



**ENHANCED MOBILITY FOR
AGING POPULATIONS USING
AUTOMATED VEHICLES**

Final Report

Contract BDV30 977-11



DISCLAIMER

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U.S. Units to Metric (SI) Units

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.070	meters	m
yd	yards	0.305	meters	m
mi	miles	0.914	kilometers	km

Metric (SI) Units to U.S. Units

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
mm	millimeteres	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi

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16. Abstract Automated vehicles (AV) offer a unique opportunity to improve the safety and efficiency of the transportation system and enhance the mobility of aging and transportation disadvantaged populations simultaneously. However, before this potential can be realized, it is important to develop a greater understanding of aging adults' travel behavior and attitudes toward AVs to determine how AVs could best meet their travel needs. To this end, the Florida Department of Transportation (FDOT) tasked a multidisciplinary team of researchers from Florida State University to conduct a research project aimed at providing information and guidance on how automated and connected vehicle technology could enhance the mobility of aging populations. This project was divided into four separate, but related, research tasks, including literature reviews of aging adult's travel behavior and safety, a survey of Floridian's attitudes toward AVs, and a social media data mining analysis of public perception of AVs. Findings indicated that aging adults have unique travel needs that often are not adequately addressed by today's transportation system. But these mobility problems could be alleviated, in part, by automated vehicle technology. Analyses of resident's attitudes toward AVs found that even though aging adults are less likely to trust AVs, over half of Florida's residents are interested in AVs. In summary, this study affirmed AVs' potential to provide safe and efficient mobility options to Florida's growing aging population, but it highlighted the importance of informing the public about AVs' potential benefits in order to develop the trust necessary for widespread adoption of the technology.			
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EXECUTIVE SUMMARY

Automated vehicles (AV) offer the promise of extraordinary improvements to the safety and efficiency of the transportation system. In addition to its potential to reduce traffic accidents and congestion, AVs possess the unique capability to provide aging and transportation disadvantaged populations the opportunity to restore their personal mobility. However, before this potential can be realized, it is important to develop a greater understanding of elderly adults' travel behavior and attitudes toward AVs to determine how AVs could best meet their travel needs. To this end, the Florida Department of Transportation (FDOT) tasked a multidisciplinary team of researchers from Florida State University (FSU research team) to conduct a research project aimed at providing information and guidance on how automated and connected vehicle technology could enhance the mobility of aging populations.

This project was divided into four separate, but related, research tasks. The findings of each task are summarized below, and are followed by a brief set of conclusions and recommended steps to guide FDOT's future efforts to promote and implement AVs in Florida.

Task 1 - Literature Review of Travel Behavior and Mobility Needs of Elderly Populations

To understand how AVs could enhance the mobility of Florida's aging population, it was first necessary to develop a detailed understanding of aging adults' current travel behavior and how the current transportation system is or is not meeting their transportation needs. To this end, the FSU research team conducted a literature review of elderly adult travel behavior in the U.S. to uncover when, where, and how aging adults travel and how their travel needs differ from younger populations. This information helped the research team to assess how AVs could accommodate the travel needs of aging adults and improve their quality of life. A review of the literature revealed that the travel behavior of aging adults is significantly different than the rest of the population. Aging adults travel less often, for shorter distances, at different times, and for different reasons than the rest of the population. Many of

these changes are a result of retiring and entering a different stage in life. Aging adults typically travel during off-peak periods because they no longer have to travel at rush hour to make it to work at a specified time. When compared to other age cohorts, a higher percentage of older adults' trips were comprised of social, recreation, and shopping trips instead of work-related trips that dominated younger generations travel behavior. Despite these distinctions, one of the few ways aging adults' travel behavior is similar to the rest of the population is their continued dependence on personal automobiles for transportation.

Unfortunately, not all aging adults change their travel behavior by choice. Age-related declines in physical and mental health often inhibit aging adults' ability to drive safely, gradually forcing them to regulate when and where they drive and eventually to give up driving altogether. Since many of these health issues often make it increasingly difficult to walk, bike, or use public transit, aging adults are left with few or no transportation options and are forced to rely on rides from others. Driving cessation leaves aging adults feeling trapped in their own homes, which has detrimental effects on their health and quality of life, including social isolation and depression. As Florida's aging population continues to grow rapidly, addressing this population's unique travel needs is one of the largest transportation challenges facing Florida moving forward.

Task 2 - Literature Review of Travel Safety and Technology Adoption by Elderly Populations

This literature review focused on the aging population's driving performance and factors determining their willingness to adopt various types of advanced driving assistance systems (ADAS) and automated vehicle technologies. Safety issues associated with age-related declines in driving ability, threats to older adults' ability to remain independent after they cease driving, and how ADAS and AV technologies might be leveraged to help older drivers safely maintain their personal mobility as their ability to safely drive unassisted wanes. For these technologies to be adopted by an older population, usability must be high, usefulness must be readily apparent, and the technology must also be trustworthy and trusted.

Intelligent transportation systems (ITS) certainly have the potential to help older drivers improve their comfort and safety in certain driving situations they find to be problematic (e.g., blind spot detection while merging on the highway), but the literature evaluating ITS' capabilities is not without its flaws. First, most of the research has been carried out in the younger-old, who in many cases are not far-removed from their peak driving performance. Second, most of the research evaluating ADAS has only focused on a short learning period in the lab, during which the participant is still forming a mental model of how the particular technology works, without the opportunity to fully integrate it over a longer trial period. It is clear that more research, carried out over longer periods of time, with older-old drivers (75+) or perhaps drivers that have self-reported driving difficulty is needed before transportation planners can be confident that users will trust the technology and that the technology will be just as safe (preferably safer) as the older drivers it aims to augment or replace.

Task 3 - Survey of Elderly Residents' Attitudes toward AVs and Related Technologies

The FSU research team conducted a survey of 459 Florida residents to assess their knowledge of, interest in, and willingness to adopt and use AV technology. The survey also captured respondent preferences for AV ownership models, price points, and perceived benefits and concerns related to the technology. Since older adults tend to be less open to new technology, the survey over-sampled older adults (aged 55+). Findings indicated that Floridians are generally supportive of AV technology, with roughly half of respondents indicating a willingness to use the technology today and/or place a loved one in an AV. While supportive of the technology, the results indicated that Floridians still perceive that a large number of technical, legal, insurance, and safety issues require attention from the state and the AV industry. The survey results also 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. Analysis of the results along key sociodemographic dimensions found that, as expected, there are key factors that help to understand support for and willingness to use AVs. Among these key findings were that individuals of higher socioeconomic status and Hispanics are more supportive of AVs, whereas older adults are less supportive of the technology.

Taken as a whole, these findings point to actions and activities that may be undertaken by FDOT to sustain and further the state's AV initiative. First, it is important that the state regularly and actively track public support for AVs, as this will significantly influence the adoption rates for these vehicles once they come to market. Second, FDOT might consider partnering with industry and university partners to develop materials to educate the public about AV technology and its potential to provide mobility to groups that may have limited transportation options. Given the differing levels of support for and willingness to use AVs, these materials might be targeted at groups that report lower levels of excitement and interest in the technology. These materials should also speak to the issues perceived by residents to be among the greatest challenges to using the technology, which generally revolve around safety, security, liability and the bicycle-pedestrian interface.

Task 4 - Assessment of Social Media and Autonomous Vehicles

The FSU research team collected and analyzed geo-referenced social media data (tweets) from the Twitter platform over the period July 1, 2012, to June 15, 2015, in order to better understand public perception and sentiment regarding AV. In all, 7,252 tweets were analyzed. Tweet data were collected from historical and real-time sources, whereby the team identified various 'search terms' that would likely be relevant or capture the ongoing national conversation about AV technology (e.g., Google Self-Driving Car, self-driving, etc.). Collected tweets were subjected to a scoring process by which they were assessed in terms of whether they expressed a positive, negative, or neutral sentiment regarding AV technologies. The scoring was accomplished via an on-line crowdsourcing platform which utilizes contributors from around the globe to complete sentiment judgment tasks. As the project utilized tweets with a geographical reference, comparisons in AV sentiment were made between states, regions, and the nation as a whole, as well as over time. Moreover, sentiment differences in those states that have approved AV testing (i.e., permitting states) versus those that have not, were also examined. A key finding from the national level study was that sentiment, while generally positive, was generally persisting more negative over time, as more 'neutral' tweets focused on news and informational items have dominated recent conversation. In general, increased tweet activity relevant to AVs was found around major events such as the Google Car announcement in May 2014. When we looked at the permitting states,

we found that the conversation was often driven by events that were relevant to AV activity in those particular states. Neutral activity tended to be engaged in discussing topics related to themes such as infrastructure, policy and technology. Florida appeared to be among the most positive of permitting states in terms of how conversation sentiment related to AVs.

The results of this analysis lead to several insights that can be used to inform Florida's AV initiative. First, it is important that the state regularly and actively track public support for AVs, as this directly relates to people's understanding and acceptance, as well as potential adoption rates for these vehicles once they come to market. Monitoring social media outlets is one method of contributing to this goal. Second, as real concerns about AV safety and adoption are expressed on Twitter, public outreach undertaken by FDOT via Twitter to spread positive developments in AV technology may help to alleviate concerns in the conversation. Thirdly, the diversity and intensity found by the FSU research team in Twitter posts points more broadly to social media as a way for Florida to promote awareness and understanding of its AV initiatives and events. Fourthly, the topics identified as generating negative sentiment on social media can potentially be used to help guide the production of informational materials that would speak to public concerns, such as AV testing on public roads. Fifthly, promoting AV topics that have already gained traction in social media can potentially encourage greater participation and interest in AV initiatives by Floridians. In sum, these results can help guide future decisions about introducing AVs to the public and disseminating AV information and how those efforts might facilitate future positive conversations.

Conclusions and Recommendations

Taken as a whole, this study affirmed the potential of all levels of automated vehicle technology to provide safe and efficient mobility options to Florida's growing elderly population. Given these research findings, the project team recommends the following future actions that FDOT can take to promote the use of AVs as a solution to the transportation issues faced by Florida's aging population.

- **Build Upon Florida’s Outstanding Efforts to Test and Promote AV in the State:** Due to FDOT’s outstanding leadership, Florida is already at the forefront of AV planning and preparation efforts in the U.S. The findings of this study reinforce the importance and effectiveness of many of the Department’s ongoing efforts to promote and test AV technology.
 - **Continue Educating Planners, Engineers, and Infrastructure Providers of the Imminence and Importance of AV:** Planners and engineers will need to take a leadership role in support of AV to ensure a smooth rollout of the technology. Continuing to educate these stakeholders of the importance of preparing for AV will encourage them to see Florida as an ideal place for the early adoption of the technology.
 - **Continue Testing ADAS Technologies:** ADAS were found to significantly improve the safety of aging drivers. Facilitating the advancement of these technologies into the market as soon as possible could enhance the mobility of many aging adults in the near-term, well before fully automated vehicles are available.

- **FDOT Should Develop and Pursue an AV Education/Marketing Campaign:** The survey results indicated that even a brief informational brochure on automated vehicles improved respondents’ opinion of AVs. A comprehensive education/marketing strategy targeting key Florida constituencies would help prepare the state for the widespread adoption of AVs.
 - **AV Education and Florida’s AV Brand Matter:** The campaign should strive to inform the public about what AVs are, how they operate, and what AVs’ potential costs and benefits are. This campaign should also showcase FDOT’s efforts and leadership in preparing Florida for the emergence of AVs.
 - **Education Should Be Targeted to Age-Specific Interests and Concerns:** Survey results indicated that distinct population subgroups have differing interests and fears concerning AVs. Aging adults typically see the challenges and costs of AVs more than other age

groups, while younger generations are more favorable toward AVs. Marketing messages should be targeted to the interests and concerns of each subgroup.

- **Educational Media Should Be Tailored to the Age-Specific Preferences and Characteristics:** FDOT should also consider whether the educational medium used is appropriate to the characteristics and preferences of the age group. Social media and online applications may be excellent platforms for reaching Millennials but may not be effective with older generations who are less familiar with technology. Consequently, a multi-media approach would be most effective.
- **Use Major AV News and Events as Marketing Opportunities:** Holding and publicizing high-profile AV events are excellent opportunities to demonstrate AVs' capabilities and generating widespread interest in the technology.
- **Build Upon this Research Effort:** This project highlighted areas where additional or ongoing research is needed.
 - **Regularly and Actively Track Public Attitudes Toward AVs:** Continuing to actively assess Florida resident's attitudes toward AVs through surveys and social media is vital to FDOT's ability to identify and address the public's concerns about AVs, to evaluate the effectiveness of AV implementation efforts, and to anticipate AV adoption rates once the technology comes to market.
 - **AV and Human Factors Research: AV Simulator Studies:** Aging adults are a unique demographic group with distinct travel behaviors, heightened concerns about AVs, and unparalleled potential to benefit from AVs. Tailoring AV applications to the needs of aging adults will be vital to ensure that age-related declines in driving ability do not hinder their mobility. To this end, more detailed research on how aging adults interact with AV and ADAS technologies will be necessary.

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CHAPTER 1



Image Source: www.google.com/selfdrivingcar

Introduction

Enhanced Mobility for Aging Populations Using Autonomous Vehicles

1.1 - BACKGROUND

Automated vehicle (AV) technology is an umbrella term that includes autonomous vehicle technology and connected vehicle technology. Autonomous vehicle technology includes the use of sensors and advanced software that the vehicle uses to interpret its surroundings and make intelligent decisions on routing and maneuvering. This technology directly impacts safety-critical functions (i.e., steering, accelerating, and braking), but does not rely on information being broadcast by infrastructure or other vehicles. The National Highway Traffic Safety Administration (NHTSA) classifies vehicle automation in five levels ranging from “0” where the driver is in “complete and sole control of the primary vehicle controls” to “4,” where the vehicle is “designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip” (NHTSA, 2013).

Connected vehicle technology relies on information gathered by vehicles and the transportation infrastructure about real-time operations of the transportation network. Based on a specific vehicle’s location, information is broadcast to the vehicle so the driver is able to make informed decisions regarding routing and maneuvering. This technology does not impact safety-critical functions of the vehicle, as the driver remains in full control of the vehicle at all times.

Automated vehicles are being developed and deployed at a faster rate than existing federal and state policies can adapt. AV technologies could have a significant positive effect on public roadways by reducing traffic accidents and congestion if wide-scale adoption is realized. The level of adoption is highly dependent upon the regulatory framework surrounding AV technology.

According to the World Health Organization (WHO), road traffic crashes caused an estimated 1.24 million deaths worldwide in 2010. On U.S. roadways, more than 32,400 people died, and 2.4 million were injured in 2011. In Florida alone, over 2,400 people were killed in roadway crashes in 2012. Over ninety percent of the time, the data points to operator error as the cause. Driving under the influence claims countless lives, and distracted driving continues to increase as drivers

embrace mobile devices and constant connectivity as an integral part of daily life. In addition, persons with disabilities and the elderly have limited options for mobility.

Congestion plagues our roadways as more vehicles are put on the road and cities continue to expand. Three- and four-vehicle households are commonplace in the U.S. while average vehicle occupancy is just 1.2 persons per trip. Vast numbers of hours are wasted while drivers negotiate traffic and search for parking. The current cost of traffic congestion in Florida is estimated at \$5+ billion per year.

Automated vehicles promise to offer extraordinary improvements to both the safety and efficiency of our existing roadways and mobility systems. These benefits promise to be even more profound to aging and transportation disadvantaged populations by providing personal mobility to those who are unable to drive a car. As this technology evolves, a greater understanding of the mobility needs and other behavioral issues related to the elderly population, and attitudes of this population towards the use of autonomous vehicles and related transportation technologies is needed.

1.2 - RESEARCH GOALS AND OBJECTIVES

The main objective of this research report was to provide the Florida Department of Transportation (FDOT) with information and guidance on how autonomous and connected vehicle technologies could enhance mobility operations for certain segments of the population, including aging and the transportation disadvantaged. Para-transit and shuttle services are the most expensive modes of transportation for any public agency to operate. FDOT has recognized that automated vehicles may potentially reduce costs and expand services to the rapidly growing demographic of aging citizens. However these benefits may never be realized if the public, or more specifically aging adults, do not trust automated vehicle technology to provide safe and efficiency transportation. In this way, public perception of automated vehicles will be an important determinant of when and how AVs can be used to enhance the mobility of Florida's aging populations. This project sought to assess Florida residents' perception and willingness to adopt AVs to inform FDOT's efforts to implement applications of automated vehicle technology. Finally, this report will identify near-term and long-term challenges and opportunities associated with the implementation of automated vehicles for Florida's residents, with a particular focus on the issues related to elderly populations.

1.3 - REPORT ORGANIZATION

This research project was divided into four separate yet related research tasks. The following report is organized six chapters, one for each research task followed by a concluding chapter that makes recommendations for future steps FDOT can take to enhance the mobility of aging and transportation disadvantaged population through automated and connected vehicle technologies. The specific tasks that have been conducted as part of this research effort are listed and described below:

Literature Review of Travel Behavior and Mobility Needs of Elderly Populations (Chapter 2)

This literature review focused on issues related to the travel behavior and experiences of elderly populations, largely in a North American context. The review examined research on when, where, and how older adults travel and how their travel needs and behaviors differ from younger populations, including research deriving from the National Household Travel Survey (NHTS) and other major surveys to document current patterns and trends. The review also explored research related to issues of driving cessation and its effects on individual mobility and overall quality of life in a society that has become increasingly dependent on auto travel. This review may help to provide FDOT with an understanding of the difficult task of providing mobility to older adults, and how automated vehicles can make this task easier.

Literature Review of Travel Safety and Technology Adoption by Elderly Populations (Chapter 3)

This literature review investigated and summarized issues related to the elderly population with a focus upon driving performance and vehicle technology adoption. It summarized the evidence on the types of crashes that older drivers experience, and how they are different than crashes for other age groups. It also assessed the types of abilities that decline with age that are implicated in older driver crashes (declines in perceptual, cognitive, and psychomotor abilities). It

further served to assess which levels of automation identified by NHTSA (0 = no automation, to 4 = full automation) could help protect older adults from crashes associated with age. This review included assessments of research being conducted on older drivers and their use of different levels of vehicle automation technology by the AgeLab at MIT and by researchers at other centers. This review may serve to guide FDOT and other stakeholders on how to approach AVs and semi-AV technologies to allow older drivers to enjoy safe mobility for life.

Survey of Elderly Residents Attitudes toward AVs and Related Technologies (Chapter 4)

A survey of Florida residents was conducted to assess their knowledge of, interest in, and willingness to adopt and use AV technology. Respondents were asked their preferences assuming different stages and forms of AVs and the associated user costs relative to current travel options. The range of options included privately owned autonomous vehicles, shared-ownership vehicles, taxi-like AV services, and transit systems that rely on AV technology. The survey over-sampled certain populations of interest to FDOT (e.g., older adults aged 55+ and millennials) in order to have more detailed data on these specific population subgroups. The survey also asked question to ascertain the public's perception of the privacy and safety risks related to AVs, which could link to other research themes. The survey further included questions that help predict AV technology adoption by older adults.

Assessment of Social Media and Autonomous Vehicles (Chapter 5)

The FSU research team conducted an assessment of social media discussions to determine if automated vehicle technology is something Floridians, particularly those who use on-line social media portals (primarily Twitter) are talking about. Relevant literature was reviewed to determine ways in which social media data can inform transportation system planning and policy issues. This was followed by data mining and analysis of social media data to identify trends and evidence of AV technology in the public consciousness. The findings from this analysis may be used to inform future policy and suggest additional areas of research.

CHAPTER 2



Image Source: www.autoguide.com/auto-news/tag/elderly-driver

Travel Behavior and Mobility Needs of Aging Populations and the Role of Automated Vehicles

2.1 - INTRODUCTION

The population aged 65 and over is growing significantly in the United States. By 2050 it is projected to reach 83.7 million people, almost double current levels (Ortman, et al., 2014). This growing demographic has been identified as one of the biggest challenges facing transportation providers in the future (Newbold et al., 2005; Pilarksi, 2003). This is especially true for the state of Florida since its 3.2 million residents over the age of 65 make it the oldest state in the nation. Despite the increasing number of trips taken by walking, biking, and public transit, the automobile remains the most commonly used mode of travel for aging populations. Researchers project that by 2025, one in every five drivers will be over the age of 65 (Lynott & Figueiredo, 2011).

As drivers age, their ability to drive safely declines. Eventually aging residents are forced to stop driving entirely, leaving them with few transportation alternatives. This has far-reaching effects on their health and quality of life. Consequently, finding ways of ensuring the continued mobility of residents as they age is vital to the well-being of Florida's aging population. One strategy that has been proposed to mitigate the impact of driving cessation is Automated Vehicles (AV) or self-driving vehicles, which have the potential to fundamentally alter transportation systems and provide critical mobility to the aging and disabled (Fagnant & Kockelman, 2013). This literature review examined research on current travel behavior of older adults, and reviewed issues related to driving cessation. This is followed by a brief discussion of how AVs could help to mitigate the impact of cessation.

Some of the main findings of the literature review include the following:

Travel Behavior of Older Adults

- The percentage of trips in the United States by older drivers is increasing
- On a per capita basis, older adults are traveling less than in the past
- The private automobile remains the most popular mode choice among older adults
- Walking is the second most common mode choice, followed by public transit
- Older men travel more frequently than older women
- Trips purposes by older adults are characterized predominately by shopping, family, recreation, social engagements, and medical related travel

Driving Cessation

- More than 600,000 people aged 70 and older stop driving each year and become dependent on others to meet their transportation needs
- Driving cessation may be voluntary or involuntary, and influenced by health, costs related to driving, anxiety, family, physicians, and gender
- Many older drivers self-regulate, decreasing the number of miles and trip they make and avoiding stressful driving environments
- Former drivers were more likely to be women, older, non-white, less educated, less likely to live with a spouse, and had poorer function and health status than current drivers
- Driving cessation can cause depression, reduced life satisfaction, and social isolation stemming from a loss of mobility and independence

2.2 - TRAVEL BEHAVIOR OF AN AGING POPULATION

2.2.1 - Florida's Aging Population

Florida's warm weather and world famous beaches have made it a popular retirement home for many out of state migrants. With over 3.2 million residents over the age of 65, Florida's older population comprises 17.3% of the state's population (compared to the national average of 13%) making Florida the oldest state in the nation. Since Florida's high concentration of older residents is due to decades of attracting older generations instead of the outmigration of younger populations, as in many Midwestern states, Florida is one of the few states with a very large concentration of older residents that has continued to experience rapid growth of this demographic (Frey, 2010). **Figure 2.1** presents Florida's population by age and sex, and **Figure 2.2** presents the projected composition of Florida's population by 2030. A comparison of these figures demonstrates that as the baby boomer generation moves toward retirement, Florida's elderly population is only expected to continue growing. By 2030, Florida is projected to have over 5.6 million residents over the age of 65 and will account for almost one-fourth (24.0%) of Florida's population (BEER, 2014). As such, the growing challenge to meet the transportation needs of aging populations is especially pressing in Florida.

Figure 2.1 - Florida's Percent Population by Age and Sex, 2010

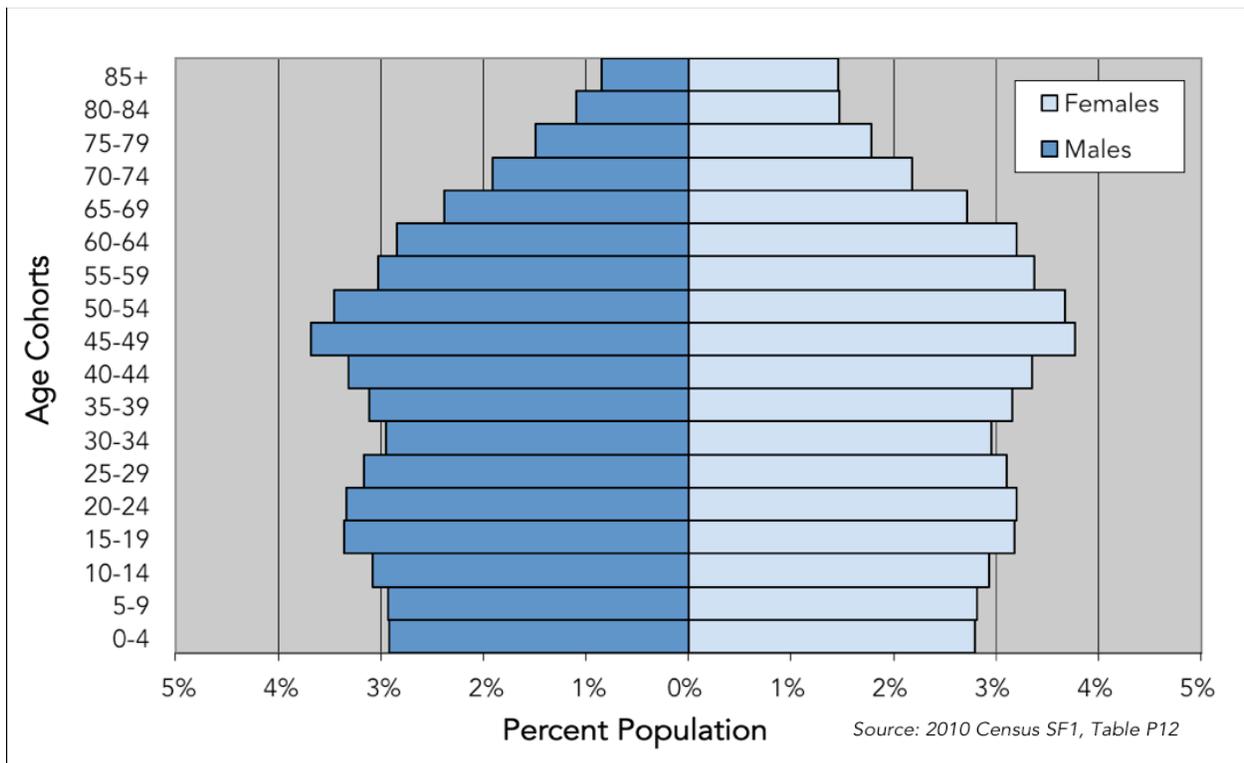
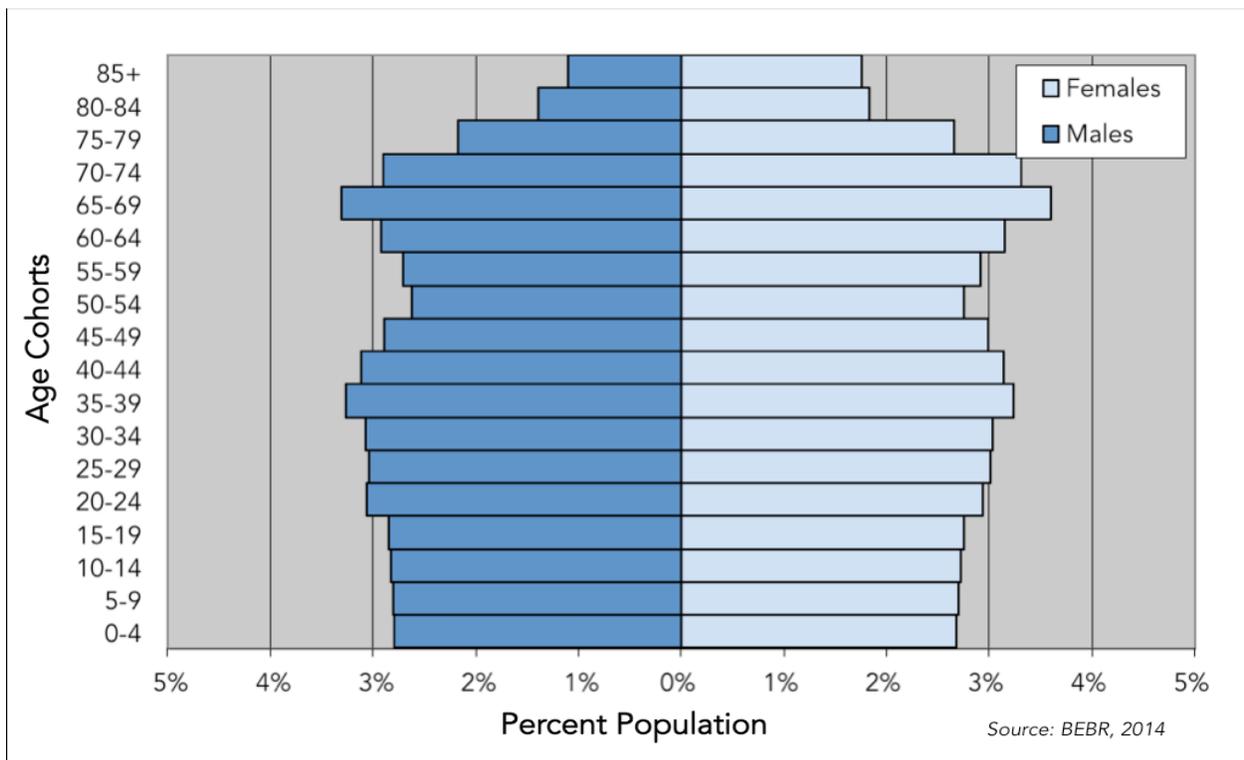


Figure 2.2 - Florida's Projected Percent Population by Age and Sex,



Another way that Florida’s distinctive age demographics will pose unique transportation concerns is that Florida’s large retirement communities create some of the largest concentrations of older residents in the U.S. For example, due in part to the presence of The Villages (one of the largest retirement communities in the nation) in Sumter County, 43.3% of Sumter County’s 2010 population was age 65 or older, which is the largest share of any county in the nation (US Census, 2010). In fact, four of the six counties (and 5 of the top 10) with the largest share of residents over 65 are found in Florida (**Table 2.1**). Florida’s large older population is even more significant considering that these population counts do not account for Florida’s seasonal residents. Florida’s Bureau of Economic and Business Research (BEBR) estimated that in 2005 that Florida’s seasonal elderly residents fluctuated from 300,000 to 800,000 depending on the time of year (Smith & House, 2006).

