter, & Yarrow, 2004; Sanbonmatsu et al., 2018; Schultz, 2001; Wu et al., 2019). Furthermore, a component capturing *safety concerns* regarding AV technology is used to extend this model, as it was found in different studies in transportation (Musselwhite, 2004; Musselwhite & Haddad, 2007). In related work, Hulse et al. (2018) assessed people's perception towards and acceptance of AVs with regards to safety by including questions pertaining to the perceived risk of AVs. (Bamberg, 2003; Liljamo et al., 2018; Liu et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018; Penmetsa et al., 2019; Qu, Xu, Ge, Sun, & Zhang, 2019; Sener et al., 2019; Shabanpour et al., 2018; Zoellick et al., 2019) evaluated whether *safety concerns* related to AV technology influences negatively the *behavioral intention* to use and adoption of AVs.

Additionally, an additional component that extends the decomposed TPB is *affinity to innovativeness*, which captures the five adopter categories established by Rogers' DoI: innovators, early adopters, early majority, late majority, and laggards. Trends in technology adoption indicate that even when a new technology is attractive to early adopters, the majority of people remain skeptical and are unwilling to accept it (Edison & Geissler, 2003; Egbue & Long, 2012). Innovativeness is an essential criterion of behavior explaining how a technology diffuses (Rogers, 1995), and hence it may be an important factor that moderates the adoption process. The importance of *affinity to innovativeness* is supported in the literature (e.g., Shin et al., 2015). Sanbonmatsu et al. (2018) found that people of higher level of awareness towards AVs have a higher *behavioral intention* to adopt AVs. Similar findings were found by Asgari and Jin (2019). Another component that extends the decomposed TPB is *driving-related sensation seeking* (DRSS*)*, derived from Zuckerman and Neeb (1979). Sensation seeking is a trait defined by the need for complex sensations and the willingness of an individual to take risks for a target experience. This trait is linked to physiological factors and an individual's personality. Sensation seeking can predict risky driving (Adell, 2010; Jonah, Thiessen, & Au-Yeung, 2001), and it has been shown to be mediated through attitudes ((Ulleberg & Rundmo, 2003). Delhomme, Verlhiac, and Martha (2009) implemented *DRSS* in a survey by focusing on comparative judgments about the risks involved in speeding among young drivers. Cestac, Paran, and Delhomme (2011) extended the basic TPB by including *DRSS* and other additional factors to assess whether these factors influence the speeding-related behavior of young drivers. Additionally, Delhomme, Chaurand, and Paran (2012) concluded that *DRSS* can predict speeding better than factors that influence ‘road rage’.

The theoretical model designed to assess the behavioral intention to ride in AVs is an extended version of the DTPB. Figure 4.1 shows the proposed theoretical model.

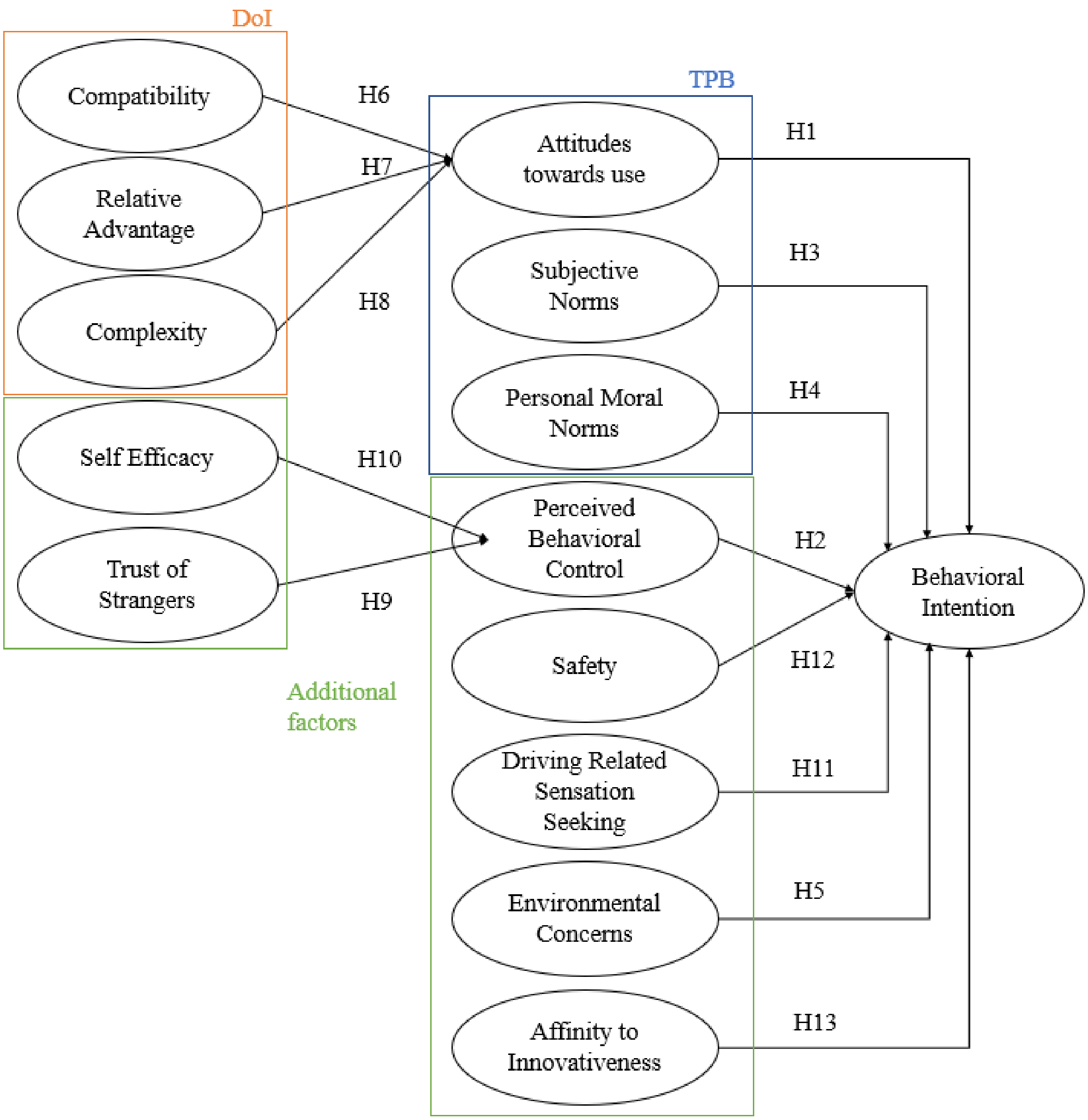

Figure 4.1: Theoretical model assessing the behavioral intention to ride in AVs

The initial hypotheses of the theoretical model that are assessed and shown in Figure 4.1 are outlined below:

H1: *Attitudes towards use* have a positive influence on *behavioral intention* (Ajzen, 1991; Beck & Ajzen, 1991; Jansson, 2011; Moons & Pelsmacker, 2012, 2015; Payre et al., 2014; Petschnig et al., 2014).

H2: *Perceived behavioral control* has a positive influence on *behavioral intention* (Ajzen, 1991; Nysveen, Pedersen, & Thorbjørnsen, 2005).

H3: *Subjective norms* have a positive influence on *behavioral intention* (Ajzen, 1991; Moons & Pelsmacker, 2015; Petschnig et al., 2014; Venkatesh et al., 2003).

H4: *Personal moral norms* have a positive influence on *behavioral intention* (Fagnant & Kockelman, 2015; Kaiser & Scheuthle, 2003, 2003; Petschnig et al., 2014).

H5: *Environmental concerns* have a negative influence on *behavioral intention* (Bamberg, 2003; Bamberg & Möser, 2007; Roy et al., 2004; Thogersen & Olander, 2006).

H6: *Compatibility* has a positive influence on *attitudes towards use* (Moons & Pelsmacker, 2015; Rogers, 1995, 2003).

H7: *Relative advantage* has a positive influence on *attitudes towards use* (Moons & Pelsmacker, 2015; Rogers, 1995, 2003).

H8: *Complexity* has a negative influence on *attitudes towards use* (Moons & Pelsmacker, 2015; Rogers, 1995, 2003).

H9: *Trust of strangers* has a positive influence on *perceived behavioral control* (Azam & Qiang, 2012; Hawes et al., 1989; Pavlou & Fygenson, 2006).

H10: *Self-efficacy* has a positive influence on *perceived behavioral control* (L. Beck & Ajzen, 1991; Moons & Pelsmacker, 2015; Taylor & Todd, 1995).

H11: *Driving-related sensation seeking* has a positive influence on *behavioral intention* (Cestac et al., 2011; Payre et al., 2014; Taylor & Todd, 1995).

H12: *Safety concerns* have a negative influence on *behavioral intention* (Musselwhite, 2004; Musselwhite & Haddad, 2007).

H13a: *Early adopters* have a positive influence on *behavioral intention* (Edison & Geissler, 2003; Egbue & Long, 2012; Moons & Pelsmacker, 2015; Rogers, 1995).

H13b: *Late adopters* have a negative influence on *behavioral intention* (Edison & Geissler, 2003; Egbue & Long, 2012; Moons & Pelsmacker, 2012; Rogers, 1995).

4.2.2 Model Specification

Firstly, the identified components (latent variables) mentioned in the hypotheses above were tested in terms of reliability and validity. In particular, the structure of these components was examined using confirmatory factor analysis (CFA) to form the measurement model. Secondly, the behavioral intention to ride in AVs was assessed using SEMs. Lastly, using the findings of the measurement model the structural model is evaluated to assess the different hypotheses and the fit of the model using various goodness-of-fit measures.

SEMs have been widely used in travel behavior research as they allow the introduction of latent constructs as dependent variables, identify the latent variables that are unobserved, and incorporate measurement errors into the modeling framework (Golob, 2003; Washington, Karlaftis, & Mannering, 2011). As the intention to ride in AVs is a complex process that is affected by individuals' perceptions and attitudes towards AVs as well as other unobserved factors, such as *DRSS* and *perceived behavioral control,* SEM analysis is preferred compared to simple regression analysis. Traditional regression analysis cannot accommodate latent variables or model the relationships among multiple constructs simultaneously (Gefen, Straub, & Boudreau, 2000). When measurements errors are incorporated in independent variables in a regression analysis, the parameter estimates are biased and can inflate the model error variance and overall, goodness-of-fit measures (Washington et al., 2011).

4.2.3 Exploratory Analysis

The latent factors explored for this model were *complexity*, *compatibility*, *relative advantage*, *attitudes towards use*, *subjective norms*, *personal moral norms*, *self-efficacy*, *trust of strangers*, *perceived behavioral control*, *environmental concerns*, *safety*, *affinity to innovativeness*, *DRSS*, and *behavioral intention* to ride in AVs. A 5-point Likert-type scale was implemented, ranging from 1 (strongly disagree) to 5 (strongly agree). An explanatory factor analysis (EFA) was conducted to test the structure of the sets of variables. This analysis was conducted using the maximum likelihood method in IBM SPSS. Thirteen factors with eigenvalues greater than 1 were identified that explained approximately 66.5% of the variance of the dataset; these factors are shown in Table 4.1. Additional factors emerged from the EFA; specifically, the factor of *affinity to innovativeness* was split into two factors: *early adopters* and *late adopters*.

Table 4.1: Exploratory factor analysis, total variance explained

Factor	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1 – Attitudes	25.212	33.616	33.616
2 – DRSS	4.931	6.575	40.191
3 – Perceived Behavioral Control	3.380	4.507	44.698
4 – Late Adopters	2.988	3.984	48.682
5 – Trust of Strangers	2.598	3.464	52.147
6 – Environment	2.013	2.684	54.831
7 – Behavioral Intention	1.598	2.131	56.962
8 – Early Adopters	1.443	1.924	58.886
9 – Subjective Norms	1.259	1.678	60.564
10 – Compatibility	1.191	1.589	62.153
11 – Perceived Moral Norms	1.153	1.538	63.691
12 – Self-efficacy	1.072	1.429	65.120
13 – Relative Advantage	1.032	1.376	66.496

The validity of the EFA was evaluated using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity (Kaiser, 1974). Both tests confirmed that the sample is adequate (KMO value of 0.951, and p-value of Bartlett's test chi-square test < 0.001). The reliability of each factor identified in the EFA was examined calculating Cronbach's alpha values. As a rule of thumb, a factor is not reliable if Cronbach's alpha value is found to be less than 0.7, at which point the factor is dismissed from further analysis. In particular, based on this analysis, the components of complexity and safety concerns were dismissed and not used to the measurement model. The Cronbach's alpha values for the factors identified in the EFA are shown in Table 4.2, along with the mean and standard deviation values for each item included on each factor. The pattern matrix obtained from the exploratory factor analysis is provided in Table B1 found in Appendix B.

Table 4.2: Exploratory factor analysis, reliability

Factor	Survey Questions	Mean	St. Dev.
1 – Attitudes (Att)		3.151	1.307
	a. I dislike/like the thought of riding in AVs.	3.050	1.269
	b. Riding in AVs would be a bad/good idea for me.	3.228	1.298

Table 4.2: continued

	c. I would find riding in AVs useless/useful for my purposes.	3.203	1.331
	d. Riding in AVs sounds stupid/smart to me.	3.310	1.244
	e. Riding in AVs sounds scary/fun to me	2.978	1.344
	f. Riding in AVs would be not suitable/suitable for my needs.	3.155	1.315
	g. For me, riding in AVs is undesirable/desirable.	3.138	1.337
2 – DRSS		2.547	1.263
	a. I would like to drive without a preplanned route and without a schedule.	3.195	1.116
	b. I often feel like being a race car driver.	2.345	1.261
	c. I would like to drive on roads with many sharp turns.	2.303	1.157
	d. I would like to learn to drive cars that can exceed the speed of 180 mph.	2.445	1.381
	e. I do not have patience for people who drive cars in a predictable and boring manner.	2.588	1.138
	f. I think I would enjoy the experience of driving very fast on a steep road.	2.408	1.302
3 – Perceived Behavioral Control (PBC)		3.168	1.093
	a. When AVs become widely available, I believe I would afford to purchase one.	2.773	1.153
	b. When AVs become widely available, I believe I would afford to ride in one.	3.178	1.077
	c. When AVs become widely available, I believe I will have the necessary means and skills to ride in an AV.	3.315	1.041
	d. When available, I will have the ability and opportunity to ride in an AV if I want to.	3.408	0.989
	e. When AVs become widely available, I would know enough to ride in one.	3.480	1.028
4 – Late Adopters (LA)		3.125	1.001
	a. I need to be convinced of the advantage of innovations by peers.	3.290	0.997
	b. I am suspicious of innovations.	2.860	1.006
	c. I will adopt innovations but do not attempt to influence others to do so.	3.295	0.900
	d. I go along with innovations out of necessity.	3.180	0.927
	e. I am resistant to change.	2.728	1.091
5 – Trust of Strangers (TS)		3.286	1.217
	a. Most people will try to take advantage of someone else, if they get the chance to do it.	3.470	0.986
	b. Most people only look after themselves.	3.458	0.970
	c. You cannot trust most people.	3.143	1.061

Table 4.2: continued

	d. You cannot trust strangers.	3.420	1.006
6 – Environment (Env)		4.091	0.845
	a. I think that people should live in harmony with nature in order to achieve sustainable development.	3.978	0.805
	b. I think individuals have responsibility to protect the environment.	4.225	0.749
	c. I think environmental problems are becoming more and more serious in recent years.	4.145	0.864
	d. I think we are not doing enough to save scarce natural resources from being used up.	4.015	0.931
7 – Behavioral Intention to Ride in AVs (Int)			
	a. I intend to ride in an AV when AVs become available.	3.095	1.162
	b. I intend to ride in an AV in the near future.	2.858	1.186
	c. I intend to frequently ride in an AV in the near future.	2.640	1.142
	d. I would recommend the use of AVs to other people.	3.010	1.122
	e. I intend to ride in an AV in the foreseeable future.	2.990	1.168
	f. I intend to frequently ride in an AV in the foreseeable future.	2.793	1.159
8 – Early Adopters (EA)		3.314	0.946
	a. I am adventurous and eager to be the first to try new innovations.	3.253	1.110
	b. I adopt innovations and influence others to do so.	3.163	1.039
	c. I am willing to follow the lead of others in adopting innovations.	3.398	0.901
	d. I am always looking for innovations.	3.273	0.978
	e. My opinion about innovations is respected by peers.	3.425	0.834
9 – Subjective Norms (SN)		3.082	1.059
	a. People who are important to me will support my decision on riding in an AV.	3.555	0.959
	b. The media make it more appealing for me to ride in an AV.	3.113	1.057
	c. People who are important to me would try to convince me to ride in an AV.	2.950	1.039
	d. People who are important to me would want me to ride in an AV.	3.043	1.017
	e. People who are important to me would prefer I rode in an autonomous vehicle.	2.903	1.042
10 – Compatibility (Comp)		3.068	1.115
	a. The thought of riding in AVs suits my lifestyle.	3.043	1.106
	b. Riding in an AV suits my daily needs.	3.128	1.116

Table 4.2: continued

	c. Riding in an AV fits well with my habits.	3.033	1.122
11 – Perceived Moral Norms (PMN)		2.966	1.094
	a. Because of my own principles, I would feel an obligation to ride an AV, if one is accessible, due to its lower fuel consumption.	2.953	1.155
	b. Regardless of what other people do, I would feel morally obliged to ride in an AV, if one is accessible, due to its lower emissions.	2.920	1.128
	c. I would feel a moral obligation to ride in an AV, if one is accessible, as it is expected to be friendlier to the environment.	2.993	1.121
12 – Self-efficacy (SE)		3.410	1.021
	a. I will have the knowledge to ride in an AV.	3.355	0.991
	b. I would be capable to ride in an AV.	3.545	1.010
	c. It would be easy for me to control all things relevant to riding in an AV.	3.260	1.032
13 – Relative Advantage (RA)		3.287	1.019
	a. AVs offer more benefits to our society than non-AVs.	3.278	0.974
	b. Riding in AVs would reduce the number of accidents compared to riding in non-AVs.	3.285	1.023
	c. Riding in AVs would be more environmental-friendly than riding in non-AVs.	3.303	0.958
	d. Riding in AVs would reduce the time that I spend sitting in traffic congestion than riding in non-AVs.	3.060	1.060
	e. I would be free to make the most of my time spent in a vehicle, if I am riding in an AV rather than riding in non-AVs.	3.510	1.036
	f. The automated driving technology installed in AVs is likely to be a better driver than I am.	3.058	1.110
	g. Riding in an AV will enable me to reach my destination safer than riding in a non-AV.	3.210	1.086
	h. While riding in an AV, I will not need to pay attention to the traffic.	2.583	1.262
	i. It would be easy for me to ride in an AV.	3.223	1.114
	j. I will find it easy to make the AV do what I want.	3.218	0.966

4.3 Estimation Results

4.3.1 Measurement Model

The latent factors explored in the theoretical model were *complexity, compatibility, relative advantage, attitudes towards use, subjective norms, personal moral norms, self-efficacy, trust of strangers, perceived behavioral control, environmental concerns, safety, early adopters, late adopters, DRSS, and behavioral intention* to ride in AVs. As mentioned above, a 5-point Likert-type scale was implemented for the structure of the survey questions, ranging from 1 (strongly disagree) to 5 (strongly agree). The latent factors identified from the exploratory factor analysis were also tested in SPSS Amos by first conducting CFA using maximum likelihood estimation to test the structure of the latent variables in terms of reliability and validity. CFA is performed in order to verify that the observed variables correctly measure the latent variables. A maximum likelihood method was used for the CFA in IBM SPSS Amos. The findings of the EFA did not support the structure of the theoretical model shown in Figure 4.1. Therefore, a revised model is estimated, and it is shown in Figure 4.2.

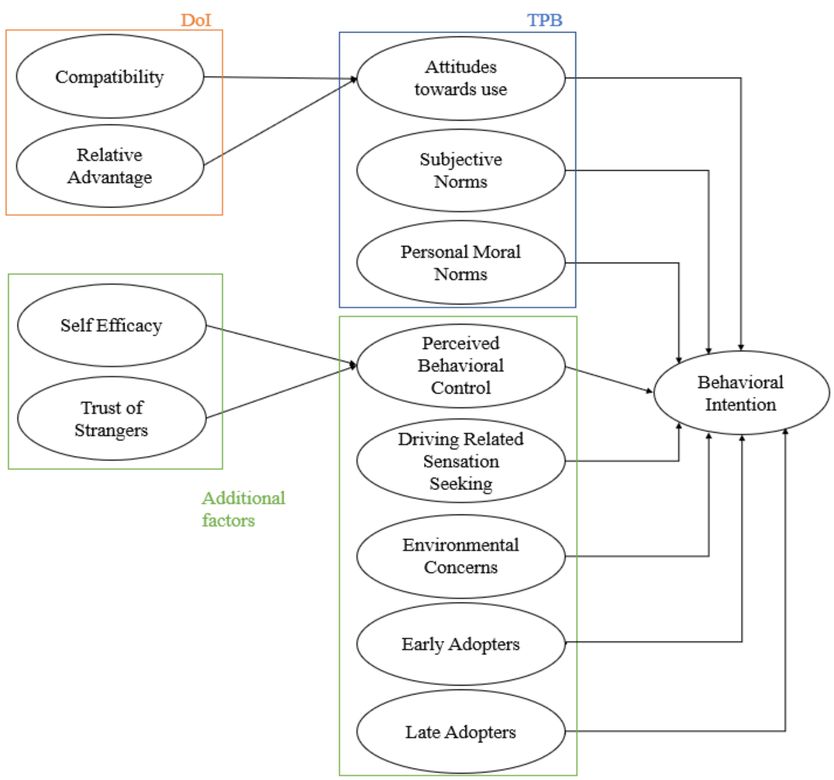

Figure 4.2: Revised model - structural model assessing the behavioral intention to ride in AVs

The reliability of each factor identified in the CFA was examined calculating Cronbach's alpha values. As a rule of thumb, a factor is not reliable if Cronbach's alpha value is found to be less than 0.7, at which point the factor is dismissed from further analysis. In particular, based on this analysis, the components were satisfactory in terms of reliability (shown in last column of Table 4.2). The results pertaining to the validity testing from the CFA include the composite reliability (CR) and average variance extracted (AVE). The obtained values of the average variance extracted (AVE) and the values of the composite reliability (CR) are higher than 0.5 and 0.7, respectively, and suggest that the revised model is reliable with no indications of convergent validity testing (Hair, 2010). The composite reliability and average variance extracted values are shown in Table 4.3.

Table 4.3: Validity testing of CFA

	Average Variance Extracted (AVE)	Composite reliability (CR)
Attitudes towards use	0.582	0.906
Driving-related Sensation Seeking	0.504	0.855
Perceived Behavioral Control	0.547	0.857
Late Adopters	0.503	0.835
Trust of Strangers	0.550	0.830
Environmental Concerns	0.540	0.824
Behavioral Intention	0.540	0.876
Early Adopters	0.534	0.851
Subjective Norms	0.587	0.877
Complexity	0.507	0.755
Perceived Moral Norms	0.520	0.764
Self-efficacy	0.512	0.759
Relative Advantage	0.541	0.921

4.3.2 Structural Model

When the CFA was completed, the structural model was evaluated. Several goodness of fit measures, as suggested by the literature (Lei & Wu, 2007; Tabachnick & Fidell, 2013; Washington et al., 2011; Schultz, 2001), were used to evaluate the SEMs developed in this study. These measures are summarized in Table 4.4. First, goodness-of-fit was evaluated using the chi-square measure divided by the degrees of freedom (DF), whose value was found to be less than 3, indicating an acceptable goodness of fit (Hu & Bentler, 1999). Additionally, the Root Mean Square Error of Approximation (RMSEA) was evaluated (Golob, 2003). This measure is based on chi-square values and measures the discrepancy between the observed and predicted values per degree of freedom. This value was found to be around 0.06, indicating that the model fits the data well (McDonald & Ho, 2002). Additional goodness-of-fit measures were used to assess the model's fit, such as the Normed Fit Index (NFI), the Relative Fit Index (RFI), the Tucker-Lewis Index (TLI), and the Comparative Fit Index (CFI). All of these indicate an adequate fit for the model, an indication that improves the significance of the reults.

Table 4.4: Goodness-of-fit measures

Goodness of fit Measure	Value
Chi-square/DF	2.595
NPAR	148
Chi-square	5527.113
DF	2130 ($p<0.001$)
NFI - Delta1	0.749
RFI - rho1	0.74
IFI - Delta2	0.829
TLI - rho2	0.822
CFI	0.829
RMSEA	0.063

The structural parameters were estimated using unstandardized values, and 9 significant relationships between the latent variables were found, as shown in Figure 4.3. The SEM results also indicate that the effects and the relationships between the observed and latent variables are all statistically significant, with p-values less than 0.01, as shown in Table B2 found in Appendix B.

