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Potential Implication of Automated Vehicle Technologies on Travel Behavior and System Modeling

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POTENTIAL IMPLICATIONS OF AUTOMATED VEHICLE TECHNOLOGIES ON TRAVEL BEHAVIOR AND SYSTEM MODELING

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Seyed Mohammad Ali Sadat Lavasani Bozorg

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To: Interim Dean Ranu Jung
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This dissertation, written by Mohammad Lavasani, and entitled Potential Implications of Automated Vehicle Technologies on Travel Behavior and System Modeling, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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DEDICATION

This dissertation is dedicated to my beloved wife, Homa Fartash for her dedicated partnership for success in my life, and my parents, Fereshteh and Mahmoud for their endless love and support.

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ABSTRACT OF THE DISSERTATION

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by

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Autonomous Vehicles (AVs) are computer equipped vehicles that can operate without human driver's active control using information provided by their sensors about the surrounding environment. Self-driving vehicles may have seemed to be a distant dream several years ago, but manufactures' prototypes showed that AVs are becoming real now. Several car manufactures (i.e. Benz, Audi, etc.) and information technology firms (i.e. Google) have either showcased their fully AVs or announced their robot cars to be released in a few years. AVs hold the promise to transform the ways we live and travel. Although several studies have been conducted on the impacts of AVs, much remains to be explored regarding the various ways in which AVs could reshape our lifestyle.

This dissertation addresses the knowledge gap in understanding the potential implications of AV technologies on travel behavior and system modeling. A comprehensive review of literature regarding AV adoption, potential impacts and system modeling was provided. Bass diffusion models were developed to investigate the market penetration process of AVs based on experience learned from past technologies. A stated preference survey was conducted to gather information from university population on the

perceptions and attitudes toward AV technologies. The data collected from the Florida International University (FIU) was used to develop econometric models exploring the willingness to pay and relocation choices of travelers in light of the new technologies. In addition, the latest version of the Southeast Planning Regional Model (SERPM) 7.0, an Activity-Based Model (ABM), was employed to examine the potential impacts of AVs on the transportation network. Three scenarios were developed for short-term (2035), mid-term (2045) and long-term (2055) conditions.

This dissertation provides a systematic approach to understand the potential implications of AV technologies on travel behavior and system modeling. The results of the survey data analysis and the scenario analysis also provide important inputs to guide planning and policy analysis on the impacts of AV technologies.

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LIST OF ACRONYMS

AV	Autonomous Vehicles
ABM	Activity-Based Model
ACC	Adaptive Cruise Control
ADAPTS	Agent-based Dynamic Activity Planning and Travel Scheduling
AMOS	Activity Mobility Simulator
ASC	Alternative Specific Constant
CBDs	Central Business Districts
CEMDAP	Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns
CNG	Compressed Natural Gas
CT-RAMP	Coordinated Travel Regional Activity-Based Modeling Platform
DAP	Daily Activity Pattern
DARPA	Defense Advanced Research Project Agency
DaySim	Daily Simulator
EPFL	Ecole Polytechnique Federale de Lausanne
EV	Electric Vehicles
FAMOS	Florida Activity Mobility Simulator
FIU	Florida International University
FSU	Florida State University
GDP	Gross Domestic Product
GPS	Global Positioning System
GTA	Greater Toronto Area
HAGS	Household Attributes Generation System
HEV	Hybrid Electric Vehicles
HFCV	Hydrogen Fuel Cell Vehicle
HOV	High Occupancy Vehicle
IIHS	Insurance Institute for Highway Safety
IRB	Institutional Review Board
LIDAR	Light Detection and Ranging
LPG	Liquefied Petroleum Gas
MAZ	Micro-Analysis Zones
ML	Mixed Logit Model
MNL	Multinomial Logit Model
MPH	Miles Per Hour
NHTSA	National Highway Traffic Safety Administration
PCATS	Prism-Constrained Activity-Travel Simulator
PMT	Person Miles-Traveled
PROMETHEOUS	PROgraMme for a European Traffic of Highest Efficiency and Unprecedented Safety
PSRC’s	Puget Sound Regional Council
SAV	Shared Automated Vehicles
SED	Socio-Economic and Demographic
SERPM	Southeast Florida Regional Planning Model
TASHA	Travel/Activity Scheduler for Household Agent

TAZs	Traffic Analysis Zones
TOD	Time of Day
U.S.	United States
UCF	University of Central Florida
UF	University of Florida
USF	University of South Florida
V2I	Vehicle to Infrastructure
V2V	Vehicle to Vehicle
VMT	Vehicle Miles Traveled
VOT	Value of Time
WTP	Willingness to Pay

CHAPTER 1. INTRODUCTION

1.1. Background

One of the major accomplishments of 21^{st} century in transportation engineering is the development of fully automated vehicles. Autonomous Vehicles (AVs), also known as driverless vehicles, driver-free cars or robot cars, are computer-equipped vehicles which can sense the surrounding environment and make logical decisions based on that to transport passengers and freights between origins and destinations. AVs were only a distant dream several years ago. As early as 1933 General Motors showcased cars powered by an embedded electric grid and controlled by a radio based system; later, in 1950, tests of autonomous highway systems took place, but the idea that having fully autonomous vehicles would be possible in less than 100 years, was still unlikely.

Since then, several other experiments have been conducted to test this technology. The first self-driving car was invented in 1977 by Japanese engineers. This driverless vehicle has the ability to track white street markers and reach to the speed of 20 miles per hour (mph). Later the Eureka PROMETHEOUS (PROgraMme for a European Traffic of Highest Efficiency and Unprecedented Safety) project resulted in the development of autonomous vehicle in Europe during the 1990's and the USA's DARPA (Defense Advanced Research Projects Agency) Challenge in 2004 showed there is an omnipresent will to have autonomous vehicles around the world. Google presented the most recent application. Incredibly, Google's self-driving vehicles traveled more than 1.7 million miles without human intervention between 2009 and 2016 (Google, 2016). Today, several car manufacturers (i.e. Benz, Audi, etc.) and information technology firms (i.e. Google) have either invented their fully AV's or announced their robot cars to be released in a few years (Dowling, 2015; Musil, 2015; Tesla Motors, 2015; Google, 2016).

Besides technology advancements regarding autonomous vehicles, movements can be seen in legislation part also. Several bills have been considered across the nation regarding AV tests and implementations. Since 2012 several states including California, Florida, Michigan, Nevada, Tennessee, Utah, and the District of Columbia began to enact laws, concerning testing of autonomous vehicles. Also in 2016, 13 other states began considering bills related to autonomous driving (Cyberlaw, 2016). This may serve as an indicator that AV technologies may become available in the market sooner than previously anticipated. However, technology and public policy are not the only factors effecting AV deployment; there is a serious need for public-policy and technology to progress together.

1.2. Problem Statement

AVs have the potential to change several aspects of human life including increasing safety, reducing travel time, and altering commuting departure times. Several studies including hypotheses-based discussions, scenario-based investigations, and survey-based reports have supported some of the expected impacts of AVs such as:

- ✓ *reducing traffic accidents/fatalities due to decreased and/or eliminated human errors (Global Driving Risk Management, 2011; Mearian, 2013; Engelberg et al., 2015),*
- ✓ *increasing network capacity and traffic flow efficiency due to improved platooning and more efficient use of existing capacity (Van Arem et al., 2006; Tientrakool et al.,*

2011; Silberg and Wallace, 2012; Pinjari et al., 2013; Fagnant and Kockelman, 2015),

- ✓ *creating new trip makers within the system (Anderson et al., 2014; Fagnant and Kockelman, 2015),*
- ✓ *reducing driving costs and increasing social welfare (Anderson et al., 2014; Fagnant and Kockelman, 2015),*
- ✓ *shifting auto-ownership and car sharing models (Silberg and Wallace, 2012; Anderson et al., 2014),*
- ✓ *changing usual location (residential, job) selection pattern (Fagnant and Kockelman, 2013; Labi and Saeed, 2015), and*
- ✓ *improving land use patterns (Snyder, 2014; Labi and Saeed, 2015).*

Several other implications are anticipated once AVs are added to the network fleet. Considering the incredible potential of AV technologies, it is critical for policy-makers and planners to understand and assess the impacts of these technologies even though much remains to be explored regarding the various ways in which AVs could reshape humanity.

One of the main variables that may change several other forecasts regarding AVs is prediction of AV user adoption. This unknown will show how the market will react toward AV production, which groups of people will adopt sooner, and the extent of the AV's market penetration. In each adoption process, there are several barriers such as high initial cost and unfamiliarity of public users. Even if these barriers are covered for AV technology, user preference will still tend to impact AV's market penetration. Not all the people will adopt these cars at once, adoption process will certainly be a gradual process in several years. Therefore, a comprehensive market penetration model is required in order to facilitate the exploration of the interrelations of these factors.

Although, this technology may be available as early as 2018, based on Google's projections (Driverless User, 2012), it may take some time before these vehicles become affordable, represent a significant share of all the vehicles, and begin to make meaningful impacts on system performance. It is essential to identify the size and characteristics of the potential markets for AV technologies, which have great implications on many other aspects of AV impacts. Positive attitudes and willingness to adopt do not directly translate into willingness to pay, as pricing plays an important role on the actual adoption and usage of these technologies. For example, the markets that show positive attitude and high acceptance may not be the ones that actually will and/or can purchase these cars. A better understanding of these early adopters, known as innovators in market penetration literature, will help planners and decision-makers prescribe user oriented policies and investment decisions.

The potential changes in land use and urban development patterns which will be ushered in by the era of driverless cars is another aspect that may have profound impacts in shaping policies and regulations. Many researchers have predicted future parking demand and growth patterns (Anderson et al., 2014; Litman, 2015), very few conducted quantitative analysis, mostly based on simulations (Kim et al., 2015; Zhang et al., 2015). These analyses were only as good as the assumptions they relied on. Lack of data is a major obstacle in this regard. A study is needed to focus on some behavioral aspects that people may follow after adopting AVs, and the implications of new patterns on the network.

After a market penetration model is predicted and behavioral aspects are studied, the implications of them on a real model should be explored. Although several discussions have been made on the implications of AVs, there are only few studies focusing on modeling and simulating the impacted network in a real model. This is a considerable gap in the current AV literature. Most of the existing studies are either speculations of experts based on their knowledge/experience, or personal preference surveys. It is essential to understand how the network and system-wide attributes will change after conventional cars are replaced by AVs. This type of study will enlighten implications of AVs, not only in general, but in detailed values which are more useful for planners.

1.3. Research Goals and Objectives

Given the various uncertainties with respect to manufacture technology development, government regulations and policies, and user acceptance, the overarching goal of this research is to provide a framework which incorporates AV considerations into the transportation demand analysis and planning processes. From a systematic approach, this study aims to focus on the following objectives:

- ✓ *The Market Adoption Prediction*

The first objective of this study is to develop a market penetration model that can predict how people are going to react toward AV market. As mentioned before, this is an important factor which should be taken into account by policy makers and this study will contribute to the literature by providing a mathematical-based market penetration model for autonomous vehicle technology.

- ✓ *User Adoption*

The second objective of this study is to develop a user adoption model for AV technology based on survey data. User adoption is known as mental acceptance and use of new products. In order to further study the impacts of this technology, it is important to understand the gradual adoption process, the pioneers for adopting this technology, and the adoption rate. This objective will serve to find characteristics of persons and households which adopt this technology and also the method of adoption.

- ✓ *Scenario Analysis*

The adoption of AV will change transportation networks considerably in many different ways. Networks can have higher capacity with the existing infrastructure, travelers will be able to reallocate their travel time to activities other than driving, value of time (VOT) for different income levels will change, travel time between origin and destination may decrease and consequently travelers' departure time and mode choice may change. However, these changes will not happen instantaneously and some of them will only be noticeable over several years. The third objective of this study is to develop scenarios, in which AV adoption results can be analyzed in meaningful ways. An impact analysis will be conducted to help reveal the implications of AVs on individuals' travel behavior and impacts on the network.

1.4. Dissertation Organization

The rest of this dissertation is organized as follows: Chapter 2 will provide a comprehensive review of the past research efforts in the field of autonomous vehicles;

especially attention will be placed on the market penetration and implications of AVs. The structure of Activity-Based Modeling (ABM) of travel demand will also be discussed in this chapter. Chapter 3 will present the methodology in which data collection, modeling, and simulation will be conducted. Chapter 4 will explore the development of market penetration prediction models. The survey results and modeling will be discussed in Chapter 5 and Chapter 6 will provide scenario and simulation analysis. Chapter 7 of this dissertation will provide the conclusion and discussion of further research opportunities.

CHAPTER 2. LITERATURE REVIEW

In this chapter a comprehensive review of related studies is presented. Each study was examined due to the similarity to this dissertation's tasks and objectives. First, the history of AV technologies will be explored. Following this, AV technologies will be introduced, basic terms will be defined, and levels of these technologies will be presented. Next, studies concerning the potential impacts of AV technologies on traveler behavior will be reviewed; this section will help lay the foundation for a framework to focus on some critical points of the study. The third section will explore public opinion surrounding AVs. More specifically, it will review AV market penetration studies in order to estimate the time that policy-makers have to prepare infrastructure and the whole network for the emergence of AVs. After this, there will be a brief introduction to Activity-Based Models (ABM) as well as various families of ABMs as well as the similarities and differences between these families. More detailed review on the studies focused on three major areas of this study including willingness to pay behavior, likeliness to relocate residential location and the preferred method of using AV will be conducted in this section.

2.1. Autonomous Vehicle Technologies History

In recent history it was a farfetched dream to travel from a country to another one in less than a day, or ride a train travelling as fast as 250 mph. However, as technology advanced these dreams transformed into parts of daily lives. Regarding the automobile industry, modern vehicles are being offered with new options such as Adaptive Cruise Control (ACC), Global Positioning System (GPS), and parking assistance systems. All of these are attempts to change driving to an automated task in order to increase safety and decrease the burden placed on the driver; the eventual goal of all these efforts is to have fully automated vehicles.

Autonomous vehicles possess the ability to drive themselves on existing roads using computerized features and this dream is now closer than ever. The sight of Google's car fleet on San Francisco's streets in 2010 is an evidence. As of recent, the fleet has surpassed 1.7 million miles traveled without human interaction (Google Self-Driving Car Monthly Report, 2016). Following Google's lead, several major automobile manufacturers have also initiated plans to have their own AVs ready for market in up-coming decade.

Very first attempts to add automated features to vehicles dates back to the first decades of 20th century. In 1933 the first AV technology was showcased by General Motors at the World Fair. At the showcase, General Motors displayed cars powered by an electric grid in the roadway and maneuvered by a radio control system. Shortly thereafter, the first automatic transmission was introduced by General Motors in 1939 and was made available in the 1940 Oldsmobile (Car History, 2015). The automatic transmission was followed by the invention of cruise control systems, by Ralph Teetor, in 1945. Unlike the automatic transmission, this technology took longer to be adopted into production models of cars; this technology first appeared in Chrysler's 1958 Imperial (Bellis, 2014). A huge leap was made by Japanese engineers, in 1977, when the first self-driving car was realized (Trends Magazine, 2010). Inspired, the European Commission began to develop the Eureka PROMETHEUS (PROgraMme for a European Traffic of Highest Efficiency and Unprecedented Safety) project for a driverless car in 1978. This was the largest research and development project in the field of autonomous vehicles at that time. It involved several universities and car manufacturers; its funding reached €750 million in current money. Upon its completion, the project produced a modified S-Class Mercedes Benz which made a 1,000 round-mile trip from Germany to Denmark and back. During this trip, nearly 100 miles were performed autonomously by the vehicle. Incredibly, this driverless car recorded speeds of 115 mph on a German freeway, and performed passing maneuvers when other cars were present (Oagana, 2016).

After the European project, Defense Advanced Research Project Agency (DARPA) an agency in U.S. Department of Defense, got involved in developing new technologies, and conducted an urban challenge to enhance American skill to accelerate the development of Autonomous Vehicles that can be applied in military requirements. Teams from universities and robotics across the world participated in the 2004 challenge; developing an autonomous vehicle which is able to complete the specified route. While none of the teams could finish the route successfully, in 2005 challenge, five teams were able to finish the course. The last challenge was completed by six teams, the winner AV experienced an average speed of 14 mph (Thompson, 2015).

In January of 2014 the first commercial self-driving car, the Navya Shuttle, was introduced by a French company. At this point, although the technology existed and was viable, it is not authorized to be used in public roads. Just two of them are currently being used in Switzerland's Ecole Polytechnique Federale de Lausanne (EPFL) and by the United Kingdom Atomic Energy Authority (Kelly, 2014). In September 2016, the first autonomous vehicle being used in a city mass transit system was introduced by French city of Lyon. The fully electric and autonomous shuttles with capacity of 15 people started to serve a 1,350 meter circular route in Lyon business district. Residents are able to take this shuttle for free and shuttle is traveling at 12 mph, while it is able to reach 28 mph (Pultarova, 2016). In the same month, Uber announced pre-selected users in a 12-square-miles of Pittsburgh downtown have the option of riding in a self-driving car with a human engineer at the wheel just to take control of vehicle in case things get risky (Davies, 2016).

As stated by the National Highway Traffic Safety Administration (NHTSA), this technology can be organized into five levels. This organization begins at level 0 which corresponds to conventional vehicles without any automated features, and ends with level 4 which is a fully automated vehicle (NHTSA, 2013). Level 4 of automated vehicle technologies may also be called as autonomous vehicles. These groups are explained below:

- ✓ *Level 0, No-Automation*

Vehicles in this level require the driver to perform all the controls including operating the brake, navigation, starting power, and parking.

- ✓ *Level 1, Function-Specific Automation*

In this level one, or more, specific function of driving is automated. For instance, the pre-charged brake system, which helps the driver to keep control of the vehicle while braking and assists a more rapid deceleration than would be possible with manual braking systems.

- ✓ *Level 2, Combined Function Automation*

As indicted by the title, at least two primary functions of controlling the vehicle are automated in this level. For example, the use of adaptive cruise control and lane centering function. When combined, these can relieve the driver from maintaining the vehicle in the travel lane and maintaining speed.

- ✓ *Level 3, Limited Self-Driving Automation*

This level of automation is a big step forward from Level 2. This class enables the automation of all critical vehicle function control, but only under certain traffic and environmental conditions. Although the responsibility is significantly reduced, the driver should be available for occasional control under adequate transmission time. Google's AV is an example of this level of automation.

- ✓ *Level 4, Full Self-Driving Automation*

In Level 4 the entire process of driving is automated. Once the driver selects a destination, there is no addition input required.

2.2. Autonomous Vehicles' Implications

Several studies have been conducted to examine lifestyle and travel behavior implications of Autonomous Vehicles. A thorough review of the literature identifies two fundamental dimensions that can help provide a meaningful classification for the past and ongoing research efforts. They include:

- ✓ *The time horizon considered (or assumed) for AV implementation:*

Time horizon is particularly of the essence. First, there is a general consensus among stakeholders that AV implementation will not be a quick turn-a-round, it will rather take time to be introduced into the automobile market and later into the real-life transportation system. Hence, it is reasonable to assume that market penetration gradually increases year by year. Due to this, its consequences will be more pronounced as time passes. Second, a quick review of policy implications in today's world reflect significant differences and even occasional contradictions between short-term and long term effects. This is more tangible when it comes to human factors and travel behavior decisions, as behavioral responses are usually subject to instant fluctuations before they reach a stable state of equilibrium.

- ✓ *The methodology applied to estimate/quantify the consequent impacts:*

Several methodologies have been adopted by researchers in order to provide reliable forecasts for AV implications. In general, they can be classified into speculative (hypothetical) studies, actual analysis, and survey design/outcomes. Speculative studies tend to provide meaningful assumptions for AV market penetration in future years based on information and data from several stakeholders as well as analyzing results from similar technology adoption rates in recent years. Actual analytical studies use the pre-defined assumptions in order to simulate the traffic network and activity/travel behavior of individuals under different AV implementation scenarios. Survey studies include design/employment/result analysis of specific questionnaires which target different aspects of AV market such as adoption rates, public knowledge of AV technology, market segmentation, impact analysis, etc. Regardless of the methodology applied and the parameters being analyzed, one common issue in all the existing AV studies is the huge "uncertainty" involved in current analyses as there is very little revealed preference data on AVs due to their limited applications. With the above in mind, the highlights of AV implications are presented in the upcoming sections.

2.2.1. Long-term Implications (2055 and later)

The long-term impacts of AVs mainly affect location choices and land-use patterns. It is theorized that residential, work, and school location selections are likely to shift after AVs are gradually introduced to the network. This mainly stems from the consequent benefits such as relaxed driving, less congested network, higher speed profiles and shorter travel times, which could be interpreted as an overall reduction in travel costs. Therefore, people can traverse longer distances with little to no difference in their associated general travel costs. This provides users with more flexible residential, work, and school location choice sets, which can bring about a variety of economic and social benefits (Anderson et al. 2014; Labi and Saeed, 2015).

In a speculative study, Anderson et al. (2014) discussed the contradictory scenarios of AV impacts on land use. Based on the discussion in this study, transportation cost will be decreased considerably because drivers and passengers would be able to do tasks other than driving in the car while being driven to the destination in an autonomous vehicle. This cost reduction may free a balance of household budgets consequently a group of people may be able to afford larger houses in better residential lands. Also because the driving task would be much easier and farther distance can be driven in shorter time, a group may decide to relocate from urban area to suburban area. On the other hand, the considerable reduction in parking demand can provide an attractiveness for people to move and live in urban areas while they do not need to pay for parking anymore and live closer to their jobs. This is also feasible assuming demand-responsive driverless taxis which do not need parking and a car's capability to self-park outside the urban area. This hypothesis was supported by Snyder (2014) which concluded with the ability of autonomous vehicles to drop passenger and look for parking space outside Central Business District a huge amount of pressure for building parking for each destination will be removed, consequently considerable space in the high priced land area can be freed. This may result in reduced land price in urban area which is an attractive feature for relocation.

The elimination/change of parking spaces is not limited to parking garages only, but on-street parking infrastructures will also change to AV specific drop-off locations according to a recent discussion based report by Chapin et al. (2016). Based on the discussion, this technology has the potential to eliminate the need to driver and passenger to seat in the vehicle while looking for a parking, thus farther and cheaper areas for parking space will be also attractive. Since the drop-off and pick-up locations can be used common between AVs, mass transit systems and ridesourcing vehicles (i.e. Uber), the existing mass transit stops can be updated for this purpose. The authors mentioned that a safe waiting area should be considered for passengers to handle this change safely.

Pendyala and Bhat (2014) discussed some of the hypothetical impacts of driverless cars. Authors discussed that travel time and distance will play less important role that now in future transportation with smart vehicles. This change will result in looking for a wider area to access better residential locations, jobs and schools, which may change overall urban development patterns Similar patterns have been suggested by several other sources (Lari and Onyiah, 2015; Alessandrini et al., 2014; Alessandrini et al., 2015).

Based on speculations, complete street concept will be more applicable and attractive in the AV period (Chapin et al., 2016). The smart concept in an autonomous vehicle such as lane change warrant provides an opportunity to design narrower lanes for AV fleeting, consequently more space can be assigned to bicycle and pedestrian modes. This will be an important matter especially in downtown area, not only because land price is high in business districts, but because of lack of space, normally pedestrian and bike safety is compromised for vehicular fleet, which can be avoided in a complete street. Figure 2-1 shows a hypothetical intersection before and after AV introduction. Except aforementioned changes, several pavement marking and signs will be replaced by Vehicle to Infrastructure (V2I) and Vehicle to Vehicle (V2V) communications.

Analytical studies mainly confirm the discussed hypotheses. Zhang et al. (2015) explored the effect of Shared Autonomous Vehicles (SAVs) on urban area parking demand using an agent-based model. The agent based model results showed that if only 2% of the hypothetical population adopt SAV system, the parking demand can be reduced by 90% for those adopted households. Although the model did not explore some important features regarding parking such as parking price, but even not considering any changes in these features, results support the idea that parking demand would be considerably reduced when more people adopt autonomous vehicle and shared taxies.

In a comprehensive parking management report, Litman (2012) estimated annual parking costs including land, construction, maintenance, and operation for CBDs, other central/urban areas and suburban areas. Based on the estimations by Litman (2012), relocating one parking lot from CBD to a non-CBD urban area can save close to $2,000 annually, which increases to $3,000 if the parking space is relocated to suburban area. This should be noticed that because of more carsharing programs in future due to AVs development, there is no need to provide same parking spaces that are actually removed from CBD area in non-CBD locations, which means saving more money. Litman (2014) study concludes each new AV will result in $250 in parking saving assuming 10% of AVs being publicly shared.

Another agent-based modeling simulation were developed by Kim et al. (2015) to explore the market penetration and potential impacts of AVs in Korea for long range. Assumptions of this study was based on Litman (2014) market penetration model and Yokota (1998) recommendations for road capacity changes due to AVs. Different years were assumed for road opening for AVs; i.e. 2020 for highways and 2050 for arterials. Two scenarios including current urban growth, and 100% AV adoption for year 2070 were explored in this study. Findings supported the hypothesis that residents do not prefer to locate close to urban center and more dispersed distributions of population was seen.

Figure 2-1. Hypothetical Land-Use Change in Intersections, Source: Chapin et al. 2016

2.2.2. Mid-term Implications (2035-2055)

Several studies have been conducted by researchers to examine the impacts of Autonomous Vehicles in the mid-term. Hypothesis and studies showed that AVs might result in several alternations for existing car ownership models by increasing the attractiveness of shared systems; impact the household financial situation by adding more expenses for high-tech vehicles and more saving due to reduced crashes, injuries, fuel consumption, etc. How travelers choose their transportation mode will also be changed due to alternations of the conventional mass transit systems. Energy consumption is also another topic in mid-term implications of AV which include more efficient utilization of fuel and energy because of the nature of automated driving.

2.2.2.1. Car Ownership

The emergence of new car sharing system has somehow changed the car ownership pattern. According to Katzev (2003), several members of shared mobility companies announced they have sold their car after being a member of the system. Today 20% of all Uber rides in San Francisco are shared. It is anticipated that increasing the share of AVs on the roads will lead to the expansion of car-sharing and ride-sharing programs. This will considerably change existing car ownership models.

Speculations for Anderson et al. (2014) and Fagnant and Kockelman (2013) support the hypothesis of vehicle ownership changes. One aspect of auto ownership change is because of more inside vehicle room which can be used for several non-driving tasks. Based on the discussion by Anderson et al. (2014), one may decide to use a larger vehicle to be able to sleep instead of driving if autonomous vehicle is in the market. The review report by Fagnant and Kockelman (2013) also suggests that several trips which are now being done by private cars can be replaced by shared taxies which will result in vehicle ownership pattern alternation.

Author could not find any analytical studies regarding AV vehicle ownership, but found some surveys, such as the survey conducted by Menon (2015) which supported the speculations. In this survey, more than 40% of respondents were likely to use AVs when they become available and approximately 20% of people could not decide about that yet.

Similar results were also reported by Schoettle and Sivak (2014). A public opinion survey was conducted focusing on familiarity with AVs in six countries in Asia, Europe and North America. Survey asked respondents, expected benefits and concerns about implementations, overall interest in owning AVs, and willingness to pay for this technology. Results showed more than half of the respondents are willing to have autonomous vehicle, interestingly people in China and India were more interested.

Another survey, conducted by the Alliance of Automobile Manufacturers, showed 60% of people will consider the new technology-based systems of the cars next time they are purchasing an automobile. Further, the survey by Cisco showed more than 55% of people would be likely to ride in a driverless car which does not require a human driver. Conversely, TE Connectivity's autonomous vehicle survey in 2013 revealed that 70% of respondents were not comfortable in an autonomous vehicle (TE Connectivity, 2013).