Table 2.1 - Top Ten U.S. Counties with the Largest Percent of Residents over 65 Years Old

Rank	Percentage Age 65 and over		
	County	State	Percent
1	Sumter County	FL	43.4%
2	Charlotte County	FL	34.1%
3	McIntosh County	ND	34.0%
4	La Paz County	AZ	32.6%
5	Highlands County	FL	32.2%
6	Citrus County	FL	31.2%
7	Alcona County	MI	31.4%
8	Lancaster County	VA	31.2%
9	Sarasota County	FL	31.2%
10	Llano County	TX	31.1%

Source: Adapted from West et al., 2014

2.2.2 - Amount of Travel

As the population over 65 years old has grown, the absolute number and share of miles traveled by older Americans has increased significantly. "In 2001, 11 percent of all trips in the United States were taken by persons age 65 and older. By 2009, that share had increased to 12 percent" (Lynott & Figueiredo, 2011). However, in comparison to younger populations, older adults make fewer trips (Bauer et al., 2008; Giuliano, Hu & Lee, 2003; Rosenbloom, 2000). On average, older adults make about one less daily trip than other age groups (Heaslip, 2007; Sikder, 2010).

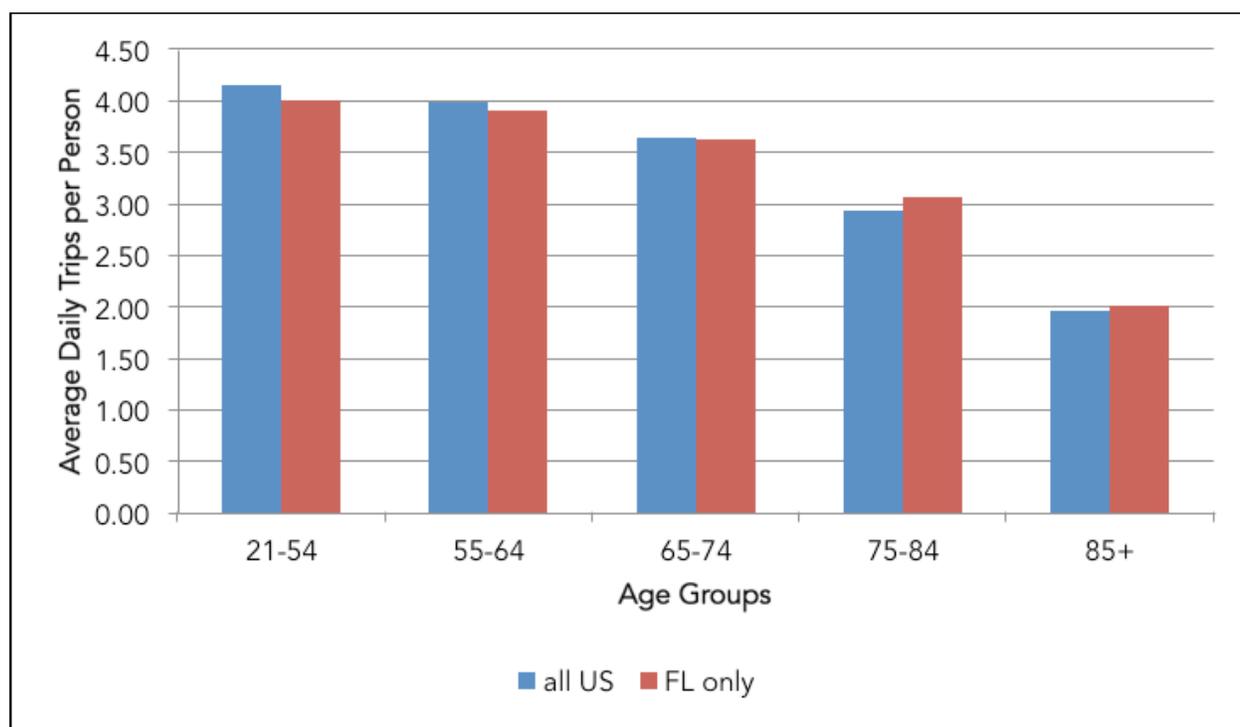
Figure 2.3 charts the average daily trips of U.S. adults and Florida adults in different age categories (as derived from the 2009 NHTS). The figure clearly demonstrates how older age cohorts make fewer trips. This is particularly apparent for the oldest group (85+), the members of which make less than half the number of trips as younger adults (21-54). The figure also demonstrates that the Florida pattern of daily trips is nearly identical to the national pattern.

Even though older adults travel less than younger generations, multiple studies have found that the baby boomer generation is more active and works later in life than previous older generations (Marottoli et al., 2000; Rosenbloom, 2001; Waldorf, 2003; Banister & Bowling, 2004; Heaslip, 2007; McGuckin & Lynott, 2012B; Samus, 2013). While this trend has not been manifested in recent years by increased travel among older adults, this is likely due to rising fuel costs and the poor economic climate of the past decade (Lynott & Figueiredo, 2011; McGuckin & Lynott, 2012A; Skufca, 2008). An analysis of the 2009 National Household Travel Survey (NHTS) revealed that, on average, older adults took 6 percent fewer trips and logged nearly 10 percent fewer miles in 2009 than in 2001 (Lynott & Figueiredo, 2011). Average daily trips are down from 3.4 to 3.2, and daily miles traveled are down from 26.3 to approximately 23.8. However, between 2009 and 2001 travel decreased among all groups, not just adults (Lynott & Figueiredo, 2011). So, as the U.S. economy improves elderly drivers are expected to increase their amount of travel significantly (Rosenbloom, 2001; Burkhardt & McGavock, 2007).

In summary, even though older adults typically travel less than younger populations, there are more older adults on the road and they are expected to be more active later into life than previous older generations. Thus, aging populations

will be a demographic change that transportation providers across the country will have to adjust to in order to ensure the needs of older adults are met. These issues will be especially significant to the State of Florida due to Florida’s exceptionally large and growing older population. Consequently, developing a better understanding of older adults travel behavior is vital to meeting older residents travel needs as Florida’s population continues to age. The remainder of this section will outline older residents travel behavior and how their travel needs differ from other generations.

Figure 2.3 - Average Daily Trips per Person by Age



2.2.3 - Mode Choice

Driving remains the most popular means of travel among adults aged 65 and older (Lynott & Figueiredo, 2011; OECD, 2001; Rosenbloom, 2000, 2003). Sandra Rosenbloom (2000) found that, regardless of where older adults live, most are extremely dependent on a private vehicle, either as a passenger or driver. In 2001, older adults made roughly 90 percent of all their trips in a car, over 45 percent as the driver of a single-occupant vehicle and 43 percent either as a driver or

passenger in a vehicle with two or more occupants (Pucher & Renne, 2003). Even without owning a car or being a licensed driver, most older adults still find ways to make the majority of their trips by car (Kostyniuk & Shope, 2003; Newbold et al., 2005). In fact, over the past couple decades, older adults have become more likely to obtain a driver's license and own a car (Rosenbloom, 2001; Alsnih & Hensher, 2003; Buehler & Nobis, 2010).

Despite the continued reliance on the automobile as the primary means of travel, older adults are taking fewer trips by personal vehicles, and are taking more trips by walking and transit than in the past (Lynott & Figueiredo, 2011; McGuckin & Lynott, 2012A). According to the 2009 NHTS, walking is the second most popular mode choice among people aged 65 and older; 8.8 percent of trips by older adults are made on foot (Lynott & Figueiredo, 2011). Public transportation use is also increasing among older adults for nondrivers and drivers alike. Although this gap is narrowing among older adults, older nondrivers account for the majority of trips taken by transit. Approximately 1.4 million older nondrivers rely heavily on public transportation (Lynott & Figueiredo, 2011). Even though the share of trips taken by transit remaining relatively small (2.2 percent), public transportation use by older adults doubled between 2001 and 2009 (Lynott & Figueiredo, 2011).

Figure 2.4 presents the percentage of trips by various modes for different age cohorts of US residents (based on the 2009 NHTS). It demonstrates how the share of people traveling by auto does not differ much by age. However, the share of people that are passengers (rather than drivers) does increase among older travelers. **Figure 2.5** presents the same information but for Florida residents only. It shows roughly the same pattern as for all US residents. The one main difference is that among Florida residents a major drop in the driving share occurs between the 65-74 group and the 75-84 group. Among all US residents, this major drop occurs between the 75-84 group and the 85+ group. Reasons for this are unclear, but it may be in part because the prevalence of Florida's retirement communities enables more aging adults to take fewer trips by car.

Figure 2.4 - Mode Share by Age among U.S. Adults

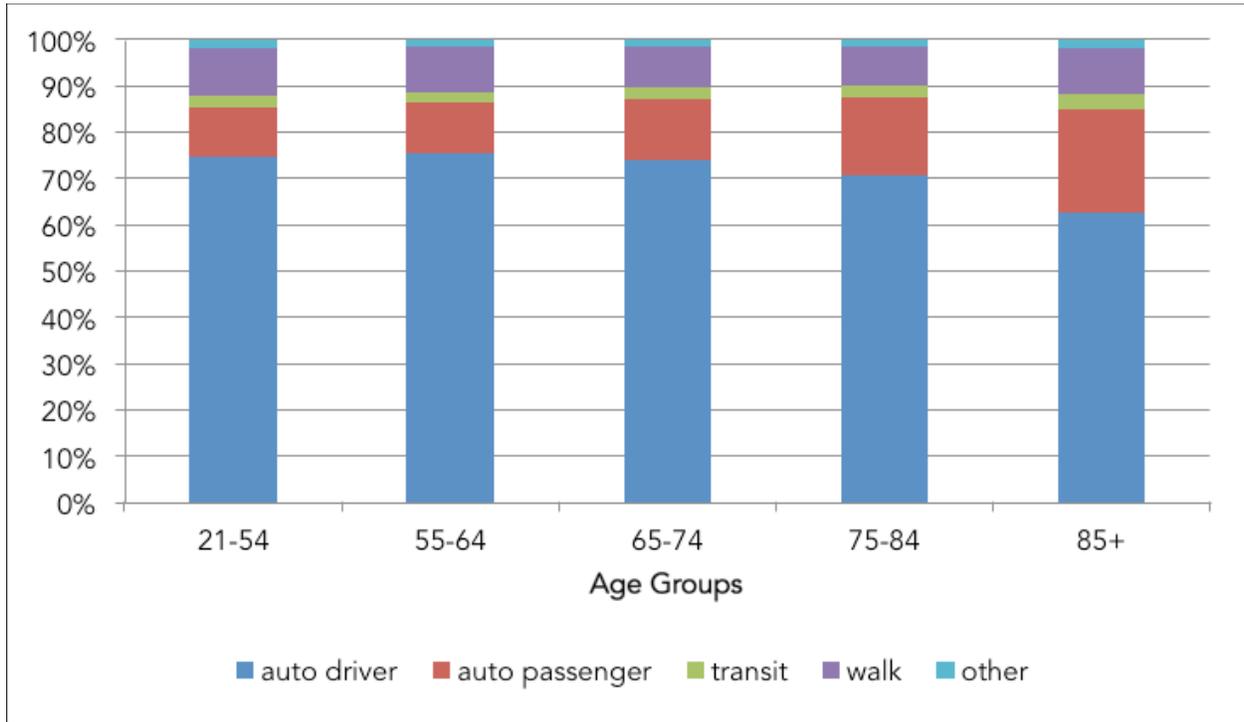
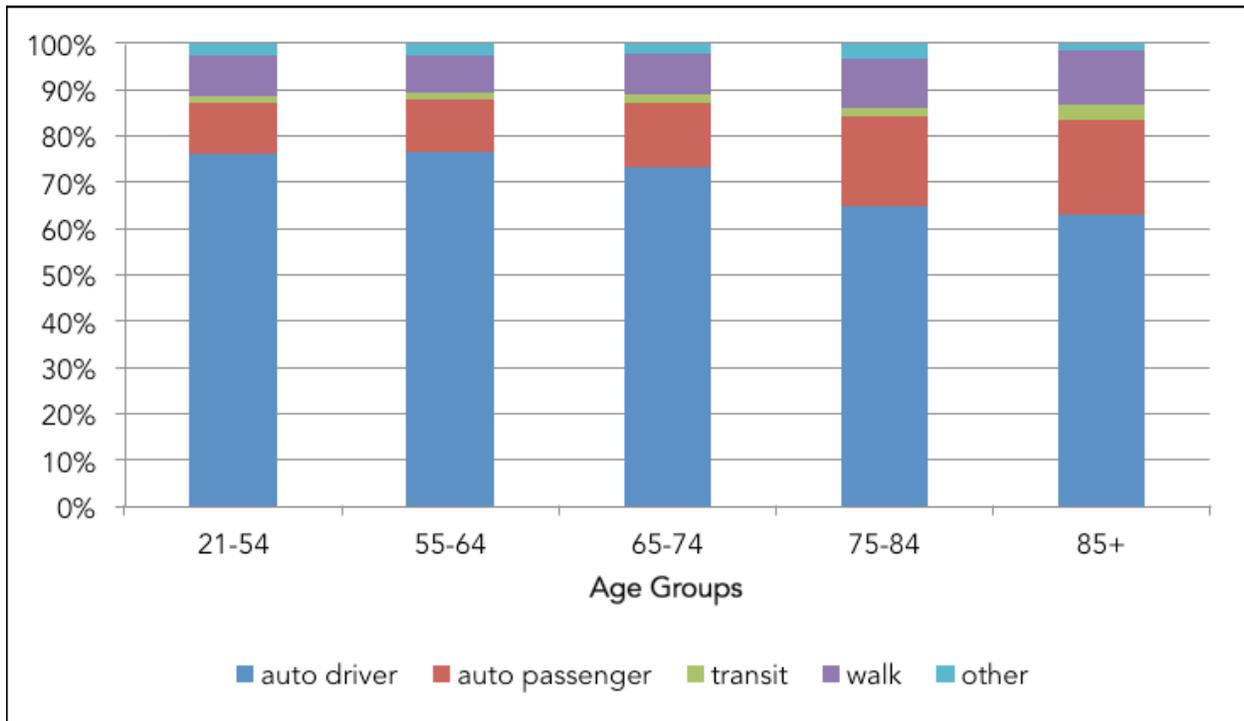


Figure 2.5 - Mode Share by Age among FL Adults



2.2.4 - Trip Length

Closely tied to mode choice is older adults' trip length. Older adults typically travel shorter distances than younger generations (Rosenbloom, 2000; Giuliano, Hu, & Lee, 2003). However, this only holds true when older adults utilize active modes of transportation (i.e., driving themselves or walking) as opposed to passive modes (i.e., riding as a car or bus passenger). A Canadian study found that when driving the average elderly adult (age 65 and older) travels five fewer kilometers per trip than younger adults (Mercado & Paez, 2009). Similarly, adults who walk tend to travel shorter distances, despite having longer walking times than younger populations (Yang & Diez-Roux, 2012). However, older adults who ride as a passenger either in a car or public transit typically travel just as far as other generations using the same modes. This may suggest that age-related physical limitations may prevent older drivers from traveling as far as they would otherwise when using active modes such as driving themselves or walking. Yet there is some evidence that the baby boomers and today's older generations are taking longer trips than previous older generations (Heaslip, 2007; Samus, 2013).

Figures 2.6 and 2.7 show the average trip distance by age for work and non-work trips, respectively (based on the 2009 NHTS). Distances clearly decline with age for both work and non-work trips. Each of these figures shows separate averages for US residents and Florida residents, but these averages generally do not differ much from each other.

Figure 2.6 - Work Trip Distance by Age

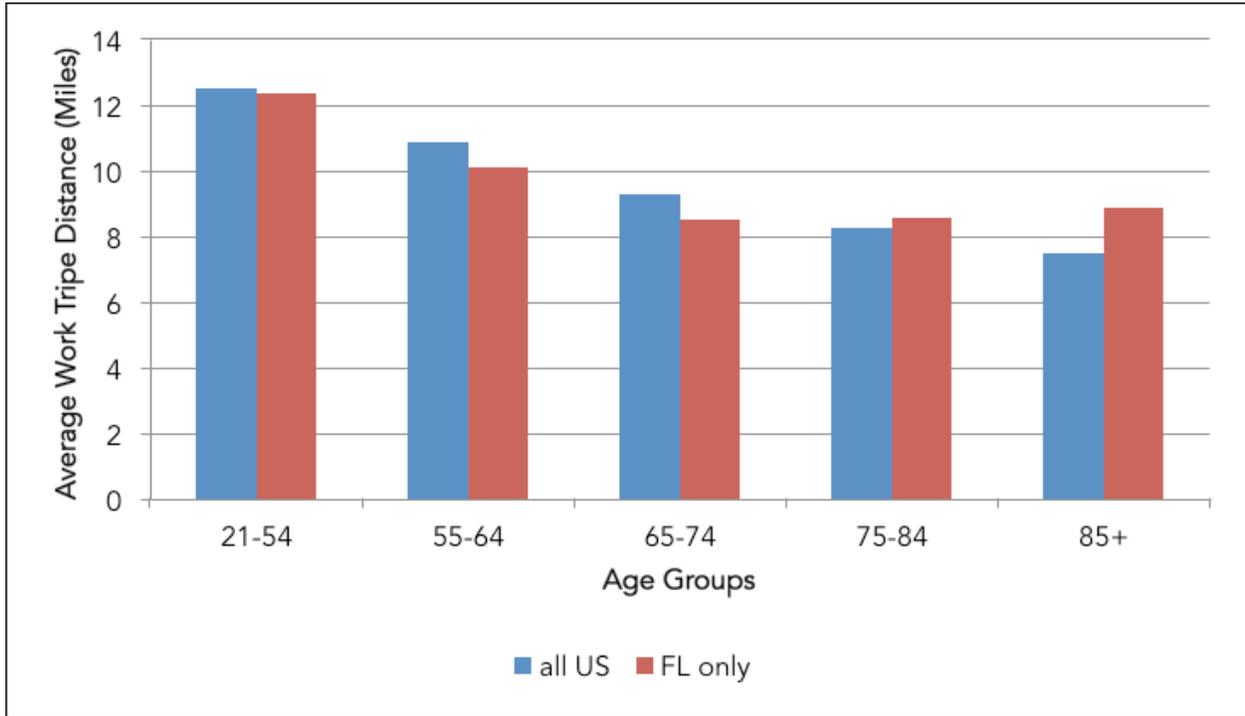
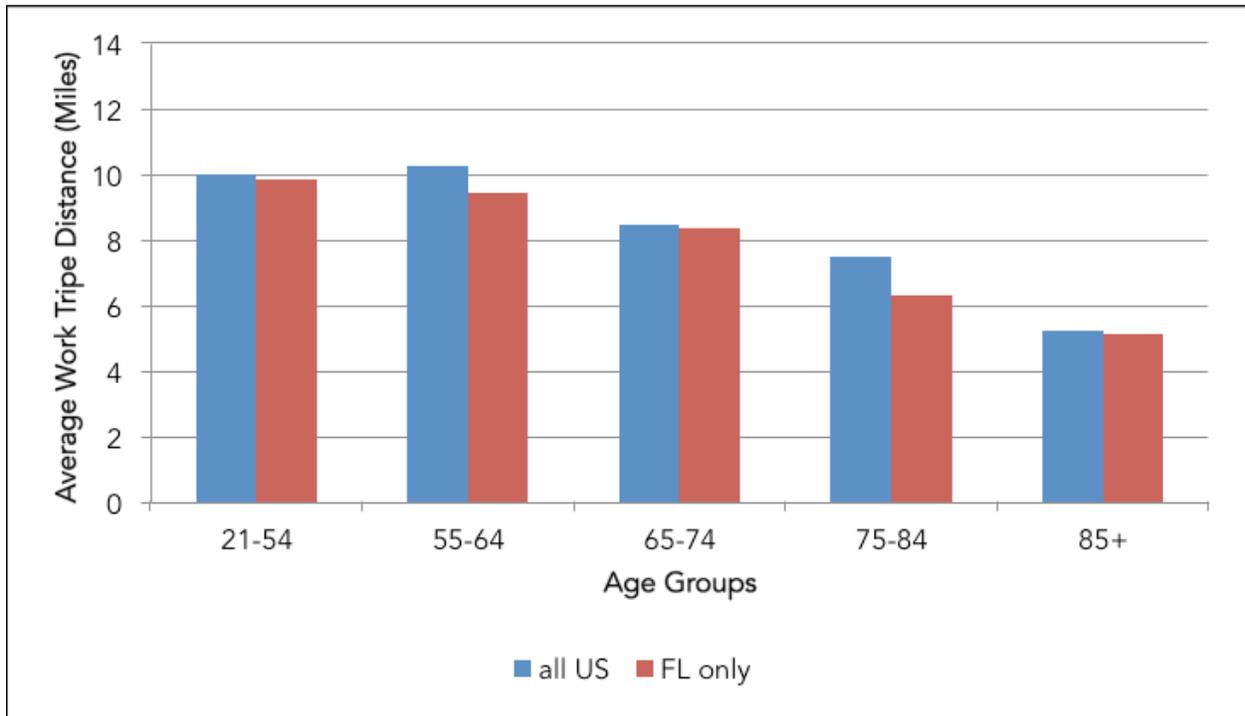


Figure 2.7 - Non-Work Trip Distance by Age



2.2.5 - Trip Purpose

The majority of trips taken by older adults are for shopping, family visits, recreation, and social engagements (Collia et al., 2003; Mattson, 2012). Compared to younger generations, older adults' travel is composed of a larger share of these engagements, rather than work-related trips typical of other age groups (Newbold et al., 2005; OECD, 2001; Rosenbloom, 2001). However, work-related trips have increased among older adults as more adults are working later in life and postponing retirement (McGuckin et al., 2013). Post retirement, leisure travel typically increases due to an increased amount of free time (McGuckin & Lynott, 2012B). In recent years, older adults are taking more leisure trips that are often by car and tend to be longer distances (McGuckin & Lynott, 2012B). Older adults' trip purposes also involve a significant amount of travel for medical purposes. Despite being a relatively small percentage of trips overall, older adults travel for medical reasons significantly more than other age groups (Mattson, 2012).

Figures 2.8 and 2.9 show the distribution of trip purposes by age for adults in the US and Florida, respectively (again based on the 2009 NHTS). As with the previous figures, Florida's pattern mirrors that of the US. These figures demonstrate the expected decline in the share of trips dedicated to work and transporting someone else among older cohorts. Further, aging cohorts make a larger share of trips for meals, shopping/errands, medical/dental purposes, and school/religious activities (this final category is most likely focused on religious activities in the case of older adults).