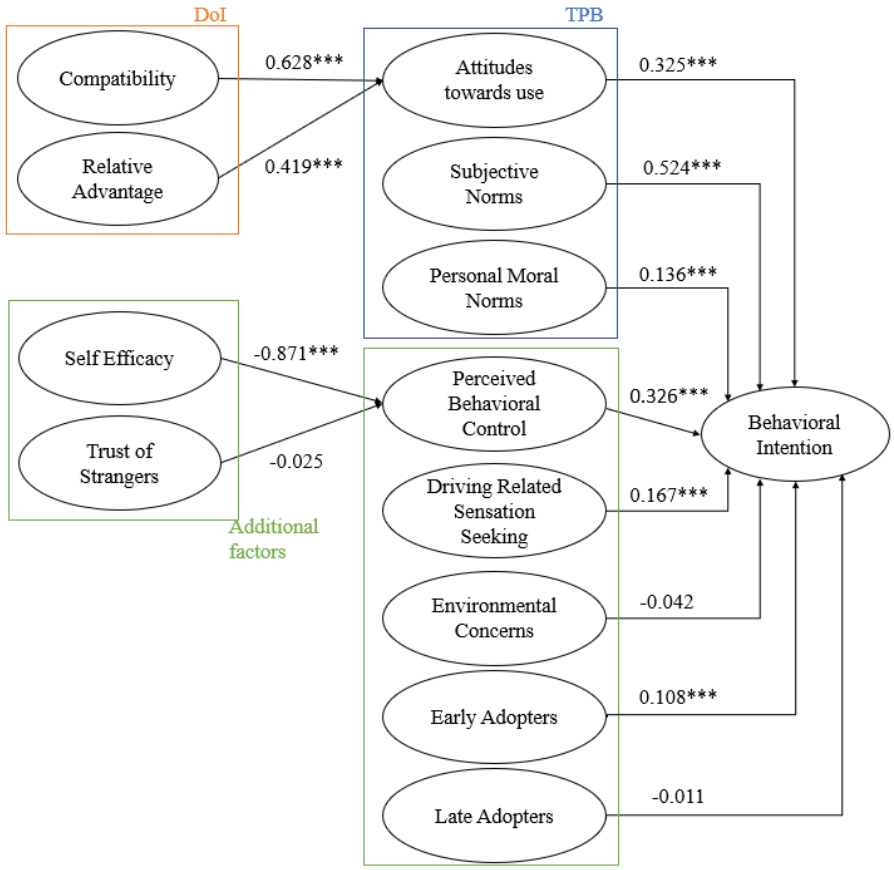

Figure 4.3: Final SEM results

4.3.3 Evaluation of Hypotheses

Table 4.5 summarizes the outcomes of the initial hypotheses developed as part of the theoretical model.

Table 4.5: Evaluation of initial hypotheses

Hypotheses	Parameter Estimates	p-value	Outcome
H1 - Attitudes towards Use have a positive influence on Behavioral Intention	.325	<0.01	supported
H2 - Perceived Behavioral Control has a positive influence on Behavioral Intention	.326	<0.01	supported

Table 4.5: continued

H3 - Subjective Norms have a positive influence on Behavioral Intention	.524	<0.01	Supported
H4 - Personal Moral Norms have a positive influence on Behavioral Intention	.136	<0.01	supported
H5 - Environmental Concerns have a negative influence on Behavioral Intention	-.042	.471	not supported
H6 - Compatibility has a positive influence on Attitudes towards Use	.628	<0.01	supported
H7 - Relative Advantage has a positive influence on Attitudes towards Use	.419	<0.01	supported
H8 - Complexity has a negative influence on Attitudes towards Use	-	-	not assessed
H9 - Trust of Strangers has a positive influence on Perceived Behavioral Control	-.025	.527	not supported
H10 - Self-efficacy has a positive influence on Perceived Behavioral Control	.871	<0.01	supported
H11 - Driving-related Sensation Seeking has a positive influence on Behavioral Intention	.167	.015	supported
H12 - Safety Concerns have a negative influence on Behavioral Intention	-	-	not assessed
H13a - ‘Early Adopters’ have a positive influence on Behavioral Intention	.108	<0.01	supported
H13b - ‘Late Adopters’ have a negative influence on Behavioral Intention	-.011	.837	not supported

This subsection summarizes the outcomes of the initial hypotheses developed as part of the theoretical model. It was found that the components of DoI, *compatibility* and *relative advantage* have a statistically significant and positive relationship with the *attitudes towards use* of AVs, confirming hypotheses H6, and H7 respectively; whereas hypotheses H7 that evaluates the influence of *complexity* towards the *behavioral intention* was not included in the revised theoretical model. This result is in line with past work (Brown et al., 2014; Daziano et al., 2017; Haboucha et al., 2017; Hulse et al., 2018; Lee et al., 2019; Payre et al., 2014; Shin et al., 2015; Zmud et al., 2016). For example, Brown et al. (2014) concluded that lifestyle needs influence mode choice decisions and that people make decisions regarding their means of transportation that are compatible with their lifestyles. Daziano et al. (2017) concluded that vehicle ownership, education level, and tendency to drive long distances affect people’s perceptions of AVs. Haboucha et al. (2017) found that parking costs can potentially affect the rates of ownership and usage of AVs.

Turning to the component of *self-efficacy*, it was found to have a positive effect on *perceived behavioral control*, thereby supporting hypothesis H10. The component of *attitudes towards use* of AVs was found to have a positive influence on *behavioral intention*, confirming hypothesis H1. Subsequently, the component of *perceived behavioral control* yields a positive association with the *behavioral intention*, validating hypothesis H2. Furthermore, it was found that that *subjective norms* and *personal moral norms* have a positive effect on *behavioral intention* to ride in AVs, supporting hypotheses H3 and H4, respectively. Likewise, the component of *perceived behavioral control* was found to have a positive influence on *behavioral intention*, supporting hypothesis H2. Payre et al. (2014) found that factors related to 'locus of control' (i.e., 'the extent to which an individual believes that he/she can control events affecting him/her') influence vehicle purchasing decisions. Furthermore, Bennett et al. (2019) concluded that the internal locus of control is associated with attitudes towards AVs for people with disabilities. In similar vein, Brown et al. (2014) indicated that the majority of generation Y consumers can be influenced by friends and family members when they make decisions regarding vehicle purchases.

The analysis showed that there is a positive relationship between tendency to *early adoption* and *behavioral intention* to ride in AVs, confirming hypothesis H13a. These results are in line with the literature (Bansal & Kockelman, 2017; Casley et al., 2013; Haboucha et al., 2017; Schoettle & Sivak, 2014a; Shabanpour et al., 2017; Shin et al., 2015; Silberg et al., 2013; Zmud et al., 2016). For example, Haboucha et al. (2017) examined the tendency of respondents to adopt a new idea before others and found that respondents who were interested the most about technology (early adopters) were more likely to indicate their preference towards AVs. On the other hand, the component of *late adopters* did not yield a statistical significant negative association with the *behavioral intention* to ride in AVs, not supporting hypothesis H13b.

The component of *environmental concerns* was not found to have a statistically significant negative relationship *behavioral intention* to ride in AVs, not supporting H5. However, Krueger et al. (2016) suggested that pro-environmental perceptions are common traits among car-sharing users and have the potential to influence consumer preferences related to the adoption of AVs. The component of s*afety concerns* was not included in the revised theoretical model. Kyriakidis et al. (2015) found that attitudes toward safety could be linked to consumers' preferences towards AVs.

Lastly, it was found that *DRSS* has a positive relationship with *behavioral intention* to ride in AVs, confirming hypothesis H11; a finding that is supported by the literature (Howard & Dai, 2014; Payre et al., 2014). For example, Howard and Dai (2014) reported that respondents who tend to drive alone stated a lower willingness to purchase an AV and preferred to have greater control of their vehicles. Payre et al. (2014) found sensation seeking to be related to the intention to use AVs. Respondents with higher reported DRSS indicated a higher intention to use AVs. On the other hand, the component of *trust of strangers* did not yield a statistically significant negative relationship with the *behavioral intention* to ride in AVs, not supporting hypothesis H9.

4.4 Discussion

The objective of this study was to assess factors influencing the behavioral intention to ride in AVs and investigate how and the extent to which this emerging technology can be diffused. This was achieved by designing a theoretical model based on TPB, that is decomposed to include components of the theory of DoI and extended to evaluate whether other components can also be determinants of the behavioral intention to ride in AVs. Responses from a survey were used, representative in terms of age and gender and included participants with a higher level of education compared to the general population of the area. EFA and CFA were conducted to test the validity and reliability of the components of the theoretical model, followed by estimation of SEM.

It was found that the components of DoI, relative advantage and compatibility indirectly affect the behavioral intention to ride in AVs and directly affect attitudes towards use of AVs; whereas the same conclusion was not found for complexity. Additionally, components of TPB were found to significantly influence behavioral intention, which validates the notion that a theoretical model based on TPB can predict the key determinants that impact behavioral intention. Regarding the decomposition of TPB, self-efficacy and personal moral norms were found to influence perceived behavioral control and behavioral intention, respectively. The component trust of strangers was not found to be statistically significant, possibly because this component might be more applicable to a study solely on SAVs and not on AVs. Similarly, among the components extending the decomposed TPB, the component of DRSS and the component of affinity to innovativeness as it relates to 'early adopters' were both found to influence behavioral intention.

5. MARKET SEGMENTATION ANALYSIS FOR AUTONOMOUS VEHICLES

This Chapter describes the identification of different adopter categories derived from the market segmentation analysis. Furthermore, a summary of the characteristics of each AV market segment is described.

5.1 Introduction

Little is known about the public acceptance of AVs, which is an important criterion for the efficient deployment of this emerging technology. Understanding who are the potential users of AVs and how the users are classified into different categories based on the adoption of the technology through a market segmentation analysis can lead to a pathway of planning and policy decisions. This classification is achieved by using as inputs the components found as significant determinants of the behavioral intention to ride in AVs. Consequently, to profile each AV market segment different socio-demographic variables and trip characteristics were considered attempting to shed light into providing insights about the public acceptance and adoption.

5.2 Methods

Each respondent of the survey was categorized into the following five categories of adopters based on the Diffusion of Innovation theory (Rogers, 2003), which is used to evaluate potential adoption: a) innovators – includes people that adopt the innovation first, even though a high degree of uncertainty exists, b) early adopters – people who are respected by their peers in a form of a role model in their social system, c) early majority - people that adopt the new idea before the average member of a system, d) late majority, and e) laggards. Cluster analysis was used to classify similar observations into clusters (Mooi & Sarstedt, 2011). The k-means procedure was selected as the partitioning method of the cluster analysis. This procedure was selected since it is least affected by outliers and it is commonly used when modeling ordered data (Mooi & Sarstedt, 2011).

The next step involved a market segmentation analysis to understand who will adopt the technology first. This can be achieved by conducting a cluster analysis. This methodology can investigate how homogenous the objects are and then can classify similar groups together that they are called clusters (Mooi & Sarstedt, 2011). The objects that belong to the same clusters have the maximum similarity among them and the maximum dissimilarity among objects that belong to different clusters. The statistically significant components derived from the analysis on the behavioral intention to ride in AVs were used as the clustering variables of this analysis. Specifically, a cluster analysis was conducted by identifying distinct market segments based on people's perception on travel characteristics and their intention to ride in AVs. The respondents will be classified using the five adopter categories established by Rogers, which include innovators, early adopters, early majority, late majority, and laggards (Rogers, 2003). This categorization will lead to the market penetration share of AVs to the system and identify which socio-demographic groups share similar attitudes towards AVs and trip characteristics.

Section 4.2.1 presented the theoretical model was designed to assess the behavioral intention to ride in AVs based on the TPB (Ajzen, 1991) including the following components: attitudes towards use, perceived behavioral control, self-efficacy, subjective norms, personal moral norms, environmental concerns, compatibility, relative advantage, complexity, trust of strangers, driving-related sensation seeking, safety concerns, affinity to innovativeness. Different clustering procedures to measure the similarity are hierarchical and partitioning methods (Mooi & Sarstedt, 2011). The partitioning methods require a pre-defined number of clusters and use the within cluster variation as a metric; whereas the hierarchical methods use the distance measure as a metric. The statistical significant components were included to conduct the cluster analysis so as to classify observations into clusters and k-means was selected as the partitioning method (Mooi & Sarstedt, 2011). Using the k-means approach the within cluster variation is minimized. This technique firstly assigns all the objects to separate clusters. Then, by decreasing the within cluster variation the previous step is repeated until the minimum distance is achieved. The cluster centers are identified by calculating the mean values of the objects included in each cluster and the interpretation (labeling) of the cluster analysis can occur. The components that were used as principal components for the cluster analysis were: attitudes towards use, perceived behavioral control, self-efficacy, subjective norms, personal moral norms, compatibility, relative advantage, driving-related sensation seeking, affinity to innovativeness, and intention to ride in AVs. This procedure was selected since it is affected to a lesser extent by outliers and it is also the natural choice when dealing with ordered data (Mooi & Sarstedt, 2011), which is the nature of the data used in this analysis. The k-means method requires a pre-defined number of clusters, which may increase subjectivity to the interpretation of the result. This is not considered a shortcoming since a well-established theory (DoI) to capture the adopter categories is used. Lastly, a market segmentation analysis is conducted to classify respondents into five categories of adoption (innovators, early adopters, early majority, late majority, and laggards) and identify distinct market segments.

5.3 Estimation Results

The next step was to interpret the results by observing the mean values of each cluster, comparing each average score and label each cluster using Rogers' adopter levels (innovators, early adopters, early majority, late majority, laggards). The average scores of each cluster is shown in Table 6.1 and Table 6.2 for Chicago and Indianapolis. According to the table, each cluster is different. The scale followed is a 5-point Likert scale, where 1 represents the strongly disagree option (most negative) and 5 represents the strongly agree option (most positive). For example, innovators have the highest score on the majority of the factors, whereas laggards have the lowest score.

Table 5.1: Average scores of each cluster - Chicago

	Attitudes	DRSS	Perceived Behavioral Control	Intention Ride	Early Adopters	Subjective Norms	Compatibility	Personal Moral Norms	Self-efficacy	Relative Advantage
Innovators	4.04	3.52	3.99	3.94	4.10	3.89	3.91	3.82	4.11	3.88
Early Adopters	4.35	2.05	3.49	3.55	3.38	3.53	3.95	3.59	3.98	3.78
Early Majority	2.95	2.55	2.95	2.79	3.11	3.01	3.04	3.05	3.06	3.03
Late Majority	2.35	2.35	3.28	2.24	3.19	2.60	2.23	1.89	3.53	2.68
Laggards	1.49	2.03	1.89	1.43	2.57	2.19	1.58	1.74	2.08	2.15

Table 5.2: Average scores of each cluster - Indianapolis

	Attitudes	DRSS	Perceived Behavioral Control	Intention Ride	Early Adopters	Subjective Norms	Compatibility	Personal Moral Norms	Self-efficacy	Relative Advantage
Innovators	4.55	3.46	4.41	4.28	4.3	4.07	4.25	4.15	4.40	4.08
Early Adopters	4.08	2.26	3.55	3.52	3.40	3.36	3.71	3.61	3.91	3.71
Early Majority	3.20	2.63	3.23	2.89	3.30	3.04	2.95	2.84	3.46	3.23
Late Majority	2.08	2.19	2.92	2.00	3.00	2.58	2.12	2.18	3.03	2.66
Laggards	1.34	2.22	1.88	1.38	2.80	1.88	1.44	1.41	2.06	2.07

Analysis of variance was conducted for the ten components for each study area. The results indicated that the average scores for each component are statistically different between the five clusters. Figure 5.1 illustrates the distribution of each adopter category (cluster) for Chicago and Indianapolis, respectively.

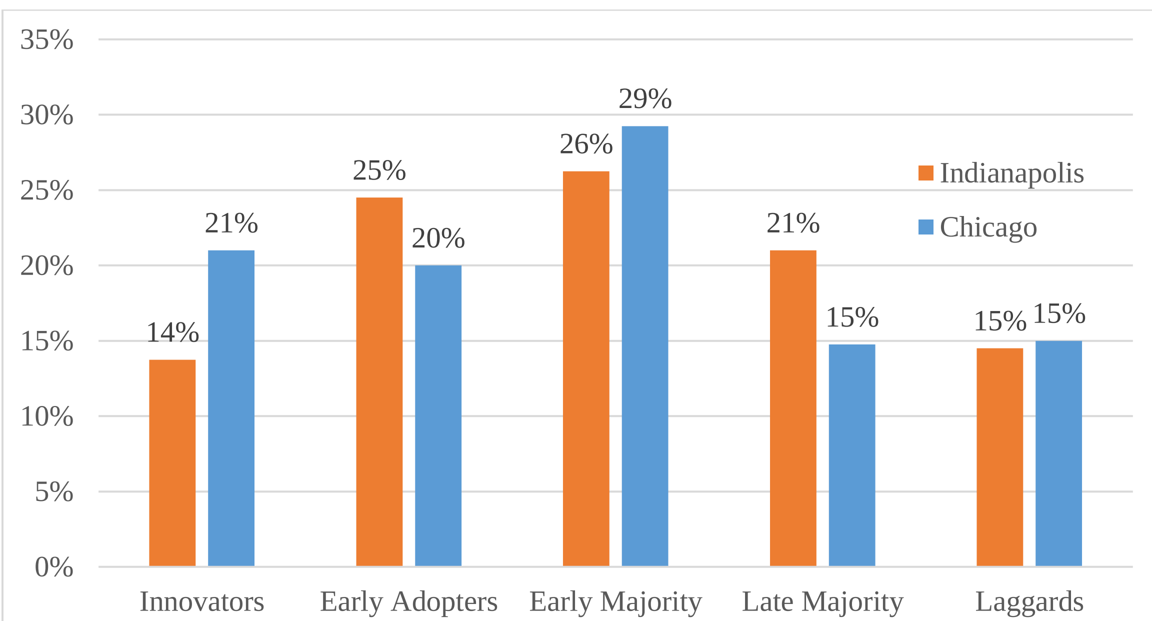

Figure 5.1: Distribution of adopter categories for each cluster - Chicago and Indianapolis

It was found that Chicago generally has a more innovative population, with a higher percentage in the first three categories (innovators, early adopters, and early majority categories). This percentage was 70% for Chicago compared with 65% for Indianapolis. Similarly, a higher number of innovators was found in Chicago compared to Indianapolis. Additionally, the percentage of the late majority category was higher in Indianapolis, while the laggards category makes up a similar proportion of each city. These results align with the expectations and the general knowledge about the study areas that Chicago is a much larger and more modern city and is often seen as more diverse, technologically savvy, and attractive to young people or innovators, compared to Indianapolis. Lastly, to profile each market segment, different socio-demographic variables and trip characteristics were used. A summary of the descriptive statistics of the variables used for the profiling is shown in Table 6.2 found in subsection 6.2.2. Table 5.3 and Table 5.4 show the summary of the cluster characteristics for each category for Chicago and Indianapolis, respectively.

Table 5.3: Summary of cluster characteristics – Chicago

	Innovators	**Early adopters**	**Early majority**	**Late majority**	**Laggards**
Level of awareness	Highest level of awareness on AVs	Higher than average level of awareness on AVs	Lower than average level of awareness on AVs	Higher than average level of awareness on AVs	Lowest level of awareness on AVs
Commuting patterns	40% use public transportation and walk to their commute trips as primary modes	20% use public transportation to their commute trips as primary modes	60% use their personal vehicles for their commute trips	80% use their personal vehicles for trips regardless the trip purpose	70% use their personal vehicles for trips regardless the trip purpose
Vehicle ownership	Half of them do not own a vehicle. 33% drove more than 15,000 miles last year (US avg)	20% of them do not own a vehicle. 40% have 1 vehicle in their household	45% do not own a vehicle. 33% drove between 5k-10k miles last year	55% have at least one vehicle in their household	35% do not own a personal vehicle

Table 5.3: continued

Use of ride-hailing services	60% use ride-hailing services for their trips (10% use ride-hailing services for social / recreational trips)	50% use ride-hailing services	40% use ride-hailing services	20% use ride-hailing services and none of them use car-sharing services	20% use ride-hailing services and 5% car-sharing services
Gender	60% are male	Equally split between male and female	60% are female	66% are male	75% are female
Age	60% are Millennials (<34 y.o.)	Most dominant category people 25-34 years old	Most dominant category people 35-44 years old	Most dominant category people 45-54 years old	50% are people over 55 years old and 25% over 65 years old
Employment status	82% work full time	60% work full time	10% are currently unemployed	25% have retired	33% have retired
Income	Higher than average income – 40% earn below $50k	Higher than average income - most dominant categories are $25k-$50k and $100-$150k	Lower than average income – 25% earn under $25k	Highest average income – most dominant categories are $75k-$100k and $100k-$150k	Lowest average income – 50% earn $25k-$50k
Education level	75% college graduates or finished grad school	45% finished grad school	33% high school graduates	75% college graduates or finished grad school	45% college graduates

Table 5.4: Summary of cluster characteristics - Indianapolis

	Innovators	**Early adopters**	**Early majority**	**Late majority**	**Laggards**
Level of awareness	Highest level of awareness on AVs	Higher than average level of awareness on AVs	Lower than average level of awareness on AVs	Higher than average level of awareness on AVs	Lowest level of awareness on AVs

Table 5.4: continued

Commuting patterns	25% use public transportation or walk to their commute trips as primary modes, 4% bike commute	15% use public transportation or walk to their commute trips as primary modes	80% use their personal vehicles for their commute trips	90% use their personal vehicles for trips regardless the trip purpose	90% use their personal vehicles for trips regardless the trip purpose, only 3% walk
Vehicle ownership	10% do not own a vehicle. They drive about 12,000 mi/year (highest of any group)	10% do not own a vehicle. They drive about 10,000 mi/year on average	10% do not own a personal vehicle	2% do not own a personal vehicle	5% do not own a personal vehicle, though this group drives the least on (avg 9000 mi/year)
Use of ride-hailing services	65% use ride-hailing services, 20% have a car-sharing service account	40% use ride-hailing services, 5% have a car-sharing service account	40% use ride-hailing services	20% use ride-hailing services and none of them use car-sharing services	10% use ride-hailing services, 0 respondents had a car-sharing account.
Gender	64% are male	54% are female	58% are female	64% are female	52% are female
Age	55% are Millennials (<34 y.o.)	Avg. age 29 y.o.	32% are Millennials (<34 y.o.)	35% are Millennials (<34 y.o.)	55% are people over 55 years old and 23% over 65 years old
Employment status	60% work full time, 13% are students	38% work full time, 8% unemployed	44% work full time, 15% part time	24% have retired	22% have retired, 10% unemployed
Income	Higher than average income – $52k on average	Higher than average income – around $50k	Lowest average income – around $45k	Average income around $48k	Average income around $48k
Education level	40% finished college degree, 10% did not graduate high school	32% finished undergraduate degree	21% are not high school graduates	17% are not high school graduates, 35% college graduates	41% finished college degree

In both cities, the separation between the categories of highest innovation (innovators and early adopters) compared with categories of lower innovation (late majority and laggards) tends to fall along lines of current modal preference and age-related characteristics. The most predictive factor for AV interest seems to be the current modal choice of respondents. Members of the innovative groups are more likely to walk, bike, or use public transportation for commuting, and are less likely to own a personal vehicle than less innovative groups. Use of ride-hailing and car-sharing technology is more typical in innovators and is very uncommon in late majority or laggards groups. The trend was much more obvious in Chicago, likely due to greater availability and usefulness practicality of non-personal-vehicle modes. In Indianapolis, with a more heterogeneous use of personal vehicle as mode of choice throughout innovation groups, the difference between these groups were not as defined, apart from at the edges.

Age-related trends are also observed in both cities, with older or retired respondents less likely to be interested in AV technology. Millennials working full time make up the majority of innovators in both cities, though the difference between groups beyond that is less defined. Laggards have the highest rate of retirement and the highest average age in both cities. Gender also appears to play a role, as does income and education. Innovative respondents were more likely to be male in Chicago, with 60% of the Innovators being male and 75% of the Laggards being female; a trend that was less clear in Indianapolis. Innovative groups also tended to have higher than average income within the respondent pool and also, a higher education level. These trends are less strong in Indianapolis, where education and income levels in general tend to be lower. It is worth to acknowledge that these differences on the market segments between Chicago and Indianapolis not only occur because of socio-demographic variables but also based on differences in cities characteristics, transportation system networks, congestion, ease of using car-sharing and ride-hailing services, and unobserved factors.