2.2.2.2. Household Financial Situation (Income/Expense)

Based on hypotheses, AV will affect household financial circumstances in both positive and negative ways. However, the positive outweighs the negative side when considering expenses. The negative way is probably seen in the higher payment for automated features in AVs, while the positive way touches several aspects, from cheaper driving to less accident related costs. Anderson et al. (2014) speculated AVs will reduce traffic costs of users, since occupants of vehicles could undertake other activities while driving. Also parking and fuel costs can be reduced as a result of using AVs. Analytical studies support this idea.

Fagnant and Kockelman (2013) suggested that autonomous vehicle technologies can help household financial system by reducing insurance, parking, gas and travel time cost. Authors considered several reductions in household costs including fewer crashes, saved lives and economic costs savings. The study claimed 10%, 50% and 90% market penetration would result in a savings of $37B billion, $211 billion, and $447 billion (U.S) respectively. Another analytical study by Morgan Stanley & Co. LLC in 2013 estimated cost reductions of $488 billion (U.S) from accident avoidance, $158 billion (U.S) due to fuel saving, $507 (U.S) billion from achieved productivity, $11 billion (U.S) fuel saving from congestion avoidance, and $138 billion (U.S) productivity gain from congestion avoidance.

Asher (2014) focused on four main types of costs including household costs, congestion costs, social costs, and emission costs to conduct a cost-benefit analysis. Results showed the household costs can be reduced because of less auto ownership costs which can be used to change household lifestyle to a higher level. On the network side, travel cost will be reduced due to more efficient driving task. Although safety analysis showed fewer crashes will result in costs reduction, but emission analysis was not certainly supporting any cost reduction.

Finally Fagnant and Kockelman (2015) made several assumptions on increased Vehicle Miles Travelled (VMT) and vehicles price due to AV technology, reduction in fatalities and injuries as a result of human error elimination, decreased travel time in the network, and reduced parking costs to explore monetary impacts of AVs. Results showed there would an economic benefit of $196 billion (U.S.) only due to AV technologies at 90% market penetration.

The existing surveys did not address the reduction in cost and change in household expenses due to AVs. This is primarily due to the fact that most of surveys were focused on individuals' familiarity with and their propensity to use AVs, or which activities users would consider in lieu of driving.

2.2.2.3. Mode Choice

Several studies have been conducted to understand the effect of autonomous vehicles on mode choice behaviors. A predictable impact of AV technologies is a decrease in the importance of traditional mass transit. This is due to the fact that people would be able to perform other tasks while being driven, a benefit currently only possible in mass transit. Although unlikely, some researchers believe that the proliferation of AVs may lead to the failure of mass transit systems in many cities. Conversely, there is also another school of thought which believes AV proliferation could lead to a renewed growth and interest in public transportation. An example of this occurred in 2013 throughout the San Francisco Bay Area; the area saw the emergence of Uber. During this time, statistics indicated an increase in transit ridership in the region (Anderson et al., 2014; Freemark, 2015; Levin and Boyles, 2015).

The speculations from discussion presented by Alessandrini et al. (2015), Pendyala and Bhat (2014) and Fagnant and Kockelman (2013) showed according to experts people are going to use more car sharing systems when AVs are available on the network. Alessandrini et al. (2015) described the current status of automated driving and a preliminary vision of the future cities; the study theorizes that one of the expected positive impacts of AV is car sharing. Pendyala and Bhat (2014) also shared this idea.

In a simulation-based study, Levin and Boyles (2015) developed a modified four-step travel demand model to study the effect of AV ownership on transit demand during the highly congested peak hours. Generalized cost formula as a function of travel time, monetary fees and fuel consumption were developed and used for mode choice. According to the model results, mass transit will be less attractive with more groups of people being able to afford AVs. The results showed a considerable increase in the number of trips, 271%, however the network speed decreased only a negligible amount.

A Revealed Preference (RP) survey to explore mode choice options while multitasking is taken into consideration was conducted by Malokins et al. (2015). Based on the survey findings, driver's involvement in non-driving tasks such as reading or using personal computer is significantly affecting mode choice utility. This effect can change the existing modal share, though small. Supporting Levis and Boyles (2015), the study results estimated a decrease in mass transit modal share and an increase of 3% in drive alone more share.

2.2.2.4. Energy Consumption

Based on the literature, the effects of different capabilities of AVs such as platooning, more efficient driving, dynamic traffic assignment, induced demand by underserved population, less travel time, lighter vehicles, elimination of parking seeking time and higher occupancy can change the energy utilization pattern when AVs become affordable in mid-term. A study on the effects of AV on energy consumptions showed a saving of more than 90% is achievable, for the scenario at which only energy consumption advantages of AVs are considered (Brown et al., 2014).

The discussion-based study of Anderson et al. (2014) stated that the environmental outcomes of AV technologies depend on the fuel efficiency of AVs, characteristics of the fuel used as AVs power and also the increase or decrease in VMT resulting from AV usage. However, the discussion mentioned that automated driving can considerably enhance fuel economy. Also, another aspect that will change in AV era is manufacturing vehicles without using heavy protective safety features, which will considerably affect fuel efficiency. Circella et al. (2015) also supported the idea of less fuel consumption of AVs in their speculations.

Popular perceptions are also supporting the aforementioned speculations. More than 60% of respondents in Menon's (2015) survey revealed that they agree with the fact that AVs will have increased fuel efficiency. Also, in an online survey by Intel, 34% of participants mentioned driverless vehicles would help future cities by reducing harmful emissions (Intel, 2014).

2.2.3. Short-term Implications (2020-2035)

Autonomous vehicles will likely change the way people live, their general lifestyle, home and leisure destinations, as well as transportation mode selection, but these only occur over time. However, there are some immediate effects of AVs which can be noted relatively recently after its inception. In the short-term, AVs will likely effect the activities engaged in lieu of driving, safety and capacity of the network, provide trip possibilities for people who previously were unable to drive, and increases in demand responsive services.

2.2.3.1. Activities

It is predicted that besides mandatory trips, which will be affected as a result of changes in usual location choices, some non-mandatory trip patterns such as shopping trips are highly prone to consequent changes (Anderson et al., 2014). As the driver may not need to be present, one could potentially send the car to a retail store to pick up an order or an item purchased from elsewhere. Another implication could be that people choose to visit stores or malls which are further away, rather than the nearest, since the burden of driving will be significantly reduced.

Pendyala and Bhat (2014) speculated using AVs, people may involve in more activities which will consequently add new trips to the network. Activity scheduling implications of AV technologies is still in the hypothetical stage and as such, no actual behavioral analysis have been completed.

2.2.3.2. Network Capacity

Freeway and highway features will have to be changed in order to accommodate autonomous vehicles in the network (Childress et al., 2015). Perhaps this is not a direct effect of AVs on travel behavior, but it will definitely change some of travel behavioral aspects indirectly; e.g. trip departure times. Studies showed network capacity can increase two to four times more than existing capacity, based on the AV fleet size (LLC, Morgan Stanley & Co, 2013; Childress et al., 2015; Shladover et al., 2012; Tientrakool et al., 2011; Pinjari et al., 2013; Global Driving Risk Management, 2011). Improvements in the network capacity would result from the precision of AV controls, the communication features, and increased reliability of travel time (Wallace and Silberg, 2012). Taking geometry into consideration, because of AV ability to communicate and sense surrounding environment much better than human driver, potential of designing narrower lanes would be probable (Pinjari et al., 2013). Another interesting possibility will arise with the advent of AVs for the freight industry. When this becomes materializes, it will allow freight to be sent into the transportation network during non-peak periods which will also add considerable capacity to the roads. .

Several speculations from discussion based reports and studies predicted that AVs will increase the network capacity and provides better mobility. Anderson et al. (2014) estimated the capacity will increase two to three times. The main justification is based on vehicle communications; since vehicle can communicate better, it is feasible to reduce the car following to a very small limit which increase the capacity without any further change in infrastructures. Lari et al. (2015) and Circella et al. (2015) also stated the same thought. Speculations support the idea of having narrower lanes, which can provide higher number of lanes with same Right of Way (ROW) in freeways and highways, consequently higher network capacity (Chapin et al., 2016).

In a simulation-based study by Childress et al. (2015) authors used an activity based model to study impacts of AV technology on the network. Authors developed four scenarios based on the Puget Sound Region in Washington using Puget Sound Regional Council's (PSRC's) activity-based travel demand model. The study obtained data from the region and used 2010 as the base year. In the first scenario, researchers assumed a 30% increase in capacity from AVs assuming AVs use existing facilities. In the second scenario, the VOTs were reduced by 65% for households with income level of \$15-\$24 per hour. The third scenario included first scenario, expanded the second scenario to all groups, and reduced the parking cost by 50% to represent AVs self-parking in cheaper locations. In the final scenario, a new transportation mode was assumed to work in the network which represents shared autonomous taxi working with \$1.65 per mile as cost. Results showed the VMT is increased due to the increase in capacity. However, the increase in VMT not only did not result in speed reduction, but the network speed increase 1 to 2 miles per hour depending on the scenario. Interestingly, the surveys conducted by Menon (2015) and Schoettle and Sivak (2014) showed that people are not in agreement with experts in this respect. In these surveys, almost half of the respondents thought there would not be less traffic congestion after AVs emerge (Schoettle and Sivak, 2014; Menon, 2015).

2.2.3.3. Safety

Another short-term implication of autonomous vehicles which will indirectly affect travel behavior is highways safety improvements. As AV technologies will completely or partially replace human drivers with computers, there will be a significant potential for safety improvements on highways. Human error as the main cause of driving related fatalities will be eliminated (or minimized) from the system which will result in fatalities and injuries reduction (Global Driving Risk Management, 2011). One study estimated that AVs can prevent 4.2 million accidents and $450 billion in and can save 21,700 lives (Mearian, 2013).

Several speculations have been constructed based on the effects of AVs on safety. Anderson et al. (2014) predicted that AVs will result in less crashes. This prediction was based on an estimate produced by the Insurance Institute for Highway Safety (IIHS) that predicted a considerable reduction in crashes and fatalities (33%) in case every vehicle is equipped with smart features such as: forward collision and lane departure warning systems, blind spot assist and adaptive headlights. Labi et al. (2015) and Fagnant and Kockelman (2013), concluded a similar result by discussing the elimination of human error related crashed by AVs. The benefit of AV and generally new technologies is not limited to human error elimination, i.e. Baratian-Ghorghi and Zhou (2016) concluded that travel behavior regarding yellow/red lights running will reduce considerably if drivers be aware they are being monitored, by a camera or a smart system. This feature will also increase safety.

These results have been supported by respondents' perceptions in surveys by Menon (2015), Schoettle and Sivak (2014), and the Alliance of Automobile Manufacturer (2013). Based on Menon (2015), close to 70% of participants stated that fewer crashes are expected and roads will be safer when AVs are available. This was similar to the rate of "very likely" and "somewhat likely" responses in the survey conducted by Schottle and Sivak (2014). According to the survey conducted by the Alliance of Automobile Manufacturer in 2013, close to 60% of participants believed that technological innovations of vehicles will result in safer cars (Alliance of Automobile Manufacturers, 2013).

2.2.3.4. Trip Making Behavior

An input of transportation demand models is trip generations to/from each node. These trips are assigned to adults with cars and the ability to drive. However, autonomous vehicles will affect the number of trips generated by providing mobility to users who previously could not travel alone, i.e. under 16 years old or disabled people.

Speculation based studies by various authors pointed out that AVs are going to add some trips to the network by providing mobility for disabled people and children (Wallace and Silberg, 2012). Anderson et al. (2014) speculated that level 4 vehicles (fully automated) will considerably increase number of trips because it provides mobility for those groups which are not able to drive using conventional vehicles. The same speculations were also mentioned by KPMG (2015), Lari et al. (2015), and Pendyala and Bhat (2014). While the study of this topic was robust, no studies focused specifically on how AVs can affect the trip making behavior.

2.2.3.5. Demand-Responsive Services

While mass transit currently plays an important role in the transportation system and has many advantages, it also is plagued by a number of disadvantages including fixed route, fixed stop location, low accessibility, limited operation hours, etc. Autonomous demand-responsive systems can provide a huge benefit to transit users either in terms of multimodal accessibility or an alternative public transport system.

A KPMG report (2015), which focused on business marketing guidelines for automobile companies, predicted that there will be an increasing desire for mobility options as well as large increase in Person Miles-Traveled (PMT). Other factors including safety needs, weather situations, premium experience, and leisure time also lead to high desirability of driverless mobility-on-demand alternatives.

In a comprehensive study at Princeton University (2013), the effect of ridesharing on the number of vehicles were explored. Researchers developed a simulation framework for autonomous taxi (aTaxi) service in New Jersey to study this effect. The study area consisted of 21 counties. Pixels of 0.5-mile squared were used to break the whole area assuming one aTaxi station in the center of each square, serving trips between each area. The simulation results showed using aTaxis can finally reduce the number of vehicles on the network (Bierstedt et al., 2014).

2.2.4. Summary

There have been considerable number of predictions regarding the impacts of AV technologies, and most have focused on safety and technological issues. Several studies have talked about positive effects of these technologies such as improved safety (Global Driving Risk Management, 2011) and transportation efficiency improvements (Van Arem et al. 2006). Others have studied the potential increase in trips to be expected as AVs make transportation easier for all users. Most of the efforts so far were based on hypothetical predictions, and quantitative studies. A considerable lack of research data can be seen in AV impact studies, especially the impacts on individual travel behavior.

2.3. Autonomous Vehicles' Market Penetration

Different studies predicted various timelines for autonomous vehicle technologies development. Multiples facet must be considered in order for AV technologies to become viable including cost, social acceptance, policy-maker desire, and many more. For AV technologies to be successful, each potential impediment should be well-defined, studied, understood, and a strategy should be constructed in order to overcome it. Following this, other criteria and law enforcement should help the technology to become second nature in society.

One significant barrier could potentially be automakers. History has shown that in most cases, such as seatbelts, air bags, and antilock brakes, automakers tend to oppose new expensive technologies regardless of the potential benefits to the society (Anderson et al., 2014). Based on several studies and predictions, AVs will be ready for use on highways within the next decade. As is often the case, the technology will exist long before it becomes accepted. Consequently, it is unclear when AVs will account for a considerable share of highway traffic (Fagnant and Kockelman, 2015).

2.3.1. Studies Predicting Autonomous Vehicle's Market Penetration

Litman (2014) predicted the market penetration of autonomous vehicles based on general fleet market and also previous vehicle related technologies adoption procedure, i.e. automatic transmission, air bags, hybrid vehicles and vehicle navigations systems. The study found a technology such as automatic transmission needed 50 years for being affordable and reliable, and still after almost a century from the first time it was invented, it could only reach to market penetration of 50% in Europe and Asia. Other technology which was studied by Litman was air bags. They were expensive and unsafe in the first years of development (1973), after 20 years the price dropped down and safety increased, so that it turned to a mandatory feature in U.S. Hybrid vehicles are also another sign showing how much market can be conservative toward new technologies. These vehicles were commercially ready in 1997, but after 15 years only slightly more than 3% of market were filled with them. A summary of Litman's study can be seen in Table 2-1.

Table 2-1. Vehicle Technology Deployment Summary (Litman, 2014)

Technology	Deployment Cycle	Typical Cost Premium	Market Saturation Rate
Air Bags	25 years	A few hundred dollars	100% (federally mandate)
Automatic Transmission	50 years	$1,500	90% (U.S.); 50% (Worldwide)
Navigation Systems	>30 years	$500; rapidly declining	Uncertain, probably >80%
Optional GPS Services	15 years	$250 annually	2-5%
Hybrid Vehicles	>25 years	$5,000	Uncertain, currently about 4%

Litman discusses although there are several benefits associated with autonomous vehicles, but it is not clear that what percent of people would actually consider those benefits over the high automated technologies costs. Litman (2014) estimated that expensive autonomous vehicles will be on streets in the 2020s, it takes at least 30 years for them to be able to obtain 80-100% of the whole market. Figure 2-2 shows Litman's (2014) market penetration projection:

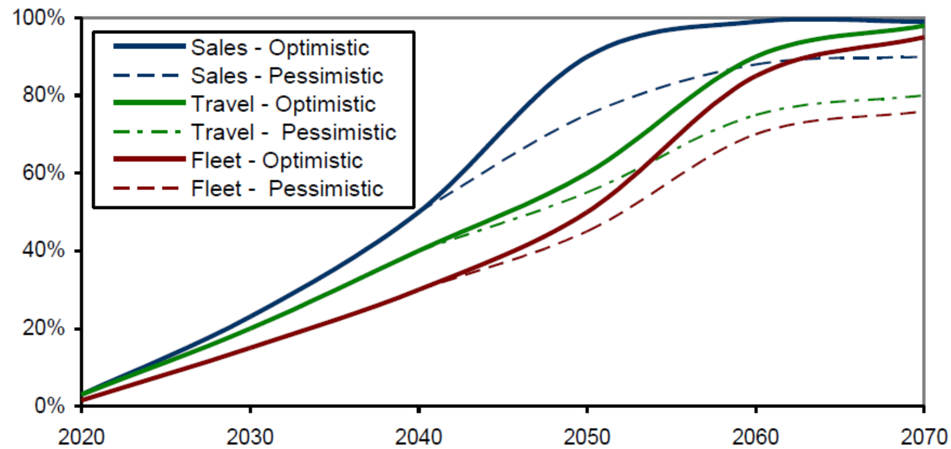


Figure 2-2. Autonomous Vehicle Sales, Fleet and Travel Projections (Litman, 2014)

Fagnant and Kockelman (2013), estimated an earlier market penetration for autonomous vehicles. Authors did not take previous technologies into account, but developed their market penetration curve based on the announcement by Nissan and Volvo. Similar to Litman (2014), authors predicted the commercial emergence of AVs will start in 2020, however they forecasted more aggressive price drop down of five years.

Other studies have considered multiple scenarios, such as Wallace and Silberg (2012) in which three possible adoption scenarios were proposed. Authors believed market adoption of this new technology will basically depend on how the various parts come together. Based on Wallace and Silberg (2012), cost, technology, consume acceptance are the most effective parts which play more important role in market penetration procedure. Figure 2-3 illustrates Wallace and Silberg (2012) proposed adoption scenarios.

2.3.2. AV Market Adoption Barriers

2.3.2.1. Personal Preference and Familiarity

Even if AV technologies are able to address all other obstacles, it still must be able to please personal preferences. A recent study of 2,000 licensed drivers showed that 61% of respondents believe they would make better decisions than a computer when driving (Vallet, 2014). Although, the study showed that more than 30% of respondents would let the computer drive the vehicle whenever possible; less than 25% of them would trust a fully automated vehicle drop kids to school. The study showed the perception about cost will considerably affect likeness of using AVs. Almost 25% of respondents stated they would never purchase a fully AV, but this dropped to 14% when informed that insurance costs would decrease by 80% due to AVs. The vehicle maker is also an important issue for drivers in adopting AVs. The majority of people (54%) stated that they trust traditional automakers (such as Honda, Ford, and Toyota), but only 15% would trust software companies (such as Google or Microsoft) (Vallet, 2013).

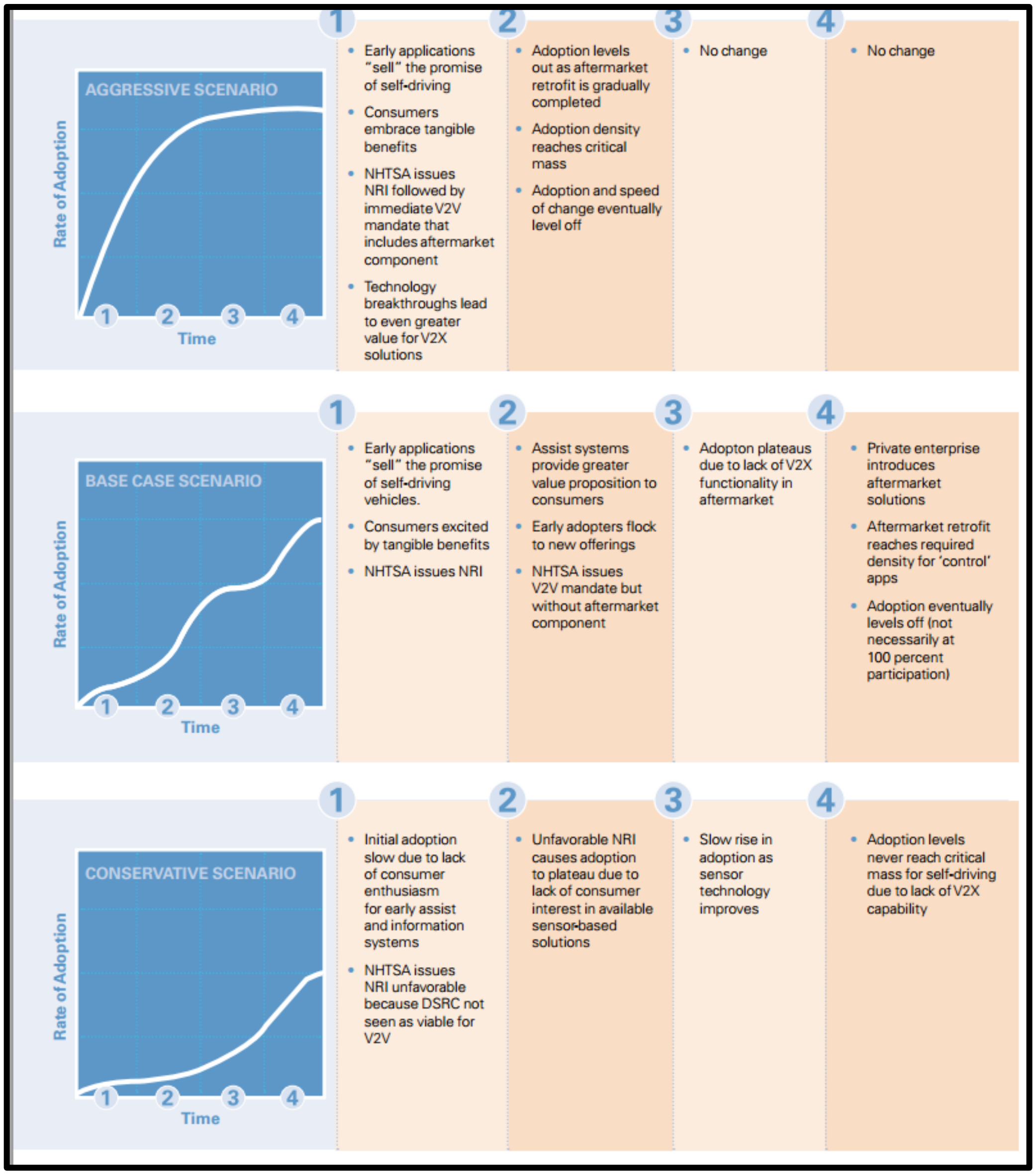


Figure 2-3. Adoption Proposed Scenarios (Wallace and Silberg 2012)

The survey by Schoettle and Sivak (2014) had also another part on public opinion about AVs in three countries including the United States, United Kingdom, and Australia. In response to the familiarity question, the majority of individuals mentioned they have heard about AVs previously; 66% were familiar with. Most of the respondents were supporting the speculations regarding AV technology will result in fewer crashes. Also other features about autonomous vehicle which were popular reported to be improved emergency response times, and better fuel economy. Comparing Level 3 and Leve 4 of automation, as expected, people are more concerned about giving full control of their vehicles to computers. A considerable share of respondents (30%) mentioned they are not interested in having a fully-automated vehicle, while 17.8% mentioned they are very interested. These rates are very close to what Power obtained from a survey in 2012. However, Cisco (2013) expressed costumers' desire for more AVs. Based on this research 57% of global consumers trust driverless cars.

2.3.2.2. Cost

One significant barrier that could potentially slow down the progress of autonomous vehicles becoming prevalent is the technology cost. As with many other new technologies, one can expect very high prices in the early years. However, like other technologies, the price will undoubtedly fall and become widely affordable. Williams (2013) stated the technological features being used in Google Car currently costs around $100,000, which is not affordable for the majority of people (Wallace and Silberg, 2012). However, the mass production and technical advancements can reduce the cost of these items considerably. Besides the technical costs related to vehicles, a considerable budget is required to prepare the necessary infrastructure for this new transportation mode (Williams, 2013).

2.3.2.3. Technology

Technology is another consideration that should be taken into account before starting the mass-production of autonomous vehicles. Many companies and universities have begun studying AVs, but more tests should be conducted before coming to conclusion about the presence of AVs in the transportation system. Considering the existing technology, significant effort is required in order to operate a fully autonomous vehicle.

Human-beings' perception of their surrounding environment plays an important role in driving performance. For instance, if a human driver sees a ball falling in front of the car, it is expected that a child may follow it into the street. On the other hand, a computer does not intrinsically make this connection. Further, while a computer can be trained to distinguish a ball and a child, but it is not as simple to train the computer to see the ball and anticipate the child as a human would. This highlights the need for technology to be able to sense the environment and make inferences as a human does (Wallace et al. 2012).

2.3.2.4. Safety, Liability, and Privacy

There is an important issue to address in terms of safety. Researchers must determine if AVs are in fact safer than the existing technology. To do this, it may be necessary to have AV-designated infrastructure so that it can be assessed without interfering with the traditional vehicles.

Issues surrounding liability have also been raised. Traditionally when an accident occurs the law determines who is at fault, but if no one was driving then who is to blame?

If AVs reduce accidents, in fact this event will not occur frequently, but the uncertainty surrounding this must be addressed.

As the technology becomes more embedded into everyday life, the issue of privacy begins to become more apparent and relevant. The amount of data sent from vehicle to vehicle, and vehicle to infrastructure, is incredible. This data would be stored and maintained for improved planning, route assignment, and optimization. However, what if the data is compromised? It is not uncommon for cyber-attacks to occur, and it has become more frequent such as the case with LinkedIn, the Democratic Party, and even the United States Government. Furthermore, there is a concern about targeted advertisement and data abuse. Security issues of automated vehicles is an issue that needs to be considered since the more advances in technology, the more advances in hacking systems will be achieves also (Bierstedt et al. 2014). If not seriously considered, the consequences could be dire. For example, one could hypothetically hack into an AV's computer and take control of it or even command it to crash. Another potential flaw could come from a system update that has corrupted software. It has become a common occurrence with cellphone updates where updates do not perform as planned and patches must quickly be released to address this issue. Luckily a corrupted update for a cellphone will not cause personal injury, but the same cannot be said for AVs. Due to this, the AV network should be established in a way which is resistant to hacking and system failures. Also the privacy policies should be able to keep user information and data safe (Williams, 2013).

2.3.1.5. Lack of Research and Data

Although considerable efforts have been applied to understand the technical aspects of autonomous vehicles, the same rigor has not been applied to research and data in terms of policy and planning (Fagnant and Kockelman, 2015). Since there are not many AVs available to conduct research with, and people are not very familiar with the concept yet, there is a significant amount of uncertainty in the outcomes of AV technologies when they come to the user's perspective and real-world applications. The fact that policy towards AV technologies can change and simultaneously change potential users' opinions only makes matters worse and increases the uncertainty surrounding AV technologies.

Fagnant and Kockelman (2015) identified several factors as the most important topics, aside from the general impacts of AVs on people's lives and travel behaviors, which should be considered in future researches; these included automated transit, shared mobility, regional planning and modeling, roadway management and operation, truck automation and opportunities, legal accelerators and brakes, automated vehicle human factors, near-term deployment opportunities, personal vehicle automation commercialization, automation systems' operational requirements, and road infrastructure needs.

The most probable reason for this lack of research it that not many autonomous vehicles are accessible for researchers. Regardless, assumptions should be made, tested, and theories should be constructed. In order for AVs to be attractive tomorrow, it is useful to identify areas for research and existing gaps today. Market penetration forecasting will also reinforce the urgency of understanding these technologies for policy-makers.