Figure 2.8 - Distribution of Trip Purposes among U.S. Adults

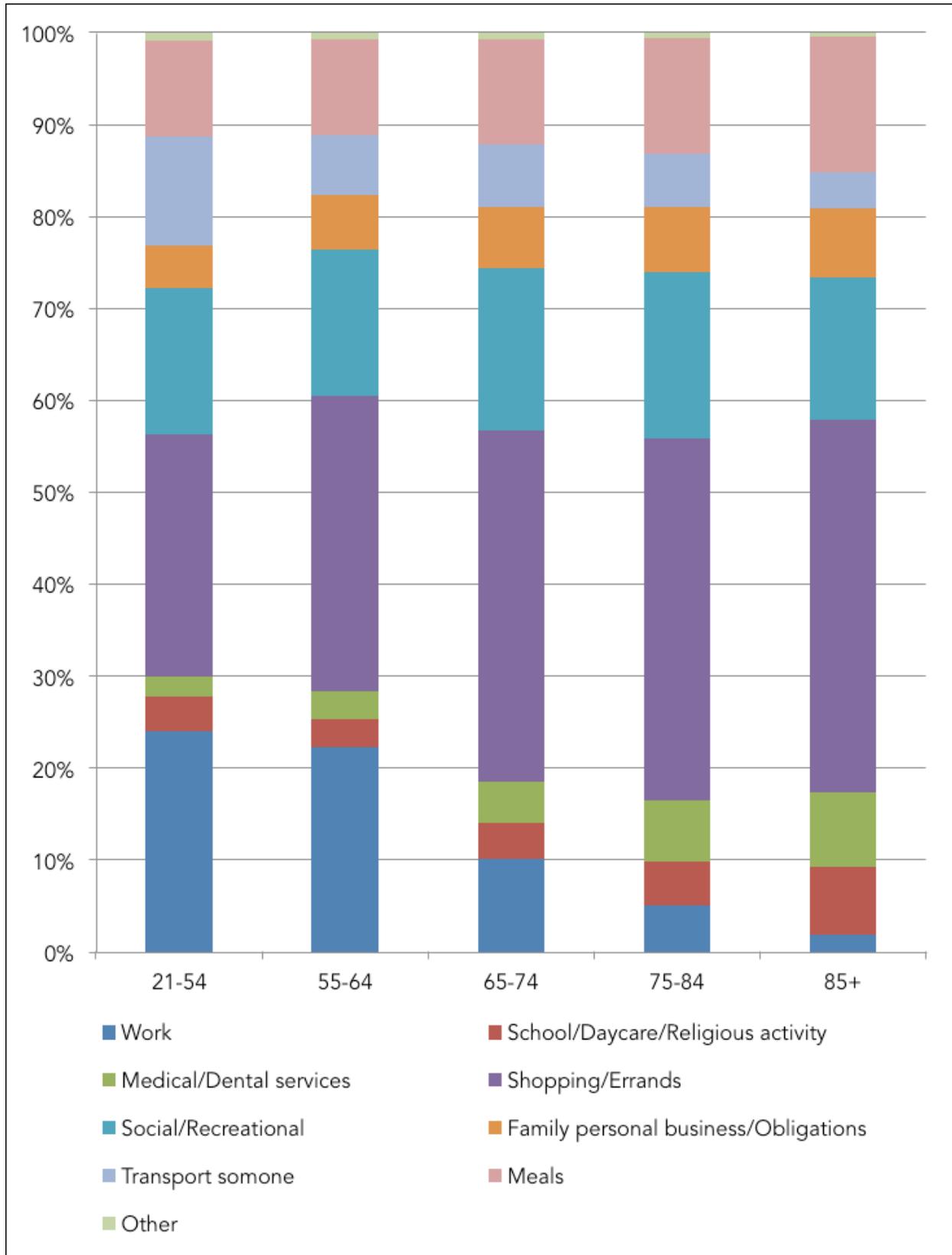
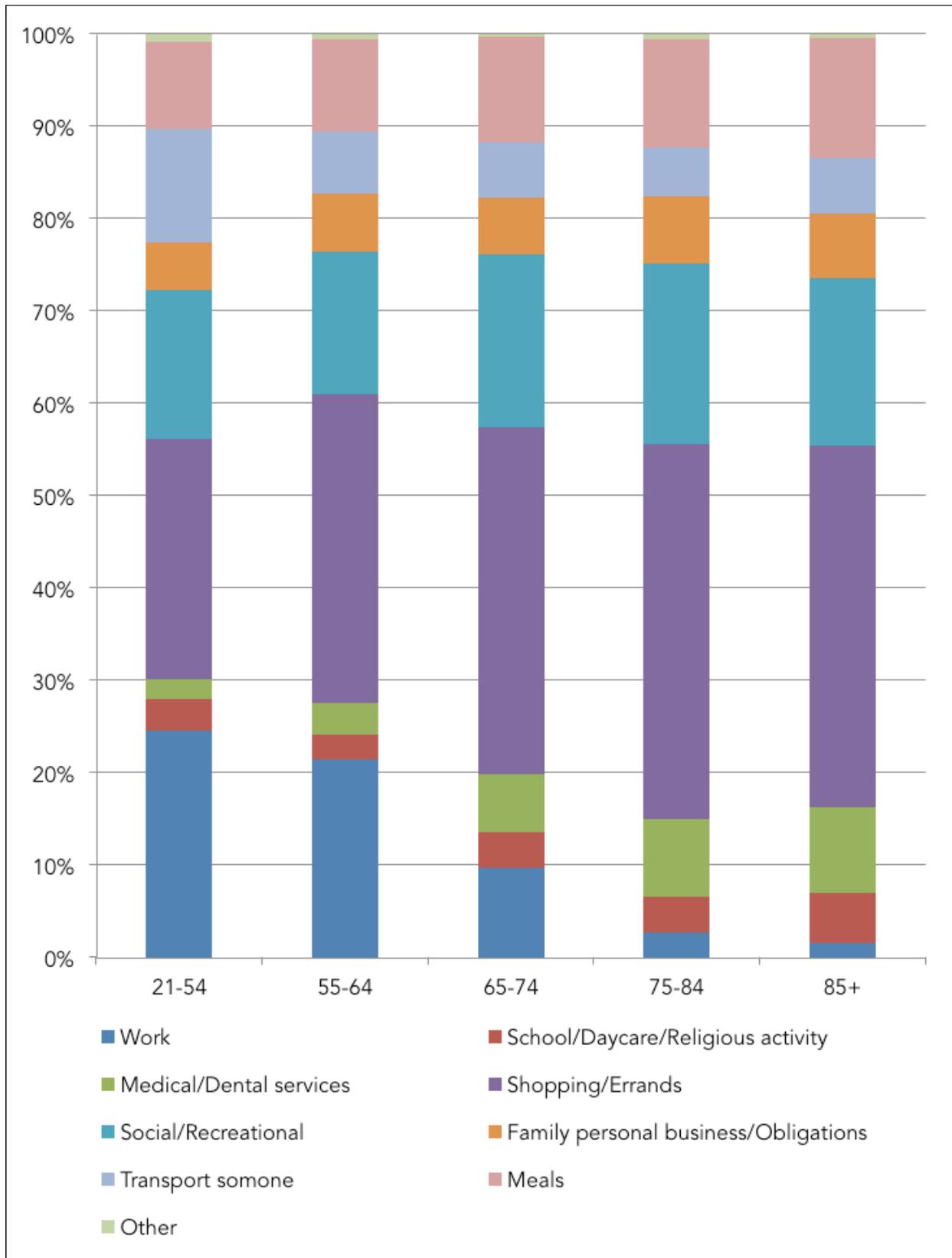


Figure 2.9 - Distribution of Trip Purposes among FL Adults

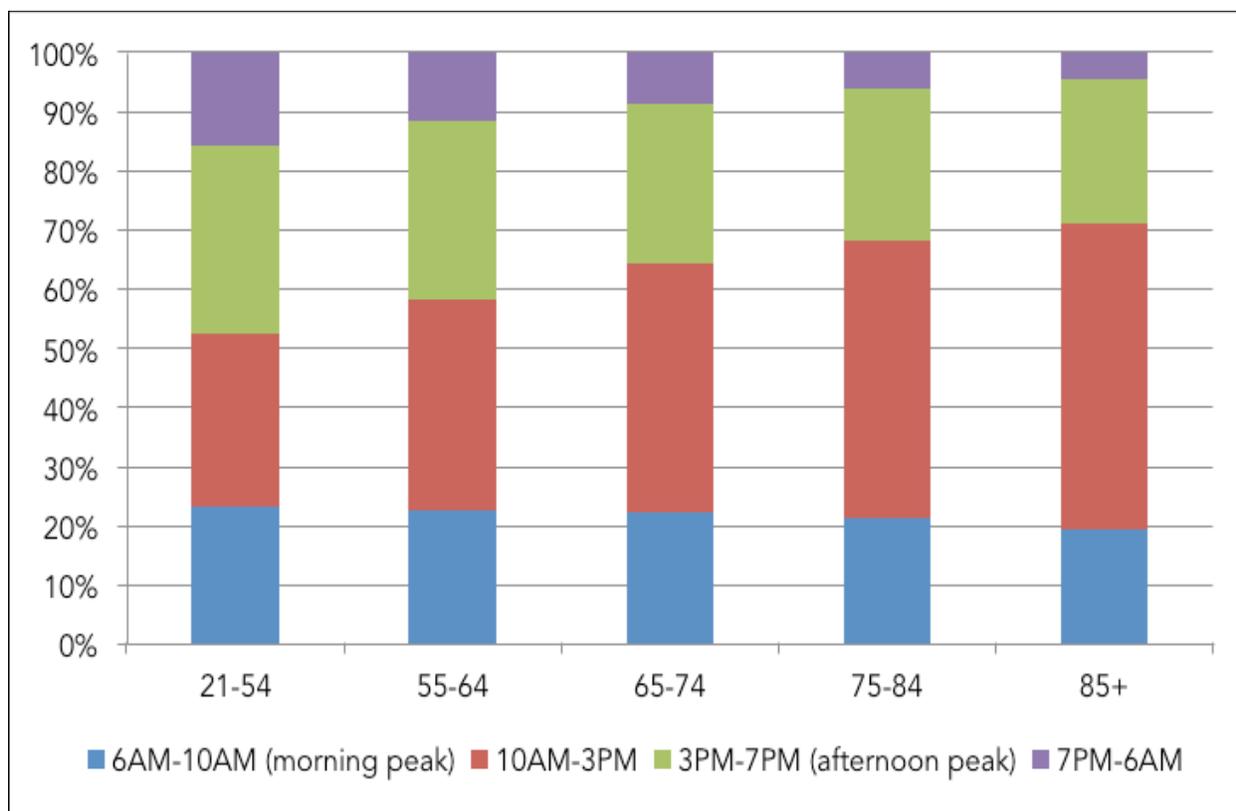


2.2.6 - Time of Travel

Older adults tend to travel when there is less traffic and better driving conditions (Collia et al., 2003; Heaslip, 2007; OECD, 2001). Since retired drivers are less likely need to travel during peak hours (i.e., 7-8 am and 5-6 pm), the majority of older adults travel during off peak hours. According to the 2001 NHTS over 60% of travel by older adults is conducted between 9:00 am and 4:00 pm (Collia et al., 2003). Peak hours for older adults typically is in the mid morning from 10 to 12 am (Collia et al., 2003; Heaslip, 2007).

Figure 2.10 demonstrates these trends by showing the distribution of trips in the US by time of day for different age cohorts (based on trip start times from the 2009 NHTS). The same chart focusing on Florida residents is not presented because it is nearly identical to the one presented in **Figure 2.10**. The figure makes it clear that older cohorts make an increasing larger share of trip during the middle of the day and have smaller shares of afternoon and nighttime trips.

Figure 2.10 - Distribution of Time of Travel by Age



2.2.7 - Behavior Differences among Older Adults

Although these general trends hold true for aging populations as a whole, older generations are not a homogenous group and travel behavior can vary significantly among older populations (Hildebrand, 2003). In particular, travel patterns among adults age 65 and older varies by age and gender. All of the previously presented figures from the 2009 NHTS demonstrate how travel behavior continues to change among the different age cohorts older than 65 years of age. As adults age beyond the 65-75 age cohort, they tend to reduce the number of trips they take and the length of their trips (Rosenbloom, 2004; Whelan et. al., 2006). This is especially evident among adults age 85 and older (Rosenbloom, 2000; Giuliano et al., 2003). At the same time, as older adults continue to age, their reliance on the automobile also increases (Hjorthol et al., 2010; OECD, 2001). Similarly, the differences between older adults and the rest of the population are magnified for older females (OECD, 2001; Lynott & Figueiredo, 2011; Mattson, 2012). Older females tend to travel even less often and take shorter trips than older males and have a higher percentage of shopping and leisure trips (Whelan et. al., 2006; Bauer et al., 2008). Thus while older adults have very distinctive travel behavior patterns from the rest of the population, this does not mean that every older adult has the same travel needs. Like any other demographic group, older residents' travel needs vary by demographic group and evolve over time as they age, and transportation planning initiatives ought to attempt to address as many of these needs as possible.

2.3 - DRIVING CESSATION

2.3.1 - What is Driving Cessation?

Unfortunately, not all of the changes in older adults' travel behavior is by choice. As drivers age, their ability to safely drive a car declines. Many older drivers change their travel behavior (when, where, and how they drive) to compensate for their declining driving ability. Eventually, older drivers are forced to give up driving completely.

Deciding when to stop driving often is a gradual process that is influenced by a number of different factors. "A person's decision to stop driving may be voluntary (e.g., recognition of a decline in health status, loss of confidence in driving, or influence by others) or involuntary (e.g., sudden onset of medical conditions, forfeiture of driving privileges)" (Oxley & Whelan, 2008). It is estimated that more than 600,000 people, aged 70 and older, stop driving each year and become dependent on others to meet their transportation needs (Foley et al., 2002). Knowing when to stop driving can be very difficult for aging drivers because the decision can profoundly affect their personal mobility and quality of life.

Figure 2.11 presents the percentage of individuals within each age cohort that are drivers (as derived from the 2009 NHTS). This number drops significantly for older groups for the US as whole and for Florida. Roughly half of those over 85 no longer consider themselves a driver. **Figures 2.12 and 2.13** respectively show the percentage of individuals within a given age group that have a medical condition that results in limiting driving to the daytime or giving up driving altogether (again based on the 2009 NHTS). There is a clear increase in driving limitations due to medical conditions for older cohorts. About half of those in the oldest cohort have medical conditions that limits driving (20% are limited to driving during the daytime and 30% are unable to drive at all).

Figure 2.11 - Percentage of U.S. Adults That Are Drivers by Age

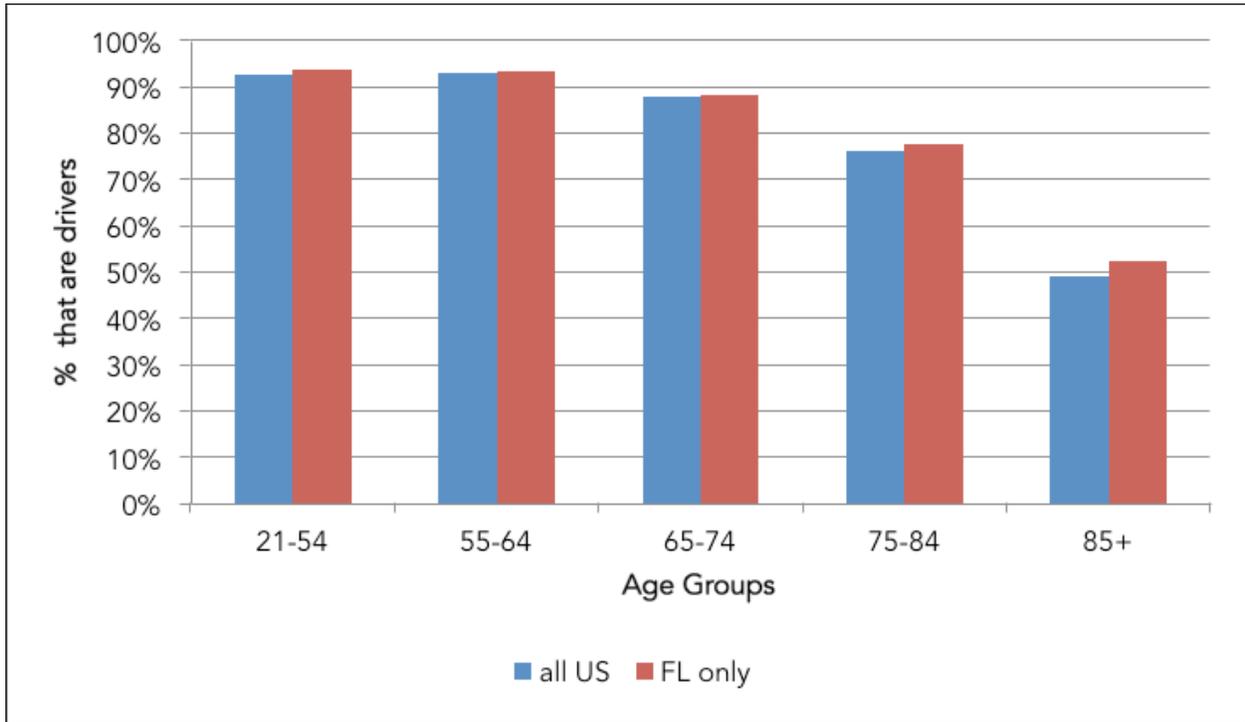


Figure 2.12 - Percentage of U.S. Adults with a Medical Condition That Limits Driving to Daytime

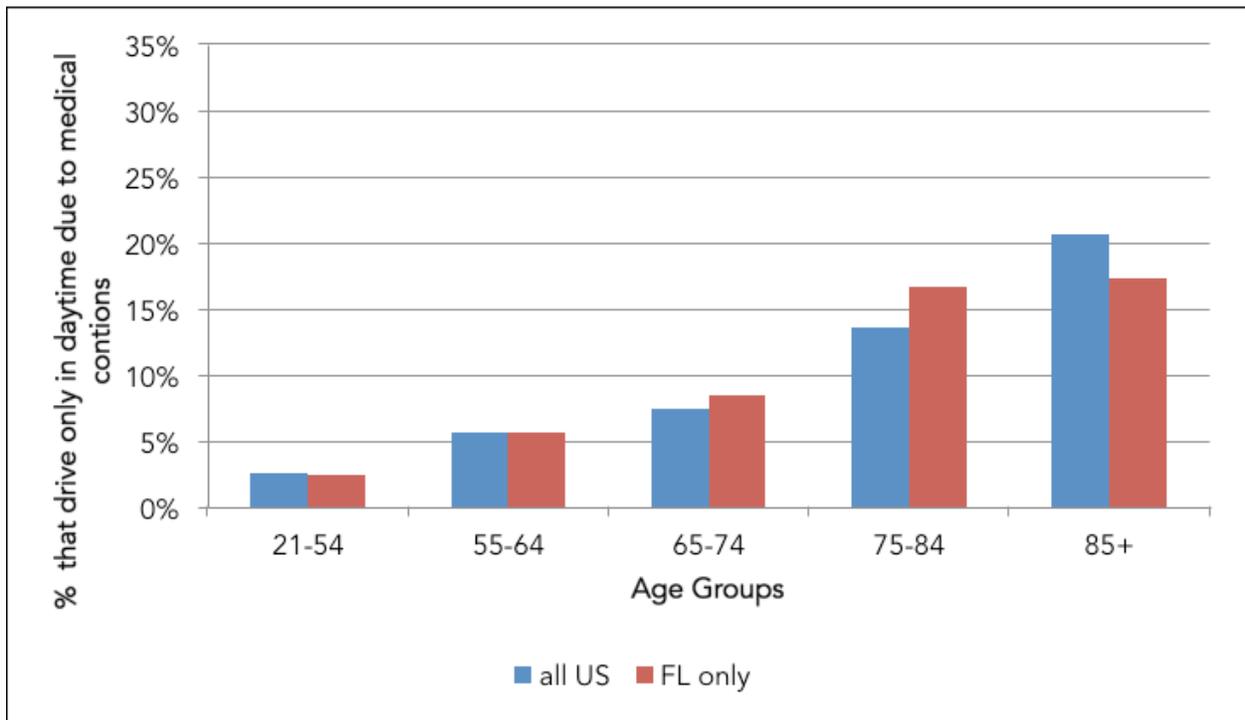
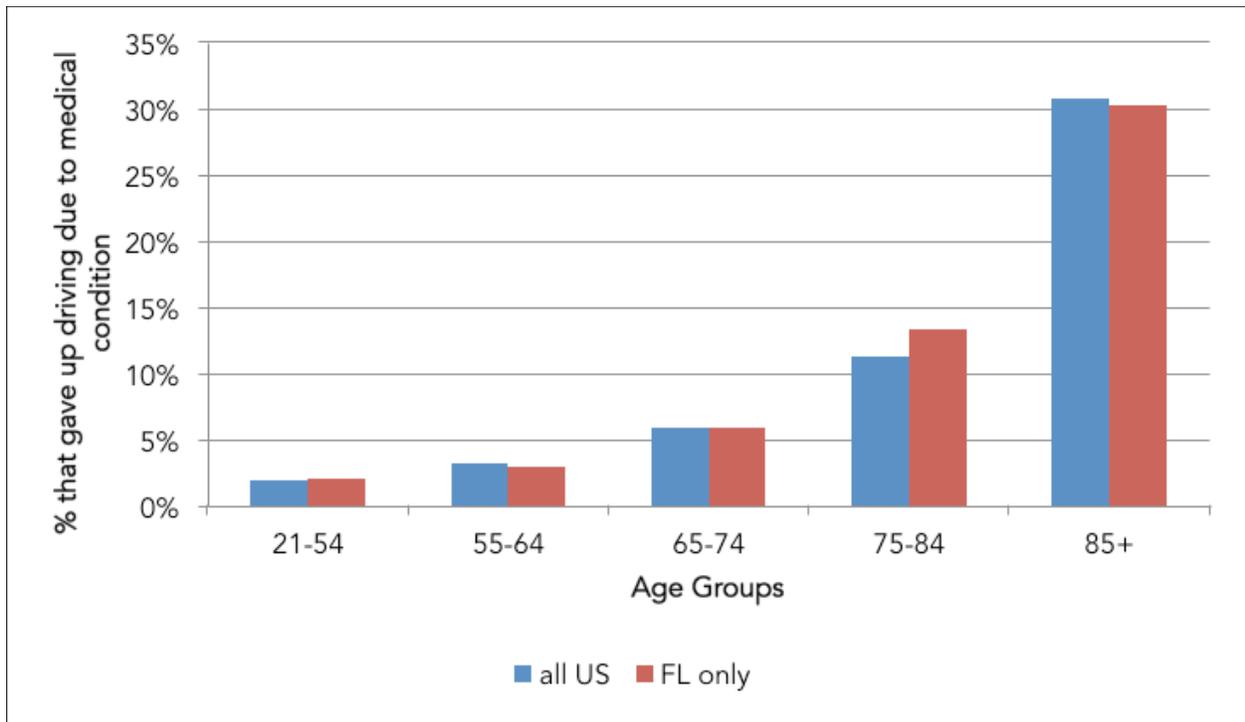


Figure 2.13 - Percentage of U.S. Adults with a Medical Condition That Result in Giving Up Driving



2.3.2 - The Wicked Problem of Driving Cessation

Studies have shown that older drivers rank second among all age groups in total number of crashes annually (after drivers ages 15-24), and have the highest number of crashes per mile driven (McGwin & Brown, 1999). According to the Centers for Disease Control and Prevention, the risk of being injured or killed in a motor vehicle crash also increases as drivers age. Per mile traveled, fatal crash rates increase starting at age 75 and rise notably after age 80. Since aging drivers can be hazardous to themselves and others, it is natural to believe they should stop driving. However, aging populations typically do not have good transportation alternatives and rely heavily on personal vehicles. Public transport is often unfamiliar or unavailable, and declining health inhibits an aging person's ability to use these modes (Dickerson et al., 2007; Donorfio et al., 2009). Asking for rides is also difficult for older adults, as they do not want to burden friends and family (Adler & Rottunda, 2006; Mezuk & Rebok, 2008). Many older drivers continue to drive because they see no other way of maintaining their mobility (Kostyniuk & Shope, 1998). Ultimately, driving cessation has the potential to profoundly impact

quality of life and has been associated with negative consequences for physical and psychosocial well-being (Fonda et al., 2001; Marottoli et al., 1997).

2.3.3 - The Causes of Driving Cessation

Driving cessation is rarely caused directly by professional recommendation (Hakamies-Blomqvist & Wahlstrom, 1998). In general, older adults prefer to make the decision to stop driving themselves. However, advice on when to stop driving is better received from physicians rather than from family and friends (Kostyniuk et al., 1998). One study found that as many as 83 percent of former drivers made the decision to stop driving voluntarily (Choi et al., 2012B). In a 2005 study, researchers Geri Adler and Susan Rottunda determined that the decision of whether or not older adults will continue to drive is influenced by a variety of factors including: health, costs related to driving, a frightening experience, family, physicians, lack of alternative transportation, and gender. Key factors related to driving cessation such as health, socioeconomic status, and demographic characteristics are discussed in more detail below.

2.3.4 - Common Characteristics of Former Drivers

Health (or self-reported health) is repeatedly cited as the most important factor in the decision to stop driving (Anstey et al., 2006; Dellinger et al., 2001; Hakamies-Blomqvist & Wahlstrom, 1998; Kostyniuk et al., 2000). Many of the health characteristics that impact aging drivers stem from the onset of chronic and acute medical conditions, which impact vision, information-processing speed, and reaction time.

Vision is often cited as one of the most important health determinants of cessation. In one study, 25 percent of survey respondents identified vision as the primary reason for deciding to stop driving (Dellinger et al., 2001). Poor mental health and performance has also been found to be a significant predictor of cessation. A reduction in mental agility impacts drivers' decision-making process and reaction time and can be even more important to driving safety than one's physical abilities (Edwards et al., 2009A; Mann et al., 2005). In fact, Anstey et al. (2006) found that

“measures of subjective health and cognitive function were more significant for predicting driving cessation than medical conditions.” Similarly, self-reported health has been found to be a strong determinant of cessation. This is likely due to the fact that cessation is usually a personal decision, and older adults who feel like they are in good health would see no reason to stop driving even if they had health conditions.

Education, household composition, and income have also been found to influence cessation. In a longitudinal study examining gender and racial disparities among older adults, Choi et al., (2012A) found that older drivers were more likely to be male, have higher levels of education, and to be married. Further, they found that married men were almost six times less likely to stop driving as non-married men. Marital status was not associated with driving cessation among women. However, other studies have found that women, particularly married women, are more likely to stop driving at earlier ages than men (Kostyniuk et al., 1998). In addition to education and household composition, lower income levels and non-employment status have been found to be associated with driving cessation, but these factors likely reflect social and economic issues rather than driving ability (Marottoli et al., 1993).

In addition to health and socioeconomic factors, demographic characteristics such as gender and race have been found to be predictors of cessation. In general, women are more likely than men to stop driving earlier (Anstey et al., 2006; Campbell et al., 1993; Choi et al., 2012A; Gallo et al., 1999; Mann et al., 2005). Studies have also found that men and women stop driving for different reasons. Men typically stop driving due to health problems. While women are also likely to stop driving because of health issues, they are affected by additional factors such as loss of confidence in driving ability (Siren et al., 2004). Hakamies-Blomqvist & Wahlstrom (1998) found the most likely reason for these gender differences is that men tend to view driving as a necessity and only stop when health problems prevent them from continuing. In their study on driving cessation in Finland, they found that 43 percent of women considered a private car to be a necessity, compared to 65 percent of male drivers (Hakamies-Blomqvist & Wahlstrom, 1998). This finding is similar to trends in the United States where, on average, men age 65 and older drive twice as many miles as women (Figueiredo & Lynott, 2011). This trend often makes cessation particularly difficult on men, as they are less likely to stop driving voluntarily and feel they have little control over the decision (Adler & Rottunda, 2006).