5.4 Discussion

The market segmentation analysis classified respondents into five adopter categories (innovators, early adopters, early majority, late majority, laggards). Regardless of study area, it was found that people classified as innovators or early adopters are more likely to use other modes for commuting than their private vehicles (walking, biking, public transportation), and they own or have access to fewer vehicles compared to their counterparts. Furthermore, these people are more likely to be members of ride-hailing and car-sharing services, younger individuals, people who work full time, and people with higher incomes and education levels. More innovators found to have a higher education and income level in Chicago compared to the group in Indianapolis.

6. PERCEIVED IMPACTS OF AVs ON PRIVATE VEHICLE OWNERSHIP AND DEMAND FOR PUBLIC TRANSPORTATION

This Chapter describes the evaluation on attributes affecting travelers' decisions to postpone the purchase of a non-AV, keep their current non-AV, or give up private ownership of their non-AV in the short and long terms. Additionally, this Chapter discusses the results on the factors assessing the intention of public transportation users to switch from public transportation to ride-sharing services operated through AVs. Part of this work is under preparation for submission in an academic journal and it is reprinted here with the authors' (Gkartzonikas and Gkritza) permission.

6.1 Introduction

6.1.1 Research Motivation and Objectives

Today, the majority of people depend on private vehicles (Anable, 2005), to the extent that the private vehicle is viewed as not just a transportation mode (Steg, 2005) but also a status symbol. AVs and on-demand mobility services, such as car-sharing and ride-hailing, have the potential to substitute for and transform the two most traditional and conventional transportation modes, namely private vehicles and public transportation (Greenblatt & Shaheen, 2015). Currently, the average household in the US has around 2.5 people and owns 1.75 vehicles (US Census Bureau, 2016), while transit ridership has increased around 30% since 1996 compared to a 20% population growth in the same period (APTA, 2018). The diffusion of AVs has the potential to change these numbers dramatically. In particular, a household can still make the same number of trips using fewer vehicles, all while achieving fuel and parking cost savings and enjoying greater productivity while riding.

From not only an individual or household perspective but also a systems perspective, understanding the modal shifts that may occur following the emergence of AVs is essential for estimating their societal impacts and enabling efficient and effective transportation planning and operations (Cohen, Jones, & Cavioli, 2017; Nikitas, Kougias, Alyavina, & Tchouamou, 2017). Evidently, AVs have the potential to drive both urbanization and suburbanization by either enabling people to move out of urban centers or alter urban living attracting more people to urban centers. For example, AVs can alleviate parking congestion in highly dense urban areas. Particularly, parking spaces would no longer need to be located near work locations or major attractions, which, while potentially increasing VMT, could reshape the urban space (Boesch, Ciari, & Axhausen, 2016; Fagnant & Kockelman, 2014). On a similar note, AVs may lead to urban sprawl by increasing accessibility to different opportunities/attractions in urban and rural areas (Childress, Nichols, Charlton, & Coe, 2015; Zhang et al., 2015). This can alter land use and location decisions and affect the economic development of certain areas. Furthermore, AVs can have a synergetic effect with transportation electrification (such as electric vehicles) and lead to lower energy use and emissions (Choi & Bae, 2013; Fagnant & Kockelman, 2014; Rios-Torres & Malikopoulos, 2017; Wadud et al., 2016; Wang, Daamen, Hoogendoorn, & Arem, 2014). It has also been argued that AVs can benefit disadvantaged groups, including those who are too young or too old to drive or people with disabilities (Harper, Hendrickson, Mangones, & Samaras, 2016).

However, as acknowledged in Milakis et al. (2017), the emergence of AVs can have implications for vehicle ownership as a second-order effect. Past work has evaluated the number of conventional vehicles that each shared autonomous vehicle SAV can replace in order to explore how AVs might enable or expedite the diffusion of automated vehicle sharing schemes, such as car-sharing and ride-hailing services (Boesch, Ciari, & Axhausen, 2016; Fagnant & Kockelman, 2014; Zhang et al., 2015). However, the perceived impacts that drive people's decisions to postpone the purchase of non-AVs in different timeframes is not well understood, though understanding these motivations is essential for moving beyond simply identifying the number of private vehicles that can be substituted by AVs to discern which factors influence these decisions. Moreover, the existing literature has focused mainly on conventional vehicles and does not provide enough information on the factors that influence decisions to switch from other transportation modes, such as public transportation, to ride-sharing services operated through AVs.

In this context, this chapter explores the potential implications of AVs on private vehicle ownership and demand for public transportation in two different study areas by (a) understanding what influences travelers' decisions to postpone the purchase of a non-AV, keep their current non-AV, or give up private ownership of their non-AV in the short and long terms and (b) assessing the intention of public transportation users to switch from public transportation to ride-sharing services operated through AVs.

6.1.2 Summary of Related Work

In general, household vehicle ownership decisions can affect safety (e.g., crash rates), energy consumption, pollution, traffic congestion, the locations of residential areas, and the financial viability of vehicle manufacturers. At the same time, public transportation has been successful in attracting and retaining ridership when its level of service is adequate (Hensher, 1998). In particular, the literature suggests that transit system reliability (i.e., its ability to run on time) is the most important factor for attracting and retaining users (Bates, Polak, Jones, & Cook, 2001; Hensher, Stopher, & Bullock, 2003; Konig, 2002), followed by comfort (Friman, Edvardsson, & Gärling, 2001; Hensher et al., 2003) and frequency of service (Hensher et al., 2003). Travel time, cost, and trip purpose are the main factors driving mode choices, with travel time being the most important factor for commuting trips (Beirão & Sarsfield Cabral, 2007). However, whether these factors will continue to be key determinants of vehicle ownership and mode choice decisions with the emergence of AVs is yet to be determined. Rather, the majority of the related literature to date has focused on assessing how the public acceptance of AVs might impact vehicle ownership and mode choice decisions.

Recent studies on AVs have mainly focused on gauging public acceptance through stated preference surveys (Becker & Axhausen, 2017; Gkartzonikas & Gkritza, 2019) in an effort to identify the determinants of AV adoption and its corresponding implications. Meanwhile, traffic congestion (Lavieri et al., 2017) and social equity issues (Pettigrew, Cronin, & Norman, 2019) can be barriers to the early adoption of AVs. Bansal et al. (2016) found that around four out of five respondents in the US indicated that they were interested in the idea of owing an AV. A study in Australia (Pettigrew, Dana, & Norman, 2019) showed that one-third of the respondents were positive toward the idea of the wide diffusion of AVs in transportation networks. Studies have found that these positive inclinations can be associated with higher levels of education (Lavieri et al., 2017), income (Bansal et al. 2016), and awareness of AVs (Sanbonmatsu et al., 2018). Additionally, Haboucha et al. (2017) concluded that individuals who drive a higher annual mileage have a greater willingness to adopt AVs, whereas König and Neumayr, (2017) suggested the opposite.

Potential associations between vehicle ownership and on-demand mobility services have also been explored in the literature in terms of SAVs. Even though (Zhang et al., 2015) concluded that there is no distinction between the scenarios of owning a private AV or relying on SAVs, other studies (Anderson et al., 2014; Fagnant & Kockelman, 2015) suggested that the emergence of AVs can create more opportunities for vehicle sharing, altering current vehicle ownership patterns. Haboucha et al. (2017) and Nielsen and Haustein, (2018) concluded that private AVs are perceived more positively than SAVs. Krueger et al. (2016) identified socio-demographic groups that are more likely to benefit from SAVs, such as males and younger people, and found that people who already using multiple transportation modes for their trips are more positive to SAVs.

As for public transportation, the emergence of AVs can reduce transit trips and non-motorized trips and increase private vehicle use mainly because AVs offer opportunities for greater productivity, are a better alternative for the elderly and disabled, and are perceived to be less stressful to use and more comfortable than public transportation (Anderson et al., 2014). However, others have argued that AVs can complement and improve the experience of public transportation by providing first/last-mile trips, feeder trips, and on-demand services with flexible routes (Boesch et al., 2016; Malokin, Circella, & Mokhtarian, 2019). Likewise, Yap, Correia, and van Arem (2016) reported that AVs can be used as egress mode for first class travelers of public transportation, indicating that income can also be a decisive factor in the adoption of AVs. Furthermore, Newman and Kenworthy (2015) explained that lifestyle and habits also play a role in these decisions. In particular, Millennials seem to be shifting away from previous generations' habits of car dependence and moving towards shared mobility and sustainability.

6.2 Data

6.2.1 Empirical Setting and Data Collection

The empirical setting studied for this project are the metropolitan areas of Chicago, Illinois, and Indianapolis, Indiana metropolitan areas. Indianapolis is mainly an automobile-oriented city, where 82% of commuters drive alone to get to work, 2% of workers use public transportation, and 10% carpool to get to work and approximately 6% use other modes (e.g., walking or biking). On the other hand, Chicago has an advanced multimodal transportation system providing different mode alternatives to its residents. Specifically, according to the most current NHTS (FHWA, 2017), around 50% of commuters in Chicago use their private vehicles, around 8% carpool, approximately 28% use public transportation, and around 14% use other modes (e.g., walking or biking). This relative high rate of public transportation usage for commuting trip purposes, where people typically value travel time highly and public transportation is not widely perceived as the most reliable mode, is bolstered by the fact that 79% of Chicago has public transportation coverage (CMAP, 2016). The percentage of public transportation usage for commuting trips in the Chicago metropolitan area is more than twice the average usage percentage (12.7%) for areas with populations over 5 million, as reported by the Bureau of Transportation Statistics (US Department of Commerce, 2016). Furthermore, more than 23% of the Chicago residents commute less than 5 minutes to work in comparison with 6.1% in Indianapolis. Indianapolis is also four times less densely populated than Chicago, and exhibits below-average transit coverage (42%) compared to Chicago (79%) (US Census Bureau, 2015).

6.2.2 Descriptive Statistics

The dependent variables examining the relationship between the decision to postpone the purchase of a non-AV in the short and long terms and various intrinsic and extrinsic factors correspond to the following three questions in the survey: (a) *How likely is it that your household will postpone the purchase of a non-autonomous vehicle due to the introduction of autonomous vehicles?*, (b) *How likely is it that your household will have one non-autonomous vehicles two years after the introduction of autonomous vehicles?*, and (c) *How likely is it that your household will have zero non-autonomous vehicles five years after the introduction of autonomous vehicles?*. The possible responses consisted of five options on a five-point Likert rating scale ranging from 1 (very unlikely) to 5 (very likely). The dependent variables chosen to examine the relationship between the intention to switch from public transportation to ride-sharing services operated through AVs correspond to the following two questions in the survey: (d) *I expect that I will be sometimes switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the near future*, and (e) *I expect that I will be sometimes switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the foreseeable future*. The possible responses consisted of five options on a five-point Likert rating scale ranging from 1 (strongly disagree) to 5 (strongly agree). A summary of the descriptive statistics of the aforementioned dependent variables as well as select independent variables is provided in Table 6.1and Table 6.2, respectively.

Table 6.1: Summary statistics of dependent variables

	Question	Description	Chicago Response Frequency	Indianapolis Response Frequency
Impact on private vehicle ownership				
a	Will your household postpone the purchase of a non-autonomous vehicle due to the introduction of autonomous vehicles?	1: No 2: Neutral 3: Yes	1: 59.50% 2: 19.00% 3: 21.50%	1: 65.75% 2: 14.75% 3: 19.5%
b	How likely is it that your household will have one non-autonomous vehicle two years after the introduction of autonomous vehicles?	1: Very unlikely 2: Unlikely 3: Neutral 4: Likely 5: Very likely	1: 26.50% 2: 13.00% 3: 24.25% 4: 21.50% 5: 14.75%	1: 34.25% 2: 15.5% 3: 17.25% 4: 21.75% 5: 11.25%
c	How likely is it that your household will have zero non-autonomous vehicles five years after the introduction of autonomous vehicles?	1: Very unlikely 2: Unlikely 3: Neutral 4: Likely 5: Very likely	1: 19.25% 2: 16.75% 3: 29.50% 4: 19.00% 5: 15.50%	1: 20.25% 2: 16.25% 3: 26.00% 4: 20.50% 5: 17.00%
Impact on public transportation usage				
d	I expect that I will be sometimes switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the near future.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	1: 17.50% 2: 21.50% 3: 31.00% 4: 24.50% 5: 5.50%	1: 15.75% 2: 25.50% 3: 28.75% 4: 24.75% 5: 5.25%
e	I expect that I will be sometimes switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the foreseeable future.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	1: 16.25% 2: 20.25% 3: 30.25% 4: 26.75% 5: 6.50%	1: 15.50% 2: 24.25% 3: 26.50% 4: 25.25% 5: 8.50%

Table 6.2: Summary statistics of independent variables

Variable Description	Chicago Response Frequency (%)	Indianapolis Response Frequency (%)
Awareness		
Respondents with the highest level of awareness of Uber's self-driving vehicles (1: yes, 0: no).	25.8/74.2	21.3/78.7
Respondents with the highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no).	54.8/45.2	37.4/62.6

Table 6.2: continued

Travel characteristics		
Respondents who indicated that their primary commuting mode of travel is a private vehicle and that they make zero social/recreational trips per week (1: yes, 0: no).	9.8/90.2	11.5/88.5
Respondents who indicated that their primary commuting mode of travel is a private vehicle and that they make 1 or less social/recreational trips per week (1: yes, 0: no).	18/82	22.7/77.3
Respondents who indicated that their primary mode of travel for social/recreational trips is bus (1: yes, 0: no).	8.3/91.7	5.4/94.6
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	7.5/92.5	6.1/93.9
Respondents who indicated that they drive less than 5,000 miles per year (1: yes, 0: no).	19.3/80.7	16.4/83.6
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no).	27/73	23.6/76.4
Respondents who indicated that they drive less than 20,000 miles per year (1: yes, 0: no).	10.5/89.5	13.8/86.2
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations - early adopters.	58.3/41.7	49.2/50.8
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms.	46/54	53.8/46.2
Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers.	17.8/82.2	20.3/79.7
Respondents who agreed or strongly agreed, on average, that AVs are compatible with their lifestyle, daily needs, or personal values and attitudes – compatibility.	42.5/57.5	34.6/65.6
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs - safety concerns.	13/87	19.1/80.9
Respondents who agreed or strongly agreed, on average, that automated driving technology installed in AVs is likely to be a better driver than they are (1: strongly agree or agree, 0: otherwise).	31/69	24.7/75.3
Mode choice-related factors		
Respondents who rated level of cost of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	54.8/45.2	61.7/48.3
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	47.8/52.2	41.9/58.1

Table 6.2: continued

Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	52.1/47.9	58.3/41.7
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	49.3/50.7	62.1/37.9
Socio-demographics		
Respondents who are between 18 and 34 years old (1: yes, 0: no).	39.5/60.5	34.25/65.75
Respondents who are between 25 and 34 years old (1: yes, 0: no).	25.3/74.7	16.5/83.5
Respondents who are 55 years old or older (1: yes, 0: no).	26.8/73.2	31.25/68.75
Respondents who have an annual income of over $100,000 (1: yes, 0: no).	19.3/80.7	16.75/83.25
Respondents who indicated that they work full time (1: yes, 0: no).	44.3/55.7	47.4/52.6
Respondents who indicated that they are students (1: yes, 0: no).	7/93	5.7/94.3
Respondents who indicated that they own or have access to 1-2 vehicles in their household (1: yes, 0: no).	73.6/26.4	84.8/15.2

6.3 Methods

A consistent point of interest for transportation planners is to better understand the number and types of private vehicles owned by households and how these numbers change dynamically. Modeling consumers' behavioral responses and studying these relationships can facilitate this question for prediction and forecasting purposes, enabling effective policymaking and alleviating some of the negative impacts of automobile dependence. Specifically, the decision for a household to own a vehicle is a very important characteristic linked with all aspects of travel. For this reason, many studies have pursued different models to address this issue (Brownstone & Train, 1998; Lave & Train, 1979; Mannering & Mahmassani, 1985; Manski & Sherman, 1980). The most common modeling technique for assessing vehicle ownership and mode choice decisions is discrete choice.

In this chapter, two different models were estimated to assess the potential implications of AVs on private vehicle ownership; the first estimates the general likelihood of postponing the purchase of a non-AV due to the introduction of AVs, and the second estimates the likelihood of owning one non-AV shortly after the introduction of AVs and zero non-AVs in the long term. A random parameters model with three outcomes (do not postpone/neutral/postpone), was estimated that accounts for the influence of unobserved heterogeneity by estimating different parameters across observations (Washington et al., 2011), which increases the predictive capability of the model (Mannering, 2018). For the purposes of this analysis, 200 Halton draws were used, and draws for numerical integration were achieved efficiently rather than randomly, a method suggested in previous work (Shaheed & Gkritza, 2014). Bivariate ordered probit models were estimated to assess the likelihood of an individual owning one non-AV in the short term (two years after the introduction of AVs) and zero non-AVs in the long term (five years after the introduction of AVs). This model specification was selected because it takes into consideration the ordinal nature of the data as well as the cross-correlation between the respective pairs of questions (correlation coefficient of 0.80). The same model specification was adopted for estimating the intention to switch from public transportation to SAVs in the short and long terms (correlation coefficient of 0.70). The existence of cross-correlation, in combination with the potential existence of unobserved factors related to both short- and long-term intentions, suggested that modeling both as a system may be most appropriate.

The final models were selected based on an evaluation of the goodness of fit, such as that obtained from McFadden's pseudo R^2 or the likelihood ratio test. Note that the variables related to respondents' opinions on AVs (willingness to be an early adopter, adherence to subjective norms, distrust of strangers, compatibility with the respondent's lifestyle, and safety concerns) could potentially be endogenous to the dependent variables. To account for this endogeneity, these variables were modeled using binary ordered probit models that included exogenous variables, such as socio-economic, demographic, and transportation-related variables. The resulting probabilities were then used as inputs for the models that explored the substitution patterns of the transportation modes.

6.4 Estimation Results

6.4.1 Likelihood of Postponing the Purchase of a non-AV due to the Introduction of AVs

The estimation results of the mixed logit model of the likelihood that people will postpone the purchase of a non-AV due to the introduction of AVs are presented in Table 6.3 and Table 6.4 for Chicago and Indianapolis, respectively. The final models explain approximately more than one-fourth of the variation. An evaluation of the results of this model can shed some light on what drives vehicle ownership decisions in terms of the purchase of non-AVs in general when AVs are commercially available.

Table 6.3: Mixed logit model estimation results - private vehicle ownership - Chicago

Variable	Will your household postpone the purchase of a non-autonomous vehicle due to the introduction of autonomous vehicles?		
	No	**Neutral**	**Yes**
	Estimated Parameter (p-value)	**Estimated Parameter (p-value)**	**Estimated Parameter (p-value)**
Constant.	-	-2.753 (<0.001)	-4.163 (<0.001)
Awareness			
Respondents with highest level of awareness of Uber's self-driving vehicles? (1: yes, 0: no).	-0.619 (0.041)	-0.557 (0.051)	-
Travel characteristics			
Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make 1 or less social/recreational trips per week (1: yes, 0: no).	-	-	0.517 (0.089)
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-	1.013 (0.072)	1.074 (0.051)
Respondents who indicated that they drive less than 5,000 miles per year (1: yes, 0: no).	-	-	1.186 (<0.001)
Perceptions / Opinions / Attitudes			
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations - early adopters**.	-	0.950 (<0.001)	1.015 (<0.001)

Table 6.3: continued

Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle - subjective norms**.	-	-	1.259 (<0.001)
Respondents who agreed or strongly agreed, on average, that automated driving technology installed in AVs is likely to be a better driver than they are (1: strongly agree or agree, 0: Otherwise)**.	1.312 (0.011)	1.517 (<0.001)	-
Mode choice-related factors			
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.254 (0.042)	-	-
Socio-demographics			
Respondents who are between 25 and 34 years old (1: yes, 0: no) [st.dev.].	-	0.779 (0.042)* [1.559 (0.087)]	0.779 (0.042)* [1.559 (0.087)]
Respondents who have an annual income over $100,000 (1: yes, 0: no).	0.968 (0.009)	-	-
Pseudo R-squared		0.319	
Log-likelihood function		-439.445	
Restricted log-likelihood		-298.847	

* Random parameter (not fixed)

** Predicted probabilities calculated using an estimated binary probit model (see the Methods section)

Table 6.4: Mixed logit model estimation results - private vehicle ownership - Indianapolis

Variable	Will your household postpone the purchase of a non-autonomous vehicle due to the introduction of autonomous vehicles?		
	No	**Neutral**	**Yes**
	Estimated Parameter (p-value)	**Estimated Parameter (p-value)**	**Estimated Parameter (p-value)**
Constant.	-	-2.256 (<0.001)	-3.784 (<0.001)
Awareness			
Respondents with highest level of awareness of Uber's self-driving vehicles? (1: yes, 0: no).	-0.412 (0.037)	-0.330 (0.028)	-
Travel characteristics			
Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make 1 or less social/recreational trips per week (1: yes, 0: no).	-	-	0.843 (0.042)
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-	0.689 (0.085)	0.817 (0.056)
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no).	-	-	0.978 (0.014)
Perceptions / Opinions / Attitudes			
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	-	-	1.291 (<0.001)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	-	0.975 (0.003)	1.106 (<0.001)

Table 6.4: continued

Respondents who agreed or strongly agreed, on average, that they have safety concerns on riding in AVs - safety concerns**.	1.741 (<0.001)	1.482 (0.014)	-
Mode choice-related factors			
Respondents who rated level of cost in travel as a very or extremely important factor when they make mode choice decisions (1:yes, 0: no).	0.474 (0.031)	0.357 (0.053)	-
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.163 (0.046)	0.139 (0.071)	-
Socio-demographics			
Respondents who are between 18 and 34 years old (1: yes, 0: no) [st.dev.].	-	-	0.681 (0.029)* [1.429 (0.061)]
Respondents who have an annual income over $100,000 (1:yes, 0: no).	0.917 (0.039)* [1.392 (0.062)]	0.784 (0.042)* [1.098 (0.077)]	-
Pseudo R-squared		0.297	
Log-likelihood function		-504.839	
Restricted log-likelihood		-354.822	

* Random parameter (not fixed)

** Predicted probabilities calculated using an estimated binary probit model (see the Methods section)

Regarding the magnitude of the estimated constants, with all else being equal, respondents seemed more likely to not postpone the purchase of a conventional vehicle (non-AV) due to the introduction of AVs. Moreover, the findings of the model show that the level of awareness regarding AVs is associated with a stronger intention to postpone the purchase of a non-AV. In particular, people who have a higher level of awareness of automated features installed in vehicles than their counterparts seem to be more willing to postpone the purchase of a non-AV and potentially switch to an AV. Results from the literature also show that awareness is associated with a positive perception of AVs (Bansal et al., 2016; Nordhoff et al., 2018; Sanbonmatsu et al., 2018). In addition to awareness, vehicle ownership decisions are also associated with respondents' travel characteristics. Specifically, people who use their private vehicles as their main commuting transportation mode and do not perform more than one social/recreational trip on a weekly basis seem to be more open to postponing the purchase of a non-AV. This can be explained by the fact that this group of people may value their travel time highly and anticipate greater productivity as riders in AVs than drivers of non-AVs. Furthermore, people who have a car-sharing account are more likely to postpone the purchase of a non-AV, a finding that is supported by the literature (Shaheen et al., 2018), where it has been found that the tendency to have a multi-modal lifestyle and use shared services is related with a more positive perception of AVs.

Attitudinal variables and opinions on AVs can also provide information related to vehicle ownership decisions. Particularly, respondents who were categorized as early adopters compared to their counterparts seem to be more willing to postpone the purchase of a non-AV, a finding that is also in line with the literature (Bansal & Kockelman, 2017b; Haboucha et al., 2017; Ramin Shabanpour et al., 2018). On a similar note, people whose social circle-family members, close friends, and organizations-supports their decisions seem to be more positively inclined towards postponing the purchase of a non-AV, a finding that it is also supported in the literature (B. Brown et al., 2014; Liu et al., 2018). Furthermore, people who believe that the automated driving technology installed in AVs results in improved driving compared to non-AVs are more positively inclined towards postponing the purchase of a non-AV, a result that other studies have found as well (Kyriakidis et al., 2015; Schoettle & Sivak, 2014a). Lastly, factors that influence mode choice decisions are associated with the decision to postpone the purchase of a non-AV. For Chicago, the estimated results show that people who consider reliability a key determinant in their mode choice decisions are more likely to postpone the purchase of a non-AV and potentially switch to an AV; whereas for Indianapolis the results show that people who consider cost and reliability as key determinants in their mode choice decisions are more like to postpone the purchase of non-AVs.

As a final point, socio-demographic variables also play a role in vehicle ownership decisions, a finding supported by the literature (Fagnant & Kockelman, 2014). The results show that people between 25 and 34 years old are more positively inclined towards postponing the purchase of a non-AV. However, the effect of age was found to be heterogeneous, in that 69.2% of young respondents were positively inclined towards postponing and 30.8% were negatively inclined towards the same decision (with a mean of 0.779 and a standard deviation of 1.559). Additionally, respondents with a reported an income greater than $100,000 seem to be unlikely to postpone the purchase of a non-AV when AVs become commercially available. These findings are also supported in the literature: younger people are more positively inclined towards AVs (Ipsos MORI, 2014; Power, 2013), and lifestyle is a key determinant of mode choice decisions (Brown et al., 2014).