2.3.3. Technology Forecasting Methods

There are several models which are used in economic studies which forecast sale volumes in various industries. The Logistics model and Gompertz model are popular technology forecasting models; another is the Bass model and it is especially useful for forecasting sales and timing of new product purchases. These models have been used to study the market penetration of new technologies including smartphones and websites. All of these three models assume the new product is independent from any other product. Normally new technologies, such as smartphones which have a short life cycle and fall in price when a newer technology is introduced, lead to changes in market penetration models. This condition is also predictable for new AV technologies, especially during the early years of the technology's development.

Generally, diffusion models assume the cumulative sales of a new product over time will be an S-shaped curve (Figure 2-4, top). The curve slope at each time point represents the adoption rate. Adoption rate starts low at the beginning periods of product launch, which reflects consumers' conservativeness regarding the new product especially if they are not familiar with the product. Gradually, the rate increases (if the product is successful), as personal recommendations, social and media commercials may persuade other to use the product. Depending on the product, market saturation will occur in a few months or years when the adoption rate starts to decrease to almost zero. The most popular first-purchase diffusion models in marketing are Bass, Fourt and Woodlock, and Mansfield (Mahajan et al., 1990). Among these, the Bass model has been used widely in market penetration forecasting of new products.

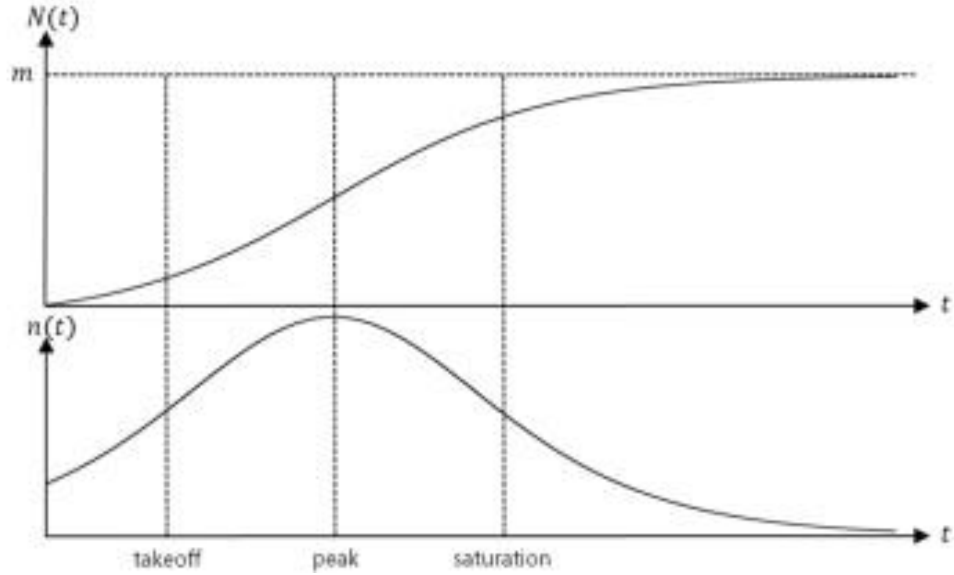


Figure 2-4. Bass model cumulative and non-cumulative adopters curve

Bass diffusion models assume adopters of a new innovation are influenced either by mass media, or by word of mouth (Mahajan et al., 1990). In other words, these two means of communication are the two most influential factors on consumers' acceptance (i.e. purchase the new product or subscribe to the new system). The people who are influenced by mass media are called innovators and the second group are known as imitators in market diffusion model literature. Based on Bass assumptions, innovators exist in the whole diffusion process while imitators join the market after several sale periods. Figure 2-4 (bottom) shows the trend of a nominal product sales during sales periods. Non-cumulative adopters will reach to a maximum point which corresponds to inflection point of cumulative S-shaped curve.

The basic Bass model equation, which is derived from a hazard function (the probability that an adoption will occur at time t, given it has not yet occurred), is shown in Equation 2-1.

$$\boldsymbol{n(t) = \frac{dN(t)}{d(t)} = p[m - N(t)] + \frac{q}{m}N(t)[m - N(t)]} \qquad 2\text{-}1$$

where *N(t)* is the cumulative number of adopters at time *t*, *m* is the potential market size, *p* and *q* are coefficients of innovation and imitation, respectively. Equation 2-1 is a first-order differential equation, which can be resolved into Equation 2-2 using integration:

$$\boldsymbol{N(t) = m(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}})} \qquad 2\text{-}2$$

However as mentioned before, the Bass diffusion model is not able to consider external influencer variables, such as cost reduction effects. For this reason, a generalized Bass diffusion model was developed to overcome the basic model limitations. Generalized Bass model includes a mapping function of *x(t)*:

$$\boldsymbol{n(t) = \frac{dN(t)}{d(t)} . x(t)} \qquad 2\text{-}3$$

Which $x(t)=x(t;\ \theta),\ \theta \in R^k$ is assumed to be nonnegative and can be integrated (Guidolin and Cinzia, 2010), the result is shown in equation 2-4:

$$\boldsymbol{N(t) = m\left(\frac{1 - e^{-(p+q)\int_0^t x(\tau)d\tau}}{1 + \frac{q}{p}e^{-(p+q)\int_0^t x(\tau)d\tau}}\right), t, p, q > 0} \qquad 2\text{-}4$$

When there are no external variables, $x(t)=1$ and generalized model will reduce to the base model. To estimate a generalized Bass model, basic Bass model coefficients (*p*, *q* and *m*) should be estimated with external variables coefficients. The mapping function is normally shown as in Equation 2-5:

$$\boldsymbol{x(T) = 1 + \beta_1 X_1 + \beta_2 X_2} \quad \text{2-5}$$

In which X_i represent an external variable, such as price and advertisement rate, and β_i is the corresponding coefficient.

Diffusion models have been used in several automobile related technology studies. These models are generally categorized into two groups based on the modeling framework: one group used conventional diffusion models (i.e. Bass) (Massiani and Gohs, 2015; Cordill, 2012, Park et al., 2015) and the other used Stated Preference (SP) surveys and developed discrete choice models (Jensen et al., 2014; McCoy and Lyons, 2014; Brown, 2013).

Massiani and Gohs (2015) developed a Bass model based on German data for new automotive technologies. New registrations for Liquefied Petroleum Gas (LPG), Compressed Natural Gas (CNG) vehicles, Electric Vehicles (EV) and Hybrid Electric Vehicles (HEV) were used in this study as sales data for new automotive technologies. The study estimated the parameters with varying levels of market size, and found that the innovation coefficient (*p*) was highly affected by changes in market size while the imitation coefficient (*q*) was not influenced by market size. The authors found an inverse relationship between the assumed market size (*M*) and the innovation coefficient in this study.

Cordill (2012) proposed a diffusion model to study the future of HEV market. Innovation (p) and imitation coefficient (q) were estimated for three EV technologies of Prius, Hybrid Civic and Ford Escape using 2000-2010 sales data besides a survey developed to define important consumer preference factors. Respondents who liked to purchase an EV in the near future were classified as the innovation group and other participants were classified as imitation group. It was concluded that selected vehicle price, fuel savings, and cost of fuel were the three most important factors for both groups Innovators were affected by emissions and reliable operation; while imitator's preference was impacted by the availability of future tax benefits and vehicle crash reports.

Park et al. (2011) developed a market penetration forecasting model for Hydrogen Fuel Cell Vehicles (HFCV) considering infrastructure and cost reduction effects for Korea. Based on their results, HFCV market will be fully-saturated in 2038 in Korea and in 2050 in the US.

Another group of market penetration studies used SP surveys and a choice modeling approach to estimate diffusion models for new automobile related technologies. McCoy and Lyons (2014) used agent-based modeling simulation for four neighborhoods with different socioeconomic and demographic properties to explore the EVs market diffusion in Ireland (McCoy and Lyons, 2014). As expected, the neighborhoods with households with higher income level showed to adopt EVs much higher than neighborhood with low income households. Brown (2013) simulated the EV diffusion model in Boston using a discrete choice model. Results showed that EVs would share 1-22% of the entire vehicle market of Boston in 2030. Author also found financial incentives are the most important factor which cane affect market share

2.3.4. Summary

Market penetration analysis is the first and foremost step for impact analysis of AV technologies. There have been various attempts related to understanding the market penetration of AV technologies, but due to the many uncertain factors (regulations, technology advancement, cost, etc.), there is still a lack of uniform understanding on when the technology will be available to the users at what level, and how much adoption will occur.

2.4. Activity Based Modeling of Travel Demand

"A model is a simplified representation of a real world event, with special attention on desired elements of that occurrence, which are important for the study" (Ortuzar and Willumsen, 2011). Travel demand models are analysis tools providing a systematic framework to show how travel demand changes as a result of network inputs. Four categories have been defined for travel demand: Sketch-Planning Models, Strategic Planning Models, Trip-Based models, and Activity Based Models (Castiglione et al., 2015). For the purpose of this study, ABM is the most suitable since these types of models focus on activities and daily travel patterns rather than individual trips. In an activity-based model, after activities have been generated for each sampled person of sampled household, destinations are assigned to the activity and based on the household, person and activity characteristics, trip mode and route will be identified.

2.4.1. Popular ABM Families

Most of the existing ABMs are using a similar structure, starting with a synthetized population. Then long-term, mid-term and short-term decisions are modeled for the population. The scenario analysis section of this study will use an ABM which will be discussed in more details later. However, for comparison, some other important and popular ABMs are introduced in this section. The following section will discuss the general procedures, differences, and similarities between the most common ABMs.

Two most famous ABMs families which are being used widely across states are CT-RAMP (Coordinated Travel Regional Activity-Based Modeling Platform) and DaySim (Daily Simulator). This study will benefit from a CT-RAMP model. Except these two, several other models exist, but are mostly used in academics such as CEMDAP, Florida Activity Mobility Simulator (FAMOS), Travel/Activity Scheduler for Household Agents (TASHA), and Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS). All these models simulate travel demand in the form of internally-consistent travel diaries.

2.4.1.1. CT-RAMP

CT-RAMP framework is illustrated in Figure 2-5. As mentioned before, the modeling framework starts with population synthesis. Based on the population, each worker or student is assigned a usual work/school location. Within the mobility section free parking eligibility, transponder ownership, and car ownership are modeled based on person and household characteristics and usual locations. Based on the modeled data, daily activity patterns will be developed.

The entire population is then assigned three types of activates: Home, Mandatory, and Non-mandatory. The frequency and Time of Day (TOD) of mandatory tour participants' trips are modeled for individual mandatory tours. Based on residual time budgets for each person, if an individual is assigned with a joint non-mandatory tour, a tour will be modeled. Allocated and discretionary tours are also modeled based on traveled time budgets. The tour mode, stop location, stop frequency, and departure time are only modeled after the Daily Activity Pattern (DAP) is modeled for each person. The final step of the CT-RAMP framework to model the trip mode, auto-parking, and assignment for each person for each tour.

2.4.1.2. DaySim

As in CT-RAMP, DaySim begins with population synthesis and network data. However, the two models differ in where locations are defined. While CT-RAMP designates location choices Traffic Analysis Zones (TAZs), DaySim instead uses land parcels. Long term choices, including work/school locations, are defined and then parking payment situations will be modeled for each person. Auto-availability is modeled based on the number of transit pass holders. The DAP in DaySim is developed based on household/person information. Except location definition, there are some other variations between two models are mostly regarding the model variables, number of TODs for network assignment, etc. Figure 2-6 illustrates a flow diagram of the relationships of the component models in DaySim (Bowman and Bradely, 2012). Also two models also differ in their activity definitions. As previously mentioned CT-RAMP has three activities (Home, Mandatory, and Non-mandatory), while DaySim only has two (work and non-work) (Srinivasan, 2012).

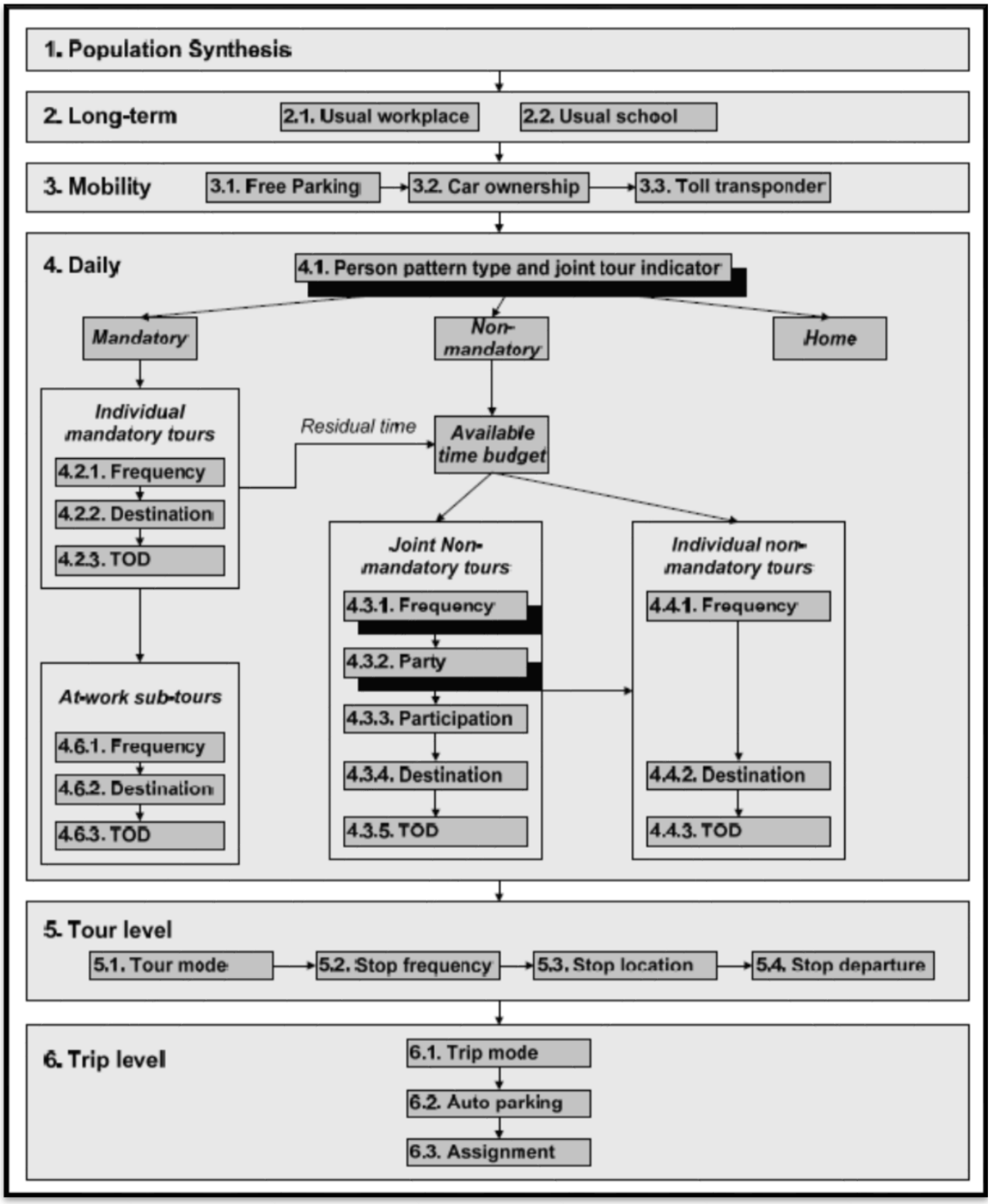


Figure 2-5. CT-RAMP Design and Linkage between Sub-Models (SERPM, 2015)

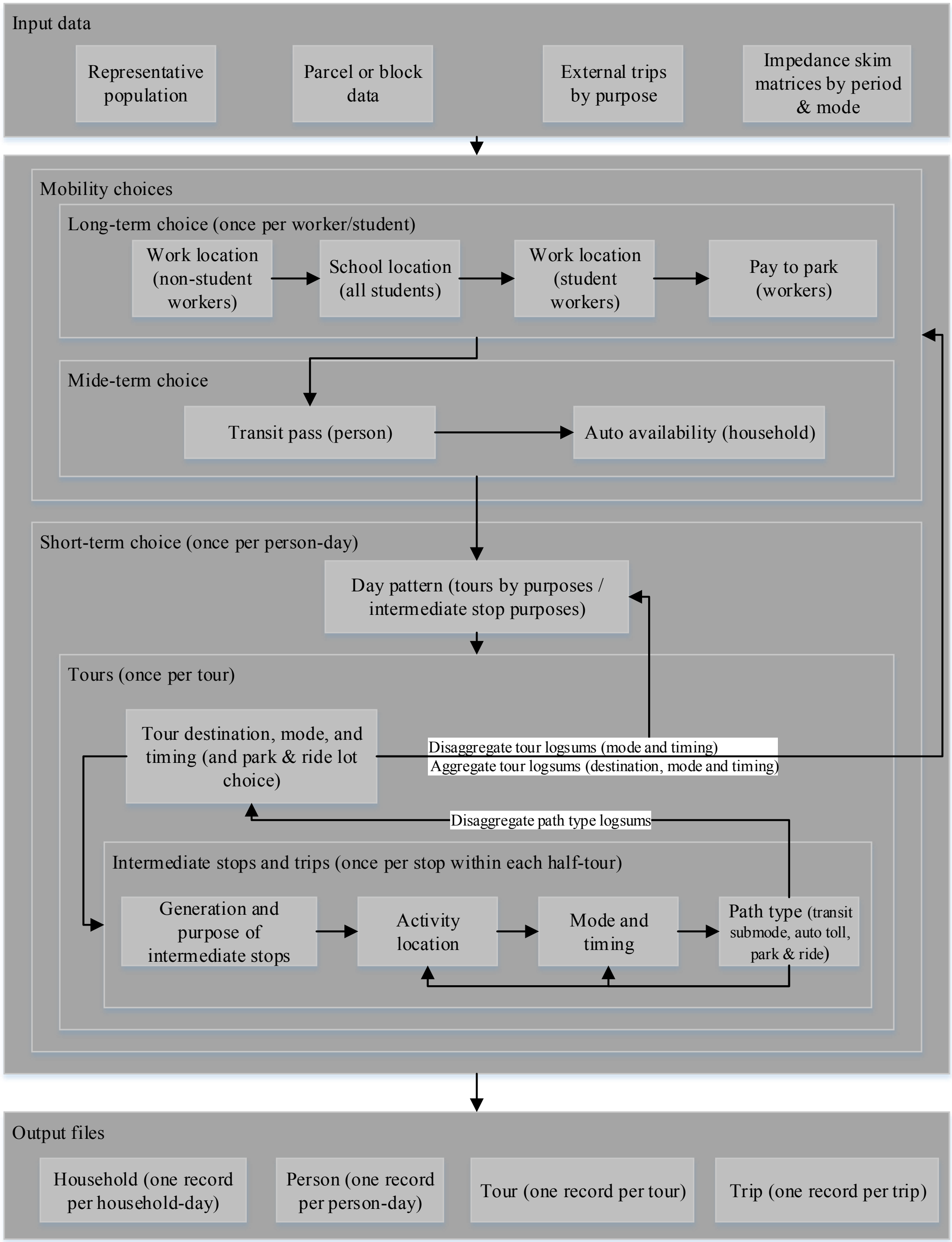


Figure 2-6. DaySim Framework (Bowman and Bradely, 2012)

The literature revealed the existence of main ABMs for transportation demand modeling, but none currently have the ability to consider autonomous vehicle adoption. The objective of this study is to develop a general framework for travel demand modeling for a time when AVs are readily accessible, in all aspects, and are being adopted.

2.4.2. Models Developed in This Study

Several studies have focused on different aspects of AVs including AV market penetration, implications and technology. However a few studies have focused on the AV willingness to pay, residential location choice models, or even characteristics of people which tend to use AVs and the form of using this technology. This lack of research is basically because of data limitations. Majority of discussion on AV adoption process are based on experts speculations and some of them are based on conducted surveys. Regarding the implications of AVs on residential relocation, only hypothetical forecasts have been provided so far. Since the modeling part of the dissertation is focused on these behaviors, in this section, previous studies on AV willingness to pay, willingness to relocate, and also willingness to adopt AVs will be explored briefly.

2.4.2.1. Autonomous Vehicle Willingness to Pay

The emergence of car sharing as a new transportation mode has changed households' car ownership and system-wide transportation landscape to some extent (Elliot et al., 2010), i.e. today 20% of all Uber rides in San Francisco is shared (Freemark, 2015). Researches showed the pattern of using AVs would be different for various households, some may decide to own AVs and some may only use them as a sharing system or mass transit (Malokins et al., 2015). So it is anticipated that autonomous vehicles change the car ownership pattern. Considering various scenarios are hypothesized for AVs period, this is very important to understand people's preference toward AVs.

As discussion in literature review section 2.2.2.1 (car ownership) several studies concluded that vehicle ownership pattern will change due to emerge of AVs. However, a very important factor that should be studied, is willingness to pay (WTP) for this technology. A few studies have been focused on AV willingness to pay, showing in average people are willing to pay $1000-$6000 for AVs. Very high values such as more than $30,000 was also observed in some studies, i.e. Kyriakidis et al. (2015), however that was only limited to less than 5% of participants. Same study predicted about 22% of people will not pay anything to own/use an AV. In a recent survey, Bansal and Kockelman attempted to forecast the long term adoption of autonomous vehicles (and connected vehicles) by Americans (Bansal and Kockelman, 2016). According to this survey, the average WTP for autonomous vehicle is approximately $6,000, higher than the WTP for Level 3 automation, only $2,438. Casley et al. (2013) conducted a survey to examine public acceptance of AVs (Casley et al., 2013). On Average participants were willing to pay $1,000 for AVs, however they believed they need to pay five times more. Also based on JD Power and Associates (2012), 37% of people are interested in paying for an autonomous vehicle. However this percent reduced to 20% after people found there would be an increase up to $3,000 in price for the automated features (JD Power and Associates, 2012).

In summary, AVs are going to change household's AV ownership. However the pattern of this change and characteristics of the group who are willing to pay for AVs is yet to be studies. Vehicle ownership is an important aspect in a transportation model which will affect other steps. A precise study on car ownership is required to understand the development of travel patterns in any area (Tsang et al., 2011). Vehicle ownership is directly related to willingness to pay.. Several variables showed to be significant in household ownership, including but not limited to household income, population density, fuel price, accessibility, socio-economic (Suits, 1958; Zhao and Kockelman, 2002; Li et al., 2010; Tsang et al., 2011; Timmermans et al., 2014; SERPM, 2015). One of the contributions of this study is to bold the significant variables in AV ownership and willingness to pay based on the conducted survey at Florida.

2.4.2.2. Residential Relocation

Another aspect of AV adoption that will be discussed in this study is the effect of this driverless cars on residential location choice. Several studies have discussed the potential long-term impacts of AVs, including location choices, land use and parking demand. The main expectation is that while AVs contribute to relaxed or more productive driving, less congested network and shorter travel times, it reduces the role of travel time and distance in trip making decisions, and the overall travel costs. As a result, people have more flexible residential and work location choice sets, better school options, and also further away destinations would be more attractive and accessible (Anderson et al., 2014; Pendyala and Bhat, 2014). Consequently, the urban/regional development patterns are likely to change. As mentioned before, a group of people may decide to live in further location, since they can arrive to their destination without any increase in travel time (Anderson et al., 2014; Kim et al., 2015).

Residential location choice decisions is actually a trade-off process (Chen et al., 2008). Those living in urbanized areas may have better access to transportation systems and other benefits of living in urban area, but will generally pay more for housing. On the other hand, better living environment with cheaper prices are provided in suburban area while the travel time and cost to job destinations which are normally in urbanized areas are too high. This should be recognized that AVs are going to bring a new choice for commuters, which will affect the residential location choice. Studies showed there is a significant impact from transportation on population distribution (Zondag and Pieters, 2005). Based on law of Hupkes (or Zahavi), "the average time that people spend per day travelling is 1-1.5 hour and the introduction of a new transportation mode with improved travel speed results in change in residential location distribution". The results of studies focused on transportation mode change in residential location, shows older and larger households, two-workers and higher income households are more mobile (Zondag and Pieters, 2005; Hunt, 2001).

2.4.2.3. Preferred Method of Adopting AV

Studying the characteristics of AV adopters is also an important matter in understanding AV market penetration. The market penetration models can predict the number of AVs which will be sold in each step of adoption, but they will not provide any other information on the features of people who adopt/do not adopt to this technology. This study focuses on the preferred way of using AVs, are people going to own them, or use them as a shared mass transit system, or even will not use them at all, and what are the characteristics of individuals and households that are selecting each option.

Menon (2015) found individuals with higher level of education and higher income values are more likely to adopt AVs. Also regarding genders, females are less likely to use AVs. This finding is similar to Danise (2015) which found women do not like AVs as much as men. A survey by Howard and Dai (2014) examined public perception of self-driving cars in Berkeley, California. Modeling results showed women are more concerned about control while men are mostly concerned about liability. Regarding effect of age Danise (2015) survey results showed there is a significant different between younger drivers (less than 30 years old) interest in having AV and older ones.

Regarding the method of using AVs, The FSU research team conducted a survey among Floridians. The survey results found that most respondents are still locked into a private ownership model for AVs, with far lower levels of support for the shared ownership and AVs for hire models (Duncan et al., 2015).

Author could only found one research focused on the implication of travel behavior pattern and perception regarding AV on adoption. According to Menon (2015), individuals who commute to work alone by private cars are likely to adopt AVs. Also the likeliness of adopting AV reduces with increase in household size. This study found familiarity with technology has a positive impact on the adoption. It was also found that individuals with positive perceptions of safety and fewer crash, less stressful driving, more productive use of time, less congestion and lower car insurance rate are more likely to adopt AVs while individuals concerned about losing control of vehicle, loss in human driving skill, system failure and liability issues are less probable for adoption.

2.5. Literature Review Summary

By looking to the existing body of literature, it can be seen that yet studies are not aggregated, by that there is not any study in which survey results are being used in simulation or modeling to show how AVs are going to impact transportation network or travelers' behavior. There are some valuable surveys and scenario-based studies; however AV technologies deserve to receive some comprehensive studies using consumers' point of view in the real network and analyze it based on the logical market penetration models. This study will use survey results for develop sub-models and use the results as the input for SERPM 7.0 model, which is the official model used in South Florida transportation and traffic projects. Other required parameters are derived from a reasonable market penetration model in order to see how AVs will change the network characteristics.

CHAPTER 3. METHODOLOGY

This study aims to develop a framework to incorporate AV technologies considerations into the travel demand modeling process. A survey was designed to collect information regarding user adoption and public acceptance for AV technologies, which is used to develop assumptions and scenarios for impact studies. The framework intends to serve as a guidance that outlines the model components and the interactions between the components that may be impacted by the adoption of AV technologies, and also provides the foundation for the scenario analysis. This chapter provides information on how the collected data from the survey are processed and models are developed.

3.1. Framework Development

To develop the modeling framework, it is required to understand which model components may be affected by the adoption of AV technologies. System-wide parameters, such as auto operating cost, and value of time will be investigated in terms of the probable extent of modifications needed based on the level of adoptions. Various model components, such as auto-ownership model, fleet choice model, tour generation model will also be examined to identify whether the adoption of AV technologies may bring meaningful impacts through these choice decisions.

The idea of this study is to accommodate AV adoption into the ABM framework. Several aspects of existing frameworks may change after AV is ready to enter the networks. By including the fleet choice of individuals, new models can be superimposed on to the ABM which is able to consider AV adoption. Based on the survey information, individuals can be divided into adopters and non-adopters. The adopter group can be divided into two major categories, people who use AVs as a commuting tool and people who will use AVs for other purposes. Another change in the framework can be seen in residential location selection, which can be developed at the household level. These decisions at the long- and mid-term levels will also lead to different choice behaviors and travel patterns in the short-term. The described framework can be accommodated into a general ABM framework, to form the desired AV-adoption ABM framework. Figure 3-1 shows the proposed sub-flow to divide individuals based on their adoption pattern and Figure 3-2 illustrates the potential framework.