Many studies have found that, at all ages, men and non-Hispanic Whites are less likely to stop driving than women and racial/ethnic minorities (Choi et al., 2012A; Choi & Mezuk, 2012; Freeman et al., 2006; Mezuk & Rebok, 2008). In particular, some studies have found that older Blacks are less likely to drive than older Whites (Choi & Mezuk, 2012; Mann et al., 2005), and that older Blacks report a higher burden of functional limitations than other groups (Kelley-Moore & Ferraro, 2001).

2.3.5 - The Process of Driving Cessation: Self-Regulation

As previously mentioned, cessation is rarely caused directly by professional recommendation. For many, it is a process that involves self-regulation, in which aging drivers gradually decrease the number of miles and trips they make and avoid driving in stressful situations such as nighttime and rush hour (Kostyniuk et al., 2000). Individuals self-regulate for a number of reasons such as health status, household composition, access to alternatives, and driving discomfort. In one study, 34 percent of older drivers reported some form of self-regulation (Gallo et al., 1999).

Although self-regulation helps aging adults transition into a non-driving lifestyle, many children of aging drivers believe that their parents are not capable of making an informed decision when it comes to deciding when to stop and that they pose a risk to themselves and others (Kostyniuk & Shope, 1998). There is also some evidence that self-regulation may not overcome the increased risk of crashes among seniors, despite their changes in travel behavior (Ross et al., 2009). In this way, "the strength of older drivers lies in their aversion to risk, but perceptual problems and difficulty judging and responding to traffic flow often counterbalance this attribute" (McGwin & Brown, 1999).

2.3.6 - Effects of Driving Cessation on Health and Quality of Life

Despite the risks associated with continuing to drive into later years, cessation may have even greater consequences for aging individuals. Without the ability to maintain personal mobility, aging populations face a declining quality of life and negative health impacts. “Cessation can cause depression, reduced life satisfaction, and social isolation which stems from a loss of independence, a lack of personal control, and reduced participation in important life roles; together, these factors can lead to greater uncertainties in personal identity, harming individuals’ psychological state and well-being” (Liddle et al., 2014).

Declining Quality of Life

Cessation can lead to a reduction in social engagement and participation in activities outside of the home. Aging adults have few alternatives to driving, and consequentially decrease the number of trips they make after they can no longer drive. In comparing seniors that do and do not drive, Bailey (2004) estimated that non-drivers make 15 percent fewer trips to the doctor, 59 percent fewer trips to shop or eat out, and 65 percent fewer trips to visit friends and family. Analyzing trends from the 2001 NHTS, researchers found that aging populations abandon social, religious, and recreational trips first when they stop driving (Decker, 2006). Furthermore, cessation has been shown to be associated with almost a 50 percent reduction in one’s network of friends (Mezuk & Rebok, 2008).

Negative Health Impacts

Many older drivers choose to stop driving due to health reasons, but cessation itself can lead to further declines in physical and mental health (Edwards et al., 2009A). Marottoli et al. (1997) found driving cessation to be one of the highest predictors of depression among older adults. Some former drivers have described cessation in terms of losing a spouse, losing a part of themselves, being in prison, and even dying (Kostyniuk & Shope, 1998; Yassuda et al., 1997). Many of the negative health impacts of cessation have also been shown to influence mortality. Edwards et al. (2009B) found that older adults who stopped driving were four to six times more likely to die over the subsequent three years than older adults who continued driving.

2.3.7 - Effects of Cessation Vary Between Retired Drivers

Driving cessation does not affect drivers equally. Studies have found that differences among former driver's personality traits, demographic characteristics, level of support from family and friends, and geographic location can impact the effects of cessation and make some former drivers worse off than others (Choi et al., 2012A). Also of significance is whether or not the decision to stop driving is made independently. Individuals who chose to stop driving, or at least "owned the decision" to give up the keys, have a better experience with cessation (Musselwhite & Shergold, 2013).

Effects of cessation are not as severe when the former driver has a supportive family and friend groups (Musselwhite & Shergold, 2013). Some former drivers rely primarily on friends and family for rides. One study reported that 67 percent of former drivers did not list an additional means of travel aside from receiving rides from friends and family (Kostyniuk & Shope, 2003). Furthermore, the effects of cessation appear to be worse for residents of small cities and rural areas, due to a greater sense of social isolation from friends and family and lack of transportation alternatives serving these areas. Living in these areas can make former drivers more vulnerable to quality of life declines and an even higher likelihood of mortality (O'Connor et al., 2013).

The effects of cessation can be significantly reduced for those who are or feel in control of the process (Musselwhite & Haddad, 2010). "Those that plan ahead, who accept and embrace a change in travel patterns, and flexibly change destinations of journeys have the prospect of a better quality of life beyond the car" (Musselwhite & Shergold, 2013). Unfortunately, many studies have found that older drivers are often reluctant to plan ahead for driving cessation because they have difficulty facing the reality of cessation, and are unwilling to make the necessary behavioral changes. Furthermore, they feel they have no transportation alternatives (Bryanton et al., 2010; King et al., 2011; Kostyniuk & Shope, 2003; Meuser et al., 2013; Yassuda et al., 1997).

2.4 - MITIGATING THE EFFECTS OF DRIVING CESSATION

2.4.1 - Traditional Strategies for Mitigating the Effects of Driving Cessation

Traditional strategies for mitigating the effects of driving cessation include keeping aging drivers on the road as long as is safely possible, improving public transportation, creating walkable places, and helping older adults plan and prepare for driving cessation.

Many studies have found that “driving affords the greatest mobility for older adults and that continued mobility means access to a private vehicle for as long as possible” (Oxley & Whelan, 2008). For this reason, a common strategy among transportation professionals is to keep aging drivers on the road as long as possible. Three strategies for keeping older drivers on the road include behavior and education measures, vehicle safety advancements, and infrastructure, road design, and operation improvements (Oxley & Whelan, 2008). Behavioral and education measures include driving refreshers and training programs such as promoting self-regulation and adoption of safe driving practices. Vehicle safety advancements address the need to design cars with older drivers in mind. This would include making the door frame, seats, mirrors, and steering wheel, more driver friendly and installing automated warning systems that alert drivers when they are entering unsafe situations such as drifting in between lanes or backing up into unseen objects. Finally, infrastructure, road design, and operation improvements can help older drivers use the transportation system more safely. This can include making signs easier to read and reducing the complexity of the traffic environment at intersections where accidents commonly occur.

Unfortunately, strategies such as improving driver education and reducing the complexity of intersections do little to improve mobility for individuals who can no longer drive. For retired drivers, public transit provides a way of maintaining

personal mobility. A 2002 study measuring driving expectancy of persons age seventy years and older in the United States found that: “men in their early 70s who stop driving will need access to transportation alternatives, such as public transportation, for an average of six years; women in the same age group will, on average, need transportation alternatives for ten years” (Foley et al., 2002). However, public transit often fails to provide the level of service retired drivers need to maintain their mobility. In general, the percentage of trips taken by alternative modes of transportation tends to decrease as individuals age (Hjorthol et al., 2010; OECD, 2001). For many former drivers, public transportation is perceived as unfamiliar and unsafe and is often unavailable. Seventy percent of Americans over fifty live where transit does not exist or serves the area very poorly (Transportation for America, 2011). Where public transit systems do exist, they have difficulty attracting senior travelers. This could be due to factors such as safety concerns or the inability of the system to match desired travel patterns (Rosenbloom, 2009). Understanding the challenges older adults face using public transit and investing in solutions that make public transit more accessible and attractive can help to mitigate the effects of driving cessation.

In addition to improving public transit, many cities across the United States are focused on enhancing connectivity and creating more walkable places. Implementing better crosswalk signalization, signage, speed management, and road markings are a few of the strategies cities are undertaking in areas and intersections frequented by older adults (Oxley & Whelan, 2008). Over 600 jurisdictions and 27 states have adopted ‘Complete Streets’ policies, which serve as guidelines to create roadways that promote safe access for all users regardless of age and mode of transportation (Smart Growth America, 2014). Investing in Transit Oriented Development (TOD) can also help mitigate the effects of driving cessation by maximizing older adults’ access to public transportation, while creating neighborhoods focused around mixed-use residential and commercial areas that promote walkability. Research has shown that non-drivers over age 65 who live in denser mixed-use areas with more public transit options are more likely to use transit (Bailey, 2004). Ultimately, TOD can help foster aging in place, and reduce the likelihood of older adults having to enter into long-term-care institutions, as many choose to do today.

Another strategy that can help to mitigate the effects of driving cessation is helping older adults plan ahead and prepare for driving cessation. Planning ahead allows older adults to address the practical issues of cessation such as when to stop, who

to tell, what to do for alternative transportation, travel budget, and disposal of the car (Adler & Rottunda, 2006). Currently, many resources exist for planning ahead including several guides and checklists sponsored by agencies such as the American Medical Association, American Automobile Association Foundation for Traffic Safety, and the American Association of Retired Persons.

2.4.2 - How Automated Vehicles Could Mitigate the Effects of Driving Cessation

Many of the existing strategies for addressing the issues related driving cessation can help to mitigate many of the mobility and quality of life difficulties faced by retired drivers. However, no current strategy has the ability to provide the same level of mobility retired drivers enjoyed prior to giving up driving regardless of where they live or how strong their support network is. The emergence of AV technology may be the first initiative with the potential to provide older adults with personalized rapid transit.

In particular, AVs could help to improve the mobility of older adults' who reside in suburban and rural areas, and help to minimize risks associated with aging driving. "Many older adults have lived their entire lives in the suburbs, and most will age in place there. The place where people live as they age is critical to the kind of support networks and mobility options available to them at home" (McGuckin & Lynott, 2012). A 2003 study found that 79 percent of adults age 65 and older live in car-dependent suburban and rural communities, which typically require frequent, long distance trips by automobiles (Rosenbloom, 2003). Since providing public transit to these areas is extremely difficult, AVs may be the only way of ensuring older adults can maintain their quality of life.

There are four levels of AV technology ranging from semi to fully autonomous. The levels, as defined by the NHTSA (2014) are as follows. Level 1, or function-specific automation, involves the use of one or more specific control functions such as brake assist, lane guidance, and cruise control. Level 2, or combined function automation, involves the use of two primary control functions or more, such as cruise control in combination with lane guidance. Level 3, or limited self-driving automation, allows the driver to rely on the vehicle for control of all safety-critical functions under certain traffic or environmental conditions, and only requires the driver to be available for occasional control when changes in the conditions occur. Level 4, or

full self-driving automation, enables both occupied and unoccupied vehicles to perform all safety-critical driveway functions for the entirety of the trip.

Each level of AV can help to improve mobility for older adults, whether they are in the process of self-regulating or have ceased driving. For older adults who are in the process of self-regulating, levels one, two and three can help to reduce the risk of crashes and reduce the anxiety of driving in stressful situations such as nighttime and rush hour. For drivers who have completely stopped driving, level four can offer them the opportunity to have complete use of the automobile and regain their driving privileges and freedom. AVs could serve to improve and extend older adults' quality of life, independence, and mobility, as well as to reduce the likelihood of being admitted to a long-term care facility. AVs provides a strategy that can potentially accommodate the travel behavior of aging populations within the context of a predominately auto-focused transportation system.

Chapter 3 will provide more insight into how and which types of automated vehicle technology are best suited to reduce the risk of age-related car crashes thereby restoring aging adults' personal mobility and improving their quality of life.

CHAPTER 3



Image Source: www.line-car.com/checklist-for-older-drivers.html

Travel Safety and Technology Adoption by Elderly Populations

ABSTRACT

This literature review focuses on the aging population's driving performance and factors determining their willingness to adopt various types of Advanced Driving Assistance Systems (ADAS) and Automated Vehicle (AV) technologies. Through a user-centered approach, we outlined safety issues associated with age-related declines in driving ability, problems that may arise when aging adults' mobility is reduced after they cease driving, and how these emerging technologies may help aging adults faced with driving cessation avoid these deleterious consequences. We reviewed pertinent literature on: 1) what age-related cognitive and sensory deficits affect driving performance and older adult compensation strategies for them; 2) crash scenarios older adults (OAs) are overrepresented in; 3) how ADAS and AV technologies can be employed to safely allow OAs to enjoy the mobility benefits of a personal vehicle; and 4) factors affecting older drivers' adoption of these technologies. Suggestions for maintaining OA mobility through the use of emergent ADAS as well as their implications for future AV technologies are provided.

3.1 - INTRODUCTION

This literature review adopts a user-centered approach focused on the older driver (age 65+) to provide insight for safely maintaining aging individuals' mobility by helping them stay behind the wheel of their own personal vehicle through the use of emerging ADAS and AV technologies. First, an overview of demographic shifts, age-related factors contributing to driving cessation, and older drivers' compensation strategies for various sensory, cognitive, and physical declines are provided. Second, factors affecting the adoption of ADAS and AV technologies are discussed. Finally, crash scenarios that older drivers are overrepresented in are reviewed, and possible ADAS/AV solutions for these crash types are identified.

3.2 - OVERVIEW OF AGING DRIVERS AND DRIVING CESSATION

3.2.1 - Issues Surrounding the Increase of Older Drivers on the Road

As of 2010, approximately 40 million (13%) of the U.S. population was over the age of 65, and by 2030, it is estimated that 72 million (19%) of the U.S. population will be older than 65 (United Nations, 2011). Individuals aged 65+ years represent the largest growing age group in the driving population, and are keeping their licenses longer and driving more miles per licensed driver than previous older generations (Lyman et al., 2002). This increase in the proportion of older drivers on the road implies that policy makers should familiarize themselves with this population's functional limitations associated with driving and possible methods of intervention to promote safe mobility for life. In particular, technologies such as advanced driving assistance systems (ADAS) and automated vehicles may provide solutions to the mobility challenge. (See Reimer, 2014 for an excellent review of the varying levels of automation and its implications on older adult safety and mobility). Age-related functional limitations such as deteriorations in vision, cognitive skills (e.g., processing speed and memory ability), and motor skills place these older drivers at increased risk of motor vehicle crashes (MVCs; Stutts et al., 1998). This population's increased physical frailty due to changes in bone composition (Chavassieux et al. 2007) also leaves them more susceptible to injury even in minor MVCs (Cunningham et al., 2001). This can lead to them having more surgical, medical, and therapy workloads before being discharged from the hospital, and significantly more complications, as well as significantly longer hospital stays.

3.2.2 - Factors Leading to Decreasing Fitness to Drive, Driving Cessation, and Associated Outcomes

Aging brings about changes in sensory, cognitive, and physical abilities that can affect driving safety. Sensory issues include decreases in visual acuity and hearing (Ivers, et al., 1999; Marottoli et al., 1998), though hearing deficits do not seem to impact driving performance as much (Anstey et al., 2005). Cognitive risk factors include behavioral slowing (Salthouse, 2010), decreases in selective visual attention (Baldock et al., 2007), and decreases in the ability to perform planned actions under time pressures (Stelmach & Nahom, 1992), all of which may lead to decreasing fitness to drive. Physical problems such as arthritis also can have an impact on driving performance as poor neck rotation has been found to double the risk of a crash (Marottoli et al., 1998). Many chronic diseases associated with aging are treated with prescription drugs and over the counter medications that can also affect driving performance (Hetland et al., 2014).

Access to some form of transportation is critical to older adults' maintaining their health, social inclusion, and independence in the later years of life (O'Neill & Carr, 2006). The decision to stop driving often comes at a time in older adults' lives in which they have less disposable income, and neurological disease, cataracts, decreased physical activity, and/or functional disability (Marottoli et al., 1993). Though with age, some have argued that many older adults are increasingly able to purchase a new vehicle to meet changing transportation needs (Coughlin, 2009). Due to a high variability in income in the older population, there will be older adults that have sufficient financial resources to buy vehicles equipped with assistive technologies themselves, while others in this age range might need public subsidies in order to do so. Driving cessation in those over the age of 65 is associated with reduced quality of life and psychological well-being (Adler & Rottunda, 2006; Gruber et al., 2013; Whelan et al., 2006). In fact, depressive symptoms have been found to worsen in older adults that have ceased driving, or have lessened their amount of driving (Fonda et al., 2001).

3.2.3 - Older Drivers' Compensation Strategies

Older drivers are often aware of their declining ability to drive and compensate in a number of ways. Michon's (1985) hierarchical structure of the driving task consists of three task levels: the strategic level (decisions made before getting behind the wheel), the tactical level (operating heuristics once behind the wheel), and the operational level (actual driving behavior). Decisions to take familiar routes, or avoid driving at night, during rush hour, or poor weather are strategic level choices often made by older drivers. Maintaining a certain speed or headway while driving represents a tactical level choice. Older drivers tend to make decisions at the strategic and tactical levels to compensate for their deficits, which provide them with more time to react at the operational level. Older adults' driving behavior might slightly benefit from their being less inclined to multi-task behind the wheel due to difficulties in sharing attention (Brouwer et al., 1991), but it is important to note that shared attention demands should be minimized in any interface design (Davidse, 2006).

3.3 - FACTORS INFLUENCING OLDER DRIVER ADOPTION OF ADAS/AV TECHNOLOGY

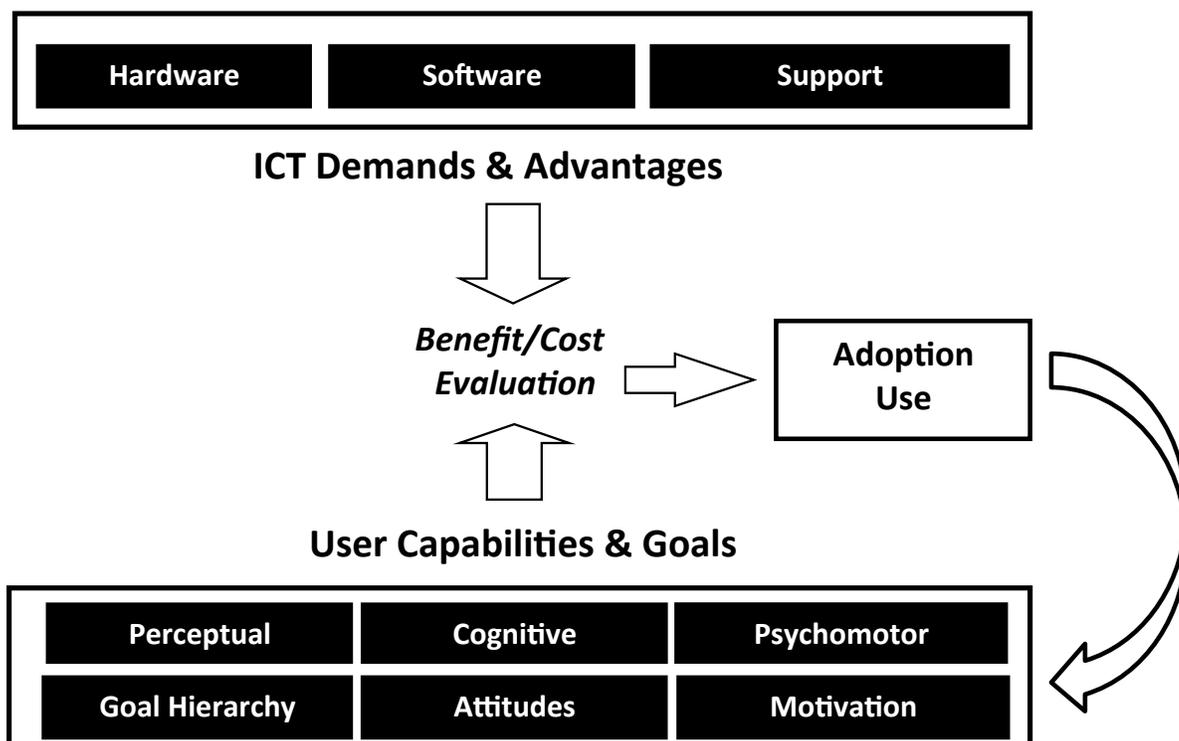
3.3.1 - Older Adults' Adoption of Technology

Many models of technology adoption follow a cost-benefit evaluation framework. One of the most influential is the Unified Theory of Acceptance and Use of Technology (UTAUT2) (Venkatesh et al., 2012). The major cost factors in UTAUT2 are effort expectancy (perceived ease of use) and price value, whereas major benefits include performance expectancy (perceived usefulness) and hedonic motivation. Other important factors are social influences, habit, and facilitating conditions such as expectations about support. Demographic predictors typically include age, gender, and technology experience. In a recent review of OA adoption of technology, Lee and Coughlin (2014) identified ten factors (value, usability, affordability, accessibility, technical support, social support, emotion, independence, experience, and confidence) as facilitators or determinants of OA technology adoption that have many parallels to UTAUT2, with the addition of distinct factors for affordability (i.e., perception of initial financial costs vs. immediacy and clarity of possible gains after purchase) and independence (i.e., preventing stigma and protecting autonomy). Of these factors, value, usability, social support, emotion, and confidence seem to be the most likely to positively affect OA adoption of ADAS/AV technology while affordability and accessibility seem to be the most limiting at present. The effects of experience, technical support, and independence on OA adoption of ADAS/AV technologies seem harder to gauge. The public has little prior experience with these emergent technologies, the form and content of these technologies' technical support is still being constructed, and it is too early to ascertain the nature of OAs' self-perceptions when using ADAS/AV technologies.

Another general framework for technology adoption and use that reflects a demand–capability framework is provided in **Figure 3.1**.

Figure 3.1 - Technology Adoption and Use Model
(adapted from Charness & Boot, accepted)

Technology Adoption & Use Framework



Motivation and attitudes influence the goals that people set about technology adoption and goals are evaluated in the context of someone’s perceptual, cognitive, and psychomotor capabilities. On the technology side, the potential demands that technology make on the potential user (perceived ease of use), coupled with the perceived benefits, and dollar cost would be expected to be weighed within the benefit/cost evaluation cycle. Experience with technology can feed back to influence motivation and attitudes, but also someone’s capabilities (e.g., a hearing aid could facilitate interactions with smartphones that provide auditory alerts).

In the case of automated vehicle technology and older adults, we would expect perceived ease of use, price value, and perceived usefulness to dominate decision-

making. When expected value, such as enablement of mobility, increases, perhaps through fears of loss of license or being able to drive safely, there should be a strong motivation to seek out automated vehicles. Fully autonomous vehicles could probably provide the greatest benefit for those who are no longer competent to drive, but, there is a great deal of uncertainty about how much older adults would be willing to pay for automated vehicle technology. Our only indications are based on prior studies of willingness to use technology to help with tasks needed for maintaining independence (Schulz et al., 2014). Kitchen (e.g., meal preparation and washing dishes) and personal care (getting in and out of bed, dressing and toileting) assistance was only worth about \$40-45 per month to baby boomers aged 45-64, for those indicating some willingness to pay. About a third of the sample was unwilling to pay anything for these services.

3.3.2 - Conceptualizing Trust in AV Systems

One potential barrier to adoption of technology-based systems is trust that the technology will work as intended, and because of this, general trust is one of the most fundamental factors governing human-automation interaction (Sheridan & Ferrell, 1974). Hoff and Bashir (2013) proposed a theoretical model for trust in automated systems that broke trust into three components that provide a useful lens to view the complex case of older adult adoption of AV technology:

1. **Dispositional Trust:** variability of individuals' instinctive tendencies to trust automation that cannot be changed in the short term. Dispositional trust is made up of culture, age, gender, and personality traits.
2. **Situational Trust:** varies depending on the specific context of an interaction and is made up of environmental variability (i.e., type of system, system complexity, type of task, perceived risks/benefits, framing of task, physical environment, organizational factors) and context-independent user variability (i.e., self-confidence, subject matter expertise, mental well-being).
3. **Learned Trust:** based on past experiences of a user relevant to a specific automated system and varies depending on the characteristics of a system. Learned trust is further divided into the user's trust prior to using the system (initial learned trust) and the user's trust while operating the system (dynamic learned trust).

Using this framework, it makes sense that older adults faced with the decision to cease driving may have higher levels of situational trust than those that remain confident in their driving abilities. The largest gains to be made in trust are in older driver's learned trust of AV technology, which will only come with increasing news of these systems' efficacy and/or positive experience using these technologies once they are available.

3.4 - OLDER DRIVER CRASH SCENARIOS AND POSSIBLE SOLUTIONS

3.4.1 - Older Drivers' Common Crash Scenarios

Older adults are more likely to get into certain crash types, often involving cross-traffic (left in the U.S.) turns at intersections (Alam & Spainhour, 2009; Hakamies-Blomqvist, 1994; Keshinen et al., 1998; McGwin & Brown, 1999; Preusser, Williams, Ferguson, Ulmer, & Weinstein, 1998). Alam and Spainhour (2009) analyzed data from the year 2000 and found that older drivers found to be at fault in fatal intersection crashes in Florida typically misjudged the speeds of other vehicles, failed to observe other vehicles, disregarded traffic signals, or made disallowed left turns. Older drivers were overrepresented in left turn crashes versus oncoming and cross traffic, and this represented 42% of the crashes in which older drivers were at fault. Interestingly, older drivers were more at risk of being hit, as opposed to hitting other drivers (Hakamies-Blomqvist, 1994). This is reflective of their relatively poor ability to gauge oncoming traffic's speed to traverse intersections and in their relative lack of non-intersection crashes (Alam & Spainhour, 2009).

Another important factor to consider is that unlike younger and middle-aged drivers, whose driving errors and lapses have not been found to be predictive of their accident involvement (Parker et al., 1995), older drivers' errors and lapses predicted their crash involvement, with passive involvement mainly being associated with lapses (Parker et al., 2000). These lapses might be avoided, with the use of ITS (intelligent transportation systems), be it augmentation of older adults' perceptual abilities through different types of ADAS (Davidse, 2006), or replacing their actual driving behavior through more highly automated technology (Reimer, 2014).

3.4.2 - Possible ADAS/AV Solutions

For a concise, yet comprehensive review of older driver weaknesses and the type of assistance needed to help overcome these weaknesses, we refer the reader to **Table 3.1** from Davidse (2006). We adapted this table to show which weaknesses, that are most relevant to safety, can be supported by ADAS/AV technologies.