6.4.2 Likelihood of Owning One non-AV in the Short Run and Zero non-AVs in the Long Run

Table 6.5 and Table 6.6 for Chicago and Indianapolis, respectively, show the results of the analysis of vehicle ownership decisions when AVs are diffused in transportation networks and specifically regarding the likelihood that households will own one non-AV in the short run (two years after the introduction of AVs) and zero non-AVs in the long run (five years after the introduction of AVs). As mentioned in the Methods section, these two dependent variables were evaluated as a system of ordered probit models because they were highly correlated. It was found that the cross-equation correlation coefficient was statistically significant ($p < 0.001$), validating the initial hypothesis that they should be modeled as a system.

Table 6.5: Bivariate ordered probit model estimation results - private vehicle ownership - Chicago

Variable	**Short run – own one non-AV**	**Long run – own zero non-AVs**
	Estimated Parameter (p-value)	**Estimated Parameter (p-value)**
Constant	0.328 (<0.001)	0.194 (<0.001)
Awareness		
Respondents with highest level of awareness of Uber’s self-driving vehicles (1: yes, 0: no).	0.079 (0.012)	-
Travel characteristics		
Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make zero social/recreational trips per week (1: yes, 0: no).	-	-0.276 (0.046)
Respondents who indicated that their primary mode of travel for social/recreational trips is bus (1: yes, 0: no).	0.138 (0.032)	0.262 (0.051)

Table 6.5: continued

Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	0.247 (0.056)	0.216 (0.037)
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no).	0.171 (0.053)	0.187 (0.084)
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations - early adopters**.	0.208 (0.019)	0.123 (0.034)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle - subjective norms**.	0.182 (0.028)	-
Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers**.	-0.097 (0.068)	-
Respondents who agreed or strongly agreed, on average, that AVs are compatible with their lifestyle, daily needs, or personal values and attitude - compatibility**.	-	0.246 (<0.001)
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs - safety concerns**.	-0.381 (<0.001)	-0.457 (<0.001)
Mode choice-related factors		
Respondents who rated level of cost of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.037 (0.069)	0.038 (0.082)
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.049 (0.066)	-
Socio-demographics		
Respondents who are 55 years old or older (1: yes, 0: no).	-0.125 (0.043)	-0.250 (0.034)
Respondents who have an annual income over $100,000 (1: yes, 0: no).	0.133 (0.084)	0.232 (0.069)
Respondents who indicated that they work full time (1: yes, 0: no).	0.197 (0.050)	0.281 (0.049)
Respondents who indicated that they are students (1: yes, 0: no).	-	0.460 (<0.001)
Respondents who indicated that they own or have access to 1-2 vehicles in their household (1: yes, 0: no).	0.096 (0.058)	-

Table 6.5: continued

Threshold parameters		
Threshold 1	0.619 (<0.001)	0.553 (<0.001)
Threshold 2	1.415 (<0.001)	1.332 (<0.001)
Threshold 3	1.979 (<0.001)	1.998 (<0.001)
Cross-equation correlation coefficient (rho)	0.603 (<0.001)	
Pseudo R-squared	0.101	
Log-likelihood function	-621.49	
Restricted log-likelihood	-558.81	

**Predicted probabilities calculated using an estimated binary probit model (see the Methods section)

Table 6.6: Bivariate ordered probit model estimation results - private vehicle ownership - Indianapolis

Variable	Short run – own one non-AV	Long run – own zero non-AVs
	Estimated Parameter (p-value)	Estimated Parameter (p-value)
Constant	0.242 (0.069)	0.133 (0.049)
Awareness		
Respondents with highest level of awareness of Uber's self-driving vehicles (1: yes, 0: no).	0.109 (0.025)	-
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no).	-	0.077 (0.064)
Travel characteristics		
Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make 1 or less social/recreational trips per week (1: yes, 0: no).	-	0.164 (0.029)
Respondents who indicated that their primary mode of travel for social/recreational trips is bus (1: yes, 0: no).	0.121 (0.028)	0.296 (0.034)
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	0.207 (0.048)	0.278 (0.024)
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no).	0.204 (0.062)	0.247 (0.068)
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	0.108 (0.017)	0.162 (0.013)

Table 6.6: continued

Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	0.164 (0.036)	0.197 (0.047)
Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers**.	-0.143 (0.074)	-0.051 (0.046)
Respondents who agreed or strongly agreed, on average, that AVs are compatible with their lifestyle, daily needs, or personal values and attitude - compatibility**.	-	0.184 (0.008)
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**.	-0.286 (0.011)	-0.248 (<0.001)
Mode choice-related factors		
Respondents who rated level of cost of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.079 (0.051)	0.038 (0.072)
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.031 (0.089)	-
Socio-demographics		
Respondents who are 55 years old or older (1: yes, 0: no).	-0.163 (0.034)	-0.219 (0.026)
Respondents who have an annual income over $100,000 (1: yes, 0: no).	0.187 (0.031)	0.227 (0.048)
Respondents who indicated that they work full time (1: yes, 0: no).	0.147 (0.038)	0.192 (0.024)
Threshold parameters		
Threshold 1	0.693 (<0.001)	0.598 (<0.001)
Threshold 2	1.342 (<0.001)	1.457 (<0.001)
Threshold 3	1.899 (<0.001)	1.936 (<0.001)
Cross-equation correlation coefficient (rho)	0.548 (<0.001)	
Pseudo R-squared	0.116	
Log-likelihood function	-604.57	
Restricted log-likelihood	-534.37	

**Predicted probabilities calculated using an estimated binary probit model (see the Methods section)

In line with the findings from the previous model (Table 6.3 and Table 6.4), a high level of awareness of AV technology is associated with a higher likelihood that people will have zero non-AVs or one non-AV in their household in the short and long terms, respectively, after the introduction of AVs for both study areas. Moreover, it was found that people who use their private vehicles for commuting trips and not social/recreational trips may choose to continue using their non-AVs five years after the introduction of AVs. This group of people might prefer the greater control that their private vehicle affords or they might simply enjoy driving. Studies have shown that people who prefer driving are associated with a weaker intention to ride in AVs (Howard & Dai, 2014; Payre et al., 2014). In contrast, it was found that people who use public transportation for their social/recreational trips are more likely to have zero non-AVs in their household five years after the introduction of AVs. This finding is in line with the literature: Haboucha et al. (2017) found that people who use public transportation or ride-hailing services are more positively inclined towards AVs. Similarly, people who drive less than 10,000 miles on a yearly basis seem to be willing to have one non-AV and zero non-AVs in their household in the short and long terms, respectively, after the introduction of AVs. The effect of this relationship was found to be somewhat similar between both models. This finding is also supported in the literature (Schoettle & Sivak, 2014b), where it has been found that people who drive less than the average US driver (the average annual mileage per person in the US is around 13,000 miles [FHWA, 2018]) are more inclined to use AVs compared to their counterparts.

Regarding respondents' attitudes, a higher affinity for innovativeness is positively associated with a higher likelihood that people will give up their conventional vehicles in their households five years after AVs are widely available, and adherence to subjective norms was found to be associated with a stronger intention to keep one non-AV in the short term for Chicago and short and long term for Indianapolis (Liu et al., 2018; Panagiotopoulos & Dimitrakopoulos, 2018). However, people who are less trustful of AV technology are hesitant to make the same decisions and are more skeptical of emerging technologies (Choi & Ji, 2015). The compatibility of riding in AVs with people's lifestyle was found to be positively associated with a higher likelihood to postpone the purchase of a non-AV in the short and long terms. Compatibility of AVs with one's lifestyle was found to influence people's perceptions of AVs in the literature as well (Brown et al., 2014; Continental, 2015). Furthermore, the analysis shows that people who have major safety concerns about AVs, with these concerns being especially strong within two years of the introduction of AVs, are not inclined to postpone the purchase of a non-AV. Kyriakidis et al. (2015) and Panagiotopoulos and Dimitrakopoulos (2018) similarly indicated that safety concerns are negatively associated with AV adoption. The analysis further shows that people who consider cost to be a very important factor in their mode choice decisions seem to be positively inclined toward having zero non-AVs five years after the introduction of AVs, possibly because they highly value their time and hope to take advantage of the increased productivity (multitasking) that AVs can offer, as several studies have suggested (Bansal & Kockelman, 2017a; Zmud et al., 2016).

As the results of the previous models (Table 6.3 and Table 6.4) indicated, age and income are associated with household vehicle ownership decisions in the short and long terms. Furthermore, it was found that respondents with one or two vehicles in their household intend to keep one private non-AV in the short term, while students expressed a higher likelihood of giving up ownership of conventional vehicles five years after AVs are widely available, a result in line with the findings of Ipsos MORI (2014).

6.4.3 Intention to Switch from Public Transportation to Ride-sharing Services that Use AVs in the Short and Long Run

The estimation results for the questions related to the intention to switch from public transportation to ride-sharing services that use AVs in the short and long run are presented in Table 6.7 and Table 6.8 for Chicago and Indianapolis, respectively. The results can help elucidate the factors that drive the intention to switch from public transportation to ride-sharing services operated through AVs. This can be achieved by assessing the factors that lead people to switch from public transportation to SAVs (which is also a shared transportation mode). Moreover, in order to account for cost and ensuring that the trip cost for both transportation modes is comparable, the average length of commuting trips were considered. The cross-equation correlation coefficient was found to be statistically significant ($p < 0.001$), validating the assumption that modeling the correlated dependent variables as a system is an appropriate modeling technique.

Table 6.7: Bivariate ordered probit model - public transportation - Chicago

Variable	Short-term Intention to Switch	Long-term Intention to Switch
	Estimated Parameter (p-value)	**Estimated Parameter (p-value)**
Constant.	-1.344 (<0.001)	-0.721 (0.098)
Awareness		

Table 6.7: continued

Respondents with highest level of awareness of a set of features called ‘autopilot’ provided in some versions of Tesla vehicles (1: yes, 0: no).	0.058 (0.082)	0.062 (0.076)
Travel characteristics		
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-	0.276 (0.057)
Respondents who indicated that they drive less than 20,000 miles per year (1: yes, 0: no).	-	0.252 (0.064)
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	0.288 (<0.001)	0.212 (0.010)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	0.727 (<0.001)	0.640 (<0.001)
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**.	-	-0.201 (<0.001)
Mode choice-related factors		
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.076 (0.099)	-
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.167 (0.008)	-
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.132 (0.029)	0.108 (0.037)
Socio-demographics		
Respondents who are between 18 and 34 years old (1: yes, 0: no).	0.271 (0.032)	0.363 (0.007)
Respondents who indicated that they are students (1: yes, 0: no).	-	0.458 (0.019)

Table 6.7: continued

Threshold parameters		
Threshold 1	0.871 (<0.001)	0.913 (<0.001)
Threshold 2	1.868 (<0.001)	1.916 (<0.001)
Threshold 3	3.254 (<0.001)	3.220 (<0.001)
Cross-equation correlation coefficient (rho)	0.739 (<0.001)	
Pseudo R-squared	0.102	
Log-likelihood function	-635.87	
Restricted log-likelihood	-571.34	

** Predicted probabilities calculated using an estimated binary probit model (see the Methods section)

Table 6.8: Bivariate ordered probit model - public transportation - Indianapolis

Variable	Short-term Intention to Switch	Long-term Intention to Switch
	Estimated Parameter (p-value)	Estimated Parameter (p-value)
Constant.	-0.817 (<0.001)	-0.594 (0.037)
Awareness		
Respondents with highest level of awareness of a set of features called ‘autopilot’ provided in some versions of Tesla vehicles (1: yes, 0: no).	0.127 (0.029)	0.108 (0.025)
Travel characteristics		
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	0.167 (0.018)	0.221 (0.020)
Respondents who indicated that they drive less than 15,000 miles per year (1: yes, 0: no).	-	0.197 (0.042)
Perceptions / Opinions / Attitudes		
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	0.184 (<0.001)	0.242 (<0.001)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	0.284 (<0.001)	0.367 (<0.001)
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**.	-0.217 (0.013)	-0.194 (0.018)

Table 6.8: continued

Mode choice-related factors		
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.106 (0.067)	-
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.154 (<0.001)	-0.171 (<0.001)
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.207 (0.021)	0.238 (0.019)
Socio-demographics		
Respondents who are between 25 and 34 years old (1: yes, 0: no).	0.149 (0.068)	0.162 (0.089)
Respondents who are over 55 years old (1: yes, 0: no).	-0.294 (0.024)	-0.367 (0.037)
Respondents who have annual income less than $50,000 (1: yes, 0: no).	0.328 (0.052)	0.379 (0.058)
Threshold parameters		
Threshold 1	0.792 (<0.001)	0.808 (<0.001)
Threshold 2	1.674 (<0.001)	1.842 (<0.001)
Threshold 3	3.018 (<0.001)	3.147 (<0.001)
Cross-equation correlation coefficient (rho)	0.628 (<0.001)	
Pseudo R-squared	0.157	
Log-likelihood function	-651.32	
Restricted log-likelihood	-548.91	

** Predicted probabilities calculated using an estimated binary probit model (see the Methods section)

The intention to switch from public transportation to ride-sharing services operated through AVs seems to be associated with factors similar to those that affect private vehicle ownership decisions. The results indicate that the greater the level of awareness of AVs, the stronger the intention to switch. Additionally, people who have a car-sharing account and therefore may have higher exposure ride-sharing services seem to be more willing to opt in to using SAVs in the foreseeable future. The literature shows similar results, where it has been found that people with prior experience with vehicle sharing services (e.g., car-sharing or ride-sharing) are more eager to use AVs (Shaheen et al., 2018). Similarly, it was found that people who drive more than the average US driver, in particular, more than 20,000 miles per year, are less willing to switch to AVs, a result in line with the findings of Haboucha et al. (2017).

Early adopters (those with an affinity to innovativeness) and respondents who tend to be influenced by their social circles (those who adhere to subjective norms) have a stronger intention to switch to the use of SAVs. However, people who have safety concerns about AV technology seem less likely to switch, a finding that is also supported by the literature (Kyriakidis et al., 2015; Schoettle & Sivak, 2014b). Mode choice-related factors such as the importance that respondents gave to the reliability, safety, and flexibility of different mode alternatives were found to be key determinants of the intention to switch, especially in the short term. In particular, reliability and flexibility were positively associated with the intention to switch, while safety was negatively associated. The former factors are linked with a stronger intention to switch, possibly because AVs are perceived to be more reliable than public transportation, especially in terms of less waiting time, but SAVs are also perceived to be more flexible than public transportation, which operates on fixed routes. However, safety is related to a weaker intention to switch because AVs are sometimes perceived as less safe than public transportation, especially as this emerging technology is first introduced. Such factors were found in the literature to be important to mode choice decisions, especially in the context of public transportation (Beck & Rose, 2016; Tyrinopoulos & Antoniou, 2008).

Regarding socio-demographic variables, younger respondents (between 18 and 34 years old) and students seem to be eager to substitute SAVs for public transportation, regardless the time period. In general, Millennials have a more positive perception of AVs and are one of the largest user groups of car-sharing and ride-sharing services (Shaheen et al., 2018). However, older respondents (over 55 years old) were found to be negatively associated with the intention to switch in Indianapolis. Lastly, respondents with a reported income less than $50,000 in Indianapolis seem to be unlikely to postpone the purchase of a non-AV when AVs become commercially available.

6.5 Discussion

The existing literature suggests that AVs have the potential to affect travel behavior and vehicle ownership decisions and substitute for private non-AV vehicles and public transportation. This chapter examined potential substitution patterns (i.e., from private vehicles to AVs and from public transportation to SAVs) and identified across two different timeframes following the introduction of AVs the factors that influence individuals' decisions to continue owning a non-AV private vehicle, postpone the purchase a new non-AV for the household, or give up private vehicle ownership and the factors that influence the switch from public transportation to ride-sharing services that use AVs.

The findings indicate that these decisions vary by individuals' socio-demographic characteristics, levels of awareness of AV technology, attitudes, and travel patterns. For example, individuals with a high level of awareness of AV technology, those who are influenced by their social circle, and those familiar with car-sharing services seem likely to shift away from private vehicle ownership and public transit use to AVs and SAVs, respectively. However, low trust of the technology and safety concerns seem to hinder the adoption of AVs. As expected, the cost of travel and trip purpose were perceived as very important factors in mode choice decisions. The cost of travel is positively associated with the likelihood of postponing the purchase of a non-AV. Results found in Chicago and Indianapolis seem to show similar trends across all the categories of variables that affect the intention to switch.

7. PERCEIVED IMPACTS OF SAVs ON MODE CHOICE DECISIONS AND EVALUATION OF VALUE TRAVEL TIME SAVINGS

This Chapter assesses the perceived impacts of SAVs on mode choice decisions - between biking, using a private vehicle, using public transportation, and using ride-hailing services operated through non-AVs - on SAVs (private and shared AV rides). Additionally, the analysis of this chapter evaluates the corresponding value travel time savings of the general population and of the categories identified by the market segmentation analysis.

7.1 Introduction

The advent of the automated technology can lead to the emergence of SAVs that can offer affordable mobility on-demand solutions leading to a more sustainable transportation system. These services can offer first or last mile solutions to commuters achieving multimodal travel behavior, thereby disrupting the mode choice decisions (Fagnant & Kockelman, 2015). Furthermore, this mobility service can also be attractive to those who are too young or old to drive and to individuals that do not own or have access to a private vehicle (Anderson et al., 2014). Various published studies on SAVs were reviewed and included in subsection 2.2 of this dissertation; where almost half of the studies used optimization modeling techniques to either maximize the profit, optimize the fleet or minimize the trip distance by SAV users. Hence, little is known about the evaluation of the attributes affecting mode choice decisions and the travel behavior impacts due to the emergence of SAVs. The design of transportation planning and policies can be enriched from such an analysis by understanding what impacts people's opinion as their preferred transportation mode.

Krueger et al. (2016) found that service attributes such as travel time, waiting time, and cost influence the preference on SAVs and multi-modal people are more willing to use SAVs than their counterparts. Kolarova et al. (2019) found that privately-owned AVs was more preferred as an option rather than SAVs; whereas the value of travel time savings (VTTS) were found as higher in the for the case of SAVs. A study that was conducted in Lisbon, Portugal found that by implementing a shared-taxi service the fleet can be reduced to 2,000 compared to the 3,100 current traditional taxis (Martinez & Viegas, 2017). Similarly, it was concluded that dynamic ride-sharing has the potential to reduce total service times and travel costs by incorporating extra pick-ups, drop-offs and non-direct routes (Fagnant et al., 2015). Zhang et al. (2015) found that the demand for parking significantly reduces even when the penetration rate of SAVs as low as 2%. Schoettle and Sivak (2014a) conducted a survey in the UK, US, and Australia evaluating the benefits and concerns of AVs and people's willingness-to-pay to evaluate different levels of vehicle automation. Similar objective was considered by (Kyriakidis et al. 2015) assessing the willingness-to-pay for all the levels of AVs. It was shown that the people who were willing to pay more, traveled longer distances, or used the cruise control feature of their private vehicles. Additionally, a study by Ipsos MORI (2014) found that younger people or people who live in dense metropolitan areas are more willing to pay more. Another study by Hohenberger et al. (2016) found that the results differ by gender, where men are more willing to use AVs. Jiang et al. (2019) argued that age, household size and trip purposes of AVs can influence the willingness-to-pay of AVs. Moreover, Talebian and Mishra (2018) found that 'word-of-mouth' influences the willingness-to-pay of AVs and Liu et al. (2018) concluded that 'social trust' (trust in people of social circle and organizations) can also increase the willingness-to-pay of AVs. Bansal et al. (2016) concluded that people were willing to pay approximate $7,000 more on average for a Level 5 fully AV and around $3,300 more for a Level 4 AV. Similarly, it was concluded by another study that people are willing to pay $3,500 for partial automation and approximately $4,900 for full automation (Daziano et al., 2017).

7.2 Data

7.2.1 Design of Choice Experiments

Choice experiments were conducted in the stated preference survey to assess the attributes affecting people's opinion as their preferred mode of transportation, if AV were deployed in the short and long run. The two attributes that were included in the choice experiments are the cost (in dollars) and traveling time (in minutes). The traveling time includes in-vehicle time and waiting time.

In total 9 scenarios are designed for the short term (AVs are implemented in the study area two weeks prior to the experiment). The first scenario (base case) included the transportation modes that are already available in the area (bike, private vehicle, public transportation, and ride-hailing service with non-AVs). The rest of the scenarios included the chosen transportation mode based on the base case scenario plus two hypothetical transportation modes; ride-hailing service operated by AVs where the passenger is traveling alone, and ride-hailing service operated by AVs where the passenger shares the ride. The same rationale was used for the design of scenarios for the long run (AVs are implemented in the study area one year prior to the experiment).

The choice experiment was designed for commuting trips, since AVs have the potential to alter commuting patterns that can affect land use and could also result in urban sprawl (Haboucha et al., 2017; Howard & Dai, 2014). Additionally, for different trip purposes such as social/recreational trips, it is difficult to capture the mode choice decisions for all existing modes; since for example, some public transportation modes may not be available during the trip time. Similarly, social/recreational trips usually include shorter trips made usually on foot; which is not the case for commuting trips. The two attributes that were included in the choice experiments were the cost and traveling time, as these attributes are very important when evaluating commuting trips.

The choice experiment was designed accordingly to the recommendations included in Hensher et al., (2005). Specifically, the choice experiment includes six alternatives that are more than two and hence behavioral conditions can be examined, instead of a simplistic binary choice. Additionally, the choice experiment introduced some elements of revealed preferences. In other words, the first four alternatives (bus, private vehicle, public transportation, and ride-hailing services with non-AVs) correspond to the actual travel behaviors of users. Furthermore, two hypothetical alternatives were introduced that correspond to stated preferences. As suggested by Hensher et al., (2005) the inclusion of stated preferences choices with existing alternatives is important for choice experiments. On another note, the different alternatives were labeled and not unlabeled that can lead to abstract alternatives that the users can face difficulties when filling out the survey.

The number of the hypothetical scenarios was based on the fractional factorial design in order to avoid confounded main effects and achieve orthogonality. Therefore, 9 scenarios were included in total for each choice experiment (base case and 8 scenarios based on the fractional factorial design). The design table is shown in Table C1 found in Appendix C, where high values (+1) indicate a 10% increase of the value adopted in the base case scenario and low values (-1) indicate a 10% decrease of the value adopted in the base case scenario.

Cheap talks and text were added to the choice experiments to account for the hypothetical bias of this specific section of the stated preference survey. Figures C1. C2, and C3 found in Appendix C indicate an example of the cheap talk and choice sets in the short and long run. The values of the parameters used in the scenarios were based on relevant literature based on scientific journal papers, technical reports (AAA, 2018; Barclays, 2016; Deloitte, 2017; IndyGo, 2017; Litman, 2019; Morgan Stanley, 2016).

7.2.2 Descriptive Statistics

As it was discussed in the survey design section (subsection 3.3), the survey consisted of 400 responses residing in Chicago and Indianapolis, respectively, and seven transportation modes were considered during the initial analysis to identify the commuting trends: a) walking; b) biking; c) private vehicle; d) public transportation; e) ride-hailing service; f) ride-sharing service; and g) car-sharing service. Figure 7.1 and Figure 7.2 include the primary transportation mode that the participants responded for work/school trip purposes. Then, moving to the choice experiments respondents indicated their willingness to commute changing from their current commuting mode (as reported in the base case scenario) to the hypothetical modes of single-passenger or shared AV. The responses of the participants are showed in Figure 7.3 - Figure 7.12.

Figure 7.1 shows that approximately two out of three respondents were commuting using their private vehicles in Chicago, 16% walk or bike, and around 20% were using shared transportation modes for their commuting trips. On the other hand, Figure 7.2 shows that at least four out of five respondents were commuting using their private vehicles in Indianapolis. Only one out of ten respondents opted for active transportation modes (walking and biking). Lastly, approximately 10% of respondents were using shared transportation modes for their commuting trips (public transportation, ride-hailing, ride-sharing and car-sharing services).