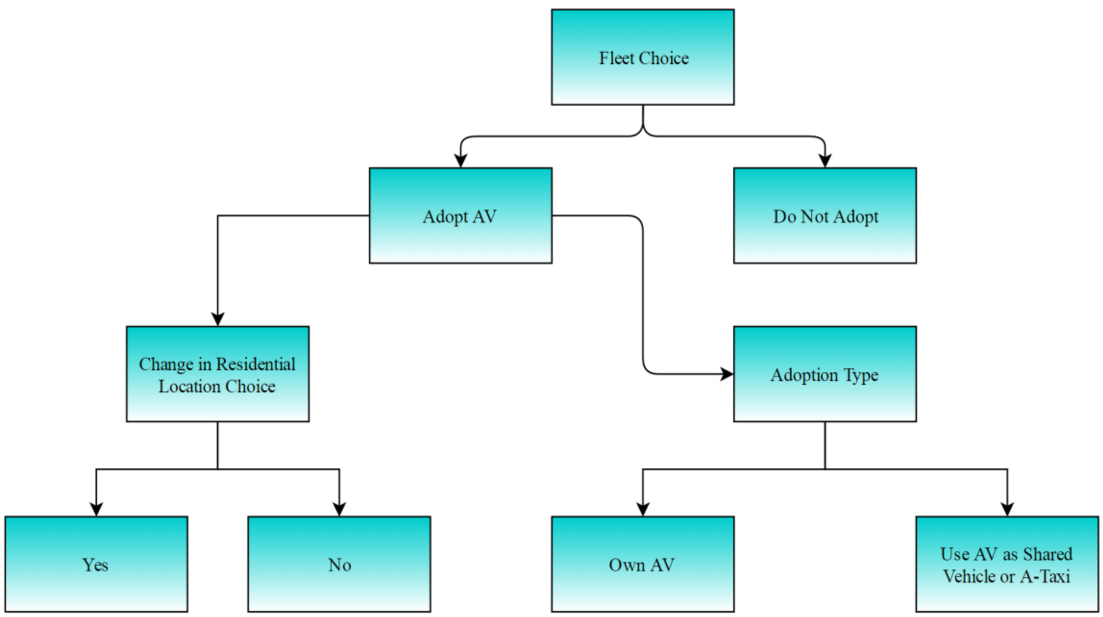


Figure 3-1. Sub-Flow to Divide Individuals Based on Their AV Adoption Pattern

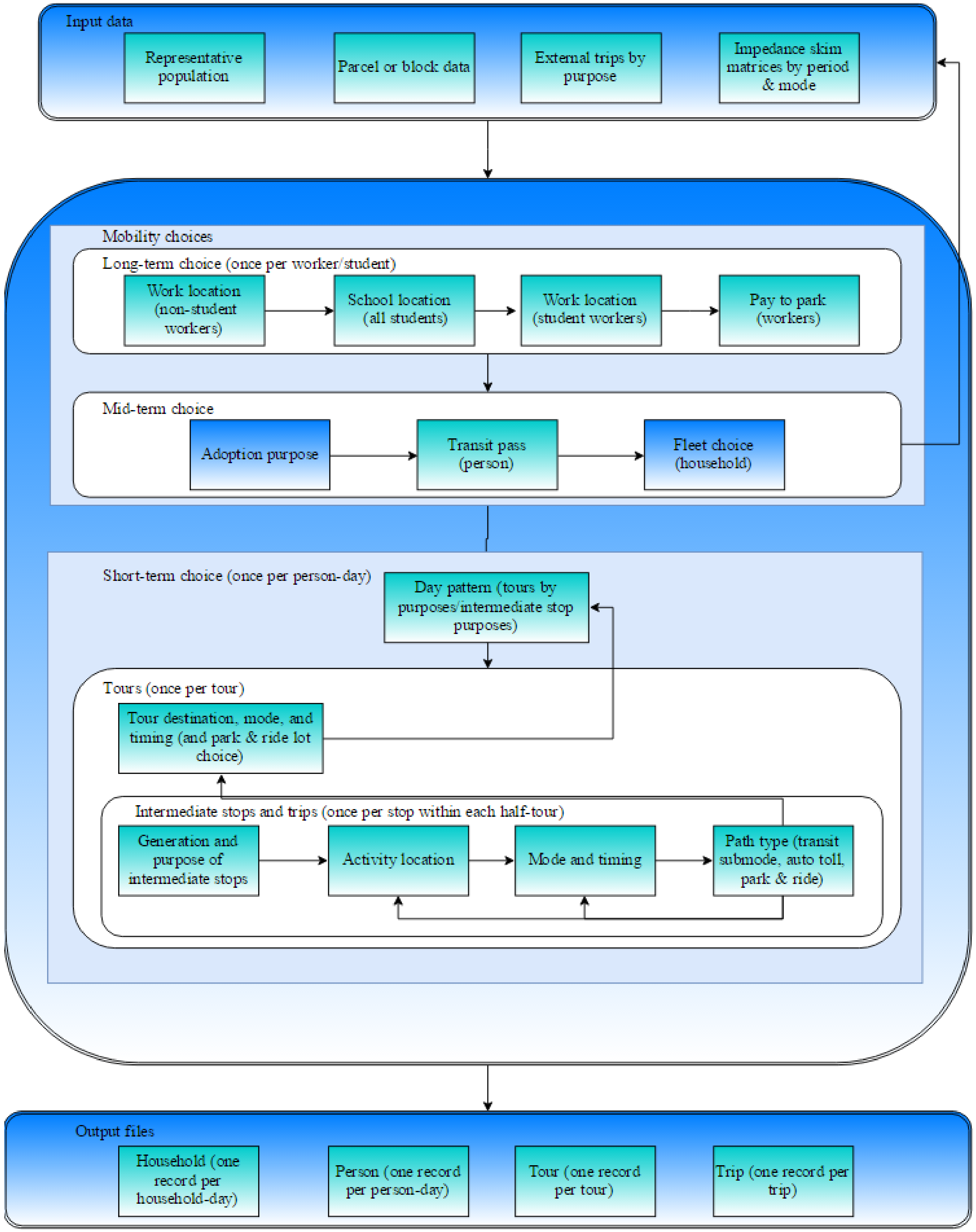


Figure 3-2. Proposed Framework

3.2. Data Collection: Survey Design and Implementation

A survey was used to collect data for this study. This section will discuss the survey design, how data was collected and what the processing procedure was.

3.2.1. Survey Design and Data Collection

The main motivation of this survey is to collect the data required to analyze user adoption due to the emergence of autonomous vehicles and the market penetration of AVs. This analysis will provide information regarding public perception of AVs and preferences for emerging technologies, while also assessing consumers' willingness to include advanced safety and automation features when purchasing a vehicle; the analysis will also help to anticipate potential impacts of AVs on future travel patterns and traffic conditions in Florida.

Based on the literature there have been no comprehensive surveys conducted regarding effects of autonomous vehicle on travel behavior, but there were some which explored familiarity with these new technologies. The motivation of this data collection effort is due to the fact that there have been no studies of the changes to residential location choice, vehicle ownership, and attitude towards specific trip purposes after the implementation of AV technologies.

Beyond collecting data, all transportation demand models are currently on conventional vehicles. The literature indicated that AV adoption could potentially have a large impact and change many components of existing frameworks. This possibility should be tested and calibrated vigorously prior to the adoption process and will be discussed in the next section.

The proposed survey was comprised of three components. Part A collected general information, Part B collected information regarding consumer perception of AVs, and Part C dealt with anticipated impacts of AVs.

In Part A, the Socio-Economic and Demographic (SED) information of respondents were collected. This data included age, gender, ethnicity, education level, household income category, occupation, home zip code, household size, and vehicle ownership information. Also the major trip components of respondent were collected in this section. This includes destination, commuting frequency, commuting mode, “grocery trip” mode, “other trip” mode, average distance (miles-minutes) for commuting trips, number of “grocery trips”, number of “other trips”, the most recent long distance trip information, and parking preference information.

To determine the effect of previous traffic accidents on behavior and choices, a portion of the collected data was concerning participants’ crash history and circumstances. The survey also requested that participants disclose which, if any, safety and automation features are available in their current vehicle.

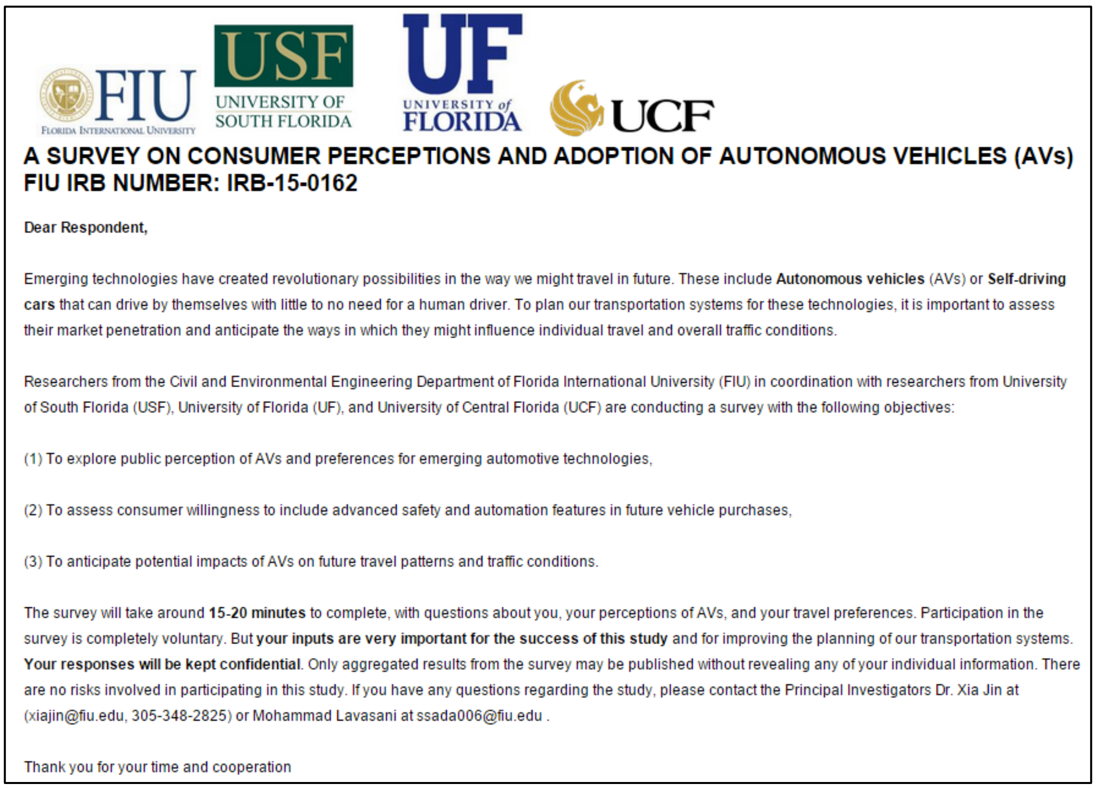
Part B of survey started by collecting data on participants’ familiarity with AVs prior to the survey, propensity to use AVs when available, perception of which transportation issues will be most affected by AVs, and concerns surrounding AVs. This section also asked how likely/unlikely a respondent is to have an AV, to retrofit their current vehicle, or to purchase a fully-autonomous vehicle. Participants were also asked about their willingness to pay for the technology in new vehicles as well as the cost of retrofitting currently owned vehicles. As ridesharing was cited in the literature, respondents' likeliness to pay more per hour (or mile), to rent an AV was also probed. These responses are used later to develop market penetration scenarios for AVs.

Part C of this survey focused on anticipated impacts of AVs. Researchers needed to know how people will budget their newly acquired free time when given access to AVs. The survey asked respondents to indicate whether or not they would change their residence location and the associated distance (in minutes) they are willing to accept.

Vehicle size and ridesharing was also questioned in the survey as both will change many geometric design concepts if people purchase smaller or larger vehicles and begin to share rides more frequently. This part also asked respondents about their opinion regarding vehicle sharing. Specifically, the frequency of use and acceptance of route deviations for other passengers was gauged. These questions asked for grocery, commuting, and long distance trips. The final questions in this part focused on respondents' concern about AV safety, privacy, higher travel time, unreliability of service, and travel cost.

The survey was conducted in coordination with researchers from University of South Florida (USF), University of Florida (UF), and University of Central Florida (UCF) to target all students, faculty, and staff of these universities. It was a web-based survey, and the link to access survey was sent to the target sample via email, starting from last week of October 2015. It was anticipated that the survey would take 15-20 minutes to complete and data would be collected over four weeks; each week a reminder email was sent to the potential participants. Responses were collected automatically in spreadsheets. A limitation of this study is that the survey was distributed to students and faculties of four universities, and it can only consider behavioral responses of mostly educated people, not the whole public.

To conduct a survey regarding human subjects, Institutional Review Board (IRB) approval was obtained prior to conducting research on the human subjects (FIU Research, 2015). The home page of the survey website can be seen in Figure 3-3.


FIU
FLORIDA INTERNATIONAL UNIVERSITY
USF
UNIVERSITY OF SOUTH FLORIDA
UF
UNIVERSITY of FLORIDA
UCF

A SURVEY ON CONSUMER PERCEPTIONS AND ADOPTION OF AUTONOMOUS VEHICLES (AVs)
FIU IRB NUMBER: IRB-15-0162

Dear Respondent,

Emerging technologies have created revolutionary possibilities in the way we might travel in future. These include **Autonomous vehicles** (AVs) or **Self-driving cars** that can drive by themselves with little to no need for a human driver. To plan our transportation systems for these technologies, it is important to assess their market penetration and anticipate the ways in which they might influence individual travel and overall traffic conditions.

Researchers from the Civil and Environmental Engineering Department of Florida International University (FIU) in coordination with researchers from University of South Florida (USF), University of Florida (UF), and University of Central Florida (UCF) are conducting a survey with the following objectives:

(1) To explore public perception of AVs and preferences for emerging automotive technologies,

(2) To assess consumer willingness to include advanced safety and automation features in future vehicle purchases,

(3) To anticipate potential impacts of AVs on future travel patterns and traffic conditions.

The survey will take around **15-20 minutes** to complete, with questions about you, your perceptions of AVs, and your travel preferences. Participation in the survey is completely voluntary. But **your inputs are very important for the success of this study** and for improving the planning of our transportation systems. **Your responses will be kept confidential**. Only aggregated results from the survey may be published without revealing any of your individual information. There are no risks involved in participating in this study. If you have any questions regarding the study, please contact the Principal Investigators Dr. Xia Jin at (xiajin@fiu.edu, 305-348-2825) or Mohammad Lavasani at ssada006@fiu.edu .

Thank you for your time and cooperation

Figure 3-3. Autonomous Vehicle Implication Survey – Page 1

The web-based survey used an e-mail introduction and also first page of survey to recruit the participants. Also in each section, in case an explanation is required, it is provided in the survey. Several data distribution channels were tried in order to distribute the survey to the potential participants.

Email: Survey invitation e-mails were sent to several academic departments at FIU. The e-mails began on October 26, 2015; reminders were sent on November 2, and November 20. For other colleges and departments, any supportive response was not received, except from department of mathematics. The survey link with description was sent to department of mathematics student, faculty and staff, by the dean on November 17, 2015. Administrators at the School of Architecture and The Arts; Art, Science and Education; Business; Hospitality and Tourism Management; Journalism and Mass Communication and Law were also visited by the author and were asked to send the survey to the faculty and students, but no response resulted from this. However, all the e-mails existing in FIU Phonebook portal were extracted and targeted by author from December 10, 2015 to January 26, 2016.

Univmail Portal: The survey was submitted to Univmail portal on November 10, 2015, so that employees would receive an e-mail with a link to the survey.

Undergraduate Courses: A few teacher assistants allowed the author to present the project and distribute the survey in undergraduate classes, especially in Departments of Civil Engineering and Biomedical Engineering.

Social Media: The survey was advertised on two student organization pages on Facebook, and also via e-mail to members of Institute of Transportation Engineers at FIU.

3.2.2 Data Processing and Analysis

As mentioned in the previous section, the data was collected automatically and stored in the spreadsheets. It was expected that some errors would be encountered, as is the case in all types of data collection. Based on Zanutto (2001) respondents may have different levels of computer expertise which may be a source of non-response or errors. The participant was faced with concerns regarding the survey and data security, as well as the privacy (Gunn, 2002). Also, there was no way to select a random sample from internet respondents. It can be assumed that the population of survey is all faculty, staff, and students at the targeted universities; the respondents are the random sample.

To clean the data, duplicate data were identified and removed. Duplicate records were assumed to be indicated by two surveys with the same information and response in separate submissions. Straight-lining and Christmas-tree responded data were also removed. Straight-lining refers to when a respondent selects the same option for all the questions, and when respondent answered the questions in a Christmas-tree pattern is known as Christmas-tree behavior. This pattern happens when the respondent selects the choices in a diagonal pattern without reading the questions. Since participating in the survey is voluntary, and it has no benefit to the subject, it was anticipated that the number of straight-lining and Christmas-tree responses would be very small. After analysis, neither of these situations were observed.

3.3. Discrete Choice Modeling Methodology

Data analysis was done using the discrete choice modeling method. The methods used in ABM of travel demand include discrete choice models, as well as other methods which can accommodate non-discrete variables in activity modeling (Bhat et al. 1999).

3.3.1. Multinomial Logit Model (MNL)

MNL model structure describes each choice alternative through a utility function. The simplest form of the utility equation is given as Equation 3-2.

$$\boldsymbol{U_1} = \boldsymbol{\beta_1 X_1} + \boldsymbol{\beta_2 X_2} + \ldots\ldots\ldots\ldots\ldots\ldots + \boldsymbol{\beta_n X_n} + \varepsilon \qquad \text{3-2}$$

In this equation, *X* represents a variable including alternative specific constants, attributes of the alternatives, attributes of the individuals, and any other descriptive variables. Each β represents the coefficient corresponding to the attribute. The estimated coefficient value implies relative importance of that attribute (*X*) in the entire model. ε, the error component accounts for any measurement error, parameter correlation, unobserved individual preferences, and other unobserved characteristics.

The probability of each alternative is estimated using Equation 3-3:

$$P_i = \frac{e^{\beta_i X_i}}{\sum e^{\beta_j X_j}} \qquad \text{3-3}$$

Where, P_i is the probability that any particular alternative *i* will be chosen and U_i is the utility of that alternative.

3.3.2. Mixed Logit Model

Mixed Logit (ML) is considered as a powerful discrete choice modeling technique as it can incorporate user heterogeneity (travelers do not need to be similar to one another) in the models. According to the mixed logit model formulation, the utility of any individual i, who choses an alternative j, can be written as Equation 3-4.

$$\boldsymbol{U_{i,j}} = \boldsymbol{\beta_i}'\boldsymbol{X_{i,j}} + \boldsymbol{\varepsilon_{i,j}} \tag{3-4}$$

Where,

i	=	Set of individuals (i = 1, 2, 3.........n)
j	=	Set of alternatives (j = 1, 2, 3...........J)
β_i	=	Aversion parameter vector of traveler i
$X_{(i,j)}$	=	Vector of independent variables which include alternative specific constants, characteristics of the individuals, characteristics of the alternative, and other descriptive variables affecting the choice
$\varepsilon_{i,j}$	=	Error components to account any measurement error, parameter correlation, unobserved individual preferences, and other unobserved characteristics of the choice making

The overall utility can be described as a summation of two parts: (1) the systematic part of the utility function and (2) the stochastic $\beta'X_{(i,j)}$ or random part of the utility function $\varepsilon_{(i,j)}$. The random term, $\varepsilon_{(i,j)}$ is assumed to be identically and independently distributed across travelers, alternatives, and choice sets. The random term of mixed logit model captures the variation between the true utility, $U_{(i,j)}$ and the deterministic utility $V_{(i,j)}$; this is calculated by the linear function $V_{(i,j)} = \beta_i' X_{(i,j)}$.

To accommodate taste variations, mixed logit models assume coefficients in the model are realization of random variables. The random variable is unknown by nature, but when a value is assigned to the random variable, that specific value is called realization of random variables. For example, in the above model formulations β_i are the realization of random variables β. Because of the realization assumption, β varies across decision makers, but is fixed in the multinomial logit model.

Mixed logit model coefficients are usually normally distributed. Some studies also consider log-normal distribution and triangular distribution. According to the mixed logit model formulation, the probability of a traveler *i* choosing an alternative *j* can be written as Equation 3-5:

$$\boldsymbol{P_{i,j}} = \int \frac{e^{\beta' \, X_{i,j}}}{\sum_{\forall q \in Q^{rs}} e^{\beta' \, X_{i,q}}} \,.\, \mathrm{f}\,(\boldsymbol{\beta} \backslash \theta)\; \mathrm{d}\boldsymbol{\beta} \qquad \text{3-5}$$

Where $f(\beta \backslash \theta)$ represents the density function of the coefficient vector β where $\theta = [b^T,W^T;\ b^R,W^R;\ b^C,W^C]$. Here, b and W are the mean and standard deviation of respective coefficients for variables which are supposed to consider having a distribution. However, the MNL part in the mixed logit can be expressed as Equation 3-6:

$$\boldsymbol{MNL_{i,j}}\ (\boldsymbol{\beta}\ ) = \frac{e^{\beta' \, X_{i,j}}}{\sum_{\forall q \in Q^{rs}} e^{\beta' \, X_{i,q}}} \qquad \text{3-6}$$

Therefore, the probability can be re-written as Equation 3-7:

$$\boldsymbol{P_{i,j}} = \int \boldsymbol{MNL_{i,j}}\ (\boldsymbol{\beta}\ )\ .\ \mathrm{f}\,(\boldsymbol{\beta} \backslash \theta)\ \mathrm{d}\,\boldsymbol{\beta} \qquad \text{3-7}$$

Since the integration cancels out the parameter β, the probability is only a function of θ. However, the integration process is not able to estimate a probability value because of the difficulties associated with the integration of the density function. Simulation is considered as the most popular solution for this issue and is used for estimating the mixed logit model coefficients.

3.3.3. Ordered Logit Model

In the ordered response structure, the dependent variable is an ordinal variable *Y*, which can have any of the integer values 1,..., *N*. The model structure assumes that there is a continuous unmeasured (latent) variable *Y**, whose values determine what the values of the observed ordinal variable *Y* will be. The continuous latent variable *Y** has various threshold points K_i. The value of the dependent observed variable *Y* depends on whether or not the continuous latent variable *Y** passes a certain threshold. Accordingly,

$Y_i=1$	if $Y^*<k_1$
$Y_i=2$	if $k_1< Y^*<k_2$
$Y_i=N$	if $Y^*> k_{(n-1)}$

where $k_1, \ldots, k_{(n-1)}$ are threshold values.

The value of latent variable Y^* is usually considered a linear combination of independent explanatory variables, as Equation 3-8:

$$\boldsymbol{Y}^* = \sum \boldsymbol{\beta}_i \boldsymbol{x}_i + \boldsymbol{\varepsilon}_i \tag{3-8}$$

where,

β_i	=	Unknown coefficients to be estimated by the model
x_i	=	Independent variables
ε_i	=	Random error term

The random error term ϵ_i can take different statistical distributions. The two popular distributions are the normal (ordered probit model) or the logistic distribution (ordered logit model). The two distributions usually provide similar results in terms of signs and significance of parameters, with logit coefficients being larger due to the higher variance of logistic distribution. Accordingly, the probabilities for each of the ordinal categories will be calculated as follows:

$$P(y_j) = \begin{cases} F(\alpha_i+\beta'X_j) & y_j=1 \\ F(\alpha_i+\beta'X_j)-F(\alpha_{(i-1)}+\beta'X_j) & 1< y_j\leq k \\ 1-F(\alpha_k+\beta'X_j) & y_j=k+1 \end{cases}$$

where,

$P(y_j)$	=	The probability of y_j falling in each of the discrete categories
α_i	=	Estimated intercept for each of the k categories
F	=	Cumulative logit distribution function
β	=	Column vector of estimated coefficients
X_j	=	Column vector of independent variables

In this study, the willingness to pay (WTP) variable is an ordered variable with four levels: below \$1,000, \$1,000-\$5,000, \$5,000-\$10,000, and above \$10,000. The willingness to relocate is a likert scale variable covering five levels: Extremely unlikely, Unlikely, Don’t know/Can’t say, Likely, Extremely likely.

Two questions were used in modeling willingness to pay and exploring willingness to relocate, as below:

✓ *What is the maximum additional price (in addition to the base vehicle price) that you are willing to spend on AV technology for your newly purchased AV?*

- *Less than $1,000*
- *$1,000-$1,499*
- *$1,500-$1,999*
- *$2,000-$4,999*
- *$5,000-$9,999*
- *$10,000-$14,999*
- *$15,000 - $19,999*
- *$20,000 or more*

✓ *AVs might help in reducing driving stress and making the travel time more productive. If you could use AVs for your trips, would you live farther away from where you are currently living, for more affordable and better housing?*

- *Extremely unlikely*
- *Unlikely*
- *Don't know/ Can't say*
- *Likely*
- *Extremely likely*

3.3.4. Nested Logit Model

If some of the choices amongst all choice sets are assumed to share common components in random error term, estimating the models using nested logit structure seems more reasonable. In this model correlation is allowed inside the nests but is not allowed between the nests. Individuals will choose the option with highest utility, as discussed in MNL model section:

$$\boldsymbol{U_{i,j}} = \boldsymbol{\beta_i}'\boldsymbol{X_{i,j}} + \boldsymbol{\varepsilon_{i,j}} \qquad 3\text{-}9$$

However the way probabilities is calculated for each option is different:

$$\boldsymbol{P_j} = \boldsymbol{Prob}[\boldsymbol{nest\ containing\ j}] \times \boldsymbol{Prob}[\boldsymbol{j, given\ nest\ containting\ j}] \qquad 3\text{-}10$$

At which *Prob [nest containing j]* is the probability of selecting an option which is located in nest *j*. For example in this study, the upper level selection is to use or not to use AV, and if the response is yes, the method of using AV is an option (own/share and rent). So in this example *Prob [nest containing j]* means probability of person accepts to use AV. *Prob [j, given nest containing j]* is probability of selecting either options in the nest (own and share/rent), given the respondent answered yes to use AV.

$$\boldsymbol{Prob}[\boldsymbol{nest\ containing\ j}] = \frac{\boldsymbol{exp(V_{ni})}}{\sum_{\boldsymbol{j \epsilon B_k}} \boldsymbol{exp(V_{nj})}} \qquad 3\text{-}11$$

And

$$\boldsymbol{Prob}[\boldsymbol{j, given\ nest\ containting\ j}] = \frac{\boldsymbol{exp(Z_{nk.}\alpha + IV_{nk})}}{\sum_{\boldsymbol{l}} \ \boldsymbol{exp(Z_{nl.}\alpha + IV_{nl})}} \qquad 3\text{-}12$$

In which *IV* represents inclusive value and is calculated as:

$$\boldsymbol{IV} = \boldsymbol{ln} \sum_{\boldsymbol{j \epsilon B_k}} \boldsymbol{exp(V_{nj})} \qquad 3\text{-}13$$

Following question is used to develop the nested logit model for type of AV ownership:

✓ *What would be your most preferred way to use AVs that can fully drive by themselves without your active control?*

- *Own (purchase or lease) AVs and use them only for personal use or use by family members*
- *Own (purchase or lease) an AV and earn extra income on the side by making it available to other drivers when not needed*
- *Own (purchase or lease) an AV and earn extra income on the side by providing rides for fellow passengers when you use it*
- *Rent an AV as the need arises*
- *Use AVs in the form of transportation (taxi, or public transit) provided by a service provider*
- *Neither interested in investing in an AV nor using AVs as a transportation service*

3.4. Market Penetration Prediction Methodology

In this study, a Generalized Bass diffusion modeling approach was used to estimate the market penetration for AVs in the US, since the basic Bass model cannot consider influences of any external variables, i.e. the effect of product price during time. Historical sales information was required to estimate the generalized Bass model. Since no sales data would be available for brand new products, a similar technology/product would be selected and it is assumed that the new product in analogous to the user adoption pattern expected for AV. One such example estimated the market diffusion model of HFCVs for Korea, based on the data obtained for HFCVs in Japan with some adjustment to the local market (Park et al. 2011).