Table 3.1 - Age-Related Weaknesses Inhibiting Aging Drivers' Ability to Drive

Age-Related Weakness	Driving Related Difficulty	Assistance Needed
Peripheral vision	Merging or changing lanes without heed to other road users	Signaling objects in driver's blind spot
Motion perception	Correctly judging the movement of other road users and their approach speed	Draw attention to oncoming traffic
Selective attention	Overlooking traffic signs and signals	Cue relevant information to driver
Speed of processing/ Making decisions	Complex traffic scenarios lead to longer reaction time	Provide warning for upcoming complex traffic scenarios
Head/Neck Flexibility	Merging or changing lanes without heed to other road users	Signaling objects in driver's blind spot
Performance under time pressure	Suboptimal decisions	Provide warning for upcoming complex traffic scenarios

Table adapted from Davidse (2006).

Because older drivers are more likely to be collided with by other drivers rather than initiating the collision themselves (Hakamies-Blomqvist, 1994), it does not appear that the actual execution of the driving task is what needs bolstering, but rather systems that help older drivers make accurate judgments at the tactical level, with enough time to execute the correct situational action at the operational level. With this in mind, and from the information presented in the table, it is clear that the most useful assistive devices will draw attention to approaching traffic, signal obstructions in the driver's blind spot, direct attention to relevant information and signage, and/or provide advance knowledge on the upcoming traffic situation. ADAS can compensate for decreased peripheral vision caused by visual declines and decreases in the neck's range of motion (Klein, 1991; Shinar & Schieber, 1991) by alerting the driver to objects in their blind spot and helping them avoid colliding with other drivers when merging or changing lanes. Declines in vision and hearing that lead to older drivers having difficulty in motion perception and errors in judging the movement or approach speed of other motorists can be compensated for by ADAS drawing attention to approaching traffic. Declines in selective attention and speed of information processing/decision-making (Brouwer et al., 1991; Quilter et al., 1983) can cause older drivers to overlook pertinent traffic signs and signals and keep them from performing necessary actions in a timely manner. ADAS may be used to direct the older drivers' attention to relevant information and provide prior knowledge on the upcoming traffic situation to allow the older driver more time to initiate the correct action.

3.4.3 - Advanced Driver Assistance Systems and Studies of their Efficacy and Adoption

The timeline to deployment of fully autonomous vehicles is a subject of speculation and debate (Saffo & Bergbaum, 2013). In the interim, advanced driver assistance systems (ADAS) that aid in certain driving tasks are being successfully developed and sold in many new cars, particularly in luxury brand vehicles. This section reviews different types of ADAS and how they can help older drivers, their availability in the marketplace, and the results of any studies looking at their use and/or adoption by older drivers.

Collision Warning Systems

Collision warning systems that draw the older driver's attention to oncoming traffic in intersections would be the most useful, and would help older drivers successfully make left turns (Davidse, 2006). Mitchell and Suen (1997) noted that the complexity of analyzing collision avoidance in intersections might lead to this form of ADAS taking longer to successfully develop. (Oxley & Mitchell, 1995) simulated such a system that gave older drivers a green light whenever there was a gap in oncoming traffic of at least 6 seconds in which they could execute a left turn while stopped at an intersection. All older participants reported that this system would be "useful" or "very useful" while driving at night, while only 63% thought the same during the day and only about half of the older participants reported willingness to pay for the system. Results showed more near-misses when older drivers used the system, and Oxley (1996) later cautioned against using uniform settings, but instead suggested the gap be adjustable to match the individual driver's characteristics, such as reaction time.

Lane Changing/Merging

While fully automated lane-changing systems have been expected to be developed within the next 20 years (Mitchell & Suen, 1997), only lane-change collision warning systems are currently available (Regan et al., 2001). These systems have not been evaluated with older drivers (Davidse, 2006). Inherent drawbacks in lane-change collision warning systems such as high false alarm rates and small windows for course-correction (in both physical space as well as time to execute) after the system has alerted the driver suggest that these lane-changing/merging assistance systems may not benefit older drivers until automation is fully incorporated.

Blind Spot & Obstacle Detection

Most useful in preventing low-speed crashes that may occur while parking, blind spot and obstacle detection systems most likely will not have a large effect on the overall road safety of older adults (Davidse, 2006). Interestingly, when two types of reversing aids were tested in a simulator by Oxley and Mitchell (1995), they enabled older drivers to park closer to objects and hence fit in to smaller spaces. Vehicle entry and egress often poses a difficulty for older adults, and leads the list of problem areas in vehicle design for the older driver (Herriotts, 2005). This might explain why Oxley and Mitchell (1995) found that most of the older drivers in their

simulator study not only found such a system useful and easy to use, but they were even willing to pay market-price for it. Blind spot and obstacle detection systems therefore might keep older adults driving their own vehicles longer more by increasing their confidence in common, previously low-confidence driving scenarios (in this case, parking and getting in and out of the car) as opposed to substantially increasing their safety in more dangerous crashes. Comfort (as well as safety) is likely to be an important consideration in driving cessation.

In-vehicle Signing Information Systems

Older drivers' difficulties in selective attention while driving may be helped by Connected Vehicles that make use of heads-up displays to highlight the next important traffic sign in a scene. Staplin and Fisk (1991) found that both younger and older adults made more accurate decisions, with shorter latencies, when upcoming sign information was available through such an in-vehicle system. In-vehicle signs have also been found to improve both younger and older drivers' stopping accuracy at traffic signals with short yellow light onsets, and significantly reduced the amount of these short yellow light onsets that older drivers drove through during baseline performance (Caird et al., 2008). However, it is important to note that not only can these in-vehicle displays shift significant amounts of the driver's attention away from the roadway (Lee, 1997), they might be relatively more detrimental to older drivers' driving performance due to OAs increased distractibility (Healey et al., 2008; Lam, 2002). It is important to keep in mind that the success or failure of technology, including these in-vehicle signing information systems, is in the specific ergonomic design, and that ergonomic design needs to take older drivers into account (Pauzié, 2003). Incorporation of Connected Vehicles should display easily decipherable warnings in ways that maximize the amount of attention the driver has on the roadway.

Adaptive Cruise Control

Adaptive cruise control (ACC), adds a distance keeping function to the speed-keeping ability of normal cruise control. Mitchell and Suen (1997) envisioned an ACC system for older adults that took cues from the road into account, similar to Connected Vehicles, such as the speed limit, yield signs, stoplights, and railroad crossings. In a questionnaire study that surveyed ACC users, Larsson (2012) found that the longer drivers had used their ACC systems, the more aware they became of its limitations. Most users reported that the ACC forced them to take control

intermittently, which discouraged full reliance on the ACC. This suggests that the previously discussed potential for gains in learned trust with repeated usage of AV technology is indeed present in this semi-automated system, though it does imply that intermittent use is necessary for this learning to occur. Unfortunately, negative behavioral adaptations have been observed with ACC, including increased lane position variability (Hoedemaeker & Brookhuis, 1998), delay in braking (Hogema et al., 1994), and increased shifting of attention away from the driving task and toward non-driving tasks (Carsten et al., 2012). A simulator study of ACC users and non-users (Bianchi Piccinini et al., 2015) found that it is easy for users to develop an exaggerated level of trust in ACC systems, which leads to slower reaction times in critical situations. Furthermore, they found that the time-to-collision was smaller during critical situations for both ACC users and non-users when they were supported by ACC compared to manual driving, suggesting that even experienced users of ACC have slower responses to critical situation when using ACC.

Highly Automated Driving

Highly automated driving adds lateral control to ACC's longitudinal control. It should be noted that lateral control disengages the driver from the driving task to a larger extent than does just longitudinal control (Carsten et al., 2012; Strand et al., 2014), leading to suboptimal levels of situation awareness (SA; Endsley, 1995) that could negatively affect the driver's ability to safely re-take control of the vehicle in an equipment or system failure (e.g., Endsley & Kiris, 1995). Greater levels of automation have been shown to reduce workload, but this reduction in workload is traded off with a losses of SA, manual skills, and routine primary task performance (in this case, driving; Onnasch et al., 2013). This trade-off has been coined the "Lumberjack hypothesis", meaning the higher the degree and/or complexity of automation, the more difficult it is for the driver to reclaim control when automation fails.

3.5 - CONCLUSION

We have outlined how automated vehicle technology may assist older drivers to maintain safe mobility for life. ITS like ADAS and AVs have the potential to improve two important outcomes, comfort and safety, for older drivers who are undergoing normative age-related changes in perceptual, cognitive, and motor capabilities that affect fitness to drive. We have also reviewed theories of technology adoption that highlight the importance of perceptions of usability, usefulness (costs & benefits), and trust, expecting that these frameworks will apply to adoption of ADAS and AVs. A compensation framework (e.g., Charness et al., 2012) might be a useful way to conceptualize the potential reliance tradeoff when developing fully automated AV technology on our roadways. Do we want to augment age-degraded human abilities with ADAS (addressing the needs of older drivers contemplating driving cessation), or do we want to substitute robotic driver technology for human drivers? There are substantial age divides in adoption of other modern forms of technology such as computers and the Internet (Charness & Boot, 2009). Some of the age-related digital divide may be attributed to age-related differences in attitudes about technology. After reviewing the literature, it is clear that most studies evaluating ADAS have focused on the learning phase of interaction with ADAS, where the user is still forming their mental models of how the technology works and figuring out how to optimally integrate it. Longer usage studies investigating the integration phase might provide more accurate insight into what behavioral adaptations are made by users after they have adopted ADAS (Saad, 2006). Given the current uncertainty about older adults' beliefs and attitudes about automated vehicles, it is essential to generate population-representative data from these age cohorts, particularly in the older-old (75+), whose driving performance has likely been more compromised than the younger-old who benefit from their driving experience and are not as far removed from their peak driving performance (e.g., Stutts et al., 1998).

CHAPTER 4



Image Source: www.history.com/topics/baby-boomers

Survey Assessment of Florida Residents' Attitudes Toward Autonomous Vehicles

4.1 - INTRODUCTION

Autonomous Vehicles (AoV) are a quickly emerging technology that could radically alter the nature of transportation in ways no technology has done since the invention of the car. Even though AoVs promise to significantly improve the safety and efficiency of the transportation system, the technology's dependence on passengers' willingness to trust a computer to safely navigate any driving situation will make the public's attitudes toward AoVs one of the most important issues in the future use and success of AoVs. In particular, the question of whether consumers will be willing to relinquish full control of the vehicle will be a major determining factor of whether and how quickly AoVs are adopted.

In addition, public opinions concerning issues surrounding AoVs' incorporation into the transportation system, including whether AoVs should have dedicated lanes and whether AoVs should be a private or public form of transportation, can help to inform policymakers on how to best guide and regulate the smooth integration of AoVs technology. However, AoVs are being developed so quickly that very little is known about the public's attitudes toward and willingness to adopt AoVs. In fact, much of the public is still unaware that AoVs exist and simply view them as a figment of an imaginary future (Howard & Dai, 2014). In this way, developing a better understanding of the public's attitudes toward and willingness to adopt AoVs is vital to the smooth and successful incorporation of AoVs into the transportation system.

To this end, the Florida Department of Transportation (FDOT) tasked a team of researchers from Florida State University to conduct a survey of Florida residents to gauge their knowledge of, interest in, and willingness to adopt AoVs. The survey assessed whether Florida residents trust autonomous vehicles enough to adopt them and identified major issues and concerns that FDOT and other actors may need to address before autonomous vehicles can be adopted on a large scale. Given the potential of AoVs to meet the transportation needs of aging and transportation disadvantaged populations, the survey gave special attention to the attitudes and concerns of Florida's older residents. This report reviews existing research evaluating the public's attitudes toward AoVs, outlines the methodology the FSU research team utilized to assess Florida's public perception of AoVs, and reports the survey's final results.

4.2 - LITERATURE REVIEW: ATTITUDES TOWARD AUTONOMOUS VEHICLES

4.2.1 - Knowledge of and Interest in Autonomous Vehicles

In the past several years, numerous surveys and internet polls have begun to examine the public's attitudes toward and willingness to adopt AoVs. Not surprisingly, the private sector has led the majority of these efforts, as technology and insurance companies attempted to gauge the profitability of AoVs. These research efforts have produced significantly different results suggesting that anywhere from 12% to 60% of Americans are ready to adopt AoVs. This has led some to make opposing claims that America 'is' or 'is not' ready for AoVs (Cisco, 2013; Gorzelany, 2013). However, further evaluation of these results revealed that much of this variation is due to differences in survey design and the specific ways that questions are asked of respondents. Closely examining how survey design impacted the results indicated that these divergent survey results tell a common story: **the majority of Americans are interested in AoVs, but are not ready to fully embrace the technology yet.** This section highlights the major findings of existing surveys examining the public's knowledge of, interest in, and willingness to adopt AoVs.

Despite the fact that AoVs are a relatively new technology, very few surveys have examined the public's knowledge of or familiarity with AoVs. In fact, only one survey has specifically asked about respondents' familiarity with AoVs. Schoettle & Sivak (2014) found that 70.9% of respondents in the U.S. had heard of AoVs. However, other surveys have found that the public's relative lack of knowledge about AoVs may be a larger issue than Schoettle & Sivak's (2014) results indicate. Howard & Dai (2014)'s survey found that many respondents did not know enough about AoVs to have a legitimate opinion about them. So, while it appears that the majority of Americans are at least vaguely familiar with AoVs, it is unclear if there is a clear understanding of what this technology is and of how close AoVs are to widespread use.

Nevertheless, most Americans are interested in AoVs. Schoettle & Sivak (2014) found that 56.3% of U.S. respondents had a positive opinion of AoVs. Further, many Americans appear to understand and anticipate that AoVs are the future of transportation. As many as 72.7% of Americans have been found to believe that the car of 2040 will not operate anything like the car of 2014 (Insurance.com, 2014). In a survey by Intel (2014), 44% of Americans indicated that they hope to live in a driverless city someday, and 34% believed it would happen in the next decade. A British survey even found that 72% of respondents believed AoVs would one day be safer than human drivers (Institution of Mechanical Engineers, 2014). As will be shown later some of this apparent readiness for AoVs appears to be because it is easier to theoretically trust AoVs in the future than to trust your life to an AV today, **but it is apparent that many Americans now expect rapid technological advancements to fundamentally alter the future of driving.**

4.2.2 - Perceived Benefits of Autonomous Vehicles

Much of the public's interest in AoVs appears to be based in part upon several benefits that AoVs are expected to provide, including improvements to the safety and efficiency of the transportation system. Previous surveys found that the majority of respondents believe that autonomous vehicles could improve the safety of roadways (Howard & Dai, 2014; Schoettle & Sivak, 2014). In particular, Schoettle & Sivak (2014) found that two-thirds of Americans felt AoVs could reduce the number and severity of automobile accidents. In addition to the potential safety improvements, the majority of Americans appear to believe that AoVs would improve the transportation system by reducing vehicle emissions, enabling better fuel economy, and improving emergency responses to crashes (Schoettle & Sivak, 2014; TE Connectivity, 2013). In fact, two separate surveys found improvements in fuel economy to be the potential benefit thought most likely to occur (Schoettle & Sivak, 2014; TE Connectivity, 2013).

4.2.3 - Barriers to Trust and Adoption

Despite widespread belief in the future benefits of AoVs, the overwhelming majority of Americans are concerned about the use of AoVs today (Seapine Software, 2014; Gorzelany, 2013; CarInsurance.com, 2013; Schoettle & Sivak, 2014). One study that found that 56.3% of respondents had a positive opinion of AoVs also reported that 87.9% were at least slightly concerned about riding in a fully autonomous vehicle and 60.1% were very concerned (Schoettle & Sivak, 2014). This apparent contradiction can likely be explained by the fact that the majority of Americans simply do not trust AoVs yet. Several focus groups conducted by KPMG (2013), a professional service firm, found that trust was the primary factor preventing people from being willing to accept AoVs. This is supported by the fact that over three-fourths of Americans have been found to believe that AoVs would not drive as safely as human drivers (Schoettle & Sivak, 2014; CarInsurance.com, 2013). **So, even though most people seem to believe that they will trust AoVs in the future, most will need to see the technology work safely and consistently before they accept it.**

Much of the apprehension and lack of trust toward AoVs appears to arise from a common set of key concerns. Foremost among these concerns is the fear of equipment failure and a reluctance to relinquish control of the vehicle (Schoettle & Sivak, 2014; TE Connectivity, 2013; Seapine Software, 2014). Once again, most people do not trust AoV technology to consistently provide safe transportation to their destination. Yet, safety is not the only issue worrying the public. The public is also concerned about several other issues that threaten to undermine the use of AoVs including legal liability in case of a crash, data privacy and location tracking, and the potential for hacking AoVs. Studies have consistently shown that the majority of Americans, between 50% and 80%, have some level of concern over these issues (Schoettle & Sivak, 2014; Seapine Software, 2014; Alliance of Automobile Manufacturers, 2013).

4.2.4 - Willingness to Adopt Autonomous Vehicles

Surveys examining the American public's willingness to adopt AoVs have produced a wide range of results suggesting that anywhere from 18% to 60% are ready to adopt AoVs. This has led to the promulgation of opposing conclusions with some claiming that Americans are ready and waiting for AoVs (Cisco, 2013), while others claim that America is not ready (Gorzelay, 2013). However, a closer examination of these studies reveals that much of the variation is simply due to differences in survey design. Taking question wording and survey design into account reveals that most of the surveys appear to tell a common story that Americans' interest in AoVs has yet to translate into widespread willingness to adopt them.

Typically surveys examining American's willingness to adopt AoVs have found that between 30% and 60% will indicate that they are willing to "ride" in an AoV (Cisco, 2013; Pew Research Center, 2014; Accenture, 2013), but only 18% to 30% are willing to "buy" an AV (JD Power, 2014; Insurance.com, 2014; Gorzelany, 2013; Schoettle & Sivak, 2014). This suggests that the public is interested and excited by AoV enough to be willing to give them a try, but most are not yet willing to adopt AoVs for everyday use. Several surveys have actually found almost identical results suggesting that only about one-fourth of Americans would be willing to purchase an AoV for \$2,000-\$3,000 more than a regular car (Schoettle & Sivak, 2014; JD Power, 2014; Insurance.com, 2014). The only notable exception to this was Howard & Dai (2013) who found that 42% would purchase an AoV, but this may be inflated because they targeted populations who were thought to be more familiar with and accepting of AoVs. In this way, the public's expectations that AoVs can and will improve the transportation system has yet to overcome their current safety concerns and lack of trust.

However, the minority of Americans who are ready to adopt AoVs appears to be growing steadily. Only two surveys have examined how attitudes toward AoVs have changed over time, and both found gradual increases in the percentage of respondents willing to adopt AoVs. According to JD Power (2014), the percentage of people willing to purchase an AoV increased from 20% to 24% between 2012 and 2014. This is almost identical to the findings of Insurance.com (2014), which found that willingness to adopt AoVs rose from 20.0% to 22.4% between 2013 and 2014. Reasons for the growing acceptance of AoVs have yet to be examined, but it

is likely due in part to AoVs' increasing publicity and successful demonstrations recently performed by automobile and tech companies (e.g., the Google Car).

In spite of the general public's growing acceptance of AoVs, there is a sizable minority who remain adamantly against AoVs and report that they will never use them. According to a survey by the Alliance of Automobile Manufacturers (2013), 42% of drivers thought AoVs were a "bad idea." Similarly, as many as 24.5% of Americans have said that they would "never" consider using an AoV (Insurance.com, 2014). Focus groups conducted by KPMG (2013) found that, for some, this resistance to AoVs is due to a love or "passion for driving." For these individuals, even automatic transmission was often too much automation (KPMG, 2013). For others, the resistance to AoVs was born out of their distrust of AoVs to safely perform on the roads. If the public does not always trust their GPS to find the correct route, how can they trust a computer to successfully navigate complex driving situations (KPMG, 2013)?

However, there is some evidence that many of those who are against AoVs may reconsider if AoVs are able to significantly reduce the time and cost of travel. The 24.5% of respondents who would "never" use an AoV dropped to 13.7% when offered 80% cheaper insurance (Insurance.com, 2014). Similarly, KPMG's (2013) focus groups found that many of the trust issues expressed by participants could be overcome if AoVs provided incentives such as reduced and consistent commute times. While there is a small minority who may still reject AoVs even if it reduces the time and cost of travel, **these findings suggest that much of the hesitation to adopt AoVs will likely dissipate if and when AoVs demonstrate that they offer significant improvements over conventional automobiles.**

4.2.5 - Attitudes Toward and Willingness to Adopt Semi-Autonomous Features

Respondents' lack of trust and hesitance to adopt fully autonomous vehicles does not extend to semi-autonomous features. A survey by the Chubb Group of Insurance Companies found that while only 18% of consumers were ready to buy an AoV, 88% would pay extra for a lane departure warning system and 70% wanted Adaptive Cruise Control (Gorzelay, 2013). Several other surveys have produced similar results finding that between 70% and 85% of respondents expressed interest in semi-autonomous features, especially those related to safety (Accenture, 2013; Alliance of Automobile Manufacturers, 2013). **So, while most consumers are not yet ready to relinquish complete control to an AoV, they are willing to adopt many of technologies that make fully autonomous vehicles possible.**

4.2.6 - Variations between Demographic Groups

Surveys have consistently found that the attitudes toward AoVs outlined above, are not uniform across the entire population. **Instead, attitudes have been shown to vary based on several demographic characteristics including age, gender, education, income, and geographic location.**

In spite of the potential benefits AoVs could provide aging populations when they are no longer able to drive, older generations were consistently found to be the least accepting of AoVs (JD Power, 2014; TE Connectivity, 2013; Caldwell, 2014). Each progressively younger generation typically has more positive attitudes, with Millennials consistently being the most accepting of AoVs (JD Power, 2014; TE Connectivity, 2013; Caldwell, 2014). The variation in acceptance between the younger and older generations is not marginal. JD Power (2014) found that 37% of those age 18-25 would be willing to purchase an AoV, compared to only 9% of those age 57-65. While this is not surprising, considering that older generations typically are less willing to adopt new technology, it is unclear if these age effects are due primarily to aging populations' general hesitance to adopt new technology or to anything inherent to AoVs.

Attitudes toward AoVs also vary significantly by gender, with men typically having more positive attitudes toward AoVs than women (JD Power, 2014; TE Connectivity, 2013; Caldwell, 2014; Payre et al., 2014; Schoettle & Sivak, 2014). Women appear to be more concerned about AoVs and are less likely to think AoVs' potential benefits will come to fruition (Schoettle & Sivak, 2014). However, the degree of variation between men and women is much less than the variation by age. Surveys have shown that only between 2.9% and 10% more men are willing to adopt AoVs than women (JD Power, 2014; TE Connectivity, 2013; Caldwell, 2014).

There is also some evidence that higher incomes and levels of education are correlated with greater willingness to accept AoVs (Pew Research Center, 2014; Schoettle & Sivak, 2014). A survey by the Pew Research Center (2014) found that 59% of college graduates would ride in a driverless car, compared to only 38% of those with a high school diploma or less. In addition to being correlated with greater acceptance of AoVs (Howard & Dai, 2014), income appears to affect the issues that respondents were most concerned about. Higher income individuals were found to be most concerned about liability issues associated with AoVs, while lower income individuals were more concerned about safety and control of the vehicle (Howard & Dai, 2014).

Finally, the public's willingness to adopt AoVs appears to be based in part on the respondent's geographic location. While few studies have examined the impact geographic location has on attitudes toward AoVs, the few that did found a distinct urban and rural divide (Pew Center, 2014; Caldwell, 2014). As many as half of urban and suburban residents have been found to be interested in AoVs compared to only one-third of rural residents (Pew Center, 2014).

4.2.7 - Key Takeaways from Survey Research to Date

Most Americans are interested in AoVs and expect them to eventually be a common form of transportation, but few are ready to adopt AoVs yet. Issues of trust and safety appear to be preventing three-fourths of Americans from being willing to adopt AoVs. However, a growing minority is already willing to adopt AoVs and evidence suggests that even those who are against the use of AoVs may change their mind if and when AoVs begins to provide tangible benefits to consumers. So, even though willingness to adopt AoVs currently remains relatively low, there is reason to believe it could increase significantly in coming years. However, many of those who could benefit most from AoVs, such as aging populations, appear to have the most negative attitudes AoVs.

4.3 - AUTONOMOUS VEHICLE SURVEY DESIGN

Per the project's scope of work, the FSU research team conducted a survey of Florida residents to assess their knowledge of, interest in, and willingness to adopt and use automated vehicle technology. Respondents were asked a set of questions regarding their preferences and assuming different stages and forms of AoVs and the associated user costs relative to current travel options. The survey successfully over-sampled certain populations of interest to FDOT (e.g., older adults aged 55+) in order to have more detailed data on these specific population subgroups. The survey also ascertained the public's perception of the privacy and safety risks related to AoVs.

The data reported below comes from a survey conducted by the FSU research team through the Florida State University Survey Research Lab. The survey was designed to capture attitudes towards and knowledge of autonomous vehicles by Florida's citizens. The full survey is shown in Appendix A at the end of this chapter. Responses to the survey were generated from a mail out/mail back or mail out/online survey of Floridians 18 years or older. Respondents had the choice of filling out the survey by hand and mailing it back in an addressed and stamped envelope, or to go online and respond to the survey digitally.

Using voter registration mailing lists, 5,000 surveys were mailed to addresses of property owners in the state. A first round of surveys was sent out in April 2015, and a second set went out in May, 2015. Each round of surveys was followed-up by a letter two weeks later encouraging completion of the survey. Because of FDOT's interest in the attitudes of older adults, the survey over-sampled for counties with large percentages of adults aged 55+. As of the final report, the total number of responses received was 459, for a response rate of 9.18%. While at first glance this seems like a low response rate, Survey Research Lab staff indicated that this rate is consistent with other mail-out surveys conducted in the last several years.

As part of the survey design, the FSU research team mailed out two rounds of questionnaires, each to a different, but randomly selected set of recipients. In the

first round recipients received only a cover letter and the survey itself. In the second round, recipients received a cover letter, survey and an additional insert that provided a basic overview of AoV technology. The insert is included in this report as Appendix B. The rationale behind this research design was to test the role of a basic level of AoV education on attitudes towards the technology. The first round of surveys (the no insert group) yielded 271 responses, and the second round (the insert group) yielded 188 surveys.

4.4 - PROFILE OF RESPONDENTS

Table 4.1 presents the respondents' socio-demographics, and compares these to the entire population of the state of Florida. Survey respondents are best characterized as older, better educated, and less diverse than the state as a whole. The most notable deviations in these socio-demographics are the far lower share of respondents that were Hispanic, a far higher percentage of respondents with at least a college degree, and a very large share of respondents who are retirees. Almost three out of five respondents report annual household incomes of at least \$50,000, which is above the Florida median household income of ~\$47,000 in 2013.