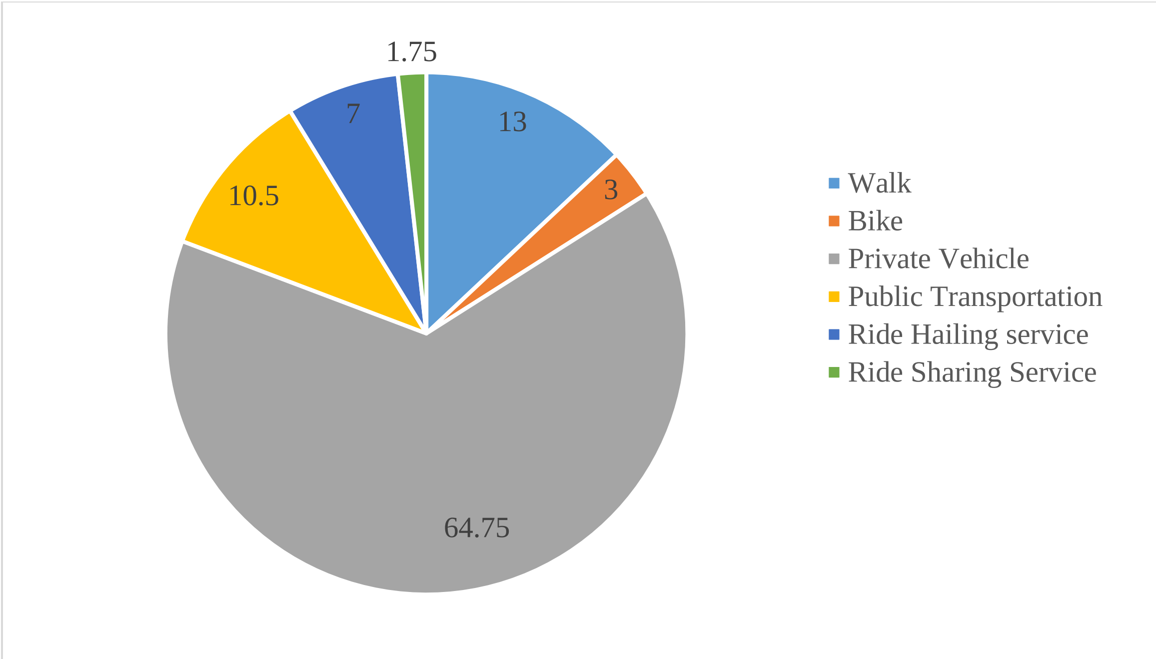

Figure 7.1: Primary mode for work/school trip purpose - Chicago

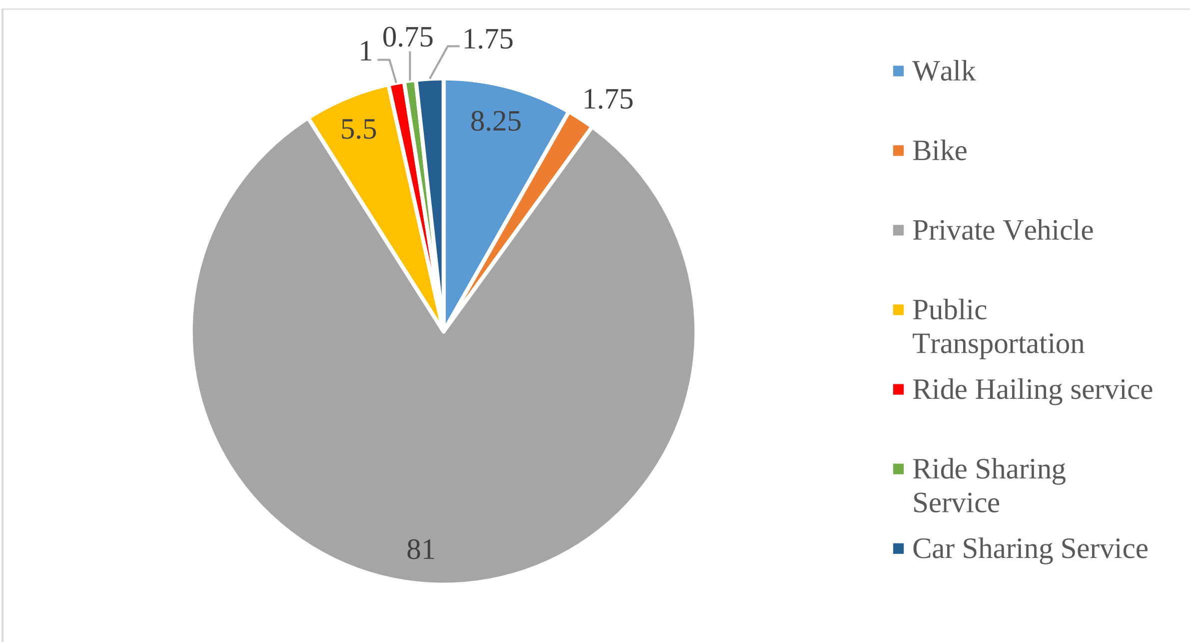

Figure 7.2: Primary mode for work/school trip purpose - Indianapolis

Figure 7.3 and Figure 7.4 show the willingness of participants who commute to their work by cycling to private AV and shared AV rides in the short and long run in Chicago and Indianapolis, respectively. In Chicago, around two out of three respondents were willing to keep using their bikes for their commute in the short and long run. A higher number of respondents is found to be willing to use the private AV rides in the short run compared to the long run; whereas the opposite trend was found for the shared AV rides. In Indianapolis, four out five respondents were willing to keep using their bikes for their commute in the short run, whereas seven out of 10 showed the same willingness in the long run. In the short run, the respondents who are willing to change their mode prefer almost equally the private AV and shared AV rides. However, in the long run more people prefer the private AV rides.

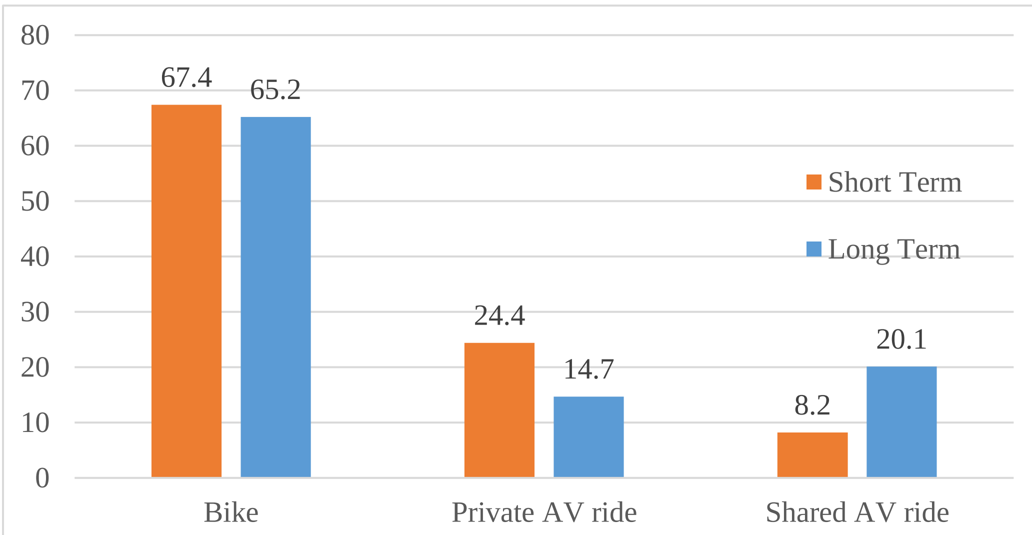

Figure 7.3: Choice experiment - bike - Chicago

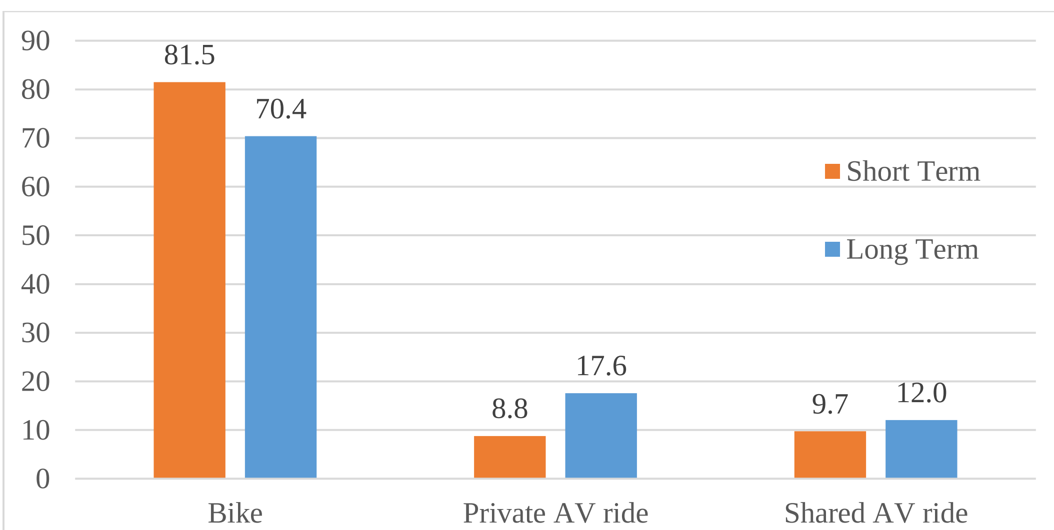

Figure 7.4: Choice experiment - bike - Indinapolis

Figure 7.5 and Figure 7.6 show the respondents who are commuting using their private vehicles in Chicago and Indianapolis, respectively. In Chicago, it was found that in the short and long run, more respondents were willing to take shared AV rides compared to private AV rides. Furthermore, a lower number of people were willing to opt in riding SAVs in Chicago than Indianapolis. In Indianapolis, it seems that almost an equal number of respondents is willing to change their transportation mode to private AV and shared AV rides regardless of the time period. Additionally, it is shown that in the long run people are more willing to opt in taking shared AV rides rather than private AV rides.

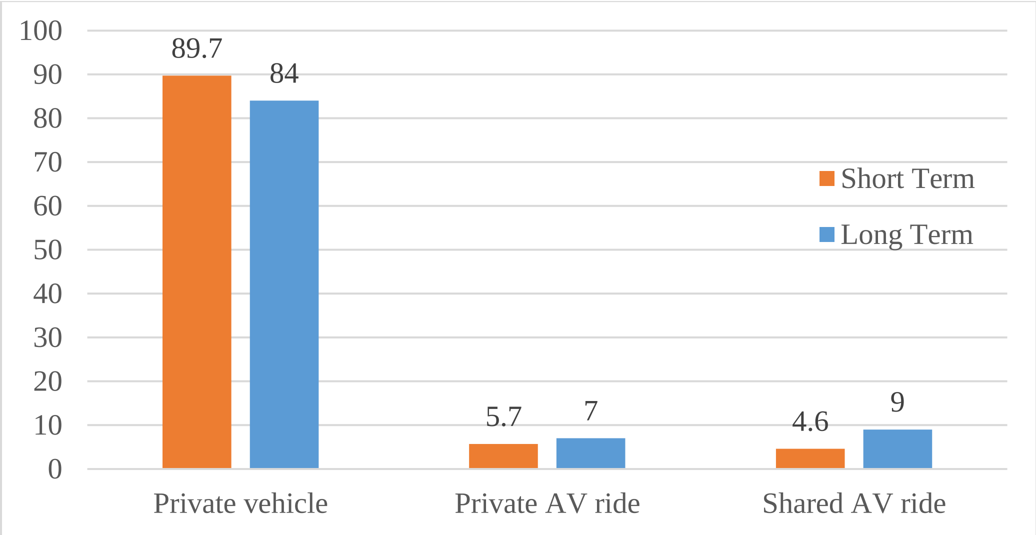

Figure 7.5: Choice experiment - private vehicle - Chicago

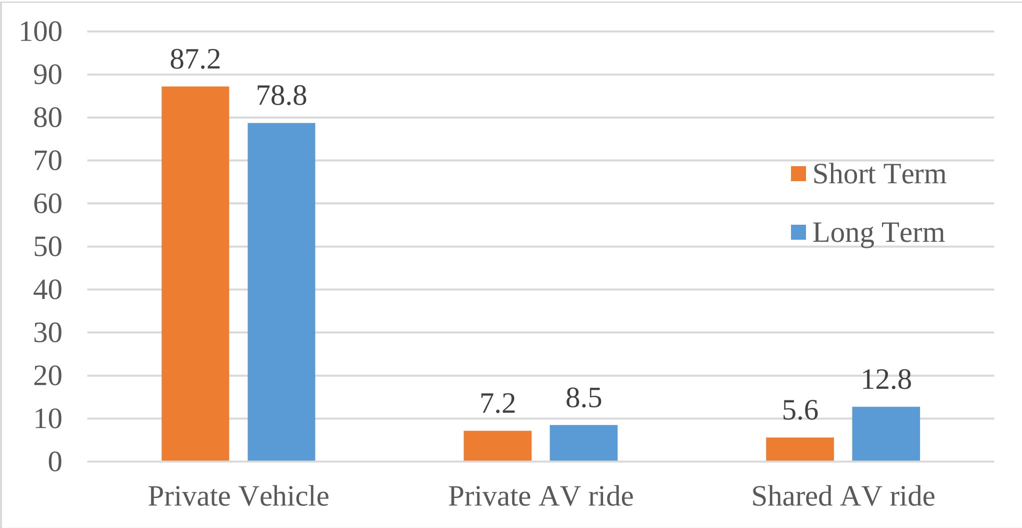

Figure 7.6: Choice experiment - private vehicle - Indianapolis

Figure 7.7 and Figure 7.8 show the willingness of people who commute using public transportation to private AV and shared AV rides in Chicago and Indianapolis, respectively. In Chicago around four out of five respondents are not willing to not opt in for automation. Furthermore, a higher number of respondents showed a preference for the private AV rides in the short run and for the shared AV rides in the long run. In Indianapolis, approximately two out of three and three out of five respondents showed a willingness to not opt in for automation in the short and long run, respectively. These percentages are lower compared to biking and private vehicles, indicating a higher willingness of people using public transportation towards AVs. On a similar note, a higher percentage of people still prefers to take shared AV rides rather than private AV rides, regardless of the time period.

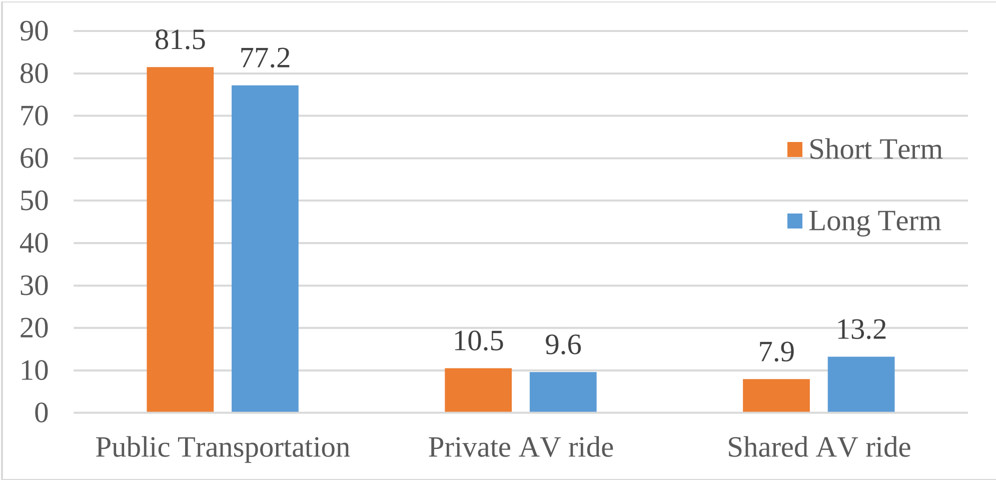

Figure 7.7: Choice experiment - public transportation - Chicago

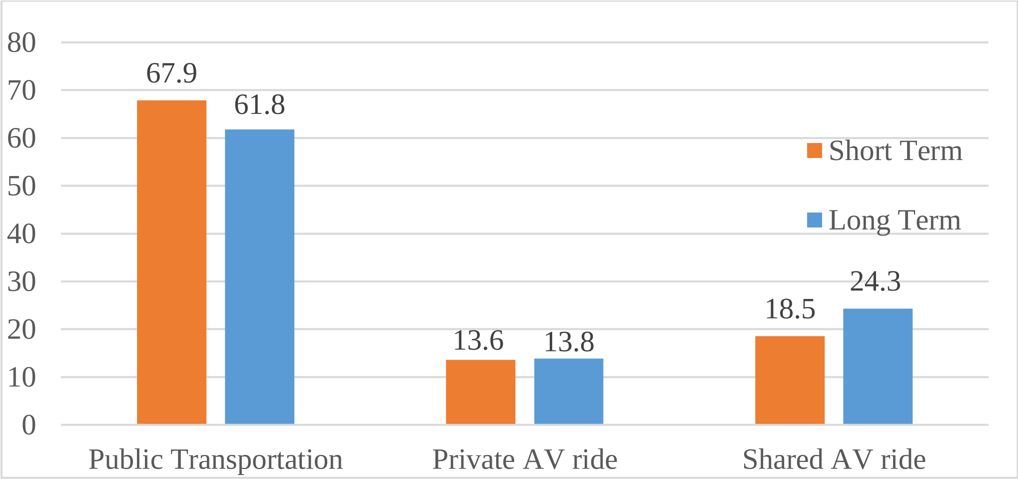

Figure 7.8: Choice experiment - public transportation - Indianapolis

Figure 7.9 and Figure 7.10 show the respondents who are commuting using ride-hailing services without AVs in Indianapolis and Chicago, respectively. In Chicago, it was found that around two out of ten were not willing to opt in for automation. Additionally, a higher number of responses was found for shared AV rides in the short and long run. In Indianapolis, approximately 15% of the respondents indicated that are willing to continue using ride-hailing services without AVs; the lowest percentage of all the modes included in the choice experiment. Furthermore, almost the same percentages were reported for the private AV and shared AV rides in the short and long run; where shared AVs attracted a greater share of respondents.

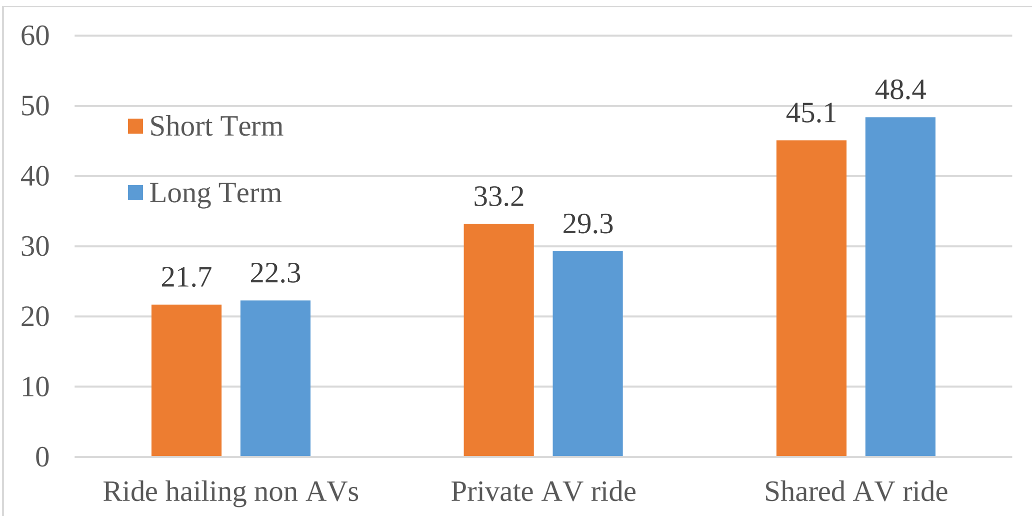

Figure 7.9: Choice experiment – ride-hailing w/o AVs - Chicago

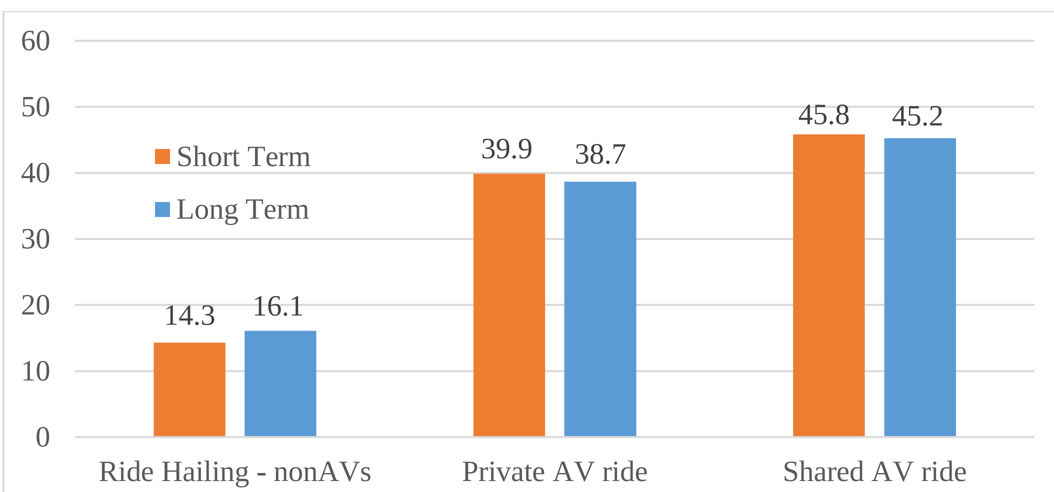

Figure 7.10: Choice experiment – ride-hailing w/o AVs - Indianapolis

Figure 7.11 and Figure 7.12 summarizes the willingness of respondents to adopt AVs as reported in the choice experiments including all the transportation modes in Chicago and Indianapolis, respectively. Unsurprisingly, commuters in both areas who already use ride-hailing services without AVs to commute are very interested in adopting AV ride-hailing, with little change between short and long term adoption; followed by public transportation, bikes and lastly, private vehicles.

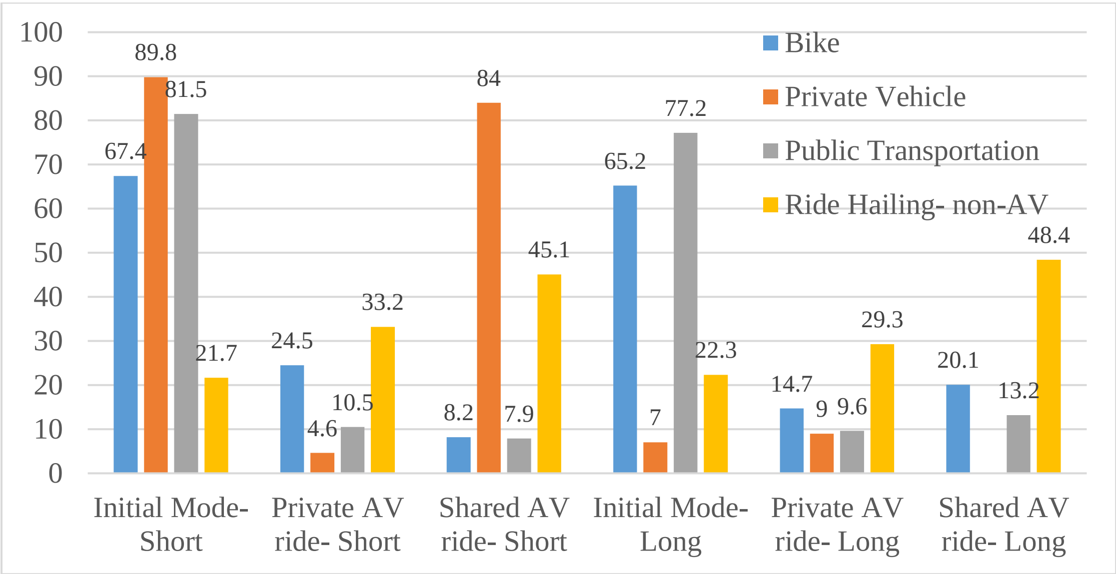

Figure 7.11: Choice experiment - willingness to adopt AVs - Chicago

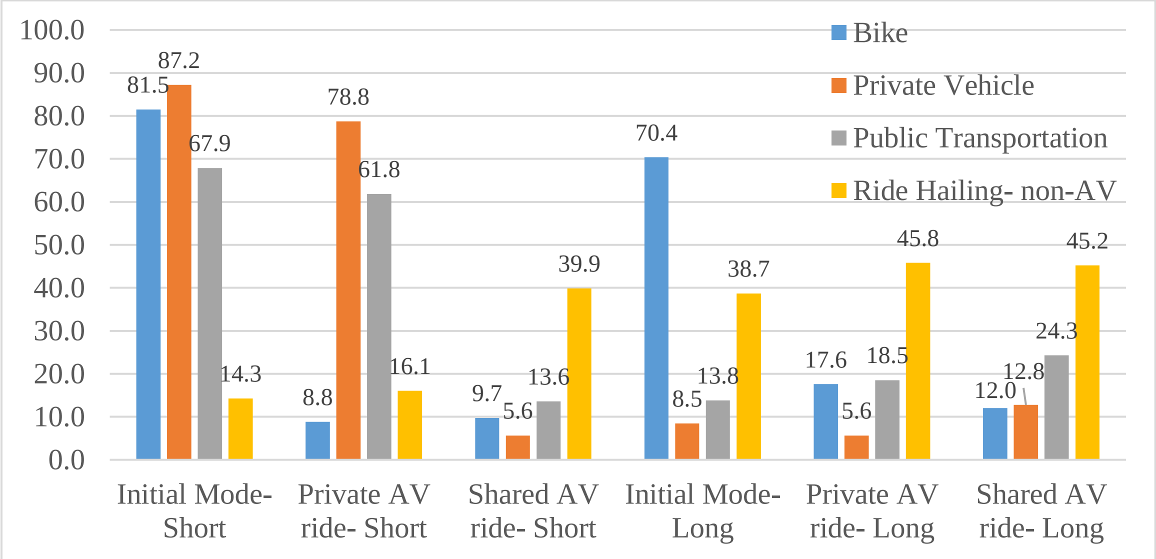

Figure 7.12: Choice experiment - willingness to adopt AVs - Indianapolis

7.3 Methods

The modeling technique that was used in order to investigate the attributes that affect mode choice decisions due to the emergence of ride-sharing services operated through AVs (SAVs) in the short and long run was the mixed logit model. The data are presumed to be well-modeled by using a random parameter logit model (mixed logit model) due to the heterogeneity across observers and estimate a personal mobility portfolio for each respondent. Two mixed logit models were estimated in order to estimate the attributes that affect mode choice decisions due to the short and long term emergence of the ride-sharing services operated through AVs.