For the study at-hand, the estimation was based on the historical sales data for HEV in the US. The assumption was that the market penetration pattern of the AVs would be similar as for that of HEVs in the US market. The HEV technology is preferred over other automotive features, such as automatic transmission or rear camera, because the latter features only changed a portion of the driving task to a limited degree and there was reduced resistance when the product was first introduced. On the other hand, the first years of HEV deployment have seen conservative and skeptical user adoption, as would be expected for AV adoptions. However, it should also be noted that HEVs would not be as revolutionary as AVs in changing the way people travel. To overcome this limitation, this study also used data from internet and cellphone adoption to adjust the diffusion model, which is discussed in more detail later in this section.

Amongst several factors which may affect the adoption behavior, AV technology price, US market technology acceptance, rate and economic wealth were considered in this study. To estimate the generalized Bass model, the historical price ratio of a representative HEV to a representative conventional vehicle was analyzed. For the technology acceptance preference of US consumers, the diffusion model used information based on internet subscription and cellphone consumption in the US market. The reason for this was that internet and cellphone usage were considered to be very revolutionary forces in their industry and are assumed to be similar to the expectations for AVs. Based on this, it is anticipated that the penetration patterns of internet and cellphone usage can reveal some insights to analyze US costumers' behavior when facing new technologies. As for the economic wealth, the US Gross Domestic Product (GDP) per capita (current US dollars) was used in this study. Several specifications of the models were estimated and compared based on model performance. Then sensitivity analysis was conducted on two important factors which may affect the adoption projection: market size and the cost ratio of AV to conventional vehicles.

To establish the basics for model estimation, it was assumed that the AV market diffusion would be similar to the pattern for HEVs. The historical sales data of a representative HEV vehicles was collected and is shown in Table 3-1. The Toyota Prius was selected as the HEV technology representative vehicle because it is the best-selling HEV whole-world; the Prius was launched in 1997 in Japan and three years later in the US. Shortly thereafter, the HEV Prius became the best-selling HEV for many years. Also, the Prius's price did not change for the first three years of sales in the US, but did see a slight drop in the fourth year. Later the price raised in-step with general inflation.

The Toyota Corolla was selected as the representative conventional vehicle in order to facilitate the price ratio factor effect in the generalized Bass model. This selection was made because it is the same size, comes from the same manufacturer, and had similar sales. The sales and price data for Prius and Toyota Corolla were obtained from an online source (Cars, 2015).

To consider external effects and estimate β in Equation 3-14, the price ratio and new technology acceptance rate variables were incorporated into the function below:

$$\boldsymbol{x(T) = 1 + \beta_1 \frac{P(t) - P(t-1)}{P(t-1)} + \beta_2 \frac{T(t) - T(t-1)}{T(t-1)}} \qquad \text{3-14}$$

In which, P(t) is Prius to Toyota Corolla price ratio during a sales period, t.

$$\boldsymbol{P(t)} = \frac{\boldsymbol{Price\ of\ Prius}}{\boldsymbol{Price\ of\ Conventional\ Vehicle\ (corolla)}} \qquad 3\text{-}15$$

As can be derived from Table 3-1, the price ratio of the two vehicles was approximately 1.56 in 2001 and dropped to 1.34 in 2014. This indicated that the Prius was priced about 56% higher than a conventional vehicle when it was first introduced, and after 14 annual periods it decreased to about 34%. This trend is known as technology price dropdown.

T(t) is the technology acceptance propensity variable. For this study, it was estimated from the data related to internet subscribers and cellphone subscribers in the US. It was deemed reasonable to assume that the sales trend of AVs may not completely obey the HEV sales data as AV technologies also involve considerable progress in the field of information technology. To account for consumers' attitudes toward technology acceptance into the diffusion model, it was assumed that the AV market penetration should have some similarities with the historical trend of cellphone or internet users' in the US.

In addition, the economic wealth of the population may also influence user adoption of new technologies; therefore, it was incorporated into the diffusion model. Other data in Table 3-1, excluding vehicle-related information, were collected from World Bank online source (World Bank, 2015).

Given the information in Table 3-1, the generalized diffusion model for AV was estimated without restricting the market size. Then sensitivity analysis were conducted to examine how the market size would affect AV technologies market penetration and how price would affect the market size as well as the diffusion process.

Table 3-1. Data for Generalized Bass Model Estimation

Year	Prius Price (US$)	Toyota Corolla Price (US$)	Prius Annual Sales (1000)	Internet Subscribers (per 100 US people)	Cellphone Subscribers (per 100 US people)	Economic Wealth (GDP per capita-current US$)
2001	18,793	12,042	15.6	43.1	38.0	37,273.60
2002	18,793	12,042	20.1	49.1	45.0	38,166.00
2003	18,793	13,283	24.6	58.8	49.0	39,677.20
2004	18,687	13,374	54.0	61.7	55.0	41,921.80
2005	19,590	13,563	107.9	64.8	63.0	44,307.90
2006	20,006	13,859	107.0	68.0	68.0	46,437.10
2007	20,419	14,040	181.2	68.9	76.0	48,061.50
2008	21,064	14,131	158.6	75.0	82.0	48,401.40
2009	21,758	15,326	139.7	74.0	85.0	47,001.60
2010	20,330	15,417	140.9	71.0	89.0	48,374.10
2011	22,108	16,284	128.1	71.7	91.0	49,781.40
2012	22,560	16,570	147.5	69.7	94.0	51,456.70
2013	22,748	16,821	145.2	79.3	96.0	52,980.00
2014	22,748	16,944	98.6	84.2	96.0	54,629.50

3.5. Scenario Analysis on Behavior Impacts

The scenarios which were considered in this study were developed based on the market penetration predictions of Autonomous Vehicle. A base scenario for the existing condition (2016) was estimated. Then, using the market penetration curve, the number of households adopting AV was estimated in different years. The time frame considered ranged from 2025 to 2065, at 5 year intervals. Based on the developed models and literature review, new scenarios were developed for each year. These scenarios investigated how AVs will impact a real transportation network and activities during its market adoption procedure.

All the scenarios were simulated using Cube software. The assumptions are presented in Chapter 6.

CHAPTER 4. MARKET PENETRATION PREDICTION

4.1. AV Market Penetration Model

To estimate the generalized Bass diffusion models in this study, non-linear least square estimation method was used with SPSS software (IBM Corp, 2012). The estimated coefficients of the models, including the basic model and the generalized model are summarized in Table 4-1. As a reference, the Bass model for conventional vehicles (auto) was also estimated based on data for the period of 1920-2014. The coefficients are shown in the first row of this table. The second and third rows show the coefficients for the Bass and the generalized Bass model for HEVs. As explained, to bring US consumer's technology acceptance taste into account, Bass model formulation was also applied on historical subscription data of internet and cellphone in the US, and the results are shown in the last two rows in Table 4-1.

Price ratio and economic wealth were incorporated as external variables for the HEV generalized Bass model. For comparison purposes, the diffusion coefficients obtained from previous studies on the adoption of new automobile technologies are also summarized and presented in Table 4-2.

Table 4-1. Estimation Result for Bass Diffusion Models

Parameter	m	p	q	Price Ratio	Economic Wealth	R^2
Bass (auto)	504,136,121	0.000242	0.091202			0.997
Bass (HEV)	1,650,320	0.010402	0.389704			0.997
G-Bass (HEV)	1,750,697	0.015459	0.341865	-1.314	8.913	0.999
Bass (Internet)	76%	0.006673	0.390604			0.992
Bass (Cellphone)	329,582,323	0.001725	0.264384			0.999

Table 4-2. Bass Model Parameters from Selected Studies

Authors	Model	Vehicle technology	p	q
Massiani and Gohs (2015)	Bass model	EV	0.0019	1.2513
Massiani and Gohs (2015)	Bass model	LPG	0.0779	0.3718
Massiani and Gohs (2015)	Bass model	CNG	0.1187	0.0349
Jensen et al. (2014)	Bass model	EV	0.002	0.23
Cordill (2012)	Regression model	EV Prius	0.0016	1.4451
Cordill (2012)	Regression model	EV Hybrid Civic	0.0034	0.0631
Cordill (2012)	Regression model	EV Ford Escape	0.0367	0.4322
Park et al. (2011)	Generalized Bass Model	HCFV	0.0037	0.3454

Comparing the estimated innovation factors (p) across the models, it is shown that the estimated value for HEV (0.010 and 0.015) in the US market is very high. The intuitive meaning of this factor represents how quickly the new technology was adopted. Considering Table 4-1 and Table 4-2, the largest values of p factor were for CNG and HEVs. Simply, it can be seen that these technologies were not that revolutionary. When HEVs were introduced in the US market around year 2000, the consumers were relatively familiar with the product. On the contrary, the p factor for conventional automobile adoption is about 0.0002, which indicates that the market was more conservative when automobiles were first introduced around 1920. The adoptions of cellphone and internet reveal a similar behavior; these had p values around 0.00067 and 0.0017, respectively. Considering that AV technology is also revolutionary in the automobile industry, that it will be accepted over many years, and taking into account the diffusion patterns of other technologies, a value of 0.001 (p = 0.001) for AV technology was chosen for this study. The assumption is that AV adoption would be quicker than the conventional automobile but more conservative than that of EVs, internet, and cellphones. However, it should be noted that this assumption can be updated when more knowledge is available about user acceptance.

The imitation factor q estimates of both base Bass and generalized models for HEV were very close to the average imitation factor values of previous studies. Unlike the innovation factor, which mostly deals with consumer's risk taking capacity, the imitation factor represents consumers' cultural and lifestyle preferences. Intuitively, the q-factor represents how quickly the technology would be adopted by imitators. It can be seen that the innovation factors vary largely for different technologies while the imitation factors are relatively close as shown in Table 4-2. This factor was estimated to be 0.0912 for conventional automobiles in the US, which indicates that society lifestyle and welfare can affect the imitation factor considerably. In this study, the estimated value of 0.341865 was used in the AV diffusion model.

The estimated market size for HEV did not seem reasonable for AV (the m-parameter), compared to the entire vehicle market in the US. Prior to 2012, a total of 254 million vehicles were registered in the US. The diffusion model for automobiles recommended a saturation market size of approximately 500 million vehicles (cumulative from 1920). AV technologies will bring considerable changes in people's life, i.e. increases social welfare, and enhances safety. Accordingly, the market size for AVs would be considerably large. The usage of the internet and the market size for cellphones, demonstrates the potential and capacity of US of consumers to adopt new technologies, especially when they are affordable. Although AV technology may not be as affordable initially, it will become more accessible as the price falls over time.

Based on the usage of internet, this study assumed a market size of 75% of households for AVs. Considering that one of the most promising features of AVs is the potential to facilitate carpool/shared use and more efficient use of the vehicles, the market size is considered as household based instead of individual based. Although U.S. households commonly enjoy multiple vehicles today, it is hypothesized that AV technology would likely reduce vehicle ownership significantly. Given that there were 115,610,216 households in the US (United States Census Bureau, 2015), the market size for AV is estimated to be nearly 87 million vehicles. Again, this assumption should be updated as more information becomes available regarding vehicle ownership. The sensitivity analysis presented later also shows the impacts of market size on the market penetration of AVs.

The estimated price ratio coefficient is negative which is reasonable and means a decrease in price ratio will lead to increase in the cumulative sale. The price ratio decreased from 1.56 to 1.34 for HEV relative to conventional vehicles during a 15-year period. It is anticipated that initially AVs would have a considerably higher price than conventional vehicles, however this ratio will decrease over time. Economic wealth showed significant effect on HEV sales. Therefore, this variable was also incorporated into the model for AV adoption. The final adopted parameters for AV market diffusion is presented in Table 5-3. The corresponding diffusing curve is illustrated in Figure 4-1.

Table 4-3. AV Market Diffusion Model Coefficients

Parameter	M	p	q	Price	Economic wealth
Bass (AV)	86,707,662	0.001	0.341865	-1.314	8.913

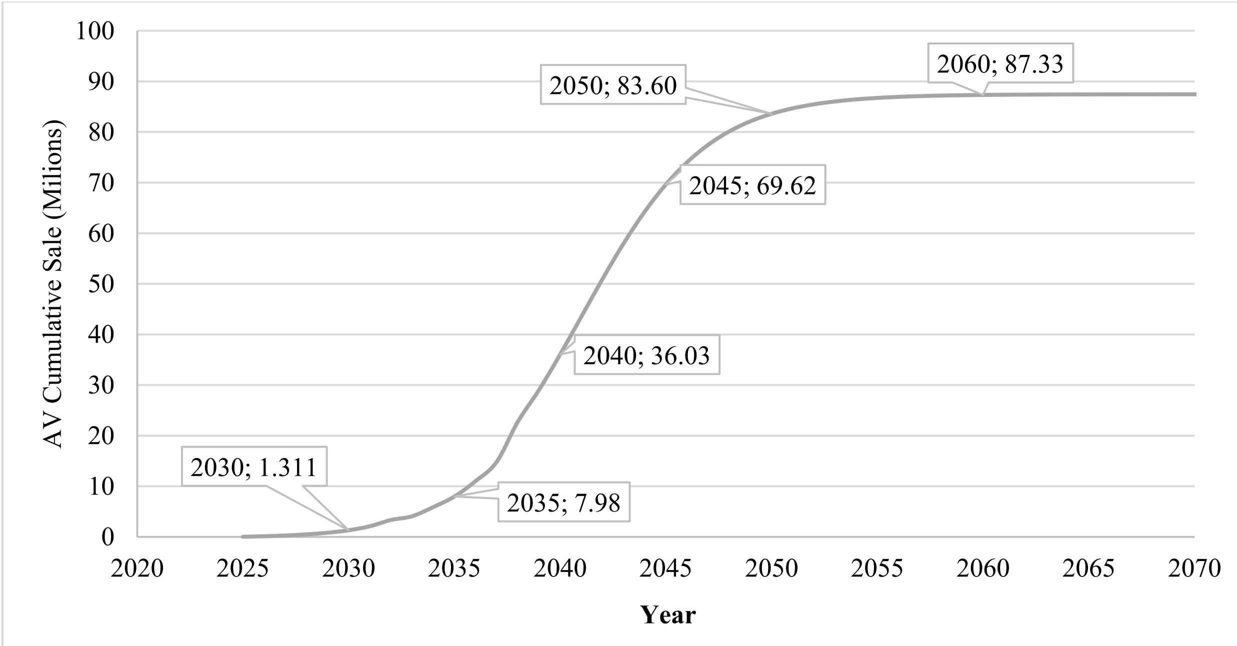


Figure 4-1. Forecasted AV market penetration curve

Figure 4-1 shows the market penetration prediction based on the assumptions indicated earlier, and considering less than 100,000 sold vehicles per year as the market saturation point. Assuming that AV sales start in 2025, the projection showed that 1.3 million vehicles be sold in the first five years, and will increase to 36 million in the next ten years. The curve shows that the market will be saturated in 2059 when approximately 87 million AVs have been sold. This projection seemed to agree with Litman's study (2014), which predicted that in the 2050s 80-100% of sold cars would be AVs.

4.2. Sensitivity Analysis

Sensitivity analysis is a useful tool in identifying model uncertainties. The assumption is to keep all other variables constant, and see how model results change based on the value changes in one factor. In this study, the market size and price ratio values may change considerably. To see how these factors may change the adoption pattern of AVs, sensitivity analysis was conducted for both of these variables.

Several sensitivity analyses were conducted assuming market sizes ranging from 20-140% of US households. Market penetration curves estimated based on different market sizes are illustrated in Figure 4-2. The figure shows much quicker adoption rates when the market size was increased, as indicated by the steeper slopes. Full market saturation did not different greatly between the earliest (2050) and latest (2060), but the number of vehicles obviously did.

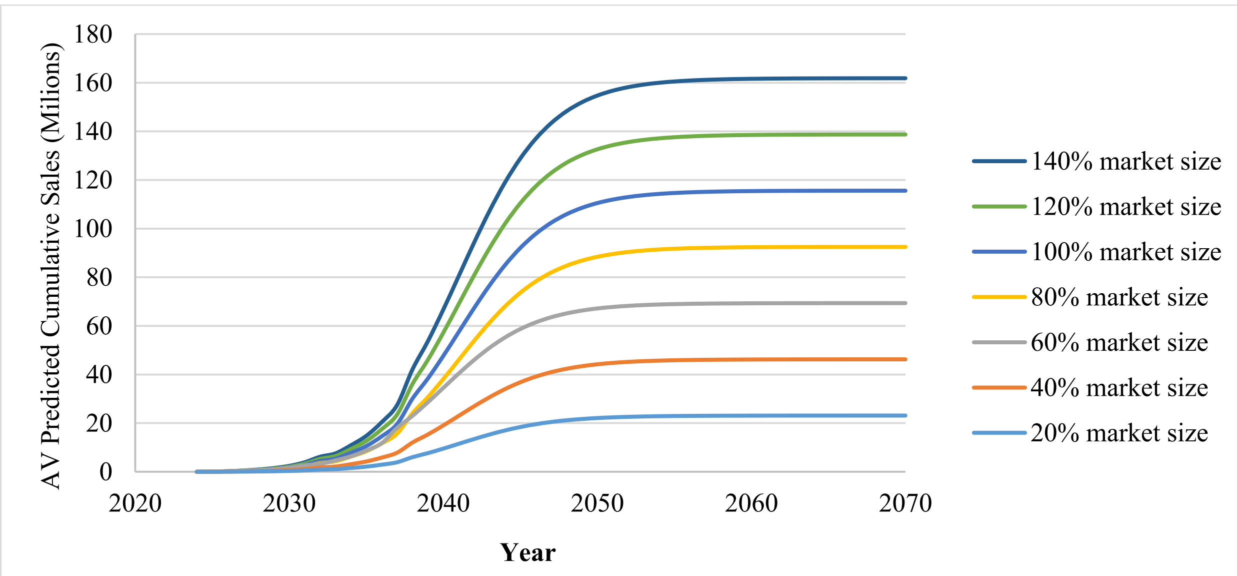


Figure 4-2. Sensitivity analysis results on market size

Regarding price ratio between AVs and conventional vehicles, according to a study by Information Handling Services (IHS) Automotive, the AV technologies will add $7,000 to $10,000 to a conventional vehicles price in 2025 (HIS, 2015). For this study, the generalized Bass model was only able to consider the effect of the initial price ratio when the new product is first introduced. Although difference between both types of vehicles may reduce eventually, the sensitivity analysis only reflects the effect on the initial price ratio.

Four different values were chosen to represent the initial additional cost for AVs, \$3,000, \$5,000, \$10,000, and \$30,000 for sensitivity analysis. In reality, an additional cost of \$30,000 is not very likely to occur, but it was chosen to test how the model would react. The diffusion curves are presented in Figure 4-3.

As shown in Figure 4-3, the penetration curves are very close, except that the diffusion curve is shifted one year later when additional cost changed from \$10,000 to \$30,000. This could indicate that the external variables have less effect in comparison with the three major variables (the market size, the innovation factor, and the imitation factor) in the Bass model. This is a limitation of the Bass model, which is not able to consider external variables' effect on market diffusion very well as indicated by Bass (Bass et al., 1995). Many other factors will likely affect AV market penetration such as legal frameworks, personal preferences, technology, and price. As such, future studies should be conducted to incorporate external factors.

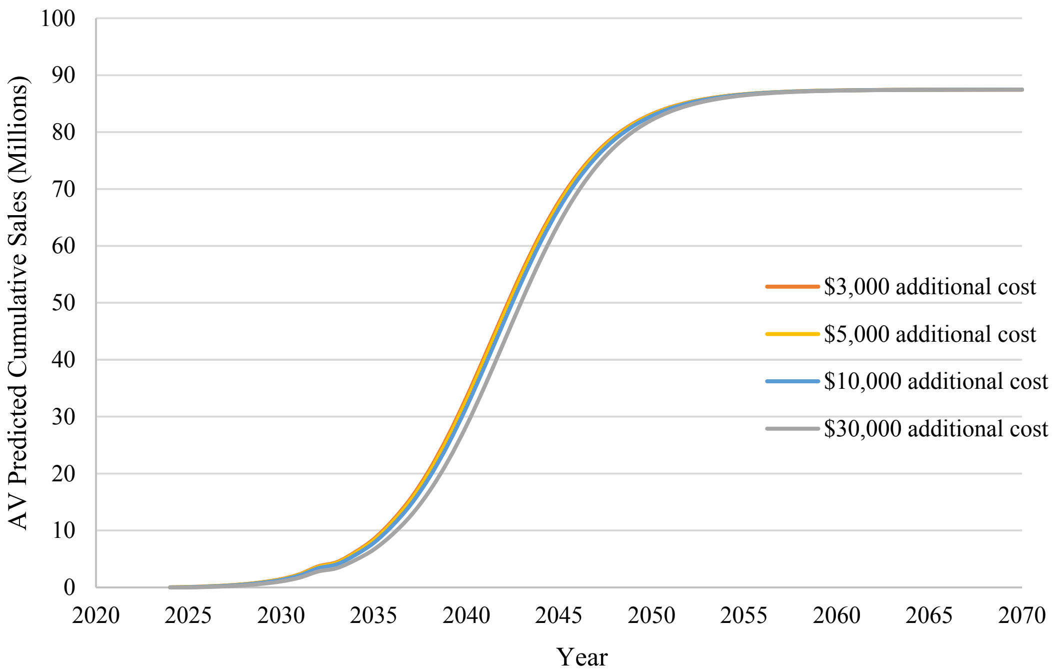


Figure 4-3. Sensitivity analysis results on additional cost of AVs

CHAPTER 5. SURVEY RESULTS ANALYSIS

This chapter includes descriptive statistical analysis of the survey results. Findings of this section were used to support the creation of assumptions for the scenarios used in the study. As mentioned, the survey was limited to Florida International University students, faculty and staffs. The recruitment resulted in a total of 221 responses, from which 147 participants completed the survey. Due to this, some questions recorded 221 responses, but others had as little as 147.

5.1. Descriptive Analysis of Survey Results

5.1.1. Demographic and Socio-economic Results

The demographic breakdown for the respondents is presented in Table 5-1 and Figure 5-1 illustrates some selected demographic information. The age distribution seemed to be reasonable and it was expected that participants would primarily be between 20 to 35 years of age. Also the gender ratio was acceptable, and close to half of the participants had a Master of Science or Ph.D. degree.

The majority of participants had an income of less than $100,000 per household, which was reasonable. 30% of the responders are living with another person in 2-people household size, followed by 4-people and 3-people families. A total of 43% of respondents mentioned that there are two or more licensed drivers in their home. A common issue with many studies is that the majority of participants are graduate students which have a very similar lifestyle, but in this study 42% of participants were undergraduate students which indicated that the results cannot be limited to people with graduate degrees.

Figure 5-1. Selected SED charts (Age, Household income and Household Size)

Table 5-1. Demographic Breakdown of Survey Respondents

Socioeconomic Information	Attributes Level	Frequency	Percent
Age Group	17 or Younger	1	0%
	18-20	22	10%
	21-24	46	21%
	25-29	54	25%
	30-34	35	16%
	35-39	13	6%
	40-44	13	6%
	45-49	11	5%
	50-54	7	3%
	55-59	5	2%
	60-64	6	3%
	65 or older	5	2%
Gender	Male	139	68%
	Female	66	32%
Highest Level of Education	High school graduate (includes equivalency)	6	3%
	Some college, no degree	39	19%
	Associate's degree	34	17%
	Bachelor's degree	34	17%
	Graduate or Professional degree (Master's/ Ph.D. or equivalent)	92	45%
Income Level	\$0 – \$24,999	39	19%
	\$25,000 – \$49,999	40	20%
	\$50,000 – \$74,999	41	20%
	\$75,000 – \$99,999	38	19%
	\$100,000 – \$124,999	15	7%
	\$125,000 – \$149,999	9	4%
	\$150,000 – \$174,999	5	2%
	\$175,000 – \$199,999	4	2%
	\$200,000 and above	12	6%
Household Size	1	25	12%
	2	61	30%
	3	41	20%
	4	46	23%
	5	21	10%
	6	5	2%
	7	3	1%
	More than 7	1	0%
Number of Licensed drivers	0	2	1%
	1	32	16%
	2	88	43%
	3	43	21%
	4	31	15%
	More than 4	7	3%
Occupation at University	Faculty	28	14%
	Undergraduate students	84	42%
	Staff	36	18%
	Graduate student	48	24%
	Other	5	2%

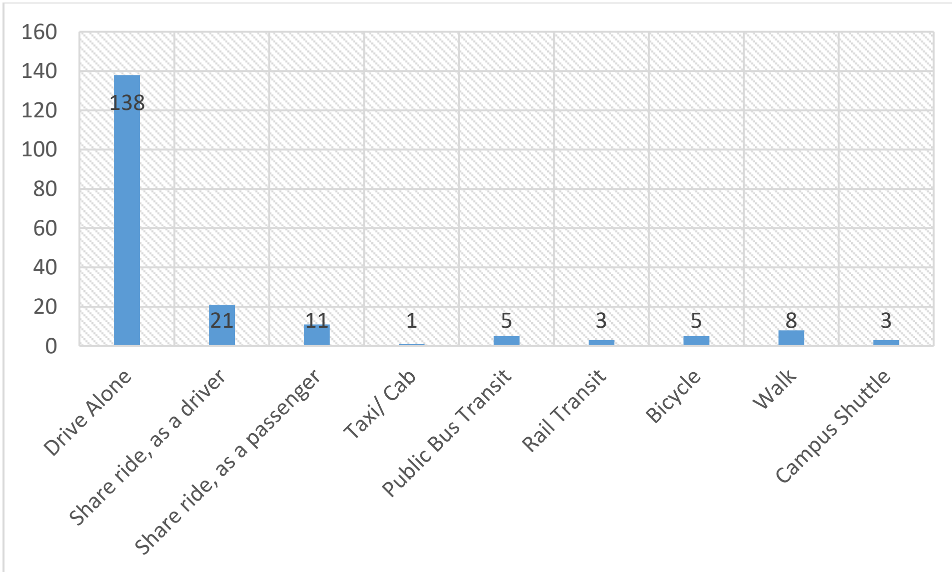
5.1.2. Trip Characteristics Results

Table 5-2 shows a summary of responses to trip characteristics questions and Figure 5-2 shows some of the responses histograms. Based on this table, slightly more than 70% of people were drove to school with their own vehicles, while 11% dropped-off someone else, and 6% were dropped-off at school. In comparison with the driving pattern for grocery trips, less people are using drive alone mode for grocery trips. However, still it is a considerable portion of, 61%. Around 30% of participants used shared vehicles for grocery trips.

Analysis of the distance between home and other destinations revealed that participants traveled 5-15 miles to school, and less than 3 miles grocery stores. This showed people allotted much less time and energy grocery trips. In light of this, the availability of AV technologies may reduce this burden and enable people to make longer grocery-related trips to stores with better quality or more affordable products.