While the demographics of the respondents do not closely match the state's demographic conditions, they do capture the attitudes of the populations most likely to be early adopters of autonomous vehicle technology, as respondents have the education and means to more easily learn about and afford this technology.

Table 4.1 - Respondent Demographics

Variable	Survey Respondents	Florida, 2013
Pct Male	49.7%	48.9%
Pct White	85.5%	78.1%
Pct Hispanic	10.9%	23.6%
Pct Aged 65+	46.6%	18.7%
Pct College Grad	62.3%	26.4%
Pct Working	42.9%	N/A
Pct Retired	45.9%	N/A
Pct HH Income > \$50,000	59.1%	N/A

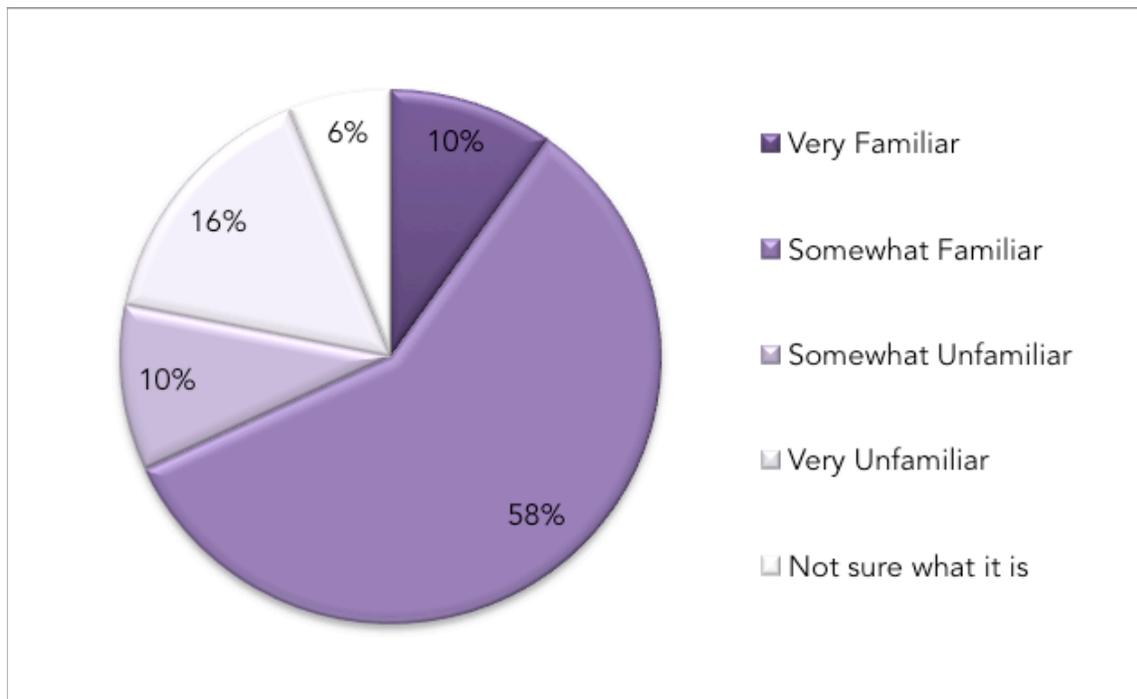
4.5 - GENERAL ATTITUDES TOWARD AUTONOMOUS VEHICLES

Several questions in the survey inquired about respondents' attitudes toward AoV technology and their willingness to use the technology. As described below, results indicate that respondents report having some familiarity with the AoV technology, and a generally favorable attitude towards it.

Q1. Familiarity with AoVs

Over two-thirds (67.6%) of respondents reported being very familiar or somewhat familiar with autonomous vehicles, and only 6.5% of respondents reported not knowing anything about the technology. **Figure 4.1** illustrates these results.

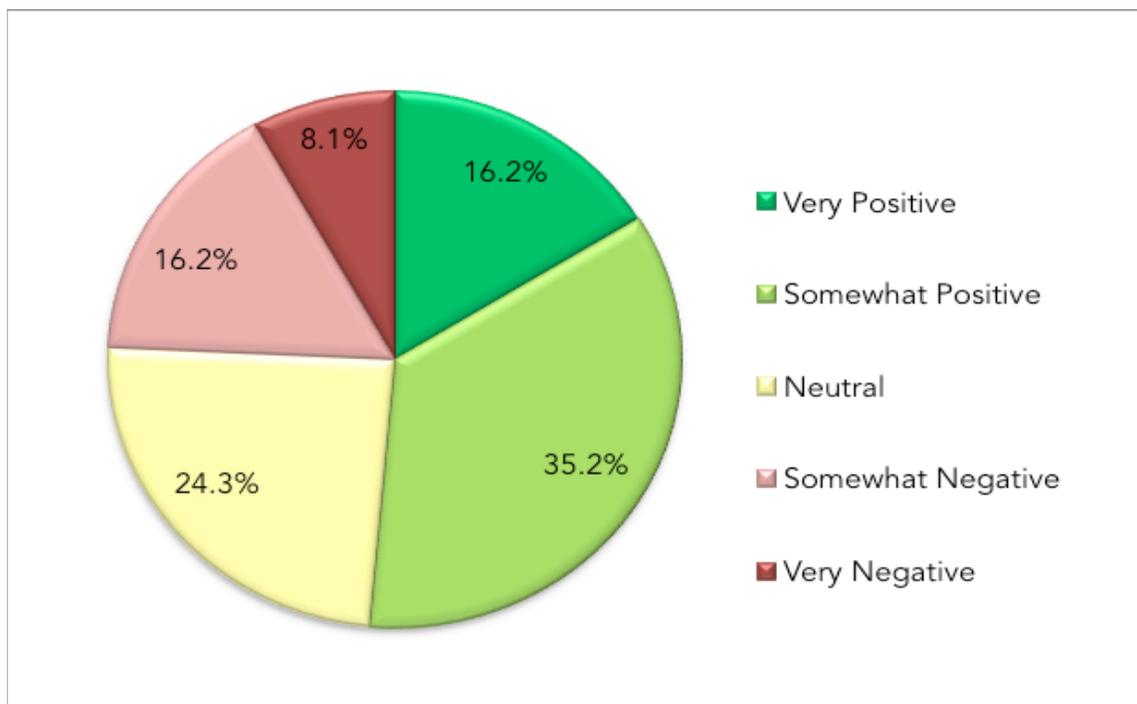
Figure 4.1 - Respondent Familiarity with AoVs



Q2. General Opinion Regarding AoVs

General opinion toward AoVs was also quite high, with over half (51.4%) of respondents reporting a favorable opinion toward the technology, and only 24.3% holding a negative opinion. The other quarter of respondents (24.3%) reported neutral feelings on AV. **Figure 4.2** illustrates these results.

Figure 4.2 - Respondent General Opinion toward AoVs



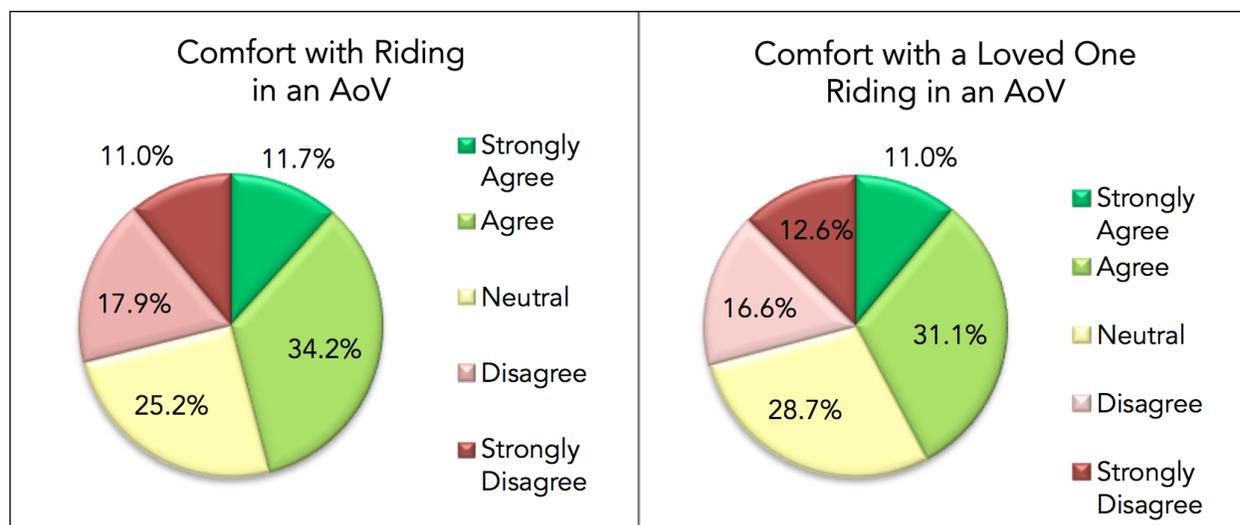
Q7a. Comfort Level Riding in an AoV

Similar to Q2, roughly half (45.9%) of respondents reported that they would be comfortable riding in an AoV, and only a quarter (28.9%) of respondents reported that they would not be comfortable riding in an AoV. The remaining respondents (25.2%) reported neutral feelings on their comfort level in riding in an AoV.

Q7b. Comfort Level Placing a Loved One in an AoV

When respondents were asked about their willingness to place a loved one (e.g., child, spouse, parent, friend) in an AoV, the percentages willing to do so drop, but not as much as one might expect from the literature review. Roughly two-fifths (42.1%) of respondents would be willing to place a loved one in an AoV, whereas 29.2% of respondents would not place their loved ones in an AV. The remaining respondents (28.7%) reported neutral feelings on their comfort level in placing a loved one in an AV. **Figure 4.3** shows the results of questions 7A and 7B side by side.

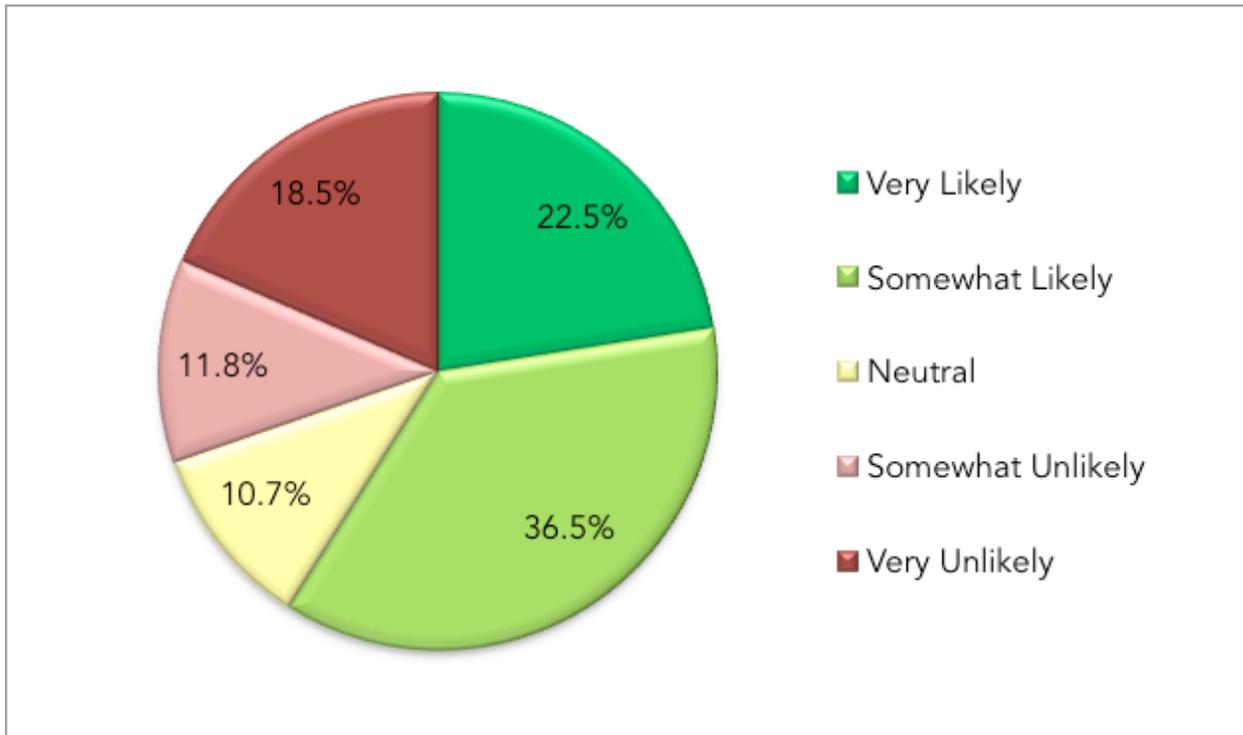
Figure 4.3 - Respondent Comfort with AoV Ridership



Q9. Willingness to Use an AoV

In a slight variation to Q2 and Q7a, this question asked directly about the respondent's willingness to use an AoV. This question yielded the most positive response, with roughly three-fifths (59.0%) of respondents indicating a willingness to use AoVs, with approximately 30% of respondents (31.3%) remaining unlikely to use the technology. **Figure 4.4** illustrates these results.

Figure 4.4 - Respondent Willingness to Use an AoV



Key Takeaway: Taken as a set, these questions indicated that Floridians hold generally positive views about AoV technology and that at least half feel comfortable enough with the technology at this stage to ride in an AoV themselves or place a loved one in an AoV.

4.6 - RELATIONSHIPS BETWEEN FAMILIARITY, OPINION, AND WILLINGNESS TO USE

Individually, measures of AoV Familiarity, AoV Opinion, and Willingness to Use AoVs are important for capturing a point in time snapshot of Florida resident attitudes toward this important technology. However, equally of interest is the relationship between these dependent variables, as each captures a different element:

- **Familiarity** measures knowledge of the technology;
- **Opinion** measures the level of favorable or unfavorable attitude towards the technology;
- **Personal Comfort** measures the respondent's level of comfort in placing one's self in an AoV;
- **Loved One** measures the respondent's level of comfort in placing a loved one in an AoV;
- **Willingness to Use** measures the level of likelihood of the respondent to actually employ the technology if it was available.

Table 4.2 below reports the results of a correlation analysis for the five dependent variables of interest. Recall that Pearson r values can be positive or negative and range from 0 to 1, with stronger relationships being indicated the closer the value gets to +1 or -1. Starred cells represent statistically significant relationships, and the greater the number stars the greater statistical likelihood of the relationship.

Table 4.2 - Summary of Pearson's R Analysis for the Attitudinal Variables

Key Variable	Q1 Familiarity with AoVs	Q2 General Opinion of AoVs	Q7a Personal Comfort in AoVs	Q7b Place Loved One in an AoV	Q9 Willingness to Use an AoV
Q1 Familiarity with AoVs	N/A				
Q2 General Opinion of AoVs	0.218 ***	N/A			
Q7a Personal Comfort in AoVs	0.093 **	0.698 ***	N/A		
Q7b Place Loved One in an AoV	0.062	0.674 ***	0.934 ***	N/A	
Q9 Willingness to Use an AoV	0.065	0.712 **	0.788 ***	0.753 ***	N/A

- * Significant at the 0.10 level
- ** Significant at the 0.05 level
- *** Significant at the 0.01 level

These results are illuminating and very important for understanding the pathway to public support for AoV technology.

- First, while Familiarity was positively correlated with Opinion and Personal Comfort, these relationships were far less robust than other relationships. Of particular note here was that Familiarity and Opinion were related, with greater familiarity being correlated with a higher opinion of AoVs.
- Second, Opinion was heavily correlated (close to 0.700, a very high level) with Personal Comfort, Loved One and Willingness to Use. This indicates that as a respondent's opinion of AoVs improves, their likelihood of using the technology goes up.
- Third, the three variables that captured likelihood of use (Personal Comfort, Loved One, and Willingness to Use) were also very highly correlated, each

above 0.750. These findings indicate that there is a tipping point at which people believe in and are ready to employ AoVs in their daily lives.

Most importantly, these results point to a causal chain that is very important for building public support for AoVs. This relationship is summarized simply as:

AoV Familiarity → AoV Opinion → AoV Use

Key Takeaway: In order to build a market for AoVs in Florida, FDOT and its partners need to recognize that willingness to use is based upon a foundation of familiarity first, and then general opinion.

4.7 - WILLINGNESS TO USE DIFFERENT AOV MODELS

The survey also asked respondents about their willingness to use different types of AoVs if they were available (Q10). This question was designed to ascertain the interest of respondents in using a privately owned AoV vs. a shared AoV vs. an AoV public transit system vs. a shared AoV for hire. The results in **Table 4.3** reveal that almost three-fifths of respondents (58.4%) indicated a willingness to use a privately owned AoV, while far fewer respondents indicated they would be likely to use other AoV modes. The lowest ranked AoV model in this survey was the shared-ownership AoV at roughly one in every four respondents (24.4%). The remaining AoV models, public transit AoV and AoV for hire came in at roughly 40% support (39.2% and 36.5%, respectively).

Key Takeaway: Taken as a whole, these results reveal the persistence of and preference for the private ownership model, and a very low level of support for a shared-ownership model, at least at this time.

Table 4.3 - Likelihood of Using Different AoV Models

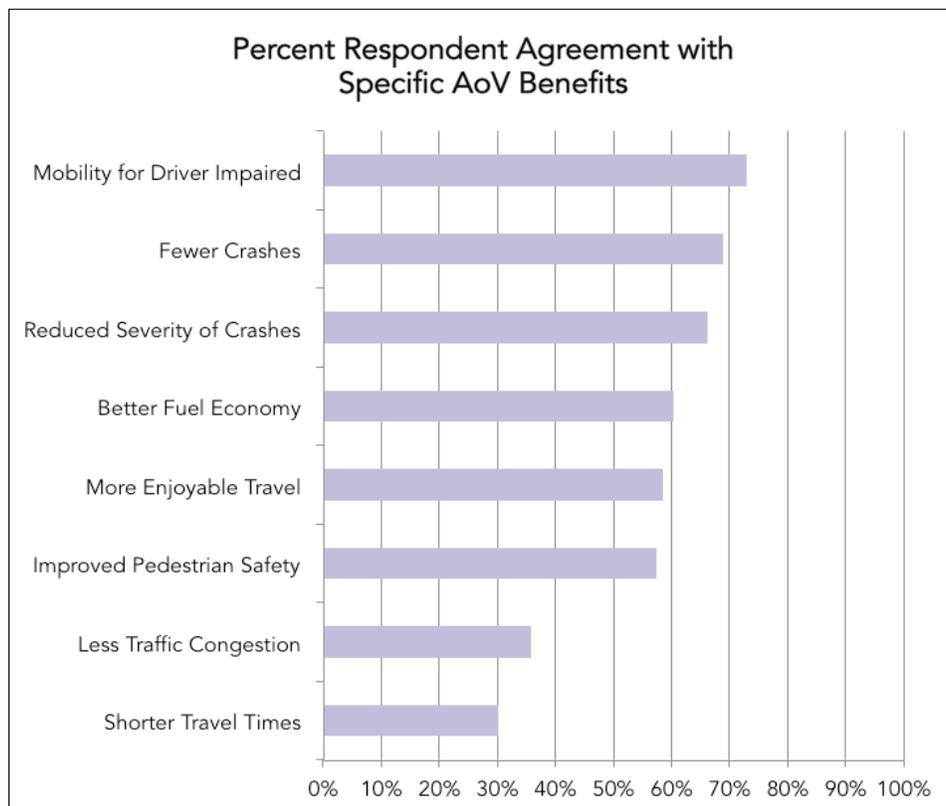
AoV Types	Likely	Neutral	Unlikely
Privately Owned AoV	58.4%	12.8%	28.9%
Shared-Ownership AoV	24.4%	23.1%	52.5%
Public Transit AoV (Bus, Train, etc.)	39.2%	17.8%	43.0%
AoV for Hire (Taxi, Limo, etc.)	36.5%	16.0%	47.5%

4.8 - PERCEIVED BENEFITS OF AOVs

The survey asked respondents their opinions on a range of potential benefits that may flow from the widespread adoption of AoV technology (Q5). Overall, as shown in **Figure 4.5**, respondents felt most confident about the ability of AoVs to provide a safer ride for users and the enhanced mobility provided by AoVs for those unable to drive. On the other hand, respondents were most skeptical of the ability of AoVs to reduce traffic congestion and provide for shorter travel times.

Key Takeaway: These results suggest that respondents believe in the promise of AoVs to deliver safer vehicles and driving conditions, as well as enhanced mobility, but that reduced system congestion and shorter travel times are not perceived to flow from the widespread adoption of AoVs.

Figure 4.5 - Respondent Agreement with Perceived Benefits of AoVs

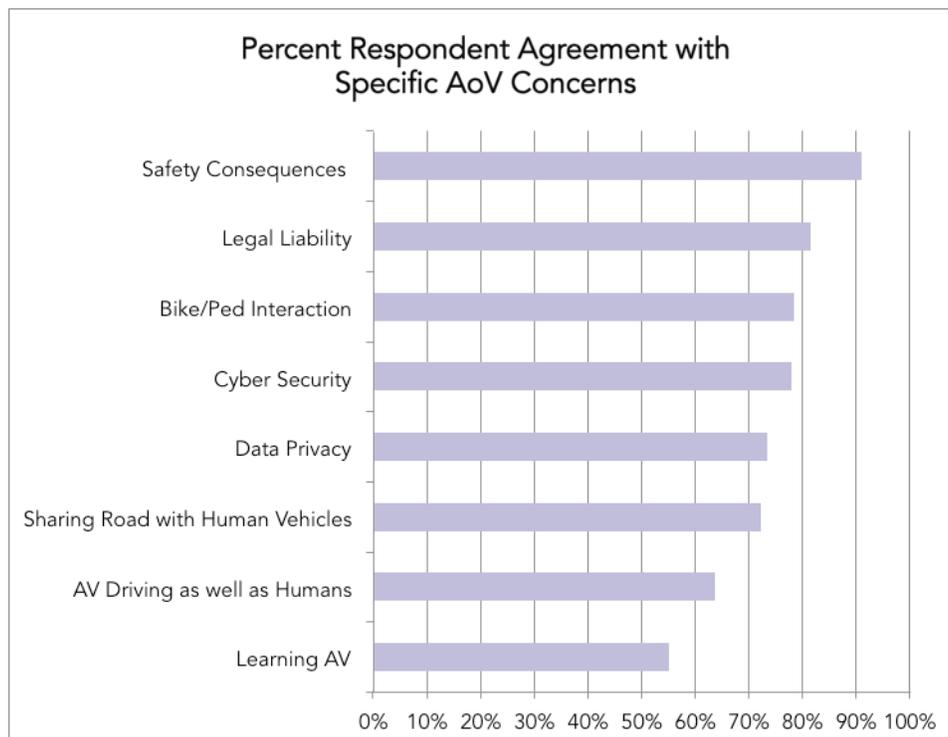


4.9 - PERCEIVED CONCERNS RELATED TO AOVs

The survey also asked respondents their opinions on a range of potential concerns that may flow from the widespread adoption of AoV technology (Q6). As shown in **Figure 4.6**, while all of these topics were a concern to at least half of all respondents, the greatest concerns revolved around the safety consequences in the case of an accident (~90%), issues of legal liability (~82%), and system security from outside agents (~78%). Potential concerns that least troubled respondents were learning how to use the AoV (~55%) and the possibility that humans will be better drivers than AoVs (~64%), although a majority of respondents were still concerned with these issues.

Key Takeaway: These results suggest that while support for AoVs is high, there remains a need to educate and reassure users about the safety and security of this technology as it moves into the marketplace.

Figure 4.6 - Summary of Perceived Concerns Surrounding AoVs



4.10 - PERCEPTIONS OF BENEFITS AND CONCERNS BY AGE

While general perceptions of benefits and concerns are useful for informing state policy and actions, it is important to recognize that perceptions vary by age in important ways. **Figures 4.7 and 4.8** summarize the level of agreement with key benefits and concerns across four major age groups: 18-34, 35-49, 50-65, and 65+. These results demonstrate that older adults (aged 65+) often see fewer benefits and worry about the concerns more than other age groups. In contrast, younger age cohorts perceive greater benefits flowing from AoVs, and worry less about certain concerns.

As for variations in perceived benefits (shown in **Figure 4.7**), there were two particularly intriguing insights. First, almost 70% of the 18-34 age cohort believed that AoVs would bring a more enjoyable driving experience, with the hypothesis being that automated vehicles will allow users to engage with their personal technology, work, or socialize in ways that human-operated vehicles do not allow. Second, the perception of increased mobility from non-drivers was highest amongst the youngest age cohort (at over 90%), which was somewhat surprising. While roughly 60% of older adults believed that AoVs will bring increased mobility to non-drivers, this was far lower than the rates for all other age cohorts.

Variations in perceived concerns also vary somewhat by age (shown in **Figure 4.8**). One finding stands out. Older adults had the greatest level of concern about learning to use AoVs (over 60% indicate this is a concern), although surprisingly, over 55% of the 18-34 cohort shared a similar concern. This suggests that there is a role for the AoVs industry and perhaps FDOT to demonstrate and reinforce to users about the ease of use of the new technology.

Key Takeaway: These results demonstrate that perceptions of the benefits of AoVs, and to a lesser extent AoV concerns, vary by age in important ways.