The standard form of multinomial logit model as it is described in (Hensher, 1998) is shown below.

$$P_n(i) = \frac{EXP\ [\beta_i X_{in}]}{\sum \exp\ (\beta_i X_{in}]} \ldots (1)$$

,where $P_n(i)$ estimates the probability of having i discrete outcomes. As mentioned above, the mixed logit model is used in this analysis to account for the parameters' variability across respondents. McFadden and Train (2000) and Train (2003) developed the mixed logit models by considering a function that estimates discrete outcome probabilities. The mixed logit model that the outcome probabilities are set as $P_n^m(i)$ and $f\left(\beta\ \middle|\varphi\right)$ is defined as the density function of β with φ is set as the vector of parameters of the set density function is shown below

$$P_n^m(i) = \int P(i)\, f\left(\beta\ \middle|\varphi\right) d\beta \ldots (2)$$

Substituting equation 1 into equation 2 gives the mixed logit model shown in equation 3.

$$P_n^m(i) = \int \frac{EXP\ [\beta_i X_{in}]}{\sum \exp\ (\beta_i X_{in}]}\, f\left(\beta\ \middle|\varphi\right) d\beta \ldots (3)$$

This expression shows that the mixed logit probabilities $P_n^m(i)$ are the weighted average of the standard MNL probabilities $P_n(i)$ with the weights determined by the density function $f\left(\beta\ \middle|\varphi\right)$. The estimation of mixed logit models is developed by applying maximum likelihood using simulation approaches due to the difficulty in computing these probabilities. The Halton draws are shown to be provide more efficient estimates rather than random draws (Halton, 1960), giving accurate probability estimations with fewer draws (Bhat, 2003; Train, 2001). For this analysis, 200 Halton draws were used, a sufficient number in order to calculate accurate estimates as it is suggested by other studies such as (Bhat, 2003; Gkritza & Mannering, 2008).

Building on previous work calculating values of willingness to pay and travel time savings (Brownstone & Train, 1998; Daziano et al., 2017; Kolarova et al., 2019), the VTTS values were estimated using the marginal rate of substitution for travel time and cost as the ratio of the coefficients of travel time and cost for different alternatives in the short and long run. The marginal rate of substitution is defined as the amount of a product that a consumer is willing to give away for another product, if both products are equally satisfying. As suggested in Hensher et al. (2005) using the marginal rate of substitution to capture the trade-off between the cost and travel time; the VTTS can be calculated that describes how much the travel cost changes for a 1 unit change of the travel time. In other words, the importance of the VTTS in choice studies in the transportation context is that it can estimate the amount of money someone is willing to spend in order to save a unit of travel time. The VTTS value can be easily compared with the average value of travel time for personal travel; evaluating the hypothetical modes separately. The VTTS was calculated for the general sample, but also for the different adopter categories derived from the market segmentation analysis.

The independent variables regarding people's opinion on AVs (willingness to be an early adopter, adherence to subjective norms, distrust of strangers, compatibility with the respondent's lifestyle, and safety concerns) may have endogeneity issues with the dependent variables. As a remedy to account for the potential inherent endogeneity, binary ordered probit models were calculated with the endogenous independent variables as dependent variables, modeled with exogenous variables (demographic, socio-economic and transportation-related variables). Therefore, the calculated probabilities of the ordered probit models were used as the independent variables in the final models to evaluate the factors affecting mode choice decisions.

7.4 Estimation Results

The estimation results of the mixed logit models that impact mode choice decisions (between biking, using a private vehicle, using public transportation, and using ride-hailing services operated through non-AVs) due to the emergence of ride-sharing services operated through AVs (SAVs) in the short run and long run are presented in Table 7.1 and Table 7.2, respectively.

The findings of both models show that the level of awareness regarding AVs is an attribute that influences mode choice decisions towards automation and has a greater effect on AV shared rides rather than single passenger AVs. Results from other studies show a similar trend; that is, a higher awareness is associated with a higher willingness to accept AVs (Bansal et al., 2016; Sanbonmatsu et al., 2018). Additionally, respondents who make fewer social/recreational trips on a weekly basis are more likely to keep using the transportation mode that they chose in the base case scenario and do not opt in for automation. This could be explained because people might believe that trips with private AV or shared AV rides are more suitable choices for social/recreational trips than other trip purposes, such as commuting. On the other hand, people who have a car-sharing account and a car-sharing or ride-hailing account in the long run scenarios, respectively, seem to be willing to use riding sharing service operated through AVs in the short run and long run, respectively, which is also supported by other studies (Haboucha et al., 2017). Furthermore, it was found that people who tend to drive less than the average US driver (the average annual mileage per person in the US is around 13,000 miles (FHWA, 2018) are willing to use private AV and shared AV rides for their trips. However, people who perceive reliability as an important factor in their mode choice decisions seem to keep using their preferred mode choice in the base case scenario and do not prefer to use ride-hailing services operated through AVs.

Regarding attributes related to respondents' attitudes, the analysis shows that people with a higher affinity for innovativeness, a higher tendency to be influenced by their social circles, and fewer safety concerns about AVs are more willing to use single passenger and shared AVs in the short and long run scenarios. In particular, people who can be considered as early adopters and tend to adopt new ideas faster than others are associated with a higher tendency to use AVs for their trips. This is in line with other studies as well (Haboucha et al., 2017). Similarly, people who adhere to subjective norms and their social circle can influence their decisions show an analogous tendency as the people with a higher affinity for innovativeness; a finding that is also supported by the literature (Kyriakidis et al., 2015). Lastly, people who have more safety concerns towards AVs show a different behavior and they prefer to keep using their selected mode choice that they indicated in the base case scenario.

As expected, socio-demographic variables are also associated with mode choice decisions in the short and long run. People between 18 and 34 years or students have a higher willingness to use single passenger and AV shared rides for their trips, in the short and long run. On the other hand, people who are older than 55 years old show an opposite behavior and they prefer to keep using their selected mode choice that they indicated in the base case scenario; possibly due to the higher uncertainty of people about AVs especially in the short run. Moreover, people with income higher than $100,000 seem to be indifferent to using ride-hailing services operated by AVs than their counterparts regardless of the time period. These findings are supported by other studies as well (Brown et al., 2014; Ipsos MORI, 2014; Shaheen et al., 2018). In the short-term scenarios, it was found that people who own or have access to more than one vehicle in their households are not willing to use single passenger or AV shared rides for their trips; another indication of the higher uncertainty and the willingness of people to switch to AVs, specifically in the short run.

Table 7.1: Mixed logit model estimation results - short run

	Chicago			**Indianapolis**		
Variable	**Mode choice (base case)**	**Private AV ride**	**Shared AV ride**	**Mode choice (base case)**	**Private AV ride**	**Shared AV ride**
	Estimated Parameter (p-value)					
Constant	-	-1.217 (<0.001)	-1.681 (<0.001)	-	-1.014 (<0.001)	-1.549 (<0.001)
Time	-0.201 (<0.001)	-0.188 (0.012)	-0.121 (<0.001)	-0.217 (<0.001)	-0.194 (0.031)	-0.104 (0.018)
Cost [st.dev]	-0.705 (<0.001) [0.863 (0.012)]	-0.769 (0.002) [1.005 (0.009)]	-0.743 (<0.001) [0.972 (0.017)]	-0.669 (<0.001)* [1.042 (0.003)]	-0.733 (<0.001)* [0.925 (0.014)]	-0.603 (<0.001)* [0.846 (0.021)]
Awareness						
Respondents with highest level of awareness of Uber's self-driving vehicles? (1: yes, 0: no)	-	0.314 (0.016)	0.314 (0.016)	-	0.271 (0.024)	0.271 (0.024)
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no)	-	-	0.168 (0.013)	-	-	-
Mode choice-related factors						
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	0.139 (0.037)	-	-	0.196 (0.039)	-	-

Table 7.1: continued

Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	0.104 (0.043)	-	-	-	-	-
Travel characteristics						
Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make zero social/recreational trips per week (1: yes, 0: no)	0.549 (0.025)	-	-			
Respondents who indicated that they make 1 or less social/recreational trips per week (1: yes, 0: no)	-	-	-	0.403 (0.037)	-	-
Respondents who indicated that their primary mode of travel for social/recreational trips is bus (1: yes, 0: no)	-	-	0.673 (0.019)			
Respondents who indicated that they have a car-sharing account (1: yes, 0: no)	-	1.072 (<0.001)	1.072 (<0.001)	-	0.761 (0.008)	0.761 (0.008)
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no)	-	0.341 (0.031)	0.341 (0.031)	-	0.384 (0.046)	0.384 (0.046)
Perceptions / Opinions / Attitudes						
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**	-	0.984 (<0.001)	0.984 (<0.001)	-	0.802 (<0.001)	0.802 (<0.001)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**	-	0.843 (0.004)	0.843 (0.004)	-	1.017 (<0.001)	1.017 (<0.001)

Table 7.1: continued

Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers**	0.590 (0.011)	-	-	-	-	-
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**	0.747 (0.016)	-	-	0.942 (0.021)	-	-
Socio-demographics						
Respondents who are between 18 and 34 years old (1: yes, 0: no) [st.dev.]	-	-	-	-	0.371 (0.018)* [0.542 (0.039)]	0.371 (0.018)* [0.542 (0.039)]
Respondents who are between 25 and 34 years old (1: yes, 0: no) [st.dev.]	-	0.363 (0.041)* [0.617 (0.023)]	0.363 (0.041)* [0.617 (0.023)]	-	-	-
Respondents who are 55 years old or older (1: yes, 0: no)	0.318 (0.049)	-	-	0.392 (0.044)	-	-
Respondents who indicated that they are students (1: yes, 0: no)	-	0.404 (0.024)	0.404 (0.024)	-	0.493 (0.029)	0.493 (0.029)
Respondents who have an annual income over $100,000 (1: yes, 0: no)	0.284 (0.036)* [0.372 (0.014)]	-	-	0.247 (0.046)* [0.309 (0.028)]	-	-
Respondents who indicated that they own or have access to more than 1 vehicle in their household (1: yes, 0: no)	-	-	-	0.163 (0.031)	-	-
Pseudo R-squared	0.308			0.293		
Log-likelihood function	-1821.603			-1987.421		
Restricted log-likelihood	-2632.847			-2812.973		

*Random parameter (not fixed)

**Predicted probabilities calculated using an estimated binary probit model

Table 7.2: Mixed logit model estimation results - long run

Variable	Chicago			Indianapolis		
	Mode choice (base case)	**Private AV ride**	**Shared AV ride**	**Mode choice (base case)**	**Private AV ride**	**Shared AV ride**
	Estimated Parameter (p-value)					
Constant	-	-1.412 (<0.001)	-1.943 (<0.001)	-	-1.260 (<0.001)	-1.871 (<0.001)
Time	-0.262 (<0.001)	-0.226 (0.014)	-0.161 (0.029)	-0.283 (<0.001)	-0.207 (0.019)	-0.148 (0.005)
Cost [st.dev]	-0.814 (0.019) [1.230 (0.028)]	-1.102 (0.011) [1.305 (0.027)]	-1.187 (0.034) [1.472 (0.012)]	-0.804 (<0.001)* [1.151 (0.003)]	-0.873 (<0.001)* [1.009 (0.011)]	-0.979 (<0.001)* [1.238 (0.008)]
Awareness						
Respondents with highest level of awareness of Uber's self-driving vehicles? (1: yes, 0: no)	-	0.439 (0.009)	0.439 (0.009)	-	0.318 (0.048)	0.318 (0.048)
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no)	-	-	0.217 (0.014)	-	0.196 (<0.001)	0.196 (<0.001)
Mode choice-related factors						
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no)	0.106 (0.042)	-	-	0.172 (0.026)	-	-
Travel characteristics						

Table 7.2: continued

Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make zero social/recreational trips per week (1: yes, 0: no)	0.628 (0.021)	-	-	0.472 (0.023)	-	-
Respondents who indicated that their primary mode of travel for social/recreational trips is bus (1: yes, 0: no)	-	-	0.791 (0.014)	-	-	-
Respondents who indicated that they have a car-sharing account (1: yes, 0: no)	-	1.226 (<0.001)	1.226 (<0.001)	-	0.834 (<0.001)	0.834 (<0.001)
Respondents who indicated that they drive less than 5,000 miles per year (1: yes, 0: no)	-	-	-	-	0.412 (0.031)	0.412 (0.031)
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no)	-	0.273 (0.038)	0.273 (0.038)	-	-	-
Perceptions / Opinions / Attitudes						
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**	-	1.106 (<0.001)	1.106 (<0.001)	-	0.694 (<0.001)	0.694 (<0.001)
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**	-	0.917 (0.006)	0.917 (0.006)	-	0.851 (<0.001)	0.851 (<0.001)
Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers**	0.661 (0.024)	-	-	-	-	-
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**	0.826 (0.019)	-	-	0.717 (0.015)	-	-

Table 7.2: continued

Socio-demographics						
Respondents who are between 18 and 34 years old (1: yes, 0: no) [st.dev.]	-	-	-	-	0.469 (<0.001)* [0.583 (0.019)]	0.371 (0.018)* [0.542 (0.039)]
Respondents who are between 25 and 34 years old (1: yes, 0: no) [st.dev.]	-	0.440 (0.037)* [0.638 (0.042)]	0.440 (0.037)* [0.638 (0.042)]	-	-	-
Respondents who are 55 years old or older (1: yes, 0: no)	0.241 (0.036)	-	-	-	-	-
Respondents who have an annual income over $100,000 (1: yes, 0: no)	0.323 (0.025)* [0.429 (0.046)]	-	-	0.261 (0.039)* [0.372 (0.016)]	-	-
Pseudo R-squared	0.289			0.261		
Log-likelihood function	-1792.638			-2013.396		
Restricted log-likelihood	-2521.519			-2725.621		

*Random parameter (not fixed)

**Predicted probabilities calculated using an estimated binary probit model

The next step when the statistical models were finalized was to calculate the VTTS using the marginal rate of substitution. Additionally, apart the general VTTS for the short and long run, the VTSS was calculated for early, mid, and late adopters using the estimated adoption rates. The group of early adopters consist people who were classified as 'innovators' and 'early adopters' (40.75% and 38.25%, for Chicago and Indianapolis, respectively), the group of mid adopters people who were classified as 'early majority' (29.50% and 26.25%, for Chicago and Indianapolis, respectively), and the group of late adopters people who were classified as 'late majority' and 'laggards' (29.75% and 35.50%, for Chicago and Indianapolis, respectively).

Table 7.3 below shows the results of this analysis. It was found that VTTS is lower for the option of sharing the ride in AVs with other passengers rather than riding alone regardless the time period, indicating that the first alternative is more attractive. In other words, the results suggest that the VTTS is higher associated with the private AV ride rather than the AV shared ride, possibly due to the higher level of comfort and lower travel time. It can also be observed that the VTTS for the option of the private AV ride is higher than the hourly VTTS of $14.20/hour reported in USDOT, (2018)[1], whereas the VTTS related to the option of people sharing the AV ride was found to be lower than the reported value by USDOT. The estimated trend between single passenger AVs and AV shared rides in the short-term scenarios (two weeks after the introduction of AVs in Indianapolis) holds for the long-term scenarios as well (one year after the introduction of AVs in Indianapolis). Interestingly, Kolarova et al. (2019) found no significant changes in the VTTS between riding alone and sharing the ride with others based on a stated-preference study in Germany. Additionally, the trends show that residents of Chicago had a higher VTTS compared to Indianapolis, which enhances the findings of the market segmentation analysis that suggests that Chicago compared to Indianapolis has more innovative respondents that are willing to use AVs. Lastly, as expected, VTTS is higher for people who were classified as early adopters, followed by the group of mid adopters and finally the group of late adopters. Early adopters seem to perceive riding in AVs as a more valuable activity, possibly due to decreased levels of stress or increased productivity during the trip, compared to the other groups. Note that the VTTS for the group of sdfearly adopters is found to be higher than the reported USDOT average value, whereas the value for the group of mid adopters is similar with the average and the value for late adopters is lower.

[1] USDOT. (2018). BCA Guidance for Discretionary Grant Programs.

Table 7.3: Value of travel time savings - short and long run

	General Population		Across Clusters		
	Private AV ride	Shared AV ride	Early adopters	Mid Adopters	Late Adopters
Chicago - Short term - WTP ($/hour)	14.67	9.77	23.01	15.13	11.24
Indianapolis - Short term - WTP ($/hour)	15.88	10.34	21.18	14.72	11.05
Chicago - Long term - WTP ($/hour)	12.31	8.14	21.74	14.08	9.19
Indianapolis - Long term - WTP ($/hour)	14.22	9.07	20.63	13.49	8.26

7.5 Discussion

This analysis shed light into how the emergence of ride-sharing services operated through AVs (i.e., SAVs) can affect the mode choice decisions (between biking, using a private vehicle, using public transportation, and using ride-hailing services operated through non-AVs) in the short and long run. A number of factors were identified as significant determinants of the potential disruption in mode shares that include (but not limited to): level of awareness, number of social/recreational trips on a weekly basis, ride-hailing/car-sharing service membership, annual mileage, mode-choice related factors (e.g. reliability), attitudinal variables (such as tendency to be influenced by their social circles, affinity to innovativeness, and safety concerns towards AVs), and socio-economic variables (such as age, annual income and private vehicle ownership). The VTTS was also calculated for the general sample and for the different adopter categories that were identified the market segmentation analysis (early adopters, medium adopters, late adopters) to capture preference heterogeneity. The results seem to suggest that the option of sharing the AV ride is not as preferred as the private AV ride across all market segments which may challenge the benefits that this emerging technology can bring to shared transportation modes. In specific, it was found that VTTS is lower for the option of sharing the ride in AVs with other passengers rather than riding alone regardless of the time period of AV implementation and the market segment. Therefore, a stronger effort needs to be made in order to make this option more popular to people (e.g. incentives, trip cost reduction).

8. CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS

The topic of this dissertation was conceived at an earlier stage of AV-related research and development, and since then interest in this area has been increasing rapidly. Studies project that over the next two decades, AVs will transform the current transportation system and half of the market share of all vehicles in the US will consist of AVs. Furthermore, vehicle ownership is expected to decline, with each SAV potentially replacing seven traditional non-AVs and cutting sharply into their market share.

This dissertation provides useful insights with respect to the public acceptance of AVs and SAVs via a behavioral experiment (stated-preference survey) and offers recommendations for practitioners and researchers. The survey was distributed in the Chicago, Illinois, and Indianapolis, Indiana, metropolitan areas and solicited responses from adults residing in both areas. The following research questions guided this dissertation:

1) Which factors affect the behavioral intention to ride in AVs when the synergistic effects between the decomposed Theory of Planned Behavior, the Diffusion of Innovation theory and additional components identified from the literature review are considered?
2) Regarding the market's adoption of AVs, what are the characteristics of the respective market segments?
3) How will the emergence of AVs affect personal vehicle ownership decisions? Specifically, which attributes influence travelers' decisions to postpone the purchase of a non-AV, keep their current non-AV, or give up private ownership of their non-AV following the emergence of AVs in the short and long terms?
4) How will the emergence of autonomous ride-sharing services operated through AVs affect public transit use and, ultimately, mode choice decisions in the short and long terms? What would be the corresponding effect on the value of travel time savings?

8.1 Key Findings

Literature Review: A thorough literature review was conducted to synthesize the state of the art on stated-preference/choice studies that address AVs, and the key findings of these studies were summarized and categorized. Various questions were identified pertaining to behavioral intention to ride in AVs that addressed the ways different components of that intention could affect the public acceptance and adoption of AVs. Furthermore, the results of the studies were summarized in terms of the benefits, barriers/concerns, and opportunities related to the deployment of AVs, while the commonalities and differences across the reported findings were highlighted. The literature review findings guided the survey design and the research framework proposed for this study and informed all research activities performed to address the research questions.

Behavioral intention to ride in AVs: The objective of the first research question was achieved by designing and evaluating a theoretical model that uses the components of the TPB (Ajzen, 1991) and that is decomposed to include components of the theory of DoI (Rogers, 1995) to assess the potential development of and opportunities for AV adoption. The model was extended to evaluate whether other attitudinal components, such as safety concerns, trust of strangers, environmental concerns, affinity to innovativeness, and driving-related sensation seeking, can also be determinants of the behavioral intention to ride in AVs. Explanatory and confirmatory factor analyses were conducted to test the validity and reliability of the components included in the theoretical model, followed by estimation of structural equation models.

Two components of the DoI theory, compatibility and relative advantage, were found to impact attitudes towards the use of AVs; however, a third component, complexity, was not found to be statistically significant. This finding might be because AVs are not widely available yet, and therefore the respondents to the survey were unsure whether riding in AVs is a complex process. All of the components of the TPB were found to significantly influence behavioral intention, which validates the notion that a theoretical model based on this theory can predict the key determinants that impact behavioral intention. Regarding the decomposition of the TPB, self-efficacy and personal moral norms were found to influence perceived behavioral control and behavioral intention, respectively. However, contrary to the findings of prior literature, the components of environmental and safety concerns were not found to be significant, possibly because previous studies used different methodologies to assess these components.

Market segmentation analysis: The market segmentation analysis classified the respondents into five adopter categories (innovators, early adopters, early majority, late majority, laggards). Regardless of the study area, it was found that people classified as innovators or early adopters are more likely to use other modes for commuting than their private vehicles (e.g., walking, biking, or public transportation), and they own or have access to fewer vehicles compared to their counterparts. Furthermore, these people are more likely to be members of ride-hailing and car-sharing services, younger individuals, people who work full time, and people with higher incomes and levels of education.

Impact of the emergence of autonomous vehicles on personal vehicle ownership: The findings of this analysis indicate that the decision to continue owning a private non-AV, postpone the purchase of a new non-AV for the household, or give up private vehicle ownership altogether vary by individuals' socio-demographic characteristics. Younger individuals, individuals with higher annual incomes, and individuals who work full time or are students have a particularly high tendency to postpone the purchase of a non-AV or switch to shared AVs. Similarly, people with higher levels of awareness of AV technology or people who view AVs in a more optimistic light are also positively inclined towards AVs rather than non-AVs. Likewise, individuals who have a car-sharing account use their private vehicles less than the average driver, or use public transportation for their social or recreational trips are also more likely to opt out of private vehicle ownership. The main differences on the variables found statistical significant between the two models (short term and long term) were mostly related to the socio-demographic variables, a finding that indicates that the market segmentation analysis can better capture the potential AV user profiles and market segments of each study area.

Impact of the emergence of autonomous ride-sharing services operated through AVs on mode choice decisions: The factors that were found to influence mode choice decisions (between biking, using a private vehicle, using public transportation, and using ride-hailing services operated through non-AVs) in the short and long terms given the emergence of shared AVs are level of awareness of AV technology, number of social/recreational trips on a weekly basis, membership in ride-hailing/car-sharing services, annual mileage traveled, mode-choice-related factors (e.g., reliability of the different modes), attitudinal variables (e.g., respondents' tendency to be influenced by their social circles, affinity to innovativeness, and safety concerns regarding AVs), and socio-economic variables (e.g., age, annual income, and private vehicle ownership). The follow-up evaluation of the value of travel time savings in SAVs (through a comparison of AV private and shared rides) suggested that the value of travel time savings is lower when an AV is shared with other passengers than when an individual uses an AV alone, regardless of the timeframe. The value of travel time savings was also calculated for three different adopter categories derived from the market segmentation analysis (early adopters, medium-term adopters, and late adopters) to capture preference heterogeneity and to examine the value of travel time savings on a disaggregated level rather than only for the general population.