Table 5-2. Trip Characteristics of Respondents

Trip Characteristic Information	Choices	Frequency	Percent
Most commonly used mode for commuting	Drive Alone	138	71%
	Share ride, as a driver	21	11%
	Share ride, as a passenger	11	6%
	Taxi/ Cab	1	1%
	Public Bus Transit	5	3%
	Rail Transit	3	2%
	Bicycle	5	3%
	Walk	8	4%
	Campus Shuttle	3	2%
Most commonly used mode for grocery trips	Drive Alone	117	61%
	Share ride, as a driver	32	17%
	Share ride, as a passenger	27	14%
	Public Bus Transit	1	1%
	Bicycle	1	1%
	Walk	13	7%
	Not Applicable	2	1%
Typical one-way distance for commute trips	Less than 1 mile	12	6%
	1-3 miles	25	13%
	3-5 miles	21	11%
	5-10 miles	45	24%
	10-15 miles	30	16%
	15-20 miles	26	14%
	20-30 miles	18	10%
	30-40 miles	8	4%
	40 miles or more	4	2%
Typical one-way distance for grocery trips	Less than 1 mile	47	25%
	1-3 miles	94	50%
	3-5 miles	25	13%
	5-10 miles	15	8%
	10-15 miles	3	2%
	15-20 miles	1	1%
	20-30 miles	1	1%
	30-40 miles	1	1%
	40 miles or more	1	1%



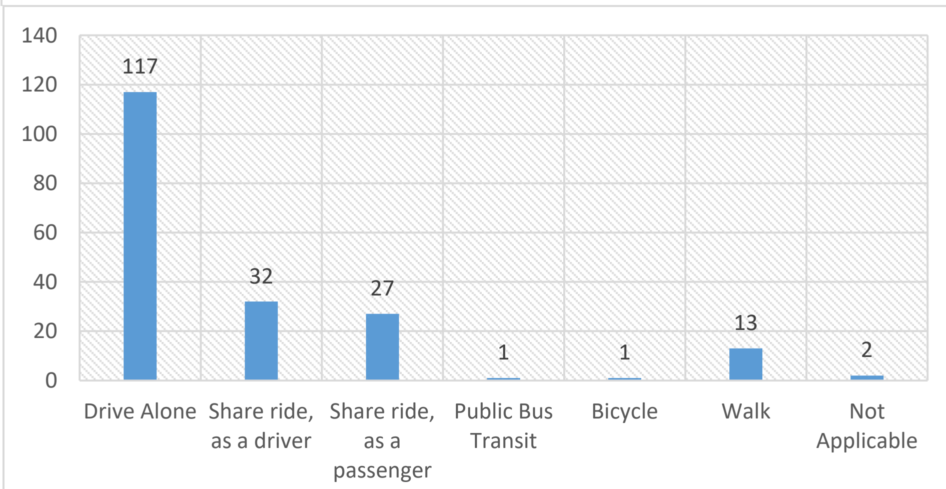


Figure 5-2. Selected SED charts (Most commonly mode used for commuting (up) and grocery trips (bottom))

5.1.3. AV Perception/Implication

After collecting adequate information regarding socio-economic and trip characteristics of each respondents, questions regarding personal perceptions about autonomous vehicles are presented. The responses show a few portions of people are not familiar with AVs at all, while more than half of the respondents were moderately or extremely familiar with AVs. This response is in accordance with previous surveys. Table

5-3 shows response frequency to this question. The responses to the question "how likely do you see yourself using AV" showed more than 50% of respondents were likely to have AVs and use them, while 12% of people were completely against having AVs.

Table 5-3. Frequency of Respondents Familiarity with AV

How familiar were you about Autonomous Vehicles (AVs) before you participated in this survey?	Not at all familiar	25	14%
	Slightly familiar	55	32%
	Moderately familiar	72	42%
	Extremely familiar	21	12%
	Total	175	

Table 5-4. People Likert Frequency about AV Use

How likely do you see yourself using AVs that can fully drive by themselves without your involvement?	Extremely unlikely	21	12%
	Unlikely	16	9%
	Don't know/ Can't say	41	24%
	Likely	55	32%
	Extremely likely	41	24%
	Total	175	

Regarding the expected benefits from AVs, 77% agreed that AVs would decrease the stress of driving and 71% agreed that they would reduce crashes. On the other hand, almost a quarter of people were not expecting less congestion and lower car insurance rates. Table 5-5 shows respondents' perception about the benefit of AVs.

Table 5-5. AV Benefits Perception

Benefits	**Extremely unlikely**	**Unlikely**	**Don't know/ Can't say**	**Likely**	**Extremely likely**
Fewer traffic crashes and increased roadway safety	5%	2%	22%	38%	33%
Less traffic congestion	7%	17%	24%	29%	24%
Less stressful driving experience	4%	5%	14%	43%	34%
Lower car insurance rates	13%	13%	29%	24%	21%
Increased fuel efficiency	2%	7%	24%	41%	26%
Lower vehicle emissions	4%	10%	37%	30%	19%

As expected, a considerable number of respondents were concerned about system failures and hacking. Performance of AVs in unexpected traffic situations ranked as the second most important concern. People were less concerned about motion sickness and also loss in human driving skill over time. Table 5-6 shows respondents concerns about AV technologies.

Table 5-6. AV Concerns Perception

Concerns	Not at all concerned	Slightly concerned	Don't know/ Can't say	Moderately concerned	Extremely concerned
System/equipment failure or hacking	4%	11%	5%	37%	43%
Performance in unexpected traffic situations, poor weather conditions (like snowstorms) and low visibility/ dark	6%	17%	9%	35%	33%
Motion sickness	48%	12%	20%	12%	7%
Giving up my control of the steering wheel to the vehicle	16%	23%	11%	31%	19%
Loss in human driving skill over time	26%	19%	10%	26%	19%
Privacy risks from data tracking on my travel locations and speed	19%	20%	7%	27%	27%
Difficulty in determining who is liable in the event of a crash	17%	19%	14%	25%	25%

In another question, participants were asked about their preference to take AVs for different trip purposes. This question was only presented to respondents that were likely to use AVs, and it seemed there was not a considerable difference between which trip purposes in which AVs would be used. Table 5-7 shows that respondents considered using AVs for their commute trips slightly more than grocery trips. This can be an important finding, since a hypothesis about AVs is that a considerable portion of grocery (and escort) trips can be done by AVs, but it seems society does not accept it yet.

Table 5-7. Usage of AV for Different Trip Purposes

Trip Purpose	Extremely unlikely	Unlikely	Don't know/ Can't say	Likely	Extremely likely
Commute/ School trips to university	2%	4%	13%	36%	46%
Grocery trips	8%	5%	12%	39%	36%
Business trip	3%	5%	10%	37%	45%
Leisure trip	3%	12%	11%	32%	42%

Regarding the car ownership, more than 75% of respondents considered owning AVs and 60% of them considered using AVs as they are using vehicles today. Slightly less than 20% of people considered sharing AVs. However ridesharing companies including Uber and Lyft claim ridesharing would change over time as people would become more accustomed and attracted to sharing system (Sherpashare, 2016). Table 5-8 shows the responses to the question regarding the preferred implementation of using AVs, however hypothesizes predict more car sharing than 20%.

Table 5-8. Most Preferred Way of Using AV

Way of using AV	Frequency	Percent
Own (purchase or lease) AVs and use them only for personal use or use by family members	70	59%
Own (purchase or lease) an AV and earn extra income on the side by making it available to other drivers when not needed	11	9%
Own (purchase or lease) an AV and earn extra income on the side by providing rides for fellow passengers when you use it	9	8%
Rent an AV as the need arises	11	9%
Use AVs in the form of transportation (taxi, or public transit) provided by a service provider	14	12%
Neither interested in investing in an AV nor using AVs as a transportation service	3	3%

The survey also questioned what participants would do rather than drive. The responses to this question are shown in Table 5-9. Approximately, 20% of respondents mentioned they will still be alert and watch the road for emergency conditions. Being relaxed and browsing internet were the next most popular activities.

Table 5-9. Activities Which Will be Done in AV while driving to Destination

Activity	Frequency	Percent
Be alert and watch the road	29	20%
Relax and enjoy the outside view	25	17%
Work or participate in teleconference	15	10%
Other (please specify)	8	5%
Watch movies or other entertainment	13	9%
Make phone calls/ text messages	14	9%
Eat/drink	1	1%
Sleep/nap	11	7%
Read	11	7%
Browse internet or online social networks	21	14%

According to the survey, most respondents would choose a vehicle that was the same size or larger. Table 5-10 shows that 66% would not consider changing their vehicle size and 30% would like a larger vehicle. However, it is possible that after AVs are introduced and people started to discover them, a higher portion may find a larger vehicle more attractive.

Table 5-10. Vehicle Size Change after AV is Available

Size	Frequency	Percent
A larger vehicle than what I own now	42	29%
Similar sized vehicle	97	66%
A smaller vehicle than what I own now	8	5%
Total	152	

Assuming the respondent would use AVs, another question considered his/her maximum one-way trip length for commuting and grocery trips. These questions were also asked in the first section. Table 5-11 shows the frequency of responses based on the maximum acceptable commuting distance for AV users. To compare the change in the acceptable commuting distance, the responses from a similar question were used; this similar question was in the first section and was related to the respondent's current acceptable commuting distance. The comparison of these two is shown in Figure 5-3.

Table 5-11. Acceptable Commuting Distance Assuming Using AV

Commuting Distance	Frequency	Percent
Less than 1 mile	2	1%
1-3 miles	4	3%
3-5 miles	11	8%
5-10 miles	23	17%
10-15 miles	25	19%
15-20 miles	17	13%
20-30 miles	18	14%
30-40 miles	12	9%
40 miles or more	20	15%

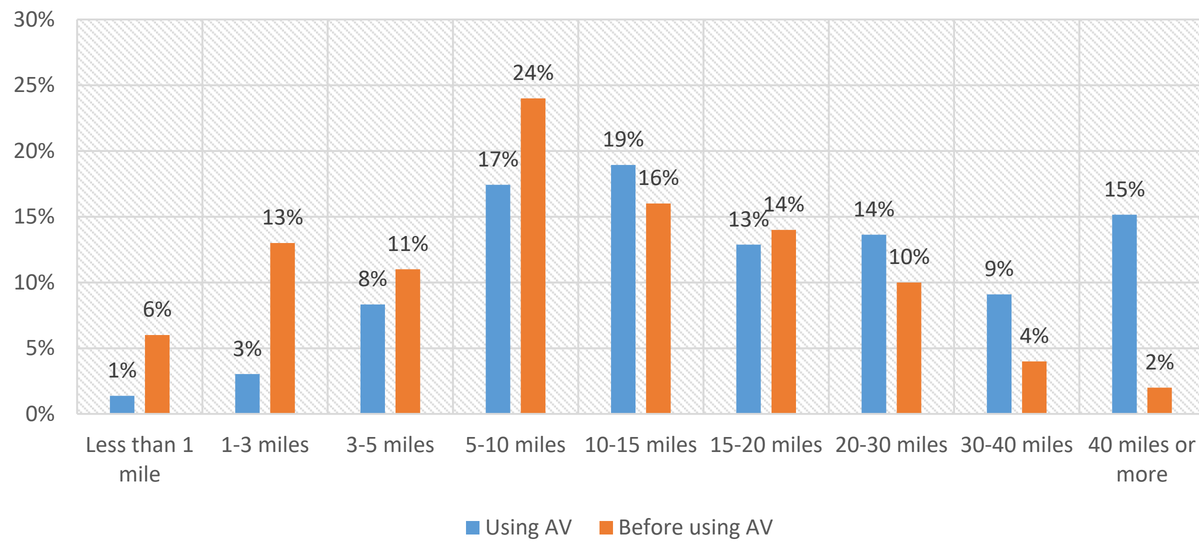


Figure 5-3. Comparing Commuting Distance Change with and without Using AV

A very similar question collected data on the acceptable distance for grocery trips. The responses are presented in Table 5-12 and Figure 5-4.

Table 5-12. Acceptable Grocery Trips Distance Assuming Using AV

Commuting Distance	Frequency	Percent
Less than 1 mile	13	1%
1-3 miles	23	3%
3-5 miles	34	8%
5-10 miles	24	17%
10-15 miles	17	19%
15-20 miles	8	13%
20-30 miles	2	14%
30-40 miles	3	9%
40 miles or more	2	15%

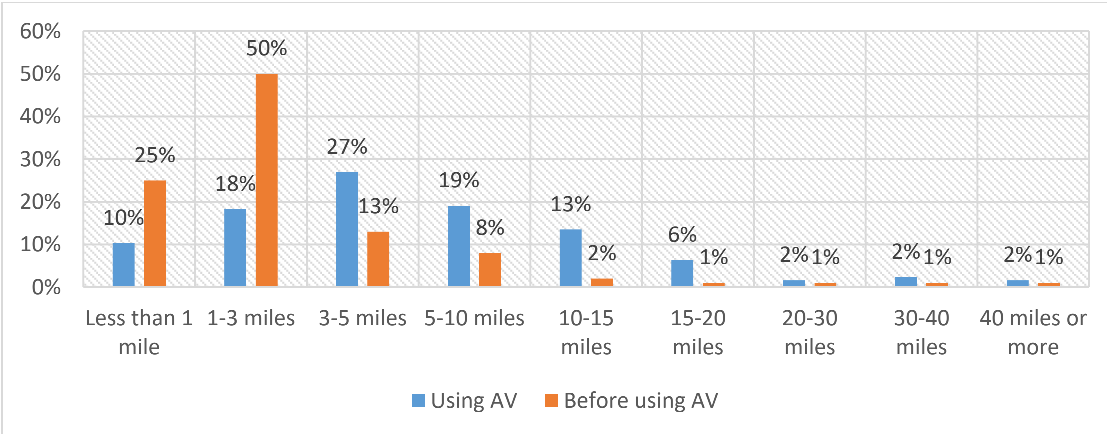


Figure 5-4. Comparing Grocery Trips Distance Change with and without Using AVs

By looking at figures, 5-3 and 5-4, it can be concluded that these AVs using respondents were willing to live further. However, it is worth noting that location changes can only be interpreted for the population which elected to use AVs. Regarding the grocery trips, people will accept only a few changes (3-15 miles) from less than 3 miles.

5.2. Discrete Choice Modeling Results

5.2.1. Willingness to Pay (WTP) Model

The first discrete choice model developed in this study is the Willingness to Pay (WTP) model. This is very popular model in transportation, marketing, and business studies. Its popularity is due to the fact that facilitates the understanding of people's willingness to pay for a new product and which variables are significant. Table 5-13 presents the results of the ordered response model for willingness to pay; four discrete categories were considered: less than $1,000, $1,000 to $5,000, $5,000 to $10,000, and greater than $10,000.

Table 5-13. Ordered Logit Model for Willingness to Pay for AVs

Parameter			**Estimate**	**t-test parameter**
Individual Characteristics	Age	Age: 18-20	3.0302	2.951
		Age: 21-24	3.1750	3.856
		Age: 25 29	3.2602	4.440
	Gender	Male	-1.2175	-2.667
	Ethnicity	Native American	-12.1772	-3.47
	Education	Bachelor's degree	1.2611	1.999
	Occupation	Undergrad student	-1.6145	-2.515
Household Characteristics	Income	Income below 50 k	-3.1941	-4.773
	HH type	Household with family members	-3.0213	-2.365
		Unmarried partners	-4.6307	-2.943
		Single person households	-3.8368	-2.693
Daily Travel and Commute	Commute days	Once a week	-3.4964	-2.112
	Commute mode	Shared mode-driver	-2.0095	-2.763
	Commute distance	More than 40 miles	-2.0813	-1.576
	Total travel time	15-30 minutes	2.6136	3.245
	Parking time	5-10 minutes	2.7151	4.325
Crash experience	Date	This year	-6.6987	-3.505
		1-5 years ago	-5.4202	-3.468
		5-10 years ago	-6.6801	-3.888
		More than 10 years ago	-7.5916	-4.323
	Severity	Injury2: Major incapacitating	5.5183	2.536
		Injury3: Major non-incapacitating	-3.3550	-2.887
		Injury4: Minor injury	-1.2851	-1.633
	Liability	Liability1: Self as the driver	5.1805	3.269
		Liability2: Driver of the other vehicle	5.9287	3.714
		Liability3: Driver of the vehicle I was in	13.0338	5.247
Last Vehicle Transaction	Date	This year	-1.2350	-2.360
		5-10 years ago	-1.2959	-1.467
	Type	New vehicle purchased	-0.7077	-1.298
	Price	Less than 10 k	1.1056	1.966
		30-40 k	2.6642	3.310
		40-50 k	2.1512	1.490
		More than 50 k	2.9895	2.713
AV Perception	Familiarity with AV	Moderate	-0.6981	-1.528
Cut Values		Intercept	-7.3983	-4.226
		Intercept	-2.7324	-1.782
		Intercept	-1.2286	-0.803
Goodness of Fit Measures		**AIC**	**319.73**	
		Residual Deviance	**249.7**	
		Chi-square test p-value	**4.39×10^{-6}**	
		Number of observations	**144**	

Various types of variables were tested in the model including individual attributes, household characteristics, daily travel pattern, commute pattern, crash experiences, and the latest vehicle transaction, familiarity with AVs, as well as overall benefits and concerns associated with AVs.

In terms of individual attributes, the results showed that younger individuals, less than 29 years of age, were the most likely to pay more for AV technologies. As risk propensity and age are generally inversely related, this result was deemed as reasonable. This was reinforced by the fact that younger people tend to be more accepting of new technologies (Schulz et al. 2013).

Interestingly, males were less likely to pay for driverless cars than females. At first glance, this might seem contradictory to the results from previous studies, but it should be noted that willingness to pay deals with monetary values rather than attitudinal preference. While males were more likely to use a driverless car (Danise, 2015; Schoettle and Sivak, 2015), the results of this study showed that they were less willing to pay more for AVs. One reason for this might be that men are generally expected to be more wary of economic issues, and therefore more likely to optimize their investments compared to females (Shin et al. 2014; Baratian-Ghorghi and Zhou, 2015; Hossan, 2015).

Among the respondents, undergraduates were less willing to pay for AVs. This seemed reasonable considering that undergraduate students are more fiscally constrained than older drivers. As expected, low income individuals (less than $50,000/year) showed lower willingness to pay. Native Americans also showed a similar trend, but the propensity of this group is more likely due to statistical bias rather than a general trend. This was determined after an investigation of the respondents which revealed that only 1 individual identified as a Native American.

Daily travel attributes were expected to have significant impacts on the model. This study considered commute length, commute distance, mode of transportation, and total travel time. The model showed that respondents with the lowest commute frequency (once per week) had the lowest willingness to pay which may indicate that people were not willing to spend more for AVs if they would not benefit from its frequent usage. Among different commute modes, shared-drivers (HOV) were the most likely to pay for the technology, probably due to the freedom and flexibility gained. People with long commute distances (40 miles and more) also showed higher WTP values. This was attributed to the benefit of improved productivity and reduced stress during commuting trips. Results also showed that people with a daily total travel time of 15-30 minutes were the most willing to pay. The same trend was observed for people who spent an average of 5-10 minutes to find parking.

Crash experience can be an index of driving attitudes and habits among individuals. Table 6-1 shows that individuals who had crash experiences were less likely to pay for AV technologies as indicated by the negative coefficients. In addition, those with recent experience (less than one year) or long ago (more than 10 years) showed a decreased willingness to pay. For people who recently experienced a crash, this may imply that they were still emotionally affected and that they were more resistant to surrender control to the AV. More investigation is required for those who reported experiencing a crash long ago.

Among those who had experienced crash, severity showed mixed impacts on the model. Interestingly, respondents that experienced major incapacitating injuries had the highest positive impact on WTP. In terms of liability issues, passengers that were in the at fault vehicle were the most likely to pay for AVs compared to other liability cases. This may indicate that when it comes to driving errors, the people in this study trusted AV technologies more than human drivers.

It is essential to consider consumers' vehicle transaction records in order to obtain a general understanding of the market trends and their influence on willingness to pay. Results showed that consumers who purchased (as opposed to leased or bought a used vehicle) a new vehicle showed lower WTP. Furthermore, the WTP decreased if this was a recent transaction (less than a year ago). In terms of price, results also showed that people who paid $40,000 to $50,000 in their last transaction had the highest willing to pay.

Respondents with moderate familiarity with the AV technologies had the lowest willingness to pay compared to all other levels. This may indicate that this group has unrealistically high expectations for the technology and as such are willing to pay more for it.

5.2.2. Willingness to Relocate Model

Similar to the previous section, an ordered response model was developed to identify contributing factors and evaluate their impact on willingness to relocate. A likert scale response variable including five levels was used to express the willingness to relocate further from their work/school locations. This model is important because the first step in several activity based travel demand models is the allocation of synthetized populations to locations. With AVs in the equation, the residential location choice models should be upgraded.

Table 5-14. Ordered Logit Model for Willingness to Relocate Model

Parameter			Estimate	t-test parameter
Individual Characteristics	Age	Age: 30-34	-1.0007	-1.874
	Gender	Male	0.6517	1.665
	Ethnicity	Asian	-1.8618	-2.928
Household Characteristics		Income below 50 k	1.1297	2.973
		Number of disabled	-0.0014	-1.268
Daily Travel and Commute	Commute mode	Drive alone	0.4540	0.827
		Shared mode- driver	1.6027	2.280
		Public transit	0.4824	0.389
Parking Demand	Average Parking Time	Less than 5 minutes	-1.2103	-2.449
		5-10 minutes	-1.1706	-2.138
		10-15 minutes	-1.3335	-2.294
Benefits Perceived		Fewer traffic crashes and increased roadway safety	0.9459	2.190
		Less traffic congestion	0.7226	1.702
		Lower car insurance rates	0.9145	2.224
		Increased fuel efficiency	-2.111	-4.093
		Lower vehicle emissions	1.3861	3.015
Concerns Perceived		Safety of the vehicle and other roadway users	-0.9562	-2.753
		Motion sickness	0.9494	2.013
		Giving up control	0.8027	1.958
		Data privacy	-0.9162	-2.476
Cut Values		Intercept	-1.9958	-2.683
		Intercept	-0.4336	-0.606
		Intercept	1.1347	1.573
		Intercept	3.3358	4.196
Goodness of Fit Measures		**AIC**	**415.34**	
		Residual Deviance	**369.34**	
		Chi-square test p-value	**6.69×10^{-8}**	
		Number of observations	**141**	

Among different age categories, results show that individuals from 30-34 years of age were the least likely to relocate. One simple inference could be that this group may have recently leased/mortgaged a house or have young children. Such constraints will play a significant role in limiting individuals' freedom toward long-term decisions such as residential relocation. This phenomenon is more noticeable when males showed higher willingness for relocation. Due to common social norms, it is reasonable to assume that females are more involved with and concerned about household-related, out-of-home errands such as escorting children and as such are probably more resistant towards relocation. The model also shows that Asians have a significant negative impact on the model.

Low-income households were more likely to relocate given the availability of AVs for the family. This may imply that low-income people were expecting gain financial benefits from living in further suburban areas (with lower long-term costs of living), while maintaining similar mobility/accessibility patterns through the use of AVs.

Results showed that the number of disabled people in the household decreased the probability of relocation. This may be due to the physical constraints imposed by disabilities which may be perceived to increase due to relocating.

Similar to the WTP, shared mode drivers were the most willing to relocate. This probably stems from the fact that using AVs will reduce the stresses and responsibilities associated with carpooling. As such, this group showed higher levels of willingness to move further away from their current residence.

It is interesting to see that parking time has a negative impact on the model. One major benefit of AVs documented in the literature is the decreased need for parking space as AVs will be designed to automatically park somewhere outside the CBD area, give demand-responsive service to other family members or return home to park. However, this benefit was not included in the survey and respondents were not informed of this potential. Hence, the negative coefficient implies that individuals were still concerned about AV parking or they did not consider any of the parking benefits of AVs to be practical.

In terms of benefits and concerns, results showed that traffic-related benefits played a significant role on residential relocation. It seems that people were willing to experience longer travel times as long as their trip would be safe, reduce congestion, and reduce air pollution. The negative coefficient for fuel efficiency shows that although AVs were expected to reduce fuel costs, respondents did not believe that such the reduction would cancel out the expenses imposed by an increased VMT due to relocation.

When it comes to concerns, mixed results were observed. Some concerns such as "data privacy" or "safety of other roadway users" were naturally perceived as concerns associated with the technology, which reflected negative impacts on willingness to relocate. This may indicate that people were not willing to change their lifestyle unless these fundamental concerns were addressed. On the other hand, some other concerns were considered to be attitudinal or personal, including motion sickness or giving up full control to the vehicle; these did not show negative impacts on the model.

5.2.3. Ownership Type (Own, Rent, None)

To understand characteristics of households and persons which has more potential to adopt autonomous vehicles, a multinomial logit model is developed based on the survey. The dependent variable selected to be the respondent's response to following questions:

✓ *What would be your most preferred way to use AVs that can fully drive by themselves without your active control?*

- *Own (purchase or lease) AVs and use them only for personal use or use by family members*
- *Own (purchase or lease) an AV and earn extra income on the side by making it available to other drivers when not needed*
- *Own (purchase or lease) an AV and earn extra income on the side by providing rides for fellow passengers when you use it*
- *Rent an AV as the need arises*
- *Use AVs in the form of transportation (taxi, or public transit) provided by a service provider*
- *Neither interested in investing in an AV nor using AVs as a transportation service*

As can be seen, six options are available for respondent to select, three of them are using AV as owner, one of them are using AV as a rental system, one is using AV as a transit and one of them is for those who despite of all benefits, will decide not to adopt AVs ever. The responses were categorized into four main classes; own, use AV as rental, use AV as transit, and no adoption.

Initially, the hypothesis was nesting the responses and using a nested logit model. The responses were classified into two nests; adopters and non-adopters. Then two sub-nests of owning AV and using AV as a transit/rent system were defined under adopters. However, the developed nested logit model did not show reasonable results. Hence, authors decided to develop a multinomial logit model based on four response categories. Table 5-15 shows the model results.