Figure 4.7 - Variations in Perceptions of Benefits by Major Age Groups

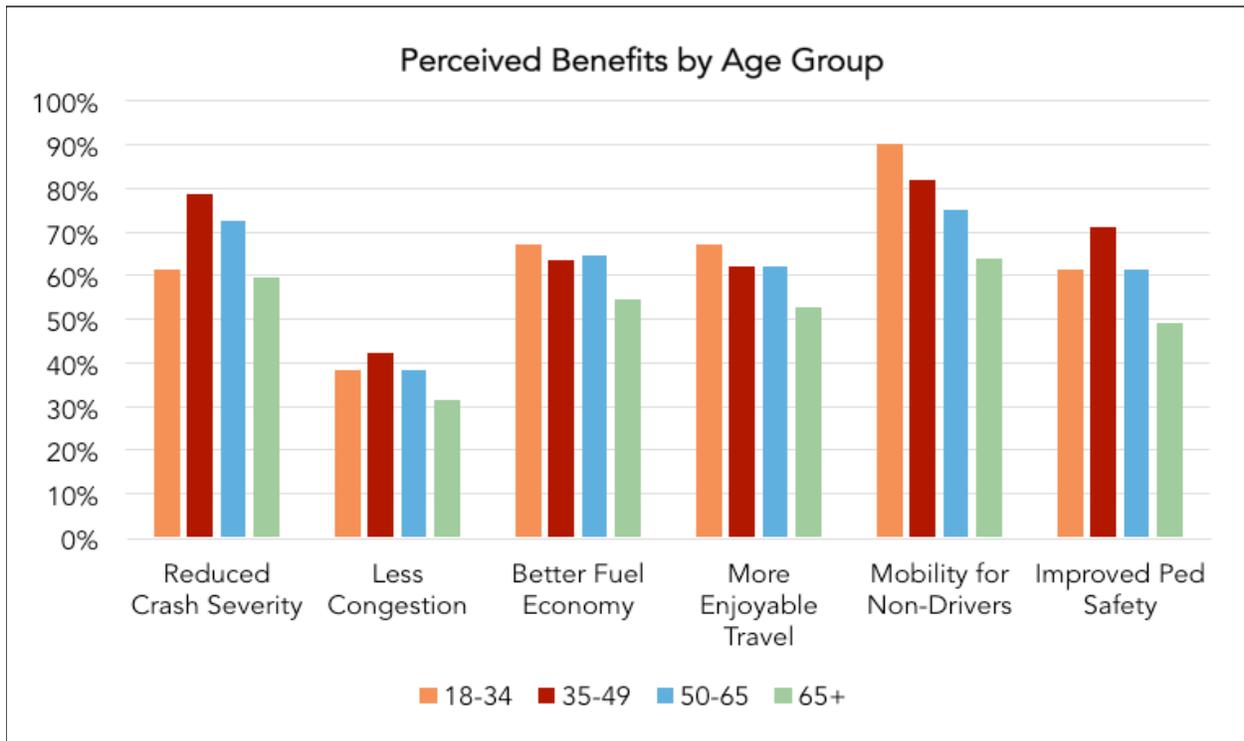
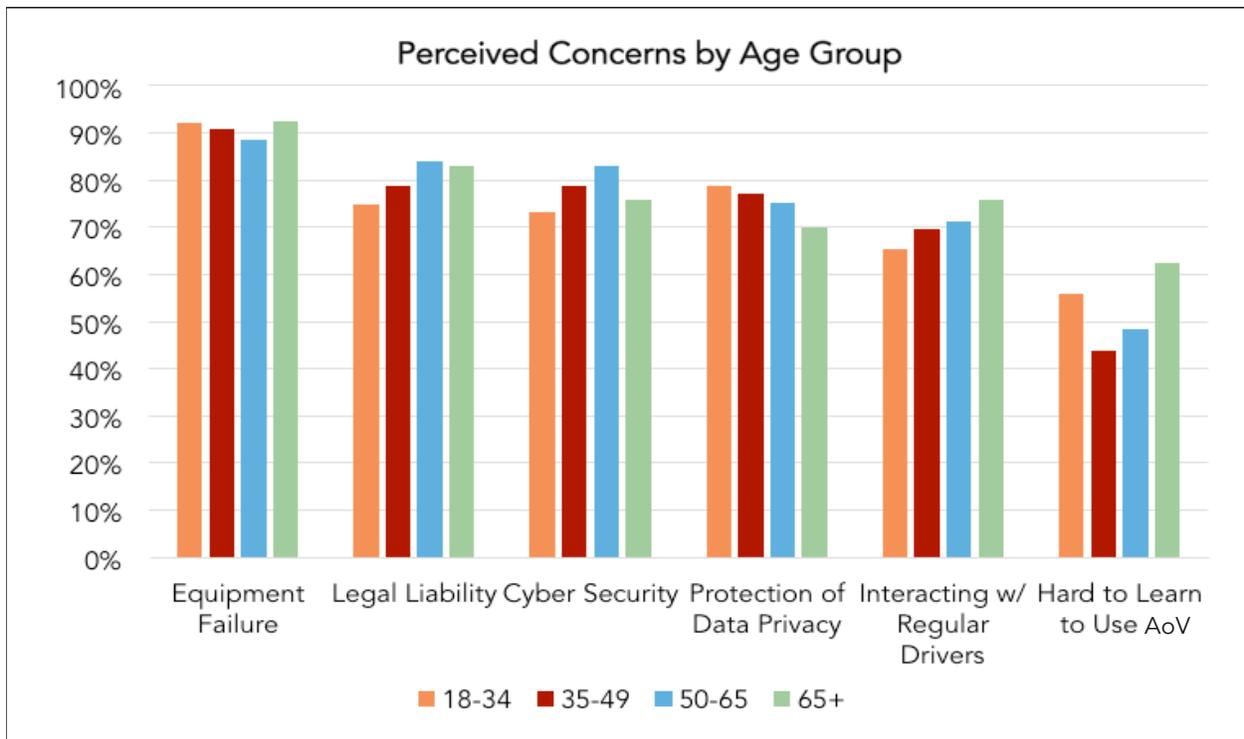


Figure 4.8 - Variations in Perceptions of Concerns by Major Age Groups



4.11 - PRICE POINTS FOR PURCHASING AN AOV

The survey asked respondents their likelihood in purchasing an AoV at different price points (Q11). While these price points were arbitrarily determined by the FSU research team, they provide some indication of the value associated with the perceived benefits of AoVs. If an AoV is priced exactly the same as a “regular car,” just over three-fifths of respondents indicated they would be likely to purchase an AoV instead of a regular car (shown in **Table 4.4**). As expected, as the price goes up the percentage of respondents willing to pay the additional cost for an AoV dropped precipitously from 50% for an additional \$1,000 to 20% for an additional \$5,000 and 6.0% for an additional \$10,000.

Key Takeaway: If an AoV is priced at \$5,000 or more than a regular car, roughly 80% of respondents reported being unwilling to pay this additional cost for these enhanced features. These results indicate that while respondents see potential benefits of AoVs, they are not yet sufficiently convinced by these benefits to pay substantially more money for AoV features in a new vehicle.

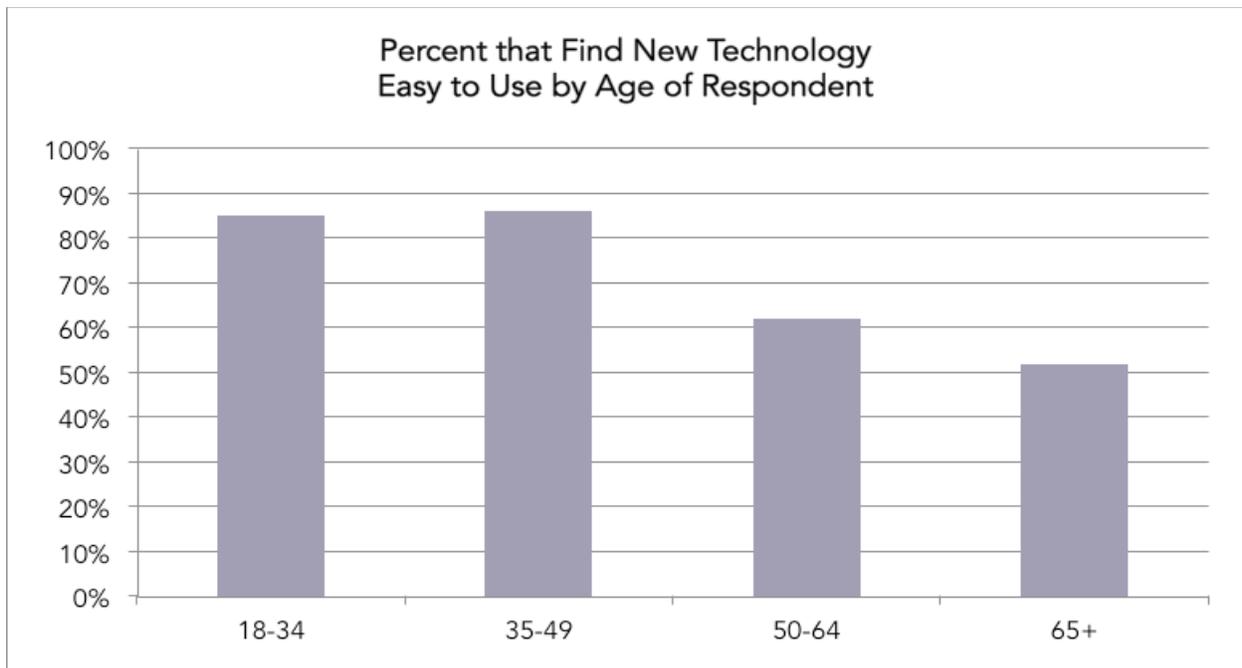
Table 4.4 - Likelihood to Purchase an AoV instead of a Regular Vehicle

AoV Price	Likely	Neutral	Unlikely
Same as a Regular Car	61.5%	10.6%	27.8%
\$1,000 More than a Regular Car	50.3%	12.8%	36.9%
\$5,000 More than a Regular Car	20.1%	17.1%	62.7%
\$10,000 More than a Regular Car	6.0%	8.7%	85.3%
\$25,000 More than a Regular Car	2.8%	5.3%	91.9%

4.12 - COMFORT WITH NEW TECHNOLOGY

As evidenced in the literature, an important factor that influences familiarity and comfort with AoVs is a general feeling of competence with technology. The survey asked respondents to indicate how much they agree with the statement: *I generally find new technology easy to use*. **Figure 4.9** illustrates the percentage of respondents by age that reported finding new technology easy to use. As expected, younger age cohorts reported higher levels of comfort with new technology than older age cohorts, with a clear break around age 50. Respondents under age 50 reported about 85% success in using new technology, whereas for respondents aged 50-64 and 65+, these percentages fell to just above 60% and 50%, respectively.

Figure 4.9 - New Technology Ease of Use by Age



Key Takeaway: As expected, older adults reported having much less success using new technology, with only half of respondents over 65+ indicating confidence that they found new technology easy to use.

4.13 - SOCIODEMOGRAPHIC VARIATIONS IN FAMILIARITY AND SUPPORT FOR AOVs

These results point to a general level of comfort and familiarity with AoVs across the entire Florida population, but of interest to the FSU research team and FDOT is how these levels of support vary across the population. At this stage of the analysis, the FSU research team has investigated how attitudes towards AoVs vary across six key dimensions: Gender (Male vs. Female), Race (White vs. Non-White), Ethnicity (Hispanic vs. Non-Hispanic), Age (18-34, 35-49, 50-64 and 65 and up), Income (Under \$25k, \$25,000-\$49,999, \$50,000-\$74,999, \$75,000-\$99,999, \$100,000-\$149,999, and \$150k and up), and Education (HS Degree and lower vs. College Graduate).

Table 4.5 summarizes these results, reporting the results of a Pearson's r analysis, which measures the magnitude and direction of the relationship between two variables. This analysis provides evidence of a statistical relationship between a sociodemographic variable of interest, such as Gender, and a dependent variables of interest: Familiarity, General Opinion, Personal Comfort with AoVs, Put Loved One in an AoV, and Willingness to Use an AoV.

The analysis presented in **Table 4.5** found several significant relationships between the demographic variables (rows) and the five dependent variables of interest. Again, Pearson r values can be positive or negative and range from 0 to 1, with stronger relationships being indicated the closer the value gets to +1 or -1. Starred cells represent statistically significant relationships, and the greater the number stars the greater statistical likelihood of the relationship.

**Table 4.5 - Summary of Pearson's R Analysis for All Respondents
(correlation values shown)**

Variable	Q1 Familiarity with AoVs	Q2 General Opinion of AoVs	Q7a Personal Comfort in AoVs	Q7b Place Loved One in an AoV	Q9 Willingness to Use an AoV
Gender (Male)	0.206 ***	0.042	0.052	0.004	0.020
Race (White)	0.032	0.055	0.015	0.019	0.041
Ethnicity (Hispanic)	-0.055	0.094 **	0.120 **	0.112 **	0.082 *
Age	-0.009	-0.188 ***	-0.126 ***	-0.079 *	-0.119 **
Income	0.204 ***	0.171 ***	0.114 **	0.069	0.090
Education (College Grad)	0.093 **	0.155 ***	0.140 ***	0.141 ***	0.162 ***

* Significant at the 0.10 level

** Significant at the 0.05 level

*** Significant at the 0.01 level

The primary takeaways from this analysis are:

- Males reported greater familiarity with AoV technology (Q1), although the correlation analysis found no other statistically significant relationship for Gender.
- Race was not significantly related to any of the dependent variables.
- Hispanics were shown to have consistently more positive views towards AoVs (Q2, Q7a, Q7b, and Q9), a consistent and somewhat unexpected finding.

- As expected, Age yielded negative relationships with all of the dependent variables (note the negative values for all of the coefficients), with statistically significant relationships with the opinion, comfort and willingness to use variables.
- The correlation analysis for Income yielded a number of statistically significant relationships, all in the expected direction. Higher incomes respondents were more familiar (Q1), held a higher opinion (Q2) and had higher comfort levels (Q7a) than lower income respondents.
- Similar to Income and also as expected, higher educated respondents also had greater familiarity of AoVs, a more positive opinion of AoVs (Q2), higher comfort levels (Q7a and Q7b) and a greater willingness to use the technology (Q9) than lower educated respondents.

Taken as a whole, these analyses of the survey data suggest that gender, ethnicity, age, and income/education are the key factors in understanding variability in attitudes towards AoVs. Most of these relationships were expected, with the caveat that the positive views of Hispanics are a potentially unique finding from this study. These findings will help the FSU research team and FDOT as they work to understand challenges to AoV adoption and usage by Florida households in the coming years.

Key Takeaway: There is substantial variation across the population regarding attitudes towards AoVs. Younger adults, Hispanics, and higher socio-economic status groups appear to be the core market for AoVs at this stage, although it is important to recognize that attitudes and tastes can change quickly.

4.14 - THE ROLE OF BASIC INFORMATION ON ATTITUDES TOWARD AOVs

As part of our survey design, the FSU research team provided basic information on AoV technology to our second round of survey recipients. This allowed the team to assess the influence of basic information on attitudes toward AoVs by Florida citizens. Recall that the first round of surveys (the no insert group) yielded 271 responses, and the second round (the insert group) yielded 188 surveys.

Table 4.6 presents information on the different levels of support for AoVs based upon whether or not respondents received a basic set of information on AoV technology. As shown in **Table 4.6**, information played a key role in shaping attitudes towards AV for three of the variables of interest; General Attitude Towards AoVs, Comfort level in Riding in an AoV, and Willingness to Use an AoV. In each case the single page insert is correlated with more positive attitudes towards AoVs.

Table 4.6 - Comparison of Attitudes toward AoVs for the No Insert vs. the Insert Groups

Variable	No Basic AoV Info Received (No Insert)	Received Basic AoV Info (Insert)	Statistically Significant
Q2. Positive View towards AoVs	44.6%	61.3%	Yes
Q7a. Comfort- Put Self in an AoV	42.7%	50.5%	Yes
Q7b. Comfort - Put Loved One in an AoV	41.2%	43.5%	No
Q9. Percent Willing to Use an AoV	56.3%	66.1%	Yes

Beyond baseline differences in responses towards the key dependent variables in the study shown in **Table 4.6**, we also analyzed the interaction of information (insert vs. no insert groups) and socio-demographics on attitudes. These results are presented in **Tables 4.7 and 4.8** below. Again, Pearson r values can be positive or negative and range from 0 to 1, with stronger relationships being indicated the closer the value gets to +1 or -1. Starred cells represent statistically significant relationships, and the greater the number stars the greater statistical likelihood of the relationship.

The primary message to be gleaned from these results is that the influence of the sociodemographic variables on citizen attitudes was moderated substantially with the inclusion of basic AoV information with the survey. **Table 4.6** shows the statistical relationships for the No Insert group, with many significant relationships. Most notably, Age was consistently and significantly related to attitudes toward AoVs; older adults had a lower Opinion and indicated less Willingness to Use the technology. For respondents in the Insert Group (**Table 4.8**), many of these significant relationships were reduced or became insignificant. While Age was still generally negatively correlated with the attitudinal variables, only one of these relationships remained significant. Similar effects are observed for the variables Hispanic, Income, and Education.

Key Takeaway: These results underscore the value of basic information and point to the value of education and marketing in garnering public support for AoV technology.

Table 4.7 - Summary of Pearson's R Analysis for Respondents Receiving No Basic AoV Information (correlation values shown)

Variable	Q1 Familiarity with AoVs	Q2 General Opinion of AoVs	Q7a Personal Comfort in AoVs	Q7b Place Loved One in an AoV	Q9 Willingness to Use an AoV
Gender (Male)	0.201 ***	0.053	0.004	-0.056	-0.034
Race (White)	0.027	0.051	0.033	0.029	0.050
Ethnicity (Hispanic)	-0.152 **	0.070	0.105 *	0.098	0.071
Age	-0.021	-0.231 ***	-0.197 ***	-0.175 ***	-0.187 ***
Income	0.305 ***	0.171 ***	0.108 **	0.069	0.080
Education (College Grad)	0.162 ***	0.118 *	0.139 **	0.150 **	0.128 **

- * Significant at the 0.10 level
- ** Significant at the 0.05 level
- *** Significant at the 0.01 level

Table 4.8 - Summary of Pearson's R Analysis for Respondents that Received Basic AoV Information (correlation values shown)

Variable	Q1 Familiarity with AoVs	Q2 General Opinion of AoVs	Q7a Personal Comfort in AoVs	Q7b Place Loved One in an AoV	Q9 Willingness to Use an AoV
Gender (Male)	0.214 ***	0.026	0.120	0.094	0.104
Race (White)	0.034	0.041	-0.034	-0.013	0.002
Ethnicity (Hispanic)	0.121	0.140 *	0.154 **	0.143 *	0.114
Age	0.012	-0.133 *	-0.032	0.052	-0.018
Income	0.034	0.177 **	0.124	0.072	0.109
Education (College Grad)	-0.016	0.193 ***	0.133 *	0.124 *	0.203 ***

- * Significant at the 0.10 level
- ** Significant at the 0.05 level
- *** Significant at the 0.01 level

4.15 - CONCLUSIONS AND FUTURE DIRECTIONS

Taken as a whole, the FSU survey of 459 respondents provides evidence of solid support for AoVs amongst Florida residents. There was a baseline of support for the technology, with over 50% of respondents holding favorable attitudes toward AoVs. Similarly, almost 60% of respondents reported being willing to use an AoV, a very robust level given that the technology has yet to hit the market. On the downside, there appears to be roughly a quarter of the population that has entrenched doubts about AoVs as a technology. Similarly, over a quarter of respondents would not purchase an AoV instead of a regular car even if the two vehicles were priced the same.

Equally telling was an assessment of the perceived benefits and costs associated with AoV technology. Florida residents reported seeing many potential benefits with the coming of AoVs. Among the highest rated benefits were several related to improved safety, more enjoyable travel, and mobility for transportation disadvantaged groups. These findings suggest that Florida residents have come to see and value the potential positives of AoV technology. However, an assessment of potential concerns mitigates this finding somewhat, as over two-thirds of respondents indicate being worried about safety, security, and liability issues related to AoVs' rollout. An assessment of the perceptions by age also found that older adults generally are more skeptical about the technology. Together these data indicate that Florida residents are bullish on AoVs in concept, but will remain skeptical of the technology until they have more personal experience with it.

Lastly, one of the key findings of the survey revolves around sociodemographic differences in attitudes toward AoVs, and the mitigation of these differences through education. Overall, the survey results illustrate that younger, higher socioeconomic status respondents are more favorably disposed to AoV technology. This is very positive news for the state, as individuals with these attributes are likely to be early adopters of the technology as it is rolled out. Another positive, but tentative finding was that Hispanic residents have more positive attitudes towards AV and are more likely to use the technology. Given Florida's large and fast-growing Hispanic population, this somewhat surprising finding can be a useful

competitive advantage for Florida as it aggressively pursues AoV technology. However, further assessment of variations by ethnicity is warranted.

Mitigating the Hispanic competitive advantage is the (expected) finding that older adults hold less positive attitudes toward the technology, and are far less likely to use AoVs. This finding is in line with a long literature that demonstrates that older adults are less familiar with, comfortable with, and willing to use technology of all kinds. Given Florida's historic trend of being the nation's oldest state and home to millions of adults aged 65+, it is important that the state find ways to inform and educate older adults about this emergent technology.

While sociodemographic factors do indeed help to shape attitudes toward AoVs, there is strong evidence that education can play an important role in allaying fears toward AoV technology and building broader support for the state's ongoing AoV initiatives. The results demonstrate that respondents that received very basic information on AoVs had more positive responses to most survey questions than those that did not receive this basic level of information.

Given these findings, the FSU research team makes the following recommendations for FDOT activities to support their ongoing AV Initiative.

- 1. FDOT Should Regularly Track Resident Attitudes Toward AoVs:** The Department should think about a regular approach for tracking citizen attitudes toward AoV technology. This can be achieved through existing FDOT survey efforts, contracting with a university or firm to complete the survey work. While annual tracking is ideal, at minimum it is recommended that a similar AoV survey be undertaken every three years by the Department. While the survey should ask the same baseline set of questions regarding attitudes and socio-demographics, it might include a different module each time to obtain more information on topics such as private vehicle vs. shared ownership, concerns about liability issues, potential impacts upon living and working locations, etc.
- 2. FDOT Should Consider Further Assessments of Subsets of the Florida Population:** Given the preliminary findings of the importance of ethnicity and age on attitudes toward AoVs, the Department should consider further and

more detailed assessments of these large and important population subgroups. FDOT could contract for surveys, focus groups, and/or market analyses of the state's large and fast-growing Hispanic population, as well as its large and similarly fast growing older adult population.

3. **FDOT Should Develop and Pursue an AoV Education/Marketing Strategy and Campaign:** The Department should pursue a strategy for educating and marketing AV technology to Florida residents, businesses, and visitors. This campaign will help these constituencies to understand the potential benefits and costs associated with AoV technology, educate them about the technology as it evolves, and showcase the state's leadership efforts in this area.
4. **The Education/Marketing Program Must be Multi-Platform and Speak to the Interests and Concerns of Key Markets:** The survey results point to important subgroups of the population that should be catered to in any FDOT-led education effort. At minimum, the survey results point to different marketing efforts aimed at (at minimum) three different cohorts:
 - **Millennials:** Millennials hold very favorable attitudes toward AoVs, see the benefits, and find technology easy to use. The literature paints this cohort as a likely early adopter, and they seek cool, "fast city" technology to enhance their quality of life. Beyond safety, which is a general concern, the younger adults worry about data security and desire an enjoyable riding experience.
 - **Mid-Lifers:** Mid-Lifers hold generally favorable attitudes toward AoVs, have good comfort with technology, and they can envision benefits from enhanced mobility. However, as they have greater assets and are more likely to have families, they need to be reassured about safety and liability concerns. Their concerns revolve around legal liability and privacy/security issues.
 - **Older Adults:** Older adults are less favorable to AoVs, and technology more generally, and see the challenges and costs of AV more than other age groups. However, this group does see some enhanced mobility advantages that might result from AoV, which represents an opportunity for building support for the technology amongst this cohort. As expected,

these groups worry about how easy the technology is to use, liability and how AV will interact with regular drivers.

Further, the approach for reaching these different groups needs to vary widely by cohort. As expected, Millennials are much more likely to be reached through social media and online campaigns that occur within the flow of their day-to-day lives. The Mid-Lifers and Older Adults are more engaged with technology than ever, but likely require more traditional marketing campaigns to be connected with. FDOT should work with industry, universities and advertising groups to develop an approach for building the brand of "Florida as an AV Innovator and Leader".

CHAPTER 5



Image Source: www.aplusseniorcomputer.com

Social Data Mining for Understanding Perceptions of Autonomous Vehicles

5.1 - INTRODUCTION

Automated vehicles represent one of the most exciting areas of transportation today and with the technology moving closer and closer to widespread real-world implementation they have begun to capture the public interest. Several states (CA, FL, MI, NV, VA) and Washington DC have embraced early exploration of this technology. For example, Florida passed legislation in 2012 allowing for autonomous vehicle testing. In September of 2014, California approved 29 automated vehicle permits to allow testing on state roadways by Google, Audi, and Mercedes-Benz (Franzen, 2014). And quite recently, in June of 2015, the state of Virginia approved autonomous vehicle testing in selected locations (Ramsey, 2015). We are in the early stages of a long transitional phase, and knowledge of how the public perceives these new technologies is presently limited. What the transportation community considers automated vehicles encompasses a wide range of new capabilities and represents major disruptions to traditional mobility paradigms.

Knowledge of how the public sees these new technologies can help inform transportation planning and policy efforts aimed at ensuring a smooth transition to automated vehicles. Capturing interest in public opinion and sentiment on transportation policy issues is nothing new, but what is possible now is extracting such knowledge from on-line social media (Schweitzer, 2014). Data from on-line social media portals can be analyzed, or mined, to learn how the public perceives transportation issues at a potentially lower cost than traditional survey methods.

This section reports on a portion of a research project sponsored by the Florida Department of Transportation where the major task was to analyze social media data as a means of learning about the public's perception of automated vehicles. The FSU research team was tasked to collect relevant social media data on autonomous vehicles for the entire U.S. over a multi-year period, determine the sentiment associated with those data, and then analyze trends in sentiment within the data. The project primarily focused on experience with Twitter, a popular social media outlet, augmented by other social media sources as appropriate. Key to our approach was the use of geotagged Twitter data, which allows for the mapping of

where opinions were being expressed and what information was being shared, hence allowing us insights into how Floridians' sentiment regarding autonomous vehicles aligns with other states and the U.S. as a whole.

5.1.1 - Project Design and Organization

The report is organized by project objectives and tasks as follows:

- **5.2 - Literature Review of Autonomous Vehicles and Social Media.** This task included reviewing literature on autonomous vehicles, social media, and data mining approaches.
- **5.3 - Collection of Historical Social Media Data.** This task involved obtaining historical Twitter data that was potentially relevant to autonomous vehicles. By historical we mean data from the time period before the project start. A series of search terms potentially relevant to autonomous vehicles were identified and used to query a large historical archive of geotagged Twitter data. Basic characteristics of these data such as their frequency, structure, and spatial distribution were analyzed.
- **5.4 - Collection of Real-Time Social Media Data.** This task involved setting up computational infrastructure to capture Twitter data in real-time, employing the same set of search terms used to query the historical Twitter data archive. This allowed the team to collect Twitter data following the time period covered by the historical Twitter data.
- **5.5 - Assessment of Tweet Sentiment by a Crowdsourcing Platform.** This task involved the assessment of the sentiment or the feelings people expressed in collected tweets on autonomous vehicles. Both the historical and real-time tweet data were assessed. An on-line crowdsourcing platform was used to obtain the tweets' sentiment. This entailed the team designing task prompts to instruct on-line contributors on how to rate Autonomous vehicles, designing test questions, and related

efforts. Volunteers from English-speaking countries assigned sentiment scores to the tweets and these scores become the basis for future analysis.

- **5.6 - Analysis of Sentiment Data in Space and Time.** As the Twitter data has location and temporal information attached to it, we reported on trends in the sentiment through a series of maps, charts, and other figures intended to highlight perceptions of autonomous vehicle technologies. We pointed out trends and insights with respect to Florida, designated permitting states, and other relevant geographies.