8.2 Practical Implications

The findings presented in this dissertation provide insights into perceptions of and attitudes toward AVs that can help transportation and urban planners, as well as original equipment manufacturers, to prepare for the deployment of AVs by designing marketing strategies to improve people's perceptions of AVs and increase market penetration. Marketing strategies and educational sessions encouraging people to embrace the concept of AVs can be rendered more effective by promoting the relative advantages of AVs compared to non-AVs, such as the benefits that AVs provide for mobility, society, and the environment; targeting specific groups, such as the market segments identified in the market segmentation analysis; and targeting specific subjective perceptions of AVs.

The findings also reinforce the need for wider testing of this technology in urban areas coupled with targeted marketing campaigns designed to increase public awareness of the technology and improve trust. The results can provide excellent information to help public agencies in these areas prepare for the emergence of AVs. This implication is clearest in two key findings. First, a few factors, such as distrust of strangers, the features installed in vehicles, level of awareness of AV technology, and age, were found to have different effects in Chicago and Indianapolis. Therefore, strategies designed to increase public awareness and acceptance of AVs by conveying the benefits of and concerns regarding AVs should be targeted and location-specific. This can be especially effective in the case of Indianapolis, where respondents were found to be less aware of the technology and to have more trust concerns than respondents in Chicago. Moreover, the survey can be replicated and distributed in metropolitan areas outside the US with more advanced multimodal transportation systems or areas within the US with traditionally higher rates of affinity to innovativeness, such as metropolitan areas in California and areas where AVs have been pilot-tested in real-world road conditions, such as Pittsburgh, Pennsylvania, and Phoenix, Arizona.

Second, the findings from the analysis of the impacts of the emergence of AVs/SAVs on private vehicle ownership and overall mode choice decisions also suggest the need for wider testing of this technology in urban areas coupled with targeted marketing campaigns. For example, Waymo's Early Rider program, which offers ride-hailing services operated through AVs in test cities such as Phoenix, Arizona, can communicate and demonstrate the benefits that AV technology can bring through first-hand experience. In this way, the perceived benefits could be made to outweigh the perceived risks, thereby removing a psychological barrier to the adoption of AVs.

Until psychological barriers are removed, it seems unlikely that conventional automobile manufacturers will lose their dominant market share. However, incentives can be provided to consumers to make AVs more attractive, such as rebates from auto insurance companies for vehicles with installed automated safety features. Similarly, public transit owners do not need to fear the loss of their ridership to AVs, at least in the short run. Nevertheless, identifying strategies to supplement traditional transit services with AVs (e.g., as feeder modes for first/last-mile trips) and providing premium on-demand services with a lower capacity than conventional buses but with greater flexibility and comfort can enhance the attractiveness of public transit.

Moreover, the findings suggest that AVs will likely substitute for commuting trips, as respondents who mainly use their private vehicles for commuting indicated that they were willing to postpone the purchase of a non-AV. Travel demand management strategies (such as road pricing) or policies conducive to AV pooling/sharing (such as imposing high tolls on zero-occupancy and single-occupancy vehicles) are recommended to mitigate the possible increase in vehicle miles traveled during morning and evening peak hours in congested urban areas. The evaluation of the value of travel time savings of SAVs (through a comparison of AV private and shared rides) when used for commuting can further provide quantifiable information to policymakers and AV operators related to pricing. Additionally, having a better idea of the anticipated demand for AVs can ultimately lead to more accurate and customized supply schemes, ensuring smooth AV deployment. The results seem to suggest that the option of sharing AV rides is not preferred, which could offset the benefits that this emerging technology can bring to shared transportation modes. Therefore, a stronger effort needs to be made to make this option more popular (e.g., incentives for shared AV rides or reductions in trip costs).

8.3 Limitations and Recommendations for Future Research

This study has some limitations, but many of these limitations also provide opportunities for further research. One limitation is that several components of the DoI theory, such as triability and observability, were not included in the theoretical model because, at the time of the study, AVs were not widely available. At some point in the future when AVs have become more diffused, these components can be included in the theoretical model and can be evaluated to determine whether they are key determinants of the behavioral intention to use AVs and of the adoption of AVs. For the same reason, the proposed model examines the intention to ride in AVs but not the actual behavior, which can also be better assessed when AVs become more diffused.

Additionally, the theoretical model did not account for respondents' attitudes toward conventional driving except the component of driving-related sensation seeking that captures the willingness of users to take risks. A study by Nielsen and Haustein (2018) that evaluated whether attitudes towards conventional driving affect the intention to ride in AVs found that people who were enthusiastic about the concept of autonomous driving were less enthusiastic about conventional driving. This component can be included in the theoretical model and evaluated to determine whether the hypothesis that people who are not enthusiastic about conventional driving have a higher intention to ride in AVs is valid.

The survey instrument that was designed based on the theoretical model proposed in this dissertation was also limited in some ways. In one regard, the current survey did not specify a particular level of automation. Therefore, respondents might have imagined different levels of AVs when they were filling out the survey. Additionally, the survey instrument was only distributed in the Chicago metropolitan area. The survey data can be tested in terms of measurement equivalence (robustness) across multiple urban areas, and, if the results hold, the survey can be transferred to and replicated in multiple study areas to test whether the effects of different variables are similar across the different study areas. Understanding the differences in the sign/magnitude of the effects of different factors across multiple geographical areas and gaining insights into whether some factors do or do not influence the behavioral intention to ride in AVs can help policymakers strategize in a more efficient way. The different study areas can be areas with a more car-oriented culture than Chicago, Illinois; areas with traditionally higher rates of affinity to innovativeness, such as metropolitan areas in California; and areas where pilot tests of AVs in real-world conditions have been or are being conducted, such as Pittsburgh, Pennsylvania, and Phoenix, Arizona. Potential study areas might also include cities outside of the US with more advanced multimodal transportation systems. For a comparison of user acceptance of AVs among different countries, refer to (Kyriakidis et al., 2015; Schoettle & Sivak, 2014b).

The inferences made in this dissertation are subject to the limitations of stated preference surveys, which ask questions that are hypothetical in nature. The methods applied herein attempted to address these limitations through appropriate data preparation and analysis, such as the removal of incomplete responses, cases of over-coverage, and passive responses; the inclusion of cheap talk to address hypothetical bias; and rigorous econometric modeling.

Moreover, this study is cross-sectional and evaluates a snapshot of a given point in time. It would be valuable to conduct a longitudinal study covering several points in time to evaluate whether the factors affecting behavioral intention to use AVs and the corresponding attitudes evolve over time. Additionally, future generations are expected to have different attitudes and perceptions towards AVs.

APPENDIX A. SURVEY

Purdue University is conducting a survey on autonomous vehicles in order to better understand attributes influencing people's opinions on their preferred mode of transportation and additionally, identify the factors and behavioral characteristics that would affect the intention to use autonomous vehicles.

SECTION 1

1.1 Level of awareness

1. Have you ever heard about Google's self-driving vehicles?

I have never heard of them
Someone told me about them
I think that I have heard of them
I have read about them more than once, but not on a regular basis
I have read about them once
I am following the news about them on a regular basis

2. Have you ever heard about Uber´s self-driving vehicles?

I have never heard of them
Someone told me about them
I think that I have heard of them
I have read about them more than once, but not on a regular basis
I have read about them once
I am following the news about them on a regular basis

3. Have you ever heard about a set of features called 'Autopilot' provided in some versions of Tesla vehicles?

I have never heard of it
Someone told me about it
I think that I have heard of it
I have read about them more than once, but not on a regular basis
I have read about it once
I am following the news about them on a regular basis

4. Do you think that adaptive cruise control (ACC) is a technology used in automated vehicles?

Yes　　No　　Not sure

SECTION 2

2.1 Travel characteristics

1. Which of the following is your primary mode of travel <u>for each</u> trip purpose? (Please select only one mode for each trip purpose).

	Walk	Bike	Private vehicle	Carpool	Public transportation	Ride sharing service
Work/School trip purpose						
Grocery and shopping trip purpose						
Personal Business trip purpose (errands)						
Social/Recreational trip purpose						

2. How many personal vehicles does your household have access to or own?
0_____ 1_____ 2_____ 3_____ > 4 ______

3. How many miles approximately did you drive last year?
I do not own a personal vehicle_____ <5,000 miles_____ 5,000-9,999 miles_____ 10,000-14,999 miles_____ 15,000-19,999 miles______ 20,000-24,999 miles_____ >25,000 miles ______

4. How many single trips did you make for the following trip purposes during the last seven days including all the modes of travel that you used? (A single trip is defined as a single journey made by an individual between two points using a specific mode of travel and a defined trip purpose).

	N/A (I do not own a vehicle)	0	1	2-3	4-5	6-7	>7
Work Trips							
School Trips							
Grocery's and Shopping Trips							
Personal Business Trips							
Social/Recreational Trips							
Other Trips							

5a. Are you a member of a car-sharing service (e.g. ZipCar, BlueIndy, etc.)?
Yes No

5b. If you are a member of a car-sharing service, how many times did you use it in the last month? _______

6a. Do you have a ride-sharing service account (e.g. Uber, Lyft, etc.)?
Yes No

6b. If you have a ride-sharing service account, how many times did you use it in the last month? _______

2.2 Attributes affecting mode choice decisions

7. In the following table, please indicate the level of importance that each attribute has when choosing a transportation mode for a short distance work trip? (A short distance work trip is defined as a trip commuting to work that is less than 50 miles).

Attribute	**Not at all Important**	**Slightly Important**	**Moderately Important**	**Very Important**	**Extremely Important**
a. Cost					
b. Travel time					
c. Waiting time					
d. Reliability (not being late)					
e. Convenience and comfort					
f. Safety					

g. Distractions (travel companions, scenery, etc.)					
h. Flexibility of travel (being able to go wherever I want to go)					
i. Ease of traveling (minimize the effort required to travel)					

SECTION 3

3.1 General Thoughts and Behaviors

1.1. I am venturesome and eager to be the first to try new innovations.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.2. I adopt innovations and influence others to do so.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.3. I am willing to follow the lead of others in adopting innovations.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.4. I need to be convinced of the advantage of innovations by peers.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.5. I am suspicious of innovations.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.6. I am always looking for innovations.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.7. My opinion about innovations is respected by peers.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.8. I will adopt innovations but do not attempt to influence others to do so.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.9. I go along with innovations out of necessity.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.10. I am resistant to change.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.1. I think that people should live in harmony with nature in order to achieve sustainable development.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.2. I think individuals have responsibility to protect the environment.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.3. I think environmental problems are becoming more and more serious in recent years.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

1.4. I think we are not doing enough to save scarce natural resources from being used up.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.1. I would like to drive without a preplanned route and without a schedule.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.2. I often feel like being a racing-driver.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.3. I would like to drive on roads with many sharp turns.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.4. I would like to learn to drive cars that can exceed the speed of 180 mph.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.5. I do not have patience for people who drive cars in a predictable and boring manner.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

2.6. I think I would enjoy the experience of driving very fast on a steep road
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.1. Most people will try to take advantage of someone else, if they get the chance to do it.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.2. Most people only look after themselves.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.3. You cannot trust most people.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.4. You cannot trust strangers.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.5. I do not lock the entrance door of my house/apartment.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.6. I believe that I am a trustworthy person.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.7. I lend money to friends.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.8. I lend personal belongings to friends.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.2 Opinions on autonomous vehicles

Please take a few minutes to tell us what you think about autonomous vehicles. There are no right or wrong responses; we are merely interested in your personal opinions. In your responses to the following questions, please share the thoughts that come immediately to mind.

Autonomous vehicles are those in which at least some aspects of a safety-critical control (such as steering, throttle, or braking) operate without direct driver input. Vehicles that provide safety warnings to drivers (for example, a forward-crash warning) but do not take control of the vehicle are not considered autonomous. Autonomous vehicles may use on-board sensors, cameras, GPS, and telecommunications to obtain information in order to make decisions regarding safety critical situations and act appropriately by taking control of the vehicle at some level. Examples of autonomous-vehicle technologies range from those that take care of basic functions such as cruise control, to completely self-driving vehicles with no human driver required.

4.1. Autonomous vehicles offer more benefits to our society than non-autonomous vehicles.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.2. Riding in autonomous vehicles would reduce the number of accidents compared to riding in non-autonomous vehicles.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.3. Riding in autonomous vehicles would be more environmental-friendly than riding in non-autonomous vehicles.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.4. Riding in autonomous vehicles would reduce the time that I spend sitting in traffic congestion than riding in non-autonomous vehicles.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

4.5. I would be free to make the most of my time spent in a vehicle, if I am riding in autonomous vehicles rather than riding in non-autonomous vehicles.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

5.1. It would be easy for me to ride in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

5.2. I will find it easy to make the autonomous vehicle do what I want.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

5.3. I think that I cannot fully exploit the technology of autonomous vehicles.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

6.1. The thought of riding in autonomous vehicles suits my lifestyle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

6.2. Riding in an autonomous vehicle suits my daily needs.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

6.3. Riding in an autonomous vehicle fits well with my habits.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

In this subsection, please select your response based on a scale from 1 to 5.

7.1. I ___ the thought of riding in an autonomous vehicle.
Dislike 1__ 2__ 3__ 4 __ 5 __ Like

7.2. Riding in autonomous vehicles will be a ___ idea for me.
Bad 1 __ 2 __ 3 __ 4__ 5__ Good

7.3. I would find riding in autonomous vehicles ___ for my purposes.
Useless 1 __ 2 __ 3 __ 4 __ 5 __ Useful

7.4. Riding in autonomous vehicles sounds ____ to me.
Stupid 1__ 2 __ 3 __ 4__ 5 __ Smart

7.5. Riding in autonomous vehicles sounds ___ to me.
Scary 1 __ 2__ 3 __ 4 __ 5 __ Nice

7.6. Riding autonomous vehicles would be ____ for my needs.
Not suitable 1__ 2__ 3 __ 4 __ 5__ Suitable

7.7. For me, riding in an autonomous vehicle is ___.
Undesirable 1__ 2 __ 3 __ 4 __ 5 __ Desirable

8.1. People who are important to me will support my decision on riding in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.2. The media make it more appealing for me about riding in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.3. People who are important to me would try to convince me to ride in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.4. People who are important to me would want me to ride in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.5. People who are important to me would prefer I rode in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

8.6. Articles in the media influence my intention to ride in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.1. Because of my own principles, I would feel an obligation to ride in an autonomous vehicle, if one is accessible, due to its lower fuel consumption.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.2. Regardless of what other people do, I would feel morally obliged to ride in an autonomous vehicle, if one is accessible, due to its lower emissions.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.3. I would feel a moral obligation to ride in an autonomous vehicle, if one is accessible, as it is expected to be more friendly to the environment.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

9.4. I would feel obliged to neglect the advantages of autonomous vehicles when making choices related to the mode of my trip.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.1. I will have the knowledge to ride in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.2. I would be capable to ride in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.3. It would be easy for me to control all things relevant to riding in an autonomous vehicle.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

10.4. When autonomous vehicles become widely available, I would know enough to ride in one.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

11.1. When autonomous vehicles become widely available, I believe I would afford to purchase one. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.2. When autonomous vehicles become widely available, I believe I would afford to ride in one. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.3. When autonomous vehicles become widely available, I believe I will have the necessary means and skills to ride in an autonomous vehicle. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
11.4. When available, I will have the ability and opportunity to ride in an autonomous vehicle if I want to. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

12.1. The automated driving technology installed in autonomous vehicles is likely to be a better driver than I am. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.2. Riding in an autonomous vehicle will enable me to reach my destination safer than riding in a non-autonomous vehicle. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.3. I have safety concerns about riding in autonomous vehicles. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.4. I believe that riding in an autonomous vehicle requires increased attention compared to riding in a non-autonomous vehicle. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.5. While riding in an autonomous vehicle, I will not need to pay attention to the traffic. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.3 Intention to ride an autonomous vehicle

12.1. I intend to ride in an autonomous vehicle when autonomous vehicles become available. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.2. I intend to ride in an autonomous vehicle in the **near future**. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.3. I intend to **frequently** riding in an autonomous vehicle in the **near future**. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.4. I would recommend the use of autonomous vehicles to other people. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.5. I intend to ride in an autonomous vehicle in the **foreseeable future**. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__
12.6. I intend to **frequently** riding in an autonomous vehicle in the **foreseeable future**. Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

Ride-sharing service is a service that arranges one-time shared rides on very short notice using technological advances such as GPS to determine the route, smartphones to request the ride and social networks to establish trust and accountability between drivers and passengers. The driver uses his/her personal vehicle and drives around until someone requests a ride. The person who requests the ride can be the only one taking the ride or sharing the ride with other people.

3.4 Intention to switch from public transportation in favor of autonomous ride-sharing services

13.1. I expect that I will be switching from public transportation in favor of using ride-sharing services on autonomous vehicles when such services become available.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

13.2. I expect that I will be **sometimes** switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the **near future**.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

13.3. I expect that I will be **frequently** switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the **near future**.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

13.4. I would recommend the switch from public transportation in favor of using ride-sharing services on autonomous vehicles to other people.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

13.5. I expect that I will be **sometimes** switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the **foreseeable future**.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

13.6. I expect that I will be **frequently** switching from public transportation in favor of using ride-sharing services on autonomous vehicles in the **foreseeable future**.
Strongly Disagree __ Disagree __ Neutral __ Agree__ Strongly Agree__

3.5 Purchase/Sale of non-autonomous vehicles

14.1. How likely is it that your household will postpone the purchase of a non-autonomous vehicle due to the introduction of autonomous vehicles?
My household is not planning to purchase a vehicle__ Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

14.2. How long does your household plan to postpone the purchase of a non-autonomous vehicle due to the introduction of autonomous vehicles in the future?
My household does not plan to purchase a vehicle __ Postpone it for less than a year __ Postpone it for 1-3 years__ Postpone it for 3-5 years __ Postpone it for more than 5 years__ My household will wait for the introduction of autonomous vehicles __ My household will postpone it indefinitely; planning to rely on the autonomous vehicles__

14.3. How likely is it that your household will have the **same number** of non-autonomous vehicles as today, **two years after** the introduction of autonomous vehicles?
My household will not own a vehicle __ Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

14.4. How likely is it that your household will have **just one** non-autonomous vehicle **two years after** the introduction of autonomous vehicles?
My household will not own a vehicle __ Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

14.5. How likely is it that your household will have **zero** non-autonomous vehicles **two years after** the introduction of autonomous vehicles?
Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

14.6. How likely is that your household will plan to purchase a non-autonomous vehicle in the **next five years**?
Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

14.7. How likely is it that your household will have **just one** non-autonomous vehicle **five years after** the introduction of autonomous vehicles?
My household will not own a vehicle __ Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

14.8. How likely is it that your household will have **zero** non-autonomous vehicles **five years after** the introduction of autonomous vehicles?
Very Unlikely __ Somewhat Unlikely__ Neutral __ Somewhat Likely__ Very Likely__

SECTION 4

4.1 Mode choice scenarios

For this section of the survey, you will be provided with a number of scenarios about your daily commute to work. Please imagine that your house and your work place are located in Indianapolis. Not all information is given, but please imagine to the best of your ability to reach a decision. There are no right or wrong responses; we are merely interested in your personal opinions.

In this scenario, the different modes of transportation that are available to your daily commute to work are: a) walk, b) bike, c) private vehicle, d) public transportation. As indicated in the table below, you can see the time (in minutes), the cost (in dollars) for each mode of transportation. Which mode of transportation will you choose for your daily commute to work?

Scenario 0 – base case scenario:

Attribute/Mode Choice	Bike	Private vehicle	Public transportation	Ride-sharing service with non-autonomous vehicles
Time (minutes)	35	20	37	24
Cost (dollars)	0	3	1.75	12
Your choice				

Autonomous vehicles became available in Indianapolis **two weeks ago**. In these scenarios, you are about to leave your house to commute to work. Your house and your work place are located in Indianapolis. Two more modes of transportation are now available: a) ride-sharing service offered via autonomous vehicles that you will be the only one taking the ride, and b) ride-sharing service offered via autonomous vehicles that you will be sharing the ride. **Considering these two new modes and your previous choice**, which mode of transportation will you choose for your daily commute to work?

Scenario 1a

Attribute/Mode Choice	Bike (or any of the other four available modes in	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride

	scenario 0 that was chosen)		
Time (minutes)	35	24	28
Cost (dollars)	0	4.5	3
Your choice			

Autonomous vehicles became available in Indianapolis **a year ago**. In these scenarios, you are about to leave your house to commute to work. Your house and your work place are located in Indianapolis. Two more modes of transportation are now available: a) ride-sharing service offered via autonomous vehicles that you will be the only one taking the ride, and b) ride-sharing service offered via autonomous vehicles that you will be sharing the ride. **Considering these two new modes and your previous choice**, which mode of transportation will you choose for your daily commute to work?

Scenario 1b

Attribute/Mode Choice	Bike (or any of the other four available modes in scenario 0 that was chosen)	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
Time (minutes)	35	24	28
Cost (dollars)	0	3.6	2.4
Your choice			

SECTION 5

5.1 Demographic Questions

1. What is the gender you were identified with?

Male__ Female__

2. What is your age range? 18-24 __ 25-34 __ 35-44 __ 45-54__ 55-64__ 65 and over__

3. What describes best your employment situation?

Work full time__ Work part time__ Currently unemployed __ Student__ Retired __ Homemaker___

Other, please specify________

4. Please indicate your approximate annual household income before taxes (include total income of all adults living in your household).

Under $25,000____ $25,000-$49,999____ $50,000-$74,999____ $75,000-$99,999____ $100,000-$149,999____ $150,000 and over____ I do not want to disclose this information____

5. What is your highest level of education?

Grade school or less__ Some high school__ High school graduate__ Technical training beyond high school__

Some college__ College graduate__ Graduate school__

6. Are you Hispanic or Latino?
Yes__ No__ I do not want to disclose this information __

7. How would you describe yourself?
American Indian or Alaska Native__ Asian__ Black or African American__ Native Hawaiian or Other Pacific Islander__
White__ I do not want to disclose this information__

8. Including yourself, how many persons are in your household? One__ Two__ Three__ Four__ Five or more__

9. Please indicate the number of children in your household under the age of 18.
None__ One__ Two__ Three__ Four or more__

10. Do you have a driver's license? Yes__ No__

11. How many crashes have you experienced while driving a car last year?
None__ One__ Two__ Three__ Four or more__

Thank you for completing this survey about autonomous vehicles!!