Table 5-15. MNL Model for Autonomous Vehicle Ownership

Category	Parameter	Alternative	Estimate	t-test parameter
Alternative Specific Constant		1: Own AV	19.0140	0.006
		2: Rent AV	18.4350	0.006
		3: Use AV as transit	14.4170	0.004
		4: None	ref	ref
Individual Specific	Age: 18-20	1: Own AV	4.3990	1.876
		2: Rent AV	2.4450	1.090
		3: Use AV as transit	-3.2300	-0.001
	Age: 25-29	1: Own AV	1.6470	0.973
		2: Rent AV	1.9520	1.193
		3: Use AV as transit	10.7010	1.709
	Age: 30-34	1: Own AV	-2.2250	-1.306
		2: Rent AV	-1.1870	-0.791
		3: Use AV as transit	7.3750	1.211
	Age: Greater than 49	1: Own AV	2.6760	0.984
		2: Rent AV	3.9110	1.444
		3: Use AV as transit	21.0060	2.189
	Ethnicity: White	1: Own AV	2.6570	1.705
		2: Rent AV	1.2560	0.824
		3: Use AV as transit	1.1860	0.550
Household Characteristic	Vehicle Size	1: Own AV	1.3160	2.101
		2: Rent AV	0.2520	0.416
		3: Use AV as transit	-1.3470	-0.981
	25k < Annual Income ≤ 49k	1: Own AV	-1.3110	-0.711
		2: Rent AV	-0.6100	-0.382
		3: Use AV as transit	2.5110	0.899
	50k < Annual Income ≤ 74k	1: Own AV	-0.6690	-0.308
		2: Rent AV	0.0930	0.045
		3: Use AV as transit	-0.8670	-0.294
	75k < Annual Income ≤ 99k	1: Own AV	-1.7980	-0.919
		2: Rent AV	-1.3390	-0.720
		3: Use AV as transit	1.8680	0.634
	99k < Annual Income ≤124k	1: Own AV	16.7690	0.003
		2: Rent AV	15.3190	0.003

Category	Parameter	Alternative	Estimate	t-test parameter
		3: Use AV as transit	-5.4030	-0.001
	125k < Annual Income ≤ 149k	1: Own AV	16.1020	0.003
		2: Rent AV	18.7670	0.003
		3: Use AV as transit	-1.3400	0.000
	Number of Drivers	1: Own AV	-0.6330	-1.008
		2: Rent AV	-0.6390	-1.018
		3: Use AV as transit	-0.6320	-0.987
	Number of Disabled	1: Own AV	-0.0040	-0.168
		2: Rent AV	-0.0020	-0.107
		3: Use AV as transit	0.0030	0.056
	Household Type: Family Household	1: Own AV	-5.0040	-2.688
		2: Rent AV	-2.3720	-1.369
		3: Use AV as transit	-1.2630	-0.516
	Household Type: Unmarried Household	1: Own AV	18.4640	0.004
		2: Rent AV	20.0440	0.004
		3: Use AV as transit	1.4620	0.000
Individuals Commuting Characteristics	Number of Commuting Days: 5 per Week	1: Own AV	2.5290	1.840
		2: Rent AV	2.8120	2.171
		3: Use AV as transit	-0.6320	-0.307
	Commute Mode: Drive Alone	1: Own AV	0.9850	0.821
		2: Rent AV	2.0370	1.737
		3: Use AV as transit	-7.2840	-1.896
	One-way Commute Distance: 20-30 miles	1: Own AV	-2.2650	-1.033
		2: Rent AV	-7.0400	-2.834
		3: Use AV as transit	6.4520	1.329
	Average Time Spent for Parking: 5 to 10 minutes	1: Own AV	3.7450	2.412
		2: Rent AV	2.6000	1.802
		3: Use AV as transit	-2.6560	-0.900
Last Vehicle Transaction	Vehicle Price: $10,000 or Less	1: Own AV	-2.3940	-1.403
		2: Rent AV	-0.3730	-0.229
		3: Use AV as transit	0.7910	0.277
	Vehicle Price: $10,000 to $20,000	1: Own AV	-3.4120	-1.998
		2: Rent AV	-1.0560	-0.657
		3: Use AV as transit	-8.5940	-2.437
AV Perception	Familiarity with AV: Slightly Familiar	1: Own AV	1.1210	0.574
		2: Rent AV	2.4710	1.296
		3: Use AV as transit	-0.3350	-0.122

Category	Parameter	Alternative	Estimate	t-test parameter
	Familiarity with AV: Moderately Familiar	1: Own AV	1.4770	0.921
		2: Rent AV	1.4550	0.972
		3: Use AV as transit	5.4010	2.019
	AV Benefit: Fewer traffic crashes and increased roadway safety	1: Own AV	-0.4370	-0.280
		2: Rent AV	1.7600	1.204
		3: Use AV as transit	0.6220	0.292
	AV Benefit: Less stressful driving experience	1: Own AV	-1.0580	-0.671
		2: Rent AV	0.2700	0.181
		3: Use AV as transit	-2.8760	-1.322
	AV Concern: System/equipment failure or AV system hacking	1: Own AV	-19.6050	-0.006
		2: Rent AV	-19.0400	-0.006
		3: Use AV as transit	-16.6970	-0.005
	AV Concern: Giving up my control of the steering wheel to the vehicle	1: Own AV	2.4060	1.806
		2: Rent AV	-0.8820	-0.783
		3: Use AV as transit	2.5640	1.033
Goodness of fit measures		**Log-likelihood**	**-78.90**	
		McFadden R2	**0.50**	
		Chi-square test p-value	**4.381×10^{-7}**	
		Number of observations	**146**	

As mentioned before, the developed model considers four option, the reference option which is not adopting AV, the three other options are using AV by owning, using as a rental system as needed and using as a transit system. A total of 146 successful responses were collected for the dependent variable question. The model fitting procedure was performed using R statistical software. Several try and errors were done to select a model with highest McFadden R^2 goodness of fit measure. The R^2 of 0.50 is an acceptable value in comparison with other similar studies, and the Chi-square test p-value shows that the fitted model is significantly different than full model.

Based on the model, age has an important effect on adoption decision and how to use AVs. According to this study, people in age group of 18-20 will more probably decide to own AVs, while the older the age group becomes, responses show to support using AV as a transit system. This finding is in accordance with literature since several other studies mentioned that young generation, if able to afford, would be the first adopters (Menon, 2015). This should be noted that studies on similar concepts, such as using cellphone applications for ridesourcing, also showed the same results. Based on Kang et al. (2016), carsharing programs are more popular in the young generation which are actually internet and smartphone generation, which was also supported by Chen (2015) study in Pittsburg. Results of this part was supported in the Rayle et al. (2015) study in San Francisco and Smith (2016) who found ridesourcing users are generally younger and also better educated than average population. This finding supports the willingness to pay model results in this study also, which based on that the younger age groups are more willing to pay for new technologies, such as AV. Another significant individual attribute is ethnicity. Based on the results, people with white ethnicity are more willing to own AVs in compare with using AV as a rental system/transit or not using AVs at all. This should be noted that from a total of 146 respondents, only 30 of them are not white or Hispanic. Hence, no conclusion can be made for other ethnicities. Also the study by FSU (2013) supports the finding about willingness to own instead of sharing AVs in Florida.

In regards with household characteristics, the vehicle size and household type show to be important in making decision about the way of using AVs. Based on the model result, households with higher number of vehicles tend to own AVs, in compare with using this technology as a rental car, transit system or not using AVs. Generally, households with higher number of vehicles may also generate more trips, and families with higher number of trips normally will be impacted more by traffic congestion and related issues. Also these families are related to higher level of income category and tend to adopt to this technology sooner. However, the probability of using AV as a transit system is less than the probability of not adopting AV for higher vehicle size households. This means families with high number of vehicles either will own AVs, or will use their conventional vehicle, and do not take AV as a transit system. This is reasonable since such families are not normally transit users, because of having enough vehicles at home, and their tendency for using mass transit is low. The finding of this study regarding effect of household size on AV adoption is similar to several studies regarding impact of vehicle size on adopting car-sharing programs. According to Katzev (2003), it was shown that people who does not own private vehicles are more likely to join shared mobility programs. Similar finding was reported in Nurul Habib (2012) which mentioned people living in zones with higher level of auto ownership will not tend to be member of car sharing programs for a long period, and also Smith (2016) which reported frequent ridesourcing users are less likely to own a car in comparison with other Americans. In general, it can be concluded the households with low vehicle size may join AV sharing programs while households with higher number of vehicles may decide to purchase and own AVs. Unexpectedly, the income variable did not show to be statistically significant, and we cannot conclude any special behavior from this model about impact of household annual income on AV adoption. However, the coefficient signs for households with less than 99k annual income is negative for owning AVs alternative, while the coefficient sign for this alternative for income groups of greater than

124k a year is positive. Another household characteristics which is significant in selecting the preferred method of using AVs is household type. Family households generally did not show to be interested in using AVs at all.

Analysis of commuting characteristics showed those with high number of commuting days are highly probable to own AVs or rent them in comparison with not using or using AVs as a transit system. This is acceptable because those individuals with high number of trips will feel the hardness of driving task more than people with few driving hours a week, so they would like to transfer the driving task burden to their computers and be more productive in their vehicles. This result is similar for those commuters which drive to destination alone. Commuters which drive relatively long distance, i.e. 20-30 miles to destination are significantly prefer not to rent AVs. A study on the characteristics of people which use sharing programs showed the finding of this study is in accordance with general literature. Chen (2015) found average trip length for commute trips performed by Uber or Lyft in Pittsburg area in 3.5 miles. Interestingly, Rayle et al. (2015) found the average trip length for ridesourcing users in San Francisco area is 3.2 miles, which is very close to Chen (2015). These findings can result to the conclusion that people which are closer to their destination may use AV sharing programs more than people with long commuting distance. The average time spent to find a parking spot and perform the maneuver also was shown to be important variable in AV adoption. Those with time spent for parking of less than 10 minutes, which can be called as short or medium parking seeking time especially in morning periods, showed to be willing to own or rent AV while those with higher time spent showed most likely they prefer to use AV as a transit system. These finding seems logical because for those with bad experience on seeking for a parking lot, taking a transit service and freeing 10 minutes and more of their time budget is significant.

The perception and understanding about autonomous vehicles will also play an important role in adopting AVs and how to use them. However except the people with concern of giving up their control of steering wheel to a computer while using AVs, other attributes did not show to be statistically significant. Considering the concerns, people which are afraid of system hacking and network failure are less probable to adopt and use AVs which seems reasonable. Generally, the conservative people will not adopt new technologies at very first stages, they will wait for other people to use the technology and make sure there is no problem associated with computers taking control of vehicles instead of humans.

5.3. Conclusions

The survey captured socio-economic characteristics of respondents first, and then asked questions to understand user's perceptions regarding autonomous vehicles and how AVs will change trip characteristics and travel behavior. Below, a summary of the survey findings is listed:

- ✓ *Currently, 60-70% of trips are done while driving alone and 17% of trips to school involved drop-offs.*
- ✓ *The majority of people lived 5-15 miles from school, and they preferred to drive 3 miles or less for grocery-related trips. This showed that travel time was an important issue for grocery trips and people were likely to choose the closest store.*

Interestingly, the survey revealed that AVs may facilitate longer grocery-related trips due to the reduced burden.

- ✓ *More than half of the respondent were familiar with AVs, but very few were totally unfamiliar or had never heard about them.*
- ✓ *A total of 12% of respondents mentioned they would not consider using AV under any circumstance. This agrees with the market penetration model developed in this study, which estimated that 13% of US households will never adopt AVs. This reasoning for these people never electing to use AVs varies from the loss of the pleasure of driving to a lack of confidence in the technology.*
- ✓ *The most common expectations stemming from AVs were less traffic crashes and less stressful driving. Although several studies have stated that AVs will dramatically reduce traffic congestions, 24% of respondents did not agree. The fear of system failure and hacking was the greatest concern.*
- ✓ *According to survey results, there was not a considerable difference between trip purposes for which people were willing to use AVs. Respondents showed similar interest in using AVs for various trip purposes including grocery trips, commuting to school, and commuting to work. The interest to use AVs for leisure trips was slightly less when compared to other trips; this may indicate that some respondents enjoy driving which enhances the quality of leisure trips.*
- ✓ *Among respondents that were eager to use AVs, 75% preferred to own AVs while 20% found them more attractive as a rental car or taxi. This is important as several car sharing companies believe that once AVs are available, people will see the*

benefits of shared vehicles on traffic and congestion which will increase the interest further.

- ✓ *20% of AV users mentioned they were going to be alert and watch the road while in an AV, 17% said they would relax, and 10% would engage in more productive activities.*
- ✓ *Regarding vehicle size, 66% of participants mentioned they would not change the size of their vehicle, but the majority was interested in having a larger one. This is reasonable because the increased size would facilitate the driver/rider to perform other tasks while the vehicle is in motion.*
- ✓ *The hypothesis that people would select further residential locations was supported by the responses. It was noted that the majority of prospective AV users were willing to live further. Also the hypothesis that people will select further destinations was supported by the survey. According to the responses, AV users were likely to accept driving up to 15 miles for their grocery trips. It should be noted that this change was only applied to households which would adopt AVs.*

This section also presented the results of an effort to examine consumers' attitudes towards AV market penetration. In particular, two major dimensions were explored: the willingness to pay and willingness to relocate in relation to AV adoption. Based on a survey conducted at the Florida International University in Miami, Florida, two ordered logit models were developed and analyzed.

The models revealed significant impacts of individual attributes, household structure, daily commute characteristics, and consumers' perceptions of benefits/concerns on both willingness to pay and relocate. In particular, results showed higher WTP values for young males (less than 30 years old) and long distance commuters. Crash experience generally decreased the willingness to pay for driverless cars. Among respondents with crash experiences, two types of respondents showed higher willingness to pay: those who were involved in major incapacitating injuries and those who had experienced travelling in the at-fault driver's vehicle. As expected, respondents who recently purchased a new vehicle were less likely to pay high values for AVs. Benefits such as more travel time productivity and lower vehicle emissions showed significant positive contributions to willingness to pay while loss in driving skills was a barrier towards willingness to pay. People with moderate familiarity showed the lowest willingness to pay, which shows the importance of education on AV technologies.

In terms of the likelihood to relocate, results showed higher willingness to relocate for males, low income households, and carpool drivers. On the contrary, household size and number of drivers in the family had a negative impact on the model. Among the benefits, traffic-related advantages such as lower congestion, fewer crashes and positive environmental impacts increased individuals' willingness to relocate. In terms of concerns, vehicle safety and data privacy were among the major discouraging factors.

The preferred method of using AVs showed that young generation prefer to own AVs versus middle age group which prefer using AVs as a transit system. Also the model results showed individuals with white ethnicity rather owning AVs than renting or using it as a transit. Regarding the household size, it was shown that families with higher number of people prefer to use AVs by owning. Although the result of this study did not show any significant impact of income on the preferred way, but the coefficient sign shows households with income less than 99k per year prefer other methods than owning AVs, while households with higher level of incomes prefer owning AVs. Considering the trip characteristics, those with high number of commuting days (five times a week) showed to be interested in owning AVs or renting rather than using them as a transit system. Individuals which normally commute to destination using drive alone mode, preferred owning while individuals which their own way distance to school was 20-30 miles preferred to use AVs a transit.

The results of this study were subject to a number of limitations. Data limitation is probably the most important shortcoming of this study. First, the sample size was relatively small (144 observations) which limits the generality of the inferences. Second, the sample is limited to university students and employees which may also bias the results.

CHAPTER 6. SIMULATION RESULTS

As mentioned in the methodology section, final part of this study is dedicated to perform a case study on the implications of AVs on a real transportation demand model and network. Next part discusses the assumptions which have been made for this case study. Most of the assumptions are either based on previous studies which have been mentioned in the literature review, or based on the results from survey which was conducted in this study. The main objective is to assume different scenarios based on previous studies and what was learned in the market penetration and survey results of this study and see how a real network will change. This should be considered that this study does not claim all the assumptions are correct and will happen for sure, however according to this study, they occurrence is very probable. This assumptions are working hypotheses, not general hypotheses.

6.1. Hypotheses Assumptions

The inputs which were manipulated in each scenario are as follows:

Population relocation: According to several studies, AVs will provide easier access to further locations without changing the existing accessibilities. Due to this, people can access further destinations with reduced travel times when compared to the existing condition. Several speculations have predicted that a portion of AV adopters will decide to live in further locations, to access a better environment and less populated areas, and cities would be more scattered. Bhat and Pendyala (2014) suggested a reduced disutility of travel time and distance (due to more productive usage of travel time) would lead to accessing more desirable and higher paying jobs, attending better schools/colleges, visiting further destinations, and overall changes in urban/regional development patterns. Also according to Kim et al. (2015), the presence of AVs would lead to a much more disperse and scattered urban growth pattern in the next five decades. To apply the population relocation in SERPM 7.0 model, the developed willingness to relocate models were incorporated into the existing household/person files, which were the main inputs of the SERPM 7.0 model. From that, the utility of each household to adopt AVs and relocate was estimated and according to the market penetration, households were selected to relocate for each scenario. It should be noticed that several other long-term choices in an activity based models are dependent on residential location choices, including school and job location.

SERPM 7.0 works with 4,200 Traffic Analysis Zones (TAZs) for highway skims and assignment, however transit calculations are based on a more detailed system of geographic zones named as Micro-Analysis Zones (MAZs). The inputs for SERPM were person files, household files, and MAZ summary files which were outputs of population synthesizer.

All TAZs were classified into low-density, medium-density and high-density based on TAZ population density indices which were calculated using Equation 6-1:

$$\boldsymbol{h = TAZ\ Density\ Index = \frac{Number\ of\ Households\ in\ TAZ}{TAZ\ Net\ area}} \qquad 6\text{-}1$$

The following rules is used to classify TAZs:

- ✓ *If h<500, TAZ will be classified as low-density TAZ*
- ✓ *If 500≤h≤1,500, TAZ will be classified as medium-density TAZ*

✓ *If h>1,500, TAZ will be classified as high-density TAZ*

Thresholds of 500 and 1,500 were defined after trying various thresholds to balance the number of high-density and low-density TAZs while maintaining 50% of the TAZs as medium-density TAZs.

For each high-density TAZ, a program which was scripted using ArcGis, Microsoft Server SQL and Visual Basic, sought a low-density TAZ approximately 10 miles from TAZ centroid. Only one low-density TAZ was assigned to each high-density TAZ. The distance of 10 miles was selected based on the survey. According to the question mentioned before, respondents commonly live an average distance of 3-20 miles away from their workplace. However if these people adopt AV, the majority of them will be living 5-30 miles away from the current destination. On average, this results in a 6-mile relocation. However, a six mile relocation could not change the model considerably so the relocation distance of 10 miles was selected instead. Figure 6-1 shows a frequency histogram of responses related to relocating.

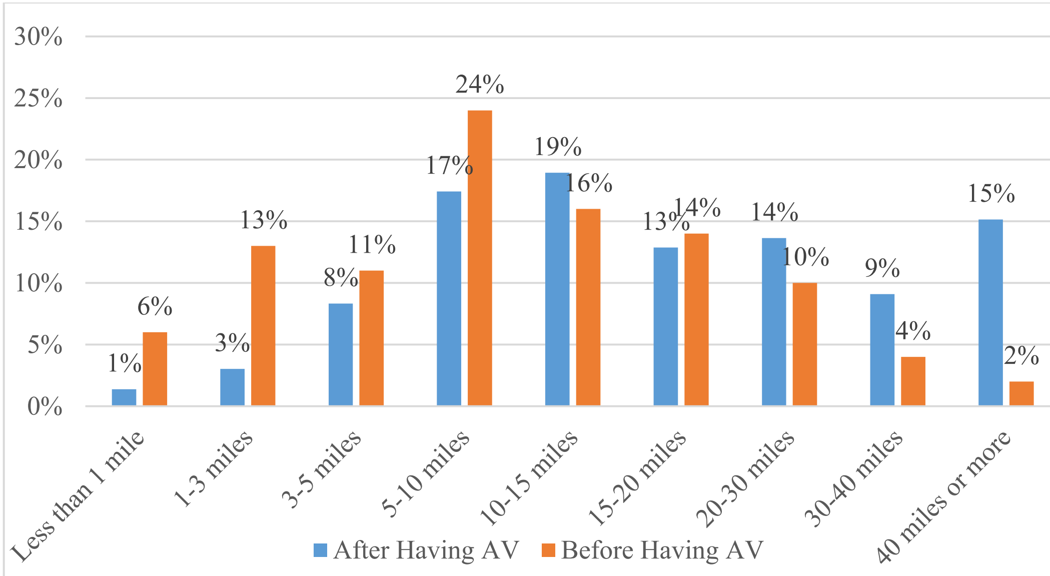


Figure 6-1. Current Commuting Distance and Desired Commuting Distance after Adopting AV

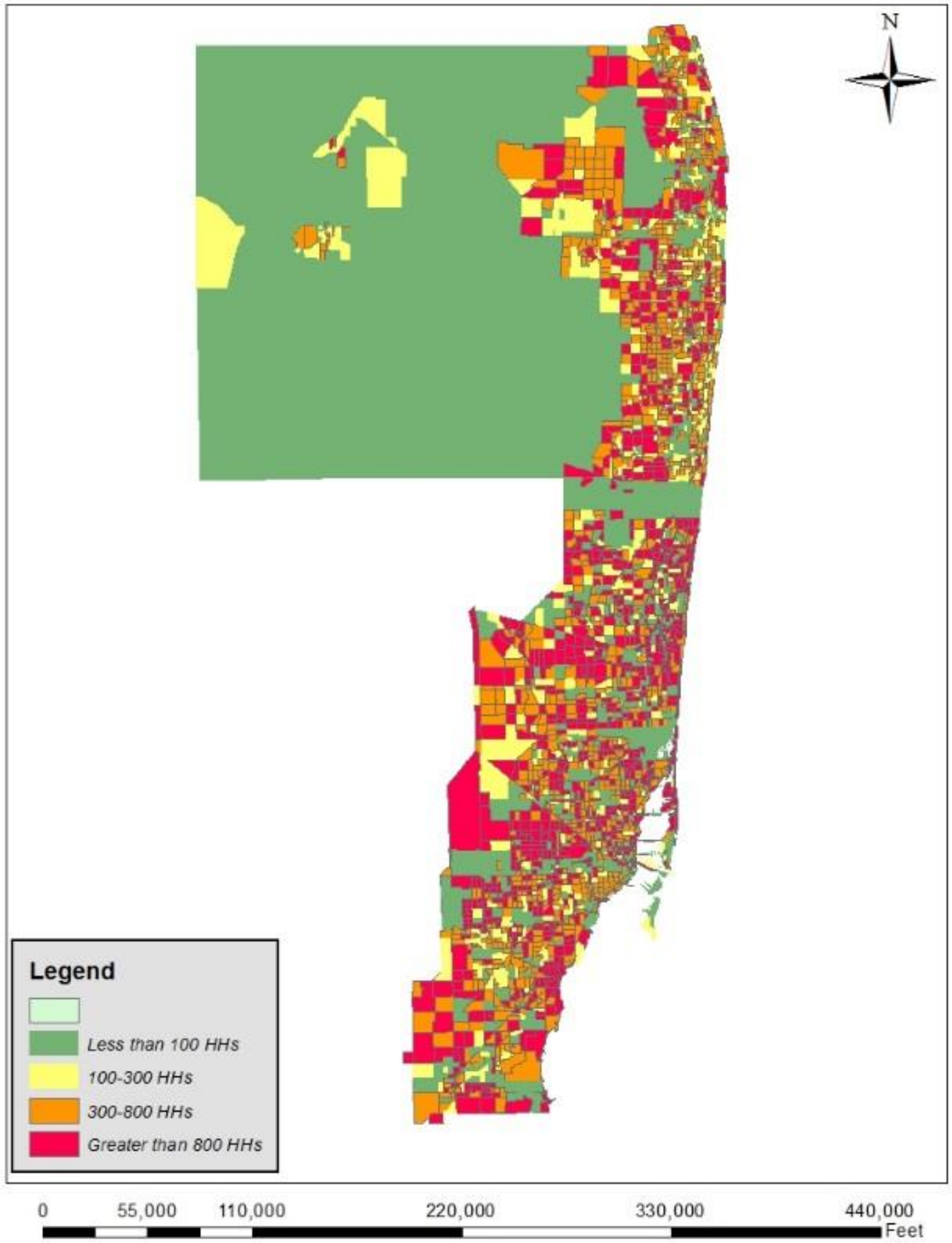
Another program explored the household file. In this program, if the household is living in one of the high-density TAZs and the utility of moving out if it was higher, the household was chosen to relocated. If the utility of moving out of the high-density TAZ was not higher, the household did not relocate. The number of households which decided to move was limited for each scenario to relocation population. The relocating population was calculated using Equation 6-2:

$$\boldsymbol{relocating\ population} = \boldsymbol{i} \times \boldsymbol{p} \qquad 6\text{-}2$$

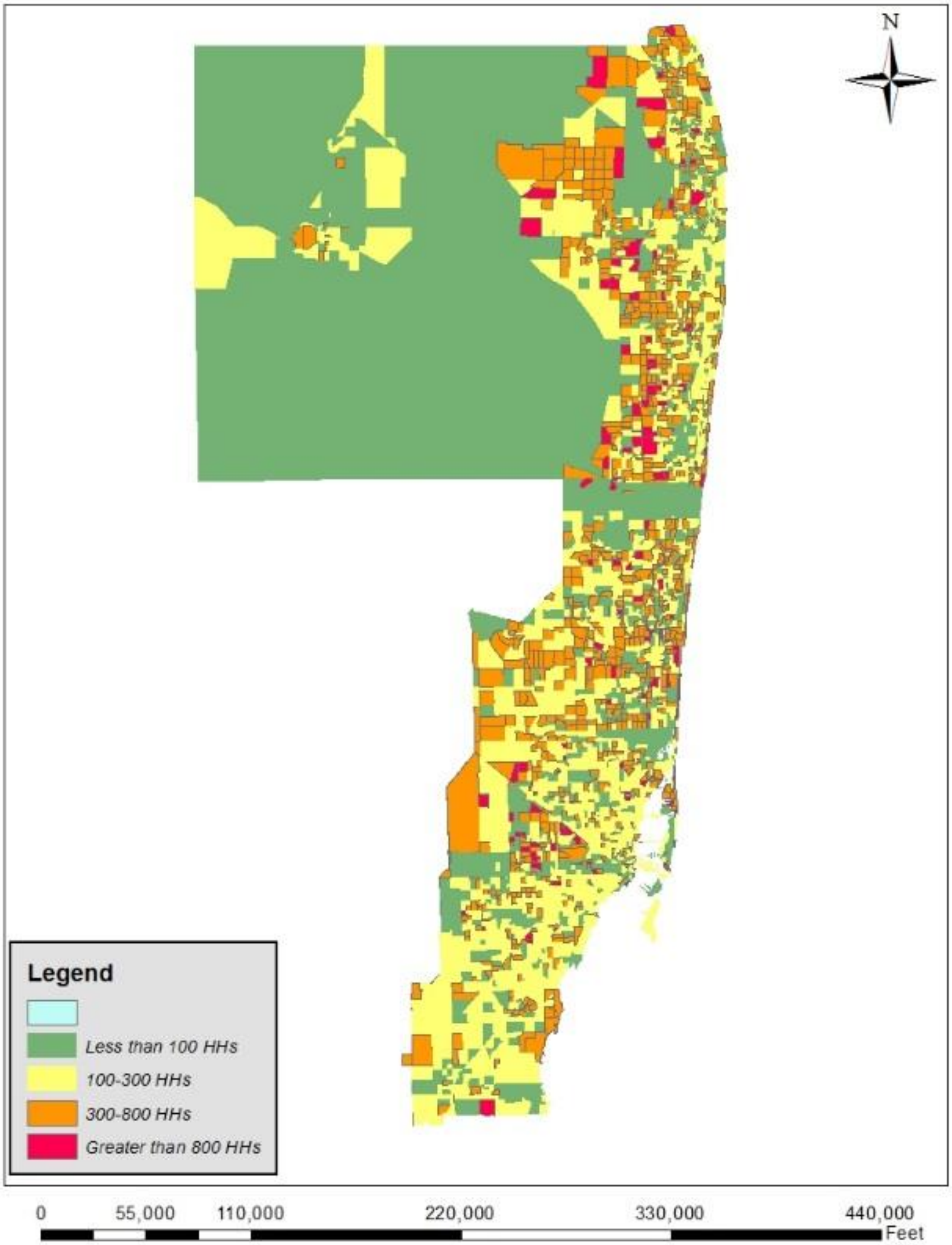
where,

i = Relocation rate
p = Number of households

Figure 6-2 shows how population relocation is affecting the distribution of population in the network.



HH distribution in 2010



Hypothetical HH Distribution in 2055

Figure 6-2. Population Distribution for Existing Condition and Long-term Scenario

Network capacity and speed: Another important factor which is supposed to change after the emergence of AVs is network capacity and speed. Based on the literature, the network capacity may triple. Also, ideal platooning of vehicles can affect the network speed. In this study, adjustments were applied to the SERPM network and are shown in Table 6-1. These adjustments were borrowed from Macmurphy and Gramah (2015) which used the same table for a similar purpose. These capacities are classified based on Facility Types (FTs). FTs refer to facility types in the SERPM model and were as follows: Freeway (10), Uninterrupted Roadway (20), Higher speed interrupted facility (40), Centroid connectors (50), Lower Speed and Collector Facility (60), Ramps (70), HOV Lanes (80), Toll Roads (90).

Table 6-1. Capacity Adjustment Applied for Study Scenarios

Scenario	**Market Penetrating**		**FT**							
	Year	AV Proportion (%)	10	20	40	50	60	70	80	90
Short-term	2035	7	1	1	1	1	1	1	1	1
Mid-term	2045	61	1.33	1.15	1.03	1	1.15	1	1.33	1.33
Long-term	2055	74	1.7	1.26	1.06	1	1.26	1	1.7	1.7

To adjust links' free flow speed, Table 6-2 as suggested by Kim et al. (2015), was used:

Table 6-2. Free-flow Speed Adjustment Applied for Study Scenarios (Kim et al. 2015)

Scenario	**Market Penetrating**		**Road Type**	
	Year	AV Proportion (%)	National Highways	Express Ways
Short-term	2035	7	1.01	1.02
Mid-term	2045	61	1.18	1.27
Long-term	2055	74	1.23	1.37

Speed adjustment values are based on Yokota et al. (1998) work. They assumed that travel time will be reduced based on a target headway of 0.5 seconds in national highways and express ways when AVs emerged.