APPENDIX B: EXPLORATORY FACTOR ANALYSIS AND STRUCTURAL EQUATION MODELS

Table B1: Pattern matrix of exploratory factor analysis

	Att	DRSS	PBC	LA	TS	Env	Int	EA	SN	Comp	PMN	SE	RA
Att1	0.839												
Att2	0.798												
Att3	0.795												
Att4	0.768												
Att5	0.738												
Att6	0.695												
Att7	0.694												
DRSS1		0.861											
DRSS2		0.796											
DRSS3		0.781											
DRSS4		0.658											
DRSS5		0.569											
DRSS6		0.532											
PBC1			0.788										
PBC2			0.78										
PBC3			0.771										
PBC4			0.687										
PBC5			0.663										

Table B1: continued

LA1	0.771				
LA2	0.739				
LA3	0.703				
LA4	0.673				
LA5	0.654				
TS1		0.782			
TS2		0.75			
TS3		0.746			
TS4		0.685			
Env1			0.772		
Env2			0.75		
Env3			0.725		
Env4			0.691		
Int1				0.78	
Int2				0.768	
Int3				0.756	
Int4				0.731	
Int5				0.697	
Int6				0.673	
EA1					0.783
EA2					0.752

Table B1: continued

EA3	0.727					
EA4	0.704					
EA5	0.685					
SN1		0.835				
SN2		0.774				
SN3		0.761				
SN4		0.739				
SN5		0.718				
Comp1			0.737			
Comp2			0.72			
Comp3			0.677			
PMN1				0.753		
PMN2				0.741		
PMN3				0.666		
SE1					0.746	
SE2					0.717	
SE3					0.683	
RA1						0.861
RA2						0.786
RA3						0.783
RA4						0.752

Table B1: continued

RA5	0.742
RA6	0.714
RA7	0.706
RA8	0.698
RA9	0.664
RA10	0.621

Table B2: Pattern matrix of exploratory factor analysis

Path	Parameter Estimates	Standard Error	Critical Ratio	p-value
The thought of riding in AVs suits my lifestyle → Compatibility	1.000			
Riding in an AV suits my daily needs → Compatibility	.994	.034	29.400	<0.01
Riding in an AV fits well with my habits → Compatibility	.975	.035	27.553	<0.01
AVs offer more benefits to our society than non-AVs → Relative Advantage	1.000			
Riding in AVs would reduce the number of accidents compared to riding in non-AVs → Relative Advantage	.968	.061	15.847	<0.01
Riding in AVs would be more environmental-friendly than riding in non-AVs → Relative Advantage	.733	.060	12.277	<0.01
Riding in AVs would reduce the time that I spend sitting in traffic congestion than riding in non-AVs → Relative Advantage	.929	.064	14.414	<0.01
I would be free to make the most of my time spent in a vehicle, if I am riding in an AV rather than riding in non-AVs → Relative Advantage	.914	.063	14.491	<0.01
The automated driving technology installed in AVs is likely to be a better driver than I am → Relative Advantage	1.012	.067	15.040	<0.01
Riding in an AV will enable me to reach my destination safer than riding in a non-AV → Relative Advantage	1.160	.063	18.549	<0.01
While riding in an AV, I will not need to pay attention to the traffic → Relative Advantage	.783	.081	9.685	<0.01
It would be easy for me to ride in an AV → Relative Advantage	1.128	.065	17.253	<0.01
I will find it easy to make the AV do what I want → Relative Advantage	.925	.058	16.061	<0.01
I will have the knowledge to ride in an AV → Self-efficacy	1.000			
I would be capable to ride in an AV → Self-efficacy	1.096	.060	18.416	<0.01
It would be easy for me to control all things relevant to riding in an AV → Self-efficacy	1.075	.061	17.593	<0.01
Most people will try to take advantage of someone else, if they get the chance to do it → Trust of Strangers	1.000			
Most people only look after themselves → Trust of Strangers	.919	.069	13.309	<0.01

Table B2: continued

You cannot trust strangers → Trust of Strangers	.941	.072	13.154	<0.01
I need to be convinced of the advantage of innovations by peers → Late Adopters	1.000			
I am suspicious of innovations → Late Adopters	1.233	.137	9.004	<0.01
I will adopt innovations but do not attempt to influence others to do so → Late Adopters	1.154	.134	8.595	<0.01
I go along with innovations out of necessity → Late Adopters	.576	.096	5.975	<0.01
I am resistant to change → Late Adopters	.814	.107	7.645	<0.01
I dislike/like the thought of riding in AVs → Attitudes towards use of AVs	1.000			
Riding in AVs will be a bad/good idea for me → Attitudes towards use of AVs	1.118	.048	23.453	<0.01
I would find riding in AVs useless/useful for my purposes → Attitudes towards use of AVs	1.152	.049	23.550	<0.01
Riding in AVs sounds stupid/smart to me → Attitudes towards use of AVs	.809	.036	22.744	<0.01
Riding in AVs sounds scary/fun to me → Attitudes towards use of AVs	1.154	.134	8.595	<0.01
Riding in AVs would be not suitable/suitable for my needs → Attitudes towards use of AVs	1.133	.049	23.345	<0.01
For me, riding in AVs is undesirable/desirable → Attitudes towards use of AVs	1.179	.048	24.319	<0.01
People who are important to me will support my decision on riding in an AV → Subjective Norms	1.000			
The media make it more appealing for me to ride in an AV → Subjective Norms	1.478	.206	7.170	<0.01
People who are important to me would try to convince me to ride in an AV → Subjective Norms	2.188	.264	8.303	<0.01
People who are important to me would want me to ride in an AV → Subjective Norms	2.305	.273	8.440	<0.01
People who are important to me would prefer I rode in an autonomous vehicle → Subjective Norms	2.266	.271	8.369	<0.01
Because of my own principles, I would feel an obligation to ride an AV, if one is accessible, due to its lower fuel consumption → Personal Moral Norms	1.000			
Regardless of what other people do, I would feel morally obliged to ride in an AV, if one is accessible, due to its lower emissions → Personal Moral Norms	1.010	.038	26.473	<0.01
I would feel a moral obligation to ride in an AV, if one is accessible, as it is expected to be friendlier to the environment → Personal Moral Norms	.959	.039	24.690	<0.01
When AVs become widely available, I believe I would afford to purchase one → Perceived Behavioral Control	1.000			

Table B2: continued

When AVs become widely available, I believe I would afford to ride in one → Perceived Behavioral Control	1.038	.076	13.747	<0.01
When AVs become widely available, I believe I will have the necessary means and skills to ride in an AV → Perceived Behavioral Control	1.151	.074	15.470	<0.01
When available, I will have the ability and opportunity to ride in an AV if I want to → Perceived Behavioral Control	1.044	.070	14.871	<0.01
When AVs become widely available, I would know enough to ride in one → Perceived Behavioral Control	1.021	.072	14.100	<0.01
I think that people should live in harmony with nature in order to achieve sustainable development → Environment	1.000			
I think individuals have responsibility to protect the environment → Environment	1.146	.103	11.141	<0.01
I think environmental problems are becoming more and more serious in recent years → Environment	1.307	.118	11.085	<0.01
I think we are not doing enough to save scarce natural resources from being used up → Environment	1.262	.121	10.404	<0.01
I am adventurous and eager to be the first to try new innovations → Early Adopters	1.000			
I adopt innovations and influence others to do so → Early Adopters	.977	.052	18.889	<0.01
I am willing to follow the lead of others in adopting innovations → Early Adopters	.476	.049	9.701	<0.01
I am always looking for innovations → Early Adopters	.794	.049	16.140	<0.01
My opinion about innovations is respected by peers → Early Adopters	.598	.043	13.790	<0.01
I would like to drive without a preplanned route and without a schedule → Driving-Related Seeking Scale	1.000			
I often feel like being a race car driver → Driving-Related Seeking Scale	2.345	.315	7.450	<0.01
I would like to drive on roads with many sharp turns → Driving-Related Seeking Scale	1.959	.269	7.272	<0.01
I would like to learn to drive cars that can exceed the speed of 180 mph → Driving-Related Seeking Scale	2.813	.371	7.593	<0.01
I do not have patience for people who drive cars in a predictable and boring manner → Driving-Related Seeking Scale	1.466	.221	6.632	<0.01

Table B2: continued

I think I would enjoy the experience of driving very fast on a steep road → Driving-Related Seeking Scale	2.556	.339	7.539	<0.01
I intend to ride in an AV when AVs become available → Behavioral Intention	1.000			
I intend to ride in an AV in the near future → Behavioral Intention	1.014	.068	14.995	<0.01
I intend to frequently ride in an AV in the near future → Behavioral Intention	1.010	.063	15.956	<0.01
I would recommend the use of AVs to other people → Behavioral Intention	.926	.066	14.118	<0.01
I intend to ride in an AV in the foreseeable future → Behavioral Intention	1.042	.064	16.209	<0.01
I intend to frequently ride in an AV in the foreseeable future → Behavioral Intention	1.055	.063	16.853	<0.01

APPENDIX C: MARGINAL EFFECTS - RESULTS ON PERCEIVED IMPACTS ON AVS

Table C.1: Marginal effects for bivariate ordered probit model estimation results - private vehicle ownership - Chicago

Variable	**Short run – own one non-AV**					**Long run – own zero non-AVs**				
	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5
Respondents with highest level of awareness of Uber’s self-driving vehicles (1: yes, 0: no).	-0.152	-0.109	0.122	0.119	0.221	-	-	-	-	-
Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make zero social/recreational trips per week (1: yes, 0: no).	-	-	-	-	-	0.034	0.026	-0.029	-0.027	-0.105
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-0.092	-0.078	0.057	0.061	0.012	-0.182	-0.099	0.087	0.154	0.240
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no).	-0.161	-0.023	0.018	0.018	0.003	-0.176	-0.128	0.081	0.102	0.222
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations - early adopters**.	-0.069	-0.033	0.028	0.026	0.004	-0.246	-0.137	0.010	0.097	0.183

Table C.1: continued

Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle - subjective norms**.	-0.143	-0.052	-0.004	0.074	0.195	-	-	-	-	-
Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers**.	0.193	0.103	-0.014	-0.164	-0.296	-	-	-	-	-
Respondents who agreed or strongly agreed, on average, that AVs are compatible with their lifestyle, daily needs, or personal values and attitude - compatibility**.	-	-	-	-	-	-0.054	-0.117	0.017	0.095	0.171
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs - safety concerns**.	0.203	0.203	-0.086	-0.272	-0.359	0.046	0.105	-0.024	-0.056	-0.150
Respondents who rated level of cost of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.168	-0.051	0.013	0.074	0.109	-0.162	-0.043	0.006	0.062	0.157
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.204	-0.134	-0.041	0.037	0.116	-	-	-	-	-

Table C.1: continued

Respondents who are 55 years old or older (1: yes, 0: no).	0.213	0.121	0.047	-0.083	-0.134	0.107	0.061	0.003	-0.054	-0.109
Respondents who have an annual income over $100,000 (1: yes, 0: no).	-0.077	-0.015	0.015	0.094	0.126	-0.148	-0.041	0.038	0.089	0.149
Respondents who indicated that they work full time (1: yes, 0: no).	-0.124	-0.049	0.017	0.068	0.135	-0.079	-0.064	0.025	0.075	0.157
Respondents who indicated that they are students (1: yes, 0: no).	-	-	-	-	-	-0.147	-0.067	0.003	0.093	0.120
Respondents who indicated that they own or have access to 1-2 vehicles in their household (1: yes, 0: no).	-0.093	-0.075	0.003	0.103	0.175	-	-	-	-	-

Table C.2: Marginal effects for bivariate ordered probit model estimation results - private vehicle ownership - Chicago

Variable	**Short run – own one non-AV**					**Long run – own zero non-AVs**				
	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5
Respondents with highest level of awareness of Uber's self-driving vehicles (1: yes, 0: no).	-0.092	-0.054	0.038	0.090	0.138	-	-	-	-	-
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no).	-	-	-	-	-	-0.076	-0.074	0.010	0.118	0.118

Table C.2: continued

Respondents who indicated that their primary commuting mode of travel is private vehicle and that they make 1 or less social/recreational trips per week (1: yes, 0: no).	-	-	-	-	-	-0.145	-0.037	0.036	0.080	0.159
Respondents who indicated that their primary mode of travel for social/recreational trips is bus (1: yes, 0: no).	-0.122	-0.073	0.014	0.087	0.135	-0.120	-0.053	0.044	0.116	0.165
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-0.128	-0.039	0.049	0.117	0.119	-0.134	-0.044	0.030	0.097	0.153
Respondents who indicated that they drive less than 10,000 miles per year (1: yes, 0: no).	-0.121	-0.050	0.014	0.109	0.117	-0.110	-0.055	0.000	0.069	0.132
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	-0.150	-0.034	0.023	0.082	0.127	-0.085	-0.020	0.022	0.064	0.159
Respondents who agreed or strongly agreed, on average, that they do not trust strangers - distrust of strangers**.	0.084	0.041	-0.015	-0.091	-0.121	0.095	0.034	-0.005	-0.066	-0.144
Respondents who agreed or strongly agreed, on average, that AVs are compatible with their lifestyle, daily needs, or personal values and attitude - compatibility**.	-	-	-	-	-	-0.145	-0.037	0.036	0.080	0.159

Table C.2: continued

Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**.	0.133	0.071	-0.006	-0.097	-0.125	0.084	0.068	-0.005	-0.090	-0.160
Respondents who rated level of cost of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.086	-0.032	0.049	0.088	0.128	-	-	-	-	-
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.116	-0.059	0.037	0.097	0.128	-0.131	-0.061	0.045	0.087	0.149
Respondents who are 55 years old or older (1: yes, 0: no).	-0.131	-0.012	0.034	0.092	0.129	-0.086	-0.042	0.047	0.074	0.142
Respondents who have an annual income over $100,000 (1: yes, 0: no).	-0.120	-0.039	0.040	0.107	0.146	-0.147	-0.017	0.026	0.092	0.164
Respondents who indicated that they work full time (1: yes, 0: no).	-0.132	-0.036	0.026	0.074	0.152	-0.141	-0.016	0.038	0.101	0.166
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	-0.115	-0.034	0.025	0.090	0.116	-0.078	-0.036	0.009	0.069	0.171

Table C.3: Marginal effects for bivariate ordered probit model - public transportation - Chicago

Variable	**Short-term – Intention to switch**					**Long-term – Intention to switch**				
	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5
Respondents with highest level of awareness of a set of features called ‘autopilot’ provided in some versions of Tesla vehicles (1: yes, 0: no).	-0.150	-0.044	0.013	0.069	0.116	-0.140	-0.075	0.001	0.089	0.129
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-	-	-	-	-	-0.100	-0.075	0.013	0.065	0.122
Respondents who indicated that they drive less than 20,000 miles per year (1: yes, 0: no).	-	-	-	-	-	-0.078	-0.074	0.029	0.082	0.118
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	-0.141	-0.030	0.001	0.119	0.131	-0.145	-0.037	0.009	0.093	0.155
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	-0.077	-0.069	0.004	0.066	0.145	-0.099	-0.070	0.029	0.076	0.171
Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**.	-	-	-	-	-	0.113	0.064	-0.001	-0.114	-0.155

Table C.3: continued

Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.103	-0.027	0.000	0.079	0.124	-	-	-	-	-
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.112	-0.068	0.027	0.069	0.163	-	-	-	-	-
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.098	-0.058	0.038	0.068	0.126	-0.106	-0.010	0.005	0.118	0.163
Respondents who are between 18 and 34 years old (1: yes, 0: no).	-0.078	-0.071	0.030	0.079	0.153	-0.137	-0.070	0.012	0.109	0.159
Respondents who indicated that they are students (1: yes, 0: no).	-	-	-	-	-	-0.101	-0.039	0.008	0.098	0.175

Table C.4: Marginal effects for bivariate ordered probit model - public transportation – Indianapolis

Variable	**Short-term Intention to Switch**					**Long-term Intention to Switch**				
	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5	Strongly disagree Ψ=1	Disagree Ψ=2	Neutral Ψ=3	Agree Ψ=4	Strongly agree Ψ=5
Respondents with highest level of awareness of a set of features called 'autopilot' provided in some versions of Tesla vehicles (1: yes, 0: no).	-0.120	-0.045	0.021	0.091	0.130	-0.139	-0.055	0.031	0.077	0.164
Respondents who indicated that they have a car-sharing account (1: yes, 0: no).	-0.132	-0.069	0.045	0.088	0.122	-0.089	-0.056	0.001	0.119	0.148
Respondents who indicated that they drive less than 15,000 miles per year (1: yes, 0: no).	-	-	-	-	-	-0.115	-0.060	0.015	0.075	0.131
Respondents who agreed or strongly agreed, on average, that they are positive towards trying innovations – early adopters**.	-0.130	-0.028	0.006	0.095	0.139	-0.123	-0.067	0.000	0.063	0.170
Respondents who agreed or strongly agreed, on average, that their decisions are affected by their social circle – subjective norms**.	-0.149	-0.062	0.015	0.063	0.136	-0.118	-0.051	0.037	0.113	0.173

Table C.4: continued

Respondents who agreed or strongly agreed, on average, that they have safety concerns about riding in AVs – safety concerns**.	0.093	0.060	-0.027	-0.114	-0.147	0.101	0.050	-0.005	-0.089	-0.154
Respondents who rated level of reliability of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.075	-0.067	0.002	0.072	0.117	-	-	-	-	-
Respondents who rated level of safety of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	0.100	0.046	0.000	-0.084	-0.147	0.083	0.066	-0.005	-0.071	-0.167
Respondents who rated level of flexibility of travel as a very or extremely important factor when they make mode choice decisions (1: yes, 0: no).	-0.078	-0.046	0.007	0.091	0.128	-0.098	-0.068	0.016	0.063	0.156
Respondents who are between 25 and 34 years old (1: yes, 0: no).	-0.076	-0.023	0.037	0.106	0.143	-0.079	-0.032	0.048	0.096	0.166

Table C.4: continued

Respondents who are over 55 years old (1: yes, 0: no).	0.113	0.036	-0.006	-0.106	-0.158	0.119	0.054	-0.032	-0.073	-0.165
Respondents who have annual income less than $50,000 (1: yes, 0: no).	-0.085	-0.056	0.035	0.096	0.125	-0.091	-0.020	0.013	0.096	0.167

APPENDIX D: CHOICE EXPERIMENT SUPPLEMENTAL MATERIAL

Table D1: Fractional factorial design table supplemental suplea

Scenarios	Choice 2 – cost	Choice 3 – cost	Choice 2 – travel time	Choice 3 – travel time
1	-1	-1	-1	-1
2	+1	-1	-1	+1
3	-1	+1	-1	+1
4	+1	+1	-1	-1
5	-1	-1	+1	+1
6	+1	-1	+1	-1
7	-1	+1	+1	-1
8	+1	+1	+1	+1
SUM (needs to be 0 for orthogonality)	0	0	0	0

*high values are noted as +1 and low values are noted as -1

2 levels of each attribute and vary cost and travel time of ERs (not conventional lanes)

- 2 levels for 4 attributes (cost of ERs and travel time of ERs)
- Full factorial design: 2^4 scenarios = 16 scenarios
- Fractional factorial design to achieve orthogonality and not having confounded main effects: $2^{(4-1)}$ = 8 scenarios

For this section of the survey, you will be provided with a number of scenarios about your daily commute to work. Please imagine that your house and your work place are located in Indianapolis. Not all information is given, but please imagine to the best of your ability to reach a decision. There are no right or wrong responses; we are merely interested in your personal opinions.

In this scenario, the different modes of transportation that are available for your daily commute to work are: a) walk, b) bike, c) private vehicle, d) public transportation. As indicated in the table below, you can see the time (in minutes), the cost (in dollars) for each mode of transportation. Which mode of transportation will you choose for your daily commute to work?

Scenario 0 - base case scenario

Attribute/Mode Choice	Bike	Private Vehicle	Public Transportation	Ride-sharing service with non-autonomous vehicles
Time (minutes)	35	20	37	24
Cost (dollars)	0	3	1.75	12

Your choice

Bike	Private vehicle	Public transportation	Ride-sharing service with non-autonomous vehicles
○	○	○	○

Figure D.1: Example of base case scenario in the choice experiment

Autonomous vehicles became available in Indianapolis two weeks ago. In these scenarios, you are about to leave your house to commute to work. Your house and your work place are located in Indianapolis. Two more modes of transportation are now available: a) ride-sharing service offered via autonomous vehicles that you will be the only one taking the ride, and b) ride-sharing service offered via autonomous vehicles that you will be sharing the ride. Considering these two new modes and your previous choice, which mode of transportation will you choose for your daily commute to work?

Scenario 1a

Attribute/Mode Choice	Private Vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
Time (minutes)	20	24	28
Cost (dollars)	3	4.5	3

Your choice

Private vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
○	○	○

Scenario 1b

Attribute/Mode Choice	Private Vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
Time (minutes)	20	24	32
Cost (dollars)	3	6	3

Your choice

Private vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
○	○	○

Figure D.2: Example of scenarios in the choice experiment in the short run

Autonomous vehicles became available in Indianapolis a year ago. In these scenarios, you are about to leave your house to commute to work. Your house and your work place are located in Indianapolis. Two more modes of transportation are now available: a) ride-sharing service offered via autonomous vehicles that you will be the only one taking the ride, and b) ride-sharing service offered via autonomous vehicles that you will be sharing the ride. Considering these two new modes and your previous choice, which mode of transportation will you choose for your daily commute to work?

Scenario 2a

Attribute/Mode Choice	Private Vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
Time (minutes)	20	24	28
Cost (dollars)	3	3.6	2.4

Your choice

Private vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
○	○	○

Scenario 2b

Attribute/Mode Choice	Private Vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
Time (minutes)	20	24	28
Cost (dollars)	3	4.8	2.4

Your choice

Private vehicle	Ride-sharing service with AV – only one taking the ride	Ride-sharing service with AV – sharing the ride
○	○	○

Figure D.3: Example of scenarios in the choice experiment in the long run

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VITA

Christos Gkartzonikas is a PhD Candidate in the Lyles School of Civil Engineering in the area of transportation and infrastructure systems at Purdue University in West Lafayette, Indiana. He grew up in Paralimni, Cyprus where he stayed until finishing high school. In 2012, he received his Diploma in Civil Engineering from the National Technical University of Athens. At the National Technical University of Athens, he worked under the supervision of Dr. George Yannis and his thesis title was '*Impact of texting on young drivers' traffic and safety on motorways by the use of a driving simulator*'. In 2014, he received his M.Sc. in Civil Engineering from the University of Cyprus, working under the supervision of Dr. Symeon Christodoulou and Dr. Loukas Dimitriou and his thesis was titled '*Entropy-based method of the operations and maintenance of roadway transport networks*'. In 2015, he was accepted to Purdue University to continue his PhD studies.

During his stay at Purdue University, he was involved with various research projects involving evaluation of opportunities to increase rail ridership, market adoption of electric roadways, public acceptance and socio-economic analysis of autonomous vehicles. His research interests include transportation planning, human factors, and transportation modeling. Specifically, he applies econometric models to evaluate the behavior intention to ride in autonomous vehicles and assess substitution patterns and impacts on mode choice decisions.

Christos has also served on the councils of the Purdue Student Chapter of the Institute of Transportation Engineers (ITE) as Treasurer (2016-2017) and Webmaster (2017-2018) and the Hellenic Student Association as Council Member and President (2018-2019).

PUBLICATIONS

- Publications

1) Pyrialakou V.D., Gkartzonikas C., Gatlin J.D., and K. Gkritza. (2020) 'Perceptions of Safety on a Shared Road: Driving, Cycling, or Walking near an Autonomous Vehicle', Journal of Safety Research, 72, 249-258.

2) Gkartzonikas, C., and K. Gkritza, (2019) 'What Have We Learned?: A Review of Stated Preference and Choice Studies on Autonomous Vehicles', Transportation Research Part C: Emerging Technologies, 98, 323-337.

3) Losada-Rojas, L., Gkartzonikas, C., Pyrialakou, V.D., and K. Gkritza. (2019). 'Exploring intercity passengers' attitudes and loyalty to intercity passenger rail: Evidence from an on-board survey,' Transport Policy, Elsevier, 73(C), 71-83.

4) Gkartzonikas, C., Losada-Rojas, L., Christ, S., Pyrialakou V.D., and K. Gkritza, 'Behavioral Intention to Ride in Autonomous Vehicles: Theoretical Constructs and Empirical Results from Three US Cities', Transportation Research Part C: Emerging Technologies (under review).

5) Konstantinou, T., Gkartzonikas, C., and K. Gkritza. 'Public Acceptance of Electric Roadways', Technological Forecasting and Social Change (under review).

6) Gkartzonikas, C., and K. Gkritza 'Travel Choice and Vehicle Ownership Implications due to Autonomous Vehicles', (under preparation)

- Presentations

1) *Podium Presentation* 'Potential Implications of Autonomous Vehicles on Personal Vehicle Ownership and Demand for Public Transit', ASCE ICTD, June 9-12, 2019, Alexandria, VA.

2) *Podium presentation* 'Assessing the Socioeconomic Implications Related to the Emergence of Shared Autonomous Vehicles', ASCE ICTD, June 9-12, 2019, Alexandria, VA.

3) *Poster presentation* 'Perceived Safety of Autonomous Vehicles: An Exploration and Critical Examination of a Common Motivator', ASCE ICTD, June 9-12, 2019, Alexandria, VA.

4) *Poster presentation* 'Electric Roadways: Market Adoption, Willingness to Pay and Impact on Emissions', ASCE ICTD, June 9-12, 2019, Alexandria, VA.

5) *Podium presentation* 'Assessment of the Socio-Economic Implications Related to the Emergence of Shared Autonomous Vehicles: the Tale of Two Midwestern Cities', ITE Great Lakes District Annual Meeting 2019, April 15-16, 2019, Indianapolis, IN.

6) *Poster presentation* 'Assessing Technology Adoption, Willingness to Pay, and Environmental Impact of Electric Roadways in Lower Los Angeles County', SELECT Annual Meeting and Showcase, October 17-18, 2018, West Lafayette, IN.

7) *Podium Presentation* 'Assessing the Behavioral Intention to Ride in Autonomous and Shared Autonomous Vehicles and Market Segmentation Analysis' at 15th International Conference on Travel Behavior Research, July 15-20, 2018, Santa Barbara, CA.

8) *Poster Presentation* 'Factors Influencing the Behavioral Intention to Ride in Autonomous Vehicles' at 2018 Global Symposium for Connected and Automated Vehicles and Infrastructure on March 7-8, 2018, Ann Arbor, MI.

9) *Podium Presentation* 'Access to Intercity Passenger Rail: Effects on Mode Choice and Trip Frequency', Transportation Research Board 97th Annual Meeting, January 7-11, 2018, Washington, D.C.

10) *Podium Presentation* 'A Literature Review on Surveys for Autonomous Vehicles' at 58th Annual Transportation Research Forum on April 20-21, 2017, Chicago, IL.

11) *Poster Presentation* 'Modeling the Behavioral Intention to Ride in Autonomous Vehicles: The Case of Chicago' at ITE Great Lakes District Annual Meeting, April 19-20, 2017, Ann Arbor, MI.