Parking Cost: Another factor which will be manipulated in this study is parking cost. As it was enlightened in the literature review section, AV technologies can relief the pressure of constructing parking lot for every building to place residents or visitors vehicles. By reduced demand in the parking, the parking price will considerably dropped in the downtown areas. The hypothesis is that in the final market saturation, the parking price will be reduced by 100%, and again obeying the market penetration curve, the reduction on parking cost for short-term and mid-term can be estimated.

Table 6-3. Parking Cost Adjustment Applied for Study Scenarios

Scenario	**Market Penetrating**		**Parking Cost (% reduction)**
	Year	AV Proportion (%)	
Existing condition	2016	0	0
Short-term	2035	7	10
Mid-term	2045	61	82
Long-term	2055	74	100

Value of Travel Time: The final factor which will be changed in the network is the Value of Travel Time. VOT is an important factor which will affect several trip/tour related behaviors. Speculations support the idea that the cost of driving will decrease in the AV era. For this study, VOT was changed based on the work done by Childress et al. (2015), which assumed that VOT would be reduced by 35% for higher income groups; the same reduction was applied in this study. However, since SERPM, does not consider different VOTs for various income levels, the VOT reduction was applied to the whole population. The existing VOT for SERPM 7.0 was $12.65/hour and was reduced by 35% in 2065. Then a linear interpolation was applied to estimate short-term and mid-term VOTs. The results of this are shown in Table 6-4.

Table 6-4. VOT Adjustment Applied for Study Scenarios

Scenario	Market Penetrating		VOT ($/hr)
	Year	AV Proportion (%)	
Existing condition	2016	0	12.65
Short-term	2035	7	11.18
Mid-term	2045	61	9.7
Long-term	2055	74	8.22

This study attempted to consider several implications of AVs, however there were some limitations. One of the limitations of this study was that it disregarded Shared Demand-responsive Autonomous Vehicles (SAVs) which will possibly be one of the scenarios that occurs in the short-term. The other limitation was that the new trips generated by those who previously were unable to drive were not considered.

6.2. Simulation Results

The determined scenarios were applied in Cube's software and the results were extracted. In order to compare how the AVs will affect the network, several network performance measures were included. The selected performance measures were Vehicle Miels Travelled (VMT), Volume over Capacity ratio (V/C), Network average speed, and number of tours; the distance and time by transportation mode were also explored. As the PM Peak period is the most critical time of day, all performance measures were calculated for this time period. Also to study how AV is affecting network, regardless of population growth, the no build condition is also analyzed. No build conditions means non of the mentioned AV implications are considered in the future year run, and only populaition growth is applied. The model outputs for the existing condition, short-term, mid-term and long-term scenarios can be seen in Table 6-5.

Table 6-5. Model Results for Different Scenarios

Scenarios	Performance Measure	VMT	V/C	Network Speed (mph)
Base (2016)	No Build	34,668,934	0.43	28.36
	Build	35,249,427	0.43	28.97
Short-term (2035)	No Build	41,437,477	0.55	28.42
	Build	42,692,109	0.54	29.78
Mid-term (2045)	No Build	42,420,326	0.61	28.37
	Build	44,377,956	0.53	33.66
Long-term (2055)	No Build	44,219,784	0.65	28.94
	Build	46,792,156	0.51	36.17

As expected, increasing the share of AVs resulted in an increase in vehicle miles travelled (VMT). The potential of AVs to increase in VMT was also reported in previous studies (Fagnant and Kockelman, 2015; Childress et al., 2015; Bierstedt et al., 2014). In previous studies the VMT increased from 5% in the short-term to 35% in high market penetration which agrees with the increase reported in this study. According to Fagnant and Kockelman (2015), enabling more users to create trips, such as young children, has the potential to increase VMT dramatically. However, the increased capacity obtained from AV features, such as platooning and congestion mitigating features, can help to mitigate the impact of the increasing demand. However, this should be noted that a part of this increase is due to population growth. The VMT for build condition, shows an annual growth of 1.11% between 2016 and 2035, while this growth reduces to 0.39% between 2035 and 2045 and 0.54% between 2045 and 2055. VMT is a network performance parameter which is estimated by multiplying the volume of vehicles in the network (PM peak period in this study) by distances. Since the distance is constant between scenarios, the main reason of difference is rooted in variations in the network volume. For no build condition, the same trend of increase in VMT is also observed. Further analysis of tours and trips will reveal more information on how differently travelers are moving in the network and can help interpreting these results.

One concern about increased capacity in network highways, is the increase in VMT which may result in higher congestion and lower speeds in comparison with existing condition. For instance, Levin and Boyles (2015) analyzed implication of AVs using a four-step modeling, and concluded that the total number of trips will be increased by 271%, which resulted in a slight decrease in network speed. However, other studies such as Childress et al. (2015), forecasted and increase in VMT and speed; this trend was noted in this study. Despite the increased VMT, the average network speed increased by nearly 1 mph and 5 mph for the short-term and mid-term scenario. It should be considered that this speed increase is attributed to an increase in capacity and free-flow speed. However, after a considerable share of transportation fleet is comprised of AVs, other benefits such as less crashes may also contribute to increasing the average network speed. The analysis of no build conditions showed network speed increase is solely due to increase in capacity and link's free flow speed which are because of AV technology.

PM period volume over capacity (v/c) showed a considerable increase for the short-term scenario, but no change between the mid-term and short-term scenario. Volume over capacity ratio is an important measure of effectiveness. The increase in volume to capacity ratio is mainly due to an increase in number of trips compared to capacity improvements. The study of non-AV scenarios shows that V/C ratio should increase considerably between 2016 and 2055 to 0.65, however emergence of AVs can help even reducing this measure of performance, resulting in a better operating network. The capacity improvement between the short-term and base scenario was zero, while this capacity showed a considerable increase from the short-term to mid-term scenario. Simply, in spite of no change in the capacity between the short-term and base scenario, the increase in number of trips (because of higher speed and a more scattered network) resulted in an increase in v/c ratio. From the short-term to mid-term scenario, both volume and capacity simultaneously increased which resulted in an insignificant change in v/c ratio. This is an important finding, especially for the short-term adoption of AVs. Policy makers should expect AVs to contribute a considerable number of new trips to the network even with very low market penetration. Adjusting infrastructure to the mixture of automated and conventional vehicles during this time may not be feasible and as such the network capacity may suffer. This may result in a considerable increase in traffic density in several corridors, which should be considered.

Table 6-6 summarizes the number of work purpose tours for each mode for build and no build scenarios which are also shown in Figure 6-3. Table 6-7 and Figure 6-4 show similar results for non-mandatory tours. It should be noted that “shared ride” in these tables refers to joint trips of household members rather than ride-sharing systems such as ZipCar or Uber.

Looking into the tables and figures, it can be found the AV technology cannot affect the number of mandatory tours, while the number of non-mandatory tours are increased. Based on the results, in average, AV emergence will result in 11% increase in number of non-mandatory tours. This trend is reasonable, AV should not affect the number of work tours because none of the inputs which were changed in this study are effective in changing people's work, however because the driving task in getting cheaper and more speed and capacity are provided in the network, people are more encouraged to perform non-mandatory trips.

Modal analysis shows that in general, the attractiveness of transit system is increased in the short-term, however in mid-term and long-term people decided to go back to using their private cars again. This was expected because in short-term, people are facing higher congestion because of increased VMT but there is not sensible network improvement, so people decide to use mass transit system. However in long-term the reduced driving cost will encourage people to use personal vehicles instead of transit. Lower VOTs as well as higher speed and capacity in major freeways and highways will provide better service for vehicle users, which will reduce the attractiveness of using mass transit. The analysis of no build conditions supports this idea. As can be seen, mass transit mode share is not changing between 2016 and 2055 considerably (for no build condition), while it increases for short-term of build scenario and then decrease considerably. Also, similar pattern was observed for both trip purposes of work and non-mandatory trips.

Considering driving modes, the largest increase due to emergence of AVs was seen in the Drive Alone mode in comparison with shared modes with one or two passengers, after changes were incorporated into the model. For work purpose trips, number of drive alone tours increased 44% for build scenario between existing condition and long-term while this increase is expected to be 37% for no build condition. This change is even greater for non-mandatory trips, 50% for build scenario versus 28% for no build scenario. This was also expected since the Value of Travel Time and the general trip costs would simultaneously decrease. When combined, these two factors will tend to increase the probability of selecting the drive alone mode. Considering no change in the number of total work purpose tours between build and no build scenario, this means 18% increase in using drive alone mode only due to easier and cheaper driving task (and not because of population growth) can be expected. However, as previously mentioned, one of the limitations of this study is that the system-wide sharing opportunities, a popular facet of AV adoption, was not considered.

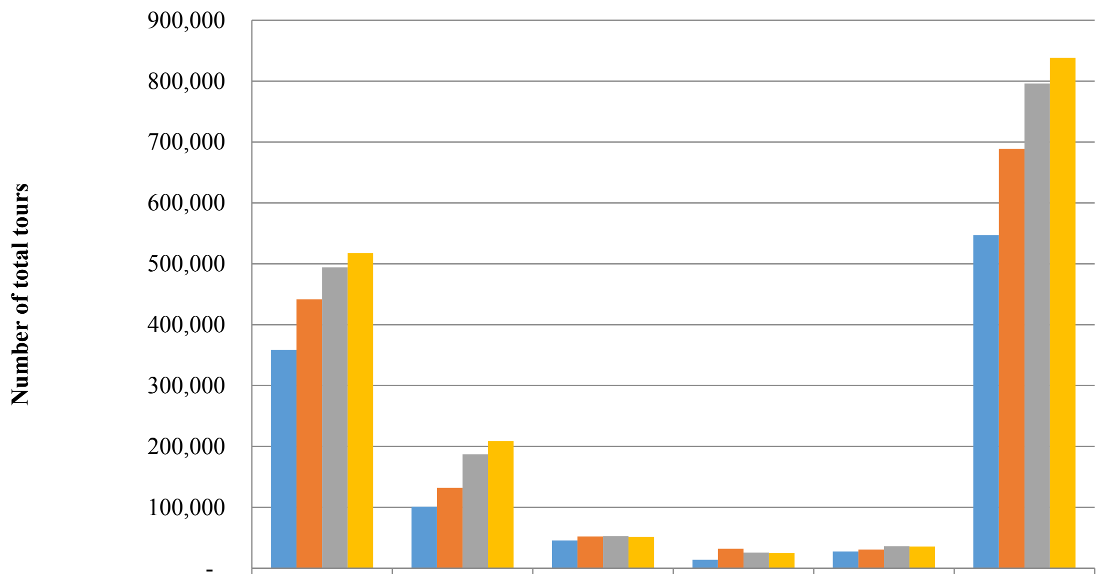
Table 6-6. Model Results for Work Purpose Tours

BUILD

TOUR MODE	Base scenario (2016)	Short-term (2035)	Mid-term (2045)	Long-term (2055)
DRIVE ALONE	358,763	441,614	494,228	517,634
SHARED 2	101,194	132,180	187,271	208,781
SHARED 3	45,672	52,284	52,633	51,347
NON-MOTORIZED	13,893	32,022	25,749	24,976
TRANSIT	27,499	30,798	36,306	35,716
TOTAL	547,021	688,898	796,187	838,454

NO BUILD

TOUR MODE	Base scenario (2016)	Short-term (2035)	Mid-term (2045)	Long-term (2055)
DRIVE ALONE	368,532	444,945	496,314	504,348
SHARED 2	97,746	129,479	165,921	197,634
SHARED 3	39,689	51,647	58,479	65,493
NON-MOTORIZED	12,987	32,714	41,359	48,883
TRANSIT	25,436	29,499	31,497	31,072
TOTAL	544,390	688,284	793,570	847,430

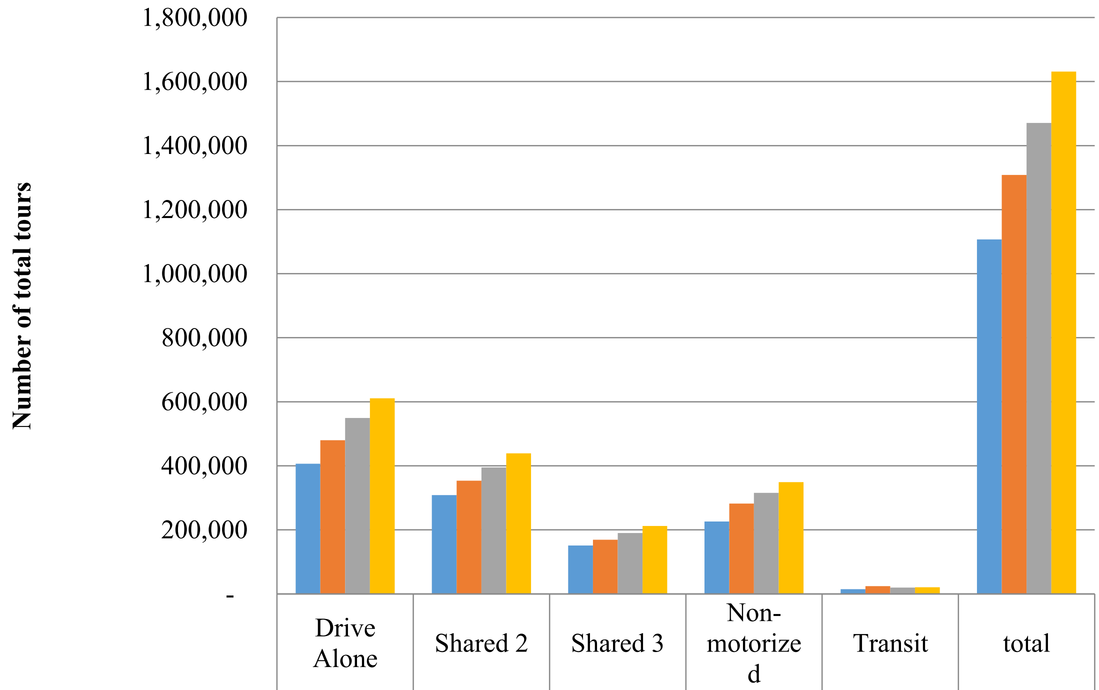


	Drive Alone	Shared 2	Shared 3	Non-motorized	Transit	total
Base scenario (2016)	358,763	101,194	45,672	13,893	27,499	547,021
Short-term (2035)	441,614	132,180	52,284	32,022	30,798	688,898
Mid-term (2045)	494,228	187,271	52,633	25,749	36,306	796,187
Long-term (2055)	517,634	208,781	51,347	24,976	35,716	838,454

Figure 6-3. Number of Work Purpose Tours by Mode

Table 6-7. Model Results for Non-Mandatory Purpose Tours

	BUILD			
TOUR MODE	Base scenario (2016)	Short-term (2035)	Mid-term (2045)	Long-term (2055)
DRIVE ALONE	406,300	479,855	549,276	610,596
SHARED 2	308,429	353,692	395,242	438,761
SHARED 3	150,971	168,954	190,296	212,015
NON-MOTORIZED	226,080	281,911	315,768	349,170
TRANSIT	15,021	24,160	20,003	20,562
TOTAL	1,106,801	1,308,572	1,470,586	1,631,104
	NO BUILD			
TOUR MODE	Base scenario (2016)	Short-term (2035)	Mid-term (2045)	Long-term (2055)
DRIVE ALONE	395,876	415,356	444,817	506,243
SHARED 2	270,882	294,681	346,017	409,730
SHARED 3	133,202	164,019	181,648	197,633
NON-MOTORIZED	210,849	283,515	297,476	318,524
TRANSIT	12,946	20,144	24,157	26,411
TOTAL	1,023,755	1,177,715	1,294,115	1,458,541



	Drive Alone	Shared 2	Shared 3	Non-motorized	Transit	total
Base scenario (2016)	406,300	308,429	150,971	226,080	15,021	1,106,801
Short-term (2035)	479,855	353,692	168,954	281,911	24,160	1,308,572
Mid-term (2045)	549,276	395,242	190,296	315,768	20,003	1,470,586
Long-term (2055)	610,596	438,761	212,015	349,170	20,562	1,631,104

Figure 6-4. Number of Non-Mandatory Purpose Tours by Mode

CHAPTER 7. CONCLUSION AND FURTHER STUDY

7.1. Summary and Conclusion

Several speculations by experts showed that AVs will affect many aspects of life, but their impact on the transportation system and people's lives may not be realized until AVs are fully functional. Putting the technological aspect aside, there are still several barriers which should be addressed before AVs can be employed including legal certifications as well as the details of liability and insurance. However, a general study on the implications of AVs is required before AVs begin operating on the roads so that planners and decisions makers can circumvent potential issues. This dissertation provided a comprehensive study on the implications of autonomous vehicles and their adoption.

A comprehensive review of the literature provided valuable information regarding AV market penetration and their implications. According to hypotheses, simulation-based studies, and surveys, AVs will have long-term, mid-term, and short-term effects on society. Regarding long-term implications, predictions are supporting a complete change in land use patterns. Studies forecast more scattered cities will be seen in 50 years due to the fact that people will be able to reach destinations easier with AVs. A considerable change in CBD land use patterns will also happen by removing parking demand once vehicles are able to drop passengers and then park outside the CBD or proceed to provide service to another user.

Mid-term implications of AVs are mostly related to financial issues and mode choice. According to hypotheses, vehicle ownership models may change after AVs are released. Some predictions even moved further and mentioned that the whole ownership procedure will be replaced by vehicle sharing systems. The future cities hypothesized by this school of thought will see the elimination of traditional public transit systems and the switch from vehicle ownership to vehicle sharing facilitated through smartphones. Other hypotheses mention that although AVs will be a very popular, but there will be some people which will never relinquish control of their vehicles to computers. Almost all of the past surveys showed that a small portion, approximately 15%, of people will not purchase or use AVs even if they can afford. Another aspect of transportation which will be affected by AVs in mid-term is energy consumption and environmental issues. Studies predicted that vehicle platooning can help reduce fuel consumption and harmful emissions.

In the short-term also AVs will affect transportation network, mostly by providing more capacity and a safer network with lower travel times. The new technology will provide shorter headways between vehicles since they will be able to communicate. This communication between vehicles will allow them to sense each other's maneuvers, which will enhance network capacity considerably. Several surveys also showed that people expected safer roads due to the elimination of human error. Although there are several concerns regarding system failure and hacking issues, the majority of people showed interest in using AVs which will result in a safer transportation network with higher average speed and consequently more reliable travel times.

A portion of the literature has focused on the market penetration of autonomous vehicles. These studies were mostly based on the previous adoption trends of other similar technologies or surveys of people and experts. Different results can be extracted from market penetration analyses, but most studies supported the idea that AV adoption will occur in the next 30 to 60 years. When considering all of these studies one common conclusion can be drawn. Initially, very few people will be able to afford AVs, but within several years the adoption rate will increase considerably. According to these studies, decision makers should be ready for smart and driverless cities by 2050.

In a portion of this study, a survey was conducted amongst Florida International University students to understand the existing travel behavior and perception regarding AV, as well as their reaction toward this technology. According to the survey, more than half of the respondent were familiar with AVs, and few had never heard about or were completely unfamiliar with the technology. A total of 12% of respondent mentioned they did not see themselves using AV under any circumstance. This agreed with the market penetration model developed in this study, which estimated that full market penetration would occur at 87% of US households. It it hypothesized that the portion of people who would never use AVs found pleasure in driving or did not trust the technology. It was also concluded that the most common expectation was less crashes and less stressful driving. Although several studies have stated AVs will dramatically reduce traffic congestion, 24% of respondents in this survey disagreed. Similar to other studies, the biggest concern of respondents was the fear of system failures and hacking.

According to the survey results, there was not a considerable difference between trip purposes for which people were willingness to use AVs. By this, people displayed similar interest in using AV for various trips purposes including grocery trips, commuting to school, and commuting to work. The desire to use AVs for leisure trips was slightly less when compared to other trips, which may suggest that respondents found pleasure in driving and that driving may enhance the trip's quality. Among respondents that were eager to use AV, 75% would rather to own while 20% preferred to use AVs as rentals/taxies. It should be noted that several car sharing companies believe when AVs become available and people witness implications of a ride-sharing system on traffic and congestion, they will be attracted to ride-sharing systems even more.

The hypothesis that people will select further residential locations was also supported by the respondents. Based on the survey results, it was seen that the majority of prospective AV users were willing relocate further from their current home. Also, the hypothesis that people will select further destinations, such as stores, for better quality products and services was supported. The survey revealed that respondents were willing to accept a trip length of 15 miles to purchase groceries when using AVs. This change was only observed for households which were willing to adopt AVs.

A market diffusion model was estimated in this dissertation to examine the penetration pattern of AVs. Understanding the market penetration pattern is critical to policy makers and planners to manage and will facilitate the adoption of new technologies. As AVs have not been introduced to the market, this dissertation used data from previous technologies. Particularly, sales and price data of conventional automobiles and HEVs, as well as internet and cellphone usage, in the US were collected and used for model estimation. Based on the adoption patterns of previous technologies, two values representing the innovation factor (risk taking capacity) and the imitation factor (culture and lifestyle preferences) were selected for AV market penetration. In addition, external variables, such as the price of the AVs relative to conventional vehicles and economic wealth, were incorporated into the model. The market size for AV adoption was determined considering a household as the unit. The model results and associated penetration curves revealed interesting results. Assuming AVs become available in 2025, the market may reach about 8 million in ten years and full-saturation may occur in 35 years assuming a 75% market size. Given the uncertainties in market size and price of AVs, sensitivity analyses were conducted to understand the possible impacts of these factors on user adoption. In general, a larger market size leads to a higher adoption rate while the initial cost of AVs, relative to conventional vehicles, did not greatly influence the diffusion process.

This dissertation presented the results of an effort to examine consumers' behavior towards AV market penetration. In particular, three major dimensions were explored: the willingness to pay, the willingness to relocate, and the adopters' characteristics. The models revealed significant impacts of individual attributes, household structure, daily commute characteristics, and consumers' perceptions of benefits/concerns on both the willingness to pay and relocate. In particular, results showed higher WTP values for young men (30 years of age or less) and long distance commuters. Crash experience generally decreased the willingness to pay for driverless cars. Among respondents with crash experience, two types of respondents showed a higher willingness to pay: those who were involved in major incapacitating injuries and those who had experienced travelling in the at-fault driver's vehicle. As expected, respondents who recently purchased a new vehicle were less likely to pay high values for AVs. Benefits such as increased travel time productivity and lower vehicle emissions showed significant positive contributions to willingness to pay, while loss of driving skills was a barrier to willingness to pay for AVs. People with moderate familiarity showed the lowest willingness to pay, which highlighted the importance of education on the adoption of AVs.

In terms of the likelihood to relocate, results showed higher willingness to relocate for males, low income households, and carpool drivers. On the contrary, household size and the number of drivers in the family had a negative impact on the model. Among the benefits, traffic-related advantages such as lower congestion, fewer crashes and positive environmental impacts increased individuals' willingness to relocate. In terms of concerns, vehicle safety and data privacy were the major causes of concern.

Younger people, individuals with white ethnicity, individuals living in higher household sizes showed to prefer using AVs by owning them, while individuals who are driving to their commute destination for more than 20 miles showed to prefer using AVs as a transit system. The most preferred way of using AV for drivers who normally drive to school by drive alone mode, showed to be either owning or renting AVs, not using them as a transit system

The scenario analysis used a real ABM model to simulate post-AV pattern. Using the market penetration model, three scenarios (short-term, mid-term and long-term implications) of AVs were studied in this research. Based on the literature, one of the changes which will accompany AVs is a potential change in residential location decisions. This speculation was evaluated and quantified in a survey, and it was shown that at market saturation, 17% of people will relocate their homes; this value was 2% and 14% in the short and mid-term scenario. This is a reasonable assumption, taking into account that distance still plays an important role in individuals' long term decisions regardless of the potential benefits of AVs. These changes were applied to the SERPM model inputs in order to simulate the presence of AVs in the system. The inputs included modification of free flow speeds and link capacities based on the links' functional class. The change in free flow speed and capacity were near 0% for the short-term, both were expected to increase for the mid-term and long-term scenario. This trend is due to the fact that the presence of a mixture of autonomous and conventional vehicles during the short-term would prevent the AVs function at full capacity, such as preventing the AVs from maintaining a 0.5 seconds headway. However, this barrier will be overcome once enough AVs have been added to the transportation fleet.

Another implication is the VOT decrease. VOT will affect several choices of travelers, especially in mode choice and assignment. It is expected that reduction in congestion and driving costs will reduce the VOT. A reduction rate for VOT was selected based on a previous study by Childress et al. (2015). Another factor which was considered in this study was reduction in parking cost in CBD after AVs become available. Results supported speculations of increased VMT, network average speed, and number of trips. However, it was seen that short-term period can be more critical in comparison with mid-term and long-term in regards to network volume to capacity ratio. Even when AVs comprise a small portion of vehicles, they are expected to add a considerable number of trips into network. Combined with the fact that speed and capacity cannot be increased considerably, due to the presence of conventional vehicles, the volume to capacity ratio will also increase. Later, in mid-term and long-term, the severity of this issue will be reduced because the increased speed and capacity will compensate for the additional trips. Also the analysis showed that the attractiveness of conventional transit system will decrease considerably and the attractiveness of driving alone will increase, as was expected due to the reduced driving cost and the simplification of driving.

7.2. Research Contributions

This dissertation had three major contributions to the existing body of knowledge:

The market penetration prediction of this dissertation contributes to the literature by providing a quantitative modeling approach of AV market penetration estimation based on past technology adoption. The study results provide valuable insight in terms of the possible market diffusion patterns and the impacts of different factors on user adoption.

The modeling section of this dissertation contributes to the literature by providing a detailed analysis on the underlying factors that contributed to the WTP for AVs, the likelihood of relocation, and AV adopters' characteristics. The results of this study provide insight as to the propensity of different market segments towards AVs as an alternative mobility option, and an understanding of the potential implications of driverless cars on residential relocation. The findings of this study can serve as important inputs for further planning and simulation analyses concerning the impacts of AVs.

The scenario analyses of this dissertation provides insight into how the implications of AVs will change the outputs of a real ABM. It is essential to understand how the network and system-wide attributes may change when conventional vehicles are replaced by AVs.

This dissertation provides a systematic approach to evaluate and quantify the potential network outcomes related to AV technologies.

7.3. Study Limitation

The market penetration prediction of this dissertation faced a major limitation related to a limitation of the Bass model. The Bass model does not consider external variables very well. Due to this, the model is not sensitive to price fluctuations.

The modeling section of dissertation is subject to limitations as well. The most prominent of these is related to the data. First, the sample size is relatively small (146 observations), which limits the generality of the inferences. Second, the sample is limited to university students and employees, which may also bias the results.

The scenario analysis portion of this dissertation is also subjected to some limitations. The SERPM model does not provide an opportunity to account for the generation of new trips stemming from the increased mobility of new users such as young children and people with disabilities. However, the negative impacts associated with these new trips may be counteracted by the positive effects of AVs which are not explored in this study. One of these unexplored benefits with great potential is shifting heavy vehicle traffic to non-peak periods; this may have the potential to increase capacity and speed simultaneously.

7.4. Recommendation for Future Research

The market prediction of this dissertation can benefit from further research in refining and updating the assumptions applied, such as the market size for vehicle ownership and technology acceptance preferences. Future studies using SP surveys could be a good approach to advance the understanding of market penetration for AVs in terms of public acceptance and user preference with special attention applied to detailed market segments.

Future modeling efforts can cover further potential activity/travel implications including joint/solo activity scheduling, destination choice, vehicle ownership, and ride-sharing.

Regarding the scenario analysis, future studies could consider defining a new transportation mode in the system based on the characteristics of automated taxis or shared-AVs. In order to accomplish this, a deep understanding of mode characteristics and trip allocation is needed.

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PUBLICATIONS AND PRESENTATIONS

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