5.2 - BACKGROUND & LITERATURE REVIEW

The prospects of autonomous, or self-driving vehicles (AoV) are no longer relegated to the domain of science fiction, and are now a very real part of the transportation options of tomorrow (Broggi et al., 2013; Cottrell and TRB, 2006; Gilbert and Perl, 2007). Besides the potential benefits of freeing drivers up to focus on other activities during travel outings (Knight, 2013), widespread use and future adoption of AoV technology portends possible environmental savings in terms of vehicle fleet size, fuel consumption, and emission reductions (Fagnant & Kockelman, 2014; Wu et al., 2011) plus numerous possible safety benefits (Lin et al., 2013).

Within the transportation community, the implications of this oncoming paradigm shift have been discussed and many point to issues of technology adoption and uncertainty as possible barriers to AoV uptake and implementation (Row, 2013). The possibility of self-driving and connected cars that interact with one another to exchange real-time information for maintaining safe roadway conditions represents a drastic departure in functionality from the current transportation system (Itoh et al., 2013; Row 2013; Waytz et al., 2014; Yang & Coughlin, 2014).

Research has identified possible groups who may have greater issues with AoV technology adoption, such as the aging population (Yang & Coughlin, 2014), though the benefit of new crash avoidance technologies, for example, is one possible motivation for why people might embrace AoVs sooner rather than later (Itoh et al., 2013). Although testing of AoVs has been authorized in a selected group of states for the last several years, it has been of a limited nature and in 2014 the State of California awarded the first 29 vehicle permits to Google, Audi, and Mercedes-Benz to drive AVs on public roadways (Franzen, 2014). In May of 2015 the state of Tennessee was the first to explicitly prohibit any future political entities from prohibiting the use of vehicles with autonomous technologies that so long as they otherwise comply with motor vehicle safety regulations (Weiner & Smith, 2015). In June of 2015 the State of Virginia was the latest to approve some form of AV testing (Ramsey, 2015). In summary, the current states and localities where AoVs has received some form of legal approval for testing include California, Florida, Nevada, Michigan, Virginia, and Washington D.C.

Industry experts, researchers, and the public all have their own areas of concern and fascination for how the technology will unveil. Government organizations around the world are conducting simulations to foresee how AoVs will affect urban mobility (ITE, 2015). The Corporate Partnership Board Report studies the impact large-scale adoption of autonomous vehicles would have on a mid-sized European city under two different scenarios: a fleet of TaxiBot multi person shared vehicles and AutoVot single passenger taxis. Depending on the configuration of the model and the chosen scenario, predictions can be made regarding potential for executable mobility, volume of car travel and congestion, parking needs, and general user satisfaction. With a specific aim toward developing preliminary policy insights, the simulations conclude that a change to a taxi system of either variety – single or shared – would result in an increased dependency on ever-improving technology and shorter life-cycle vehicle as well as significantly reduce parking demands. As such, urban mobility would be best suited by a pure self-driving fleet rather than a mix of autonomous and traditional for space and congestion efficiency.

Additional concerns on the path forward to autonomous vehicles relate to societal, legal, and regulatory issues; these are the focus of an ongoing collaborative report between the World Economic Forum and the Boston Consulting Group (Mosquet et al., 2015). Preliminary results were drawn from a nationwide survey of US drivers and interviews with original equipment manufacturing (OEM) experts, suppliers, and researchers. The report found that the likely path forward toward the general public embracing autonomous vehicles will be driven by the cost of development and commercial production, consumer demand, and technological development of vehicle sensors. Surveyed drivers were favorable toward the idea of purchasing either a partial or fully autonomous vehicle in the future due to a presumption that those vehicles will be safer and result in lower insurance premiums.

More broadly, being a newer and complex set of technologies, still not much is known about the public's perception of AoVs, their familiarity with its benefits/costs, or its rate of development. One area of opportunity to learn more about public sentiment regarding AoVs is that of social media, which is increasingly being tapped as a source of potential information on a range of public-interest issues (Ben-Harush et al., 2012; Shelton et al., 2014; Signorini et al., 2011).

5.2.1 - Social Media and Transportation

The term social media refers to a wide range of web-based technologies and portals that allow users to post their own content, usually around communities and networks of interest, and includes such well-known platforms as Twitter, Facebook, LinkedIn, Yelp, and Instagram (Gal-Tzur et al., 2014). The transportation field has begun to embrace these technologies (Gal-Tzur et al., 2014), particularly as tools that can help with assessments of policy issues and public outreach. Nowadays, it is fairly common for transportation agencies from the local to the state level to utilize social media as a public outreach tool (Birdsall, 2013; Schweitzer, 2014), as there are numerous documented strategies for doing so (Bregman & Watkins, 2013). Emblematic of this trend, a recent paper examined how social media has been used successfully to involve the public in the environmental review process for transportation projects and identify lessons learned (Camay et al., 2012). However, in transportation and a number of fields, attention to social media has also sought to gain insights into populations' attitudes toward a range of issues through the analysis of the volunteered information that users provide (Gal-Tzur, et al., 2014).

The analysis of data from social media can augment traditional research protocols to provide new insights into populations' perceptions of transportation issues, level of involvement, and other related dimensions (Evans-Cowley and Griffin, 2012; Gal-Tzur, et al., 2014). However, the credibility of social media data to inform transportation planning and policy is still being tested to ensure sufficient accuracy of text extraction methods (Grant-Muller et al., 2014). Utilizing social media platforms also requires an understanding of which sources are best suited to the aims of the transportation agency conducting the analysis. Both Twitter and Facebook are potential sources for extracting data, but for different communication purposes; while both platforms are equally suitable for disseminating general information, Twitter is better-equipped for time sensitive news and updates (Bregman, 2012).

The ease of accessing, indexing, and storing social media data has propelled the notion of Smart Cities, the application of digital technologies for studying urban environments (Sacco et al., 2013). 'Big Data' sources and mining techniques are used to perform analytics for urban sensing projects, such as the classification of activity profiles. Social media platforms that revolve around 'checking in' at a location, such as Foursquare, record GPS data to construct human activity patterns (Hasan & Ukkusuri, 2014). Social sensing of activity data using a cloud computing

infrastructure is more efficient and monetarily feasible than conventional sensing methods and devices (You et al., 2014).

5.2.2 - Mining Social Media Data

There has been a great deal of research over the last several years which attempts to 'mine' social media platforms in an effort to generate knowledge into particular problem domains. Many examples can be found from outside the field of transportation. Ben-Harush et al. (2012) wrote about the potential for social media data to inform studies of public health and physical activity, as well as marketing and consumer choice, discussing data collection protocols involving smart phones and platforms such as Facebook and Twitter (Ben-Harush et al., 2012). Related to this, Widener and Li (2014) monitored Twitter posts to examine correlations between where people lived and their perspectives on their accessibility to healthy foods (Widener & Li, 2014). Ghosh and Guha (2013) examined Twitter data to identify themes in conversations around issues of obesity and map their prevalence to locations using Geographic Information Systems (GIS) (Ghosh & Guha, 2013). Interested in people's eating behavior, Hingle et al. (2013) had their subjects report their meal activities over Twitter and mine the public stream to access that information (Hingle et al., 2013).

Aside from applications related to health, the crisis and disaster management communities have also engaged in social media analytics (Gao et al., 2011). For example, an earlier contribution by Birregah et al. (2012) identified many of the possible benefits of social media data mining and monitoring, including the possibility of augmenting emergency operations in real-time (Birregah et al., 2012). More recently, a platform described by Middleton et al. (2014) developed crisis maps which blend data on areas at risk for disasters with geolocated tweets related to extreme crisis events. Shelton et al. (2014) reviewed some of the challenges posed by using social media-derived big data as related to tweets made during Hurricane Sandy, including the limited nature of the data associated with individual tweets.

5.2.3 - Transportation Applications of Data Mining

The potential for social media applications in transportation is becoming increasingly apparent (Gal-Tzur et al., 2014) as there are opportunities to augment traditional survey data collection approaches (Efthymiou & Antoniou, 2012) with potentially low-cost, valuable information. Efthymiou and Antoniou (2012) conducted a preliminary Twitter analysis by mining geo-located tweets containing references to bike sharing, car sharing, and electric vehicles, as well as executing an email questionnaire. Social media portends new ways for transportation agencies to understand their customers' sentiment on a range of issues (Bregman, 2012), such as how Schweitzer (2012) used social media to gauge public perceptions of public transit and airline choice alternatives (Schweitzer, 2014). Collins et al. (2013) analyzed tweets related to the Chicago Transit Authority in an effort to learn more about their customers' perception of service and other issues (Collins et al., 2013).

Mai and Hranac (2013) have used Twitter to collect information about traffic incidents by analyzing the density of geo-located messages proximate to accident locations, weighted by relevance of tweet text. Combining California Highway Patrol data and tweets including transportation-traffic related keywords – collected globally over the span of two weeks – they were able to use semantic weighting for keyword combinations that indicated increased relevancy to witnessing an accident (Mai & Hranac, 2013).

5.2.4 - Sentiment Analysis: An Overview

Sentiment analysis, also known as opinion mining, is a text analytics approach for measuring emotion in documents (Vinodhini & Chandrasekaran, 2012). Types of documents can vary in size from large bodies of work, such as books or journal articles, to small documents that consist of a single line of text. This project evaluated sentiment as it was expressed on Twitter, where each tweet was considered a distinct document. Difficulties arise when documents are at either length extreme. When a document is too long, there is a potential for conflicting opinions and noise. For example, a review of a hotel stay may contain both positive and negative opinions regarding different aspects of their experience, such as hotel staff or room cleanliness (Wu et al., 2010). However, when a document is too short there is limited text from which to identify a conclusive opinion. The rise

of social media, particularly Twitter, has created new avenues for the public to express unsolicited opinions quickly and frequently. The pursuit of accurate and efficient sentiment analyses on these new media platforms has created a new market for sentiment software and tools. The data accessibility afforded by social media has resulted in the application of opinion mining research not only to marketing and sales, but to emergency management, urban planning, and psychology among many other fields.

5.2.5 - Approaches to Sentiment Analysis

There are many approaches to potentially assessing the sentiment of documents. For purposes of simplicity, we divided our discussion into assessments performed by computer software, and those assessments performed by people. On the machine side, sentiment analysis can be conducted using unsupervised machine learning, which will require a sentiment lexicon, or dictionary, as a reference to gauge the sentiment of words. In contrast, a supervised machine learning approach involves basing sentiment assessments off the knowledge contained in a pre-classified training set (e.g., assigning new tweets sentiment scores based on knowledge from tweets already scored for sentiment). In this domain there are various text analytics software options. The two most prominent sources of sentiment lexicons are SentiWordNet and SentiStrength, which were developed under significantly different conditions and can return different scores on the same set of documents (Chalothorn & Ellman 2012). SentiWordNet was constructed using a purely lexical approach using a starting seeds of paradigmatically positive or negative words and building an expanding word map (Baccianella et al., 2010). SentiWordNet only scores substantive words and excludes stopwords such as 'and', 'also', and 'but'. SentiStrength, on the other hand, was developed specifically for unstructured social media text using comments on the MySpace social platform (Thelwall et al., 2011). SentiStrength is more sophisticated than SentiWordNet in that it is able to correct to misspellings, account for negation, and incorporate all of the words in the text.

In conducting a supervised machine learning task, there can be a considerable time investment necessary to prepare a suitable training sample. Chew and Eysenbach (2010) attempted a manual sentiment classification to measure public perception of the flu during the 2009 H1N1 pandemic (Chew & Eysenbach, 2010). Using Twitter,

they tracked the rate of increase in H1N1 mentions over other flu-related terms between May 1st and December 31st. As terminology became more widely known, the public started to refer to the pandemic increasingly by its official name, rather than 'swineflu'. They termed the use of Twitter for public health: infodemiology. In order to process the data set manually, Chew and Eysenbach (2010) took a small random sampling of tweets at different time periods to manually classify and validated the findings against the proportion in the whole data set.

An alternative to the computer-based algorithmic sentiment approaches described above is to utilize crowdsourcing platforms which divide the task of determining document sentiments among a large group of contributors, such as Amazon's Mechanical Turk or Crowdfunder (Xintong et al., 2014). The classification task is outsourced for contributors to determine first whether the document is relevant to the topic, and if so, the general sentiment of the thought(s) expressed. A possible advantage of such crowdsourcing approaches is the ability for people to detect sarcasm and other subtleties of speech expressed in a document that a machine algorithm might not be able to detect. Broadly, crowdsourcing allows researchers to embrace the internet's growing role as a source of human collaboration and avenue for citizen science (Rotman et al., 2012).

5.2.6 - Sentiment Analysis Applications

All of the machine learning techniques discussed, both supervised and unsupervised, have been used to mine sentiment from social media platforms to understand a variety of phenomena. Some have looked at how sentiment polarity increases relative to corresponding popular events (Thelwall et al., 2011). It was found that events that generate trending Twitter activity increases in negative sentiment, which is speculated to be due to preexisting negative bias being presented with a relevant opportunity to voice dissent. During a discussion of a popular event, sentiment is significantly more negative during hours of high activity, during the peak of activity, and the hours immediately following peak activity.

Sentiment analysis can also be used to monitor targeted emotions. Gilbert and Karahalios (2010) found a connection between expressions of worryment on LiveJournal and fluctuations in the stock market during 2008 (Gilbert & Karahalios,

2010). An Anxiety Index was used as a classifier which was able to detect text markers based on anxiety, fear, and worry. The research was an expansion on previous research that found connections between the health of the stock market and sunny weather (Hirshleifer & Shumway, 2003), as well as pessimism expressed in Wall Street Journal columns (Tetlock, 2007). The Anxiety Index had a low rate of accuracy, with a maximum predictive accuracy at 32%, but a rate of false positives below 10%. Conversely, Twitter-based sentiment analysis can be used to study how place correlates to happiness (Mitchell et al., 2013). Using the crowdsourcing platform Mechanical Turk, 80 million geolocated tweets sent in 2011 were classified for their happiness measure. The distribution of 'happy' and 'sad' words across the United States were correlated to happiness measures such as obesity rates and education levels. They found that low happiness scores were driven by a use of regionally-specific swear words, known as 'geoprofanity', which is connected to civil unrest.

Twitter sentiment analysis has also been used to identify patterns and anomalies with regard to political opinions during elections. Diakopoulos and Shamma (2010) analyzed expressions of sentiment on Twitter during the 2008 United States presidential election (Diakopoulos & Shamma, 2010). Collecting only tweets which were sent in real time during the live debates, they were then classified using Mechanical Turk. They found that nearly twice as many negative tweets were sent than positive, 41.7% compared to 25.1%. Of the collected tweets, 33.2% were either irrelevant to the debates or neutral. The challenge when judging tweets linked to a specific, real time event is that there is no way to ensure that the tweet was in direct response to the event; it is possible that the sentiment expressed was solely a previously-held opinion or referring to a different phenomenon occurring at the same time as the debate. A similar analysis was applied to the 2009 German national election. Rather than crowdsourcing a manual assignment of classification, Tumasjan et al. (2010) used the Linguistic Inquiry and Word Count (LIWC), an unsupervised sentiment corpus (Tumasjan et al., 2010). The corpus assigned specific emotion – such as anger, uncertainty, and achievement – in addition to negative and positive sentiment. They found that discussion was concentrated to a small group of users whose content was shared through a retweet, a message that copies the original text and posts it again as a new, distinct tweet. Despite the amount of recycled content through retweets, the authors determined that there was a plausible relationship between mentions of a specific political party and their likelihood of winning the election.

Social media sentiment also has applications for improving emergency management and disaster response during a crisis event. Nagy and Stamberger (2012) collected tweets relevant to the 2010 San Bruno, California gas leak and the subsequent fires (Nagy & Stamberger, 2012). The focus of the research was to compare classification methods using SentiWordNEt, Emoticons, Artificial Neural Networks (AFNN). All three are programs with a unique corpus, but the same unsupervised method of assigning a polarity score (a polarity score expresses the cumulative sentiment of a text string based on its combination of positive vs. negative words) They also tested a Bayesian Network approach based on a training set of manually classified tweets from the Crowdflower platform.

The use of Twitter sentiment for public assessment does not need to be limited to particular events in time. Twitter discussion of dining and general food purchases can support an analysis of an individual's food habits, specifically the likelihood of making good nutritional choices as a result of the near availability of fresh produce (Chen & Yang, 2014). The study focused on geotagged tweets sent in Columbus, Ohio within Franklin County over a period of five weekdays. In addition to assessing the relationship between available dining choices and residents' food habits, the article highlights the benefits that the new data source provides to be able to collect causal information at the individual level.

5.2.7 - Sentiment Analysis in Transportation

Social media sentiment analysis has particularly great potential for transportation, specifically in regards to improvement in quality and consumer satisfaction. Traditional mailed surveys of consumer satisfaction – such as the 2000 questionnaire to gauge which service improvements for the Bay Area Rapid Transit are perceived as most important (Weinstein, 2000) – face the challenge of balancing the length of the survey in order to improve the response rate. Capturing post hoc social media data to study the same public perceptions does not face this space constraint. Collins et al. (2013) conducted a study of rider satisfaction of the Chicago Transit Authority (CTA) (Collins et al., 2013). Collecting only tweets which mention specific transit lines by users who list their primary locations in Chicago, they were able to compile valuable customer feedback information for a public entity with limited resources to otherwise do so. While

estimating that only 25% of the tweets collected were both relevant and expressed clear opinions, the rest were scored for sentiment polarity using SentiStrength.

Schweitzer (2014) used social media sentiment to take a step further from reflecting consumer attitudes of transit to broadly-held social bias and stigma of transit users by the general public. Analyzing Twitter data captured over 20 one-day periods interspersed between March 2011 and March 2014, she identified themes in language and communication style for tweets relating to transit using public parks, social programs, airlines, and police tweets for comparison. A supervised machine learning approach to sentiment analysis was combined with a manual qualitative coding of persistent text topics to determine that transit agencies which were more individually-engaging with the Twitter community – as opposed to sending out frequent blasts of information and updates – received less negative comments. The conclusion is especially notable in light of the fact that public transit receives consistently more negative comments than the airline and public park tweets.

Sentiment analysis provided by individuals can be aggregated to provide a comprehensive picture of sentiment for an area. Bertrand et al. (2013) did so by constructing a spatiotemporal map of sentiment in New York City. Rather than identifying a particular subject matter or emotion, the focus was on identifying areas of the city and times of the day with the greatest sentiment polarity (Bertrand et al., 2013). Sentiments were found to become more positive in areas proximate to Times Square, as well as in parks and gardens, and on weekends. Transportation spaces, such as bus terminals, bridges, and tunnels had exceptionally high negativity.

An understanding of sentiment change for applications to transportation can also benefit from the study of human movement patterns in urban areas. Frank et al. (2013) identified a relationship between happiness and geolocated twitter sentiment, but as a function of the contributor's movement patterns. Using a person's average location and the language used at that location, they analyze how language changes as a person moves further away from their point of origin and the impact that change has on the sentiment score of the text (Frank et al., 2013). They found that the language of a tweet becomes more positive as the person tweeting moves further away from their average point of origin. Their methodology combined sentiment analysis with GPS data collected from mobile phones. The distance and speed at which a person is able to travel varies according to the

modes of transportation available to them, and therefore would have an impact on the rate of change in sentiment as it increases with distance. As a complex methodology, sentiment analysis factoring in time-space faces the additional classification challenge of recognizing tweets which were sent by an automated twitter 'bot', which are typical of companies and organization seeking to engage in social media. This is not typically an issue when solely analyzing sentiment, but is incompatible with the tweet being tied to a specific human movement pattern.

5.3 - COLLECTION OF HISTORICAL SOCIAL MEDIA DATA

Twitter is a very popular social media site whereby people communicate with one another using (up to) 140 character length 'tweets'. Known as a micro-blogging portal, users routinely broadcast a range of communications from documenting personal details of their day-to-day lives, to commenting on public policy issues and news stories.

We obtained a collection of tweet data which had been captured via live-stream by the University of Kentucky's DOLLY Project (Digital OnLine Life and You). These were geolocated tweets captured from July 1, 2012 until September 28, 2014. A bounding box was used to limit tweets to those sent within the continental U.S., though the extent of this screen also allowed in some tweets from north and south of the U.S. border. Approximately 2-3% of all tweets are able to be located to a geographical location (Leetaru et al., 2013). Tweets were selected if they contained one of our search terms relative to automated vehicles. A fairly strict definition of 'relevant' was adopted whereby the tweet had to be referring to ground-based automated vehicle-related issues or concepts. In this way, tweets about self-driving drone airplanes or trains would be excluded from the relevant category.

Table 5.1 shows a list of our search terms along with the number of tweets relative to each query, while **Figure 5.1** displays the mapped results of the query for 'Google AND car,' aggregated to the county level for the continental U.S. Depending on the number of tweets captured by a particular search term query, different methods were used to select out tweets that are relevant to automated vehicles, including visual inspection in many cases. For example, a query that looks for the words 'self driving' in a tweet could find a text string stating:

'Today I am driving myself to the dentist. #noparents'

which would not be relevant to automated vehicles. These initial search terms were implemented based on commonly used phraseology for referencing automated vehicle technology, coupled with the FSU research team's impression of what related terms (e.g., 'zFAS' which refers to Audi's self-driving technology) might also

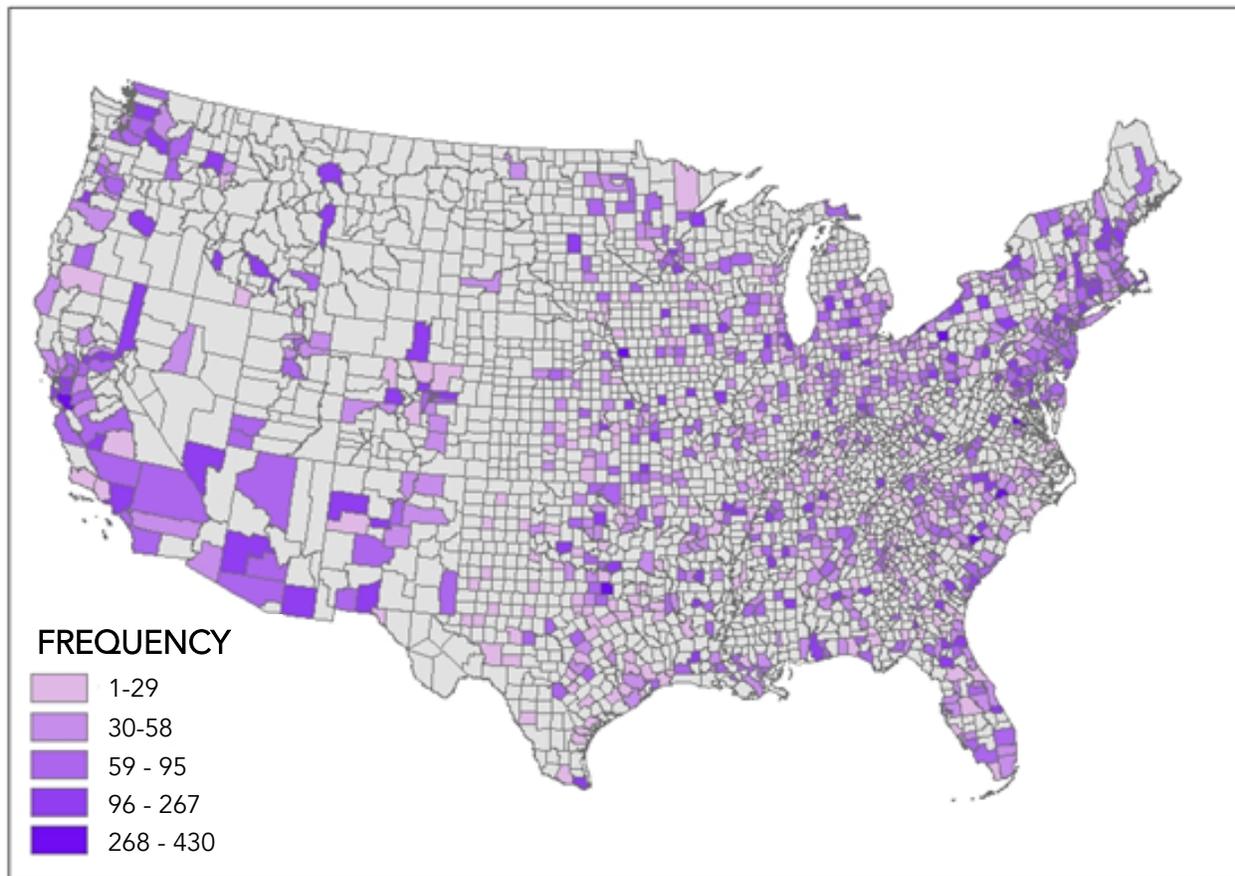
generate useful and relevant results. The base number of hits was highest for the query 'future AND car' but in terms of relevancy terms such as 'driverless' and 'self-driving' seemed to do a better job of capturing automated vehicle posts. 'Automated' yields a lower response rate than 'autonomous,' but with predominately relevant results.

Table 5.1 - Search Terms Used to Select Tweets from Historical Twitter Data

Search Terms	Number of Tweets	Number of Relevant	% Relevant	Number from FL	% Relevant from FL
audi AND test	424	16	3.8%	2	12.5%
fdot	353	261	73.9%	237	90.8%
automated AND vehicle	53	34	64.2%	-	0.0%
autonomous AND car	170	165	97.1%	10	6.1%
autonomous AND vehicle	107	96	89.7%	5	5.2%
darpa	1,991	4	0.2%	-	0.0%
driverless or driver less	1,977	1,834	92.8%	84	4.6%
future AND car	9,880	104	1.1%	3	2.9%
google AND car	6,053	1,797	29.7%	59	3.3%
pilot AND driving	732	4	0.6%	-	0.0%
self driving	3,969	3,697	93.2%	119	3.2%
semi autonomous	59	10	17.0%	1	10.0%
zFAS	4	-	0.0%	-	0.0%

Some search terms were not particularly effective at capturing relevant tweets, as for example 'DARPA' (Defense Advanced Research Projects Agency) turned up nearly two thousand tweets, but very few pertaining to automated vehicles. The query for 'Google' and 'Car' returned quite a large number of tweets (6,000+) with roughly 30% of these deemed relevant, leading to nearly 1,800 AoV-related tweets. For interest and comparison, we also included a search for the term 'FDOT' for Florida Department of Transportation. There, any tweet was deemed relevant if it was referring to the agency. About 74% of these tweets were classified as being relevant and more than 90% of this set originated from the State of Florida.

Figure 5.1 - Frequency of Search Query 'Google AND car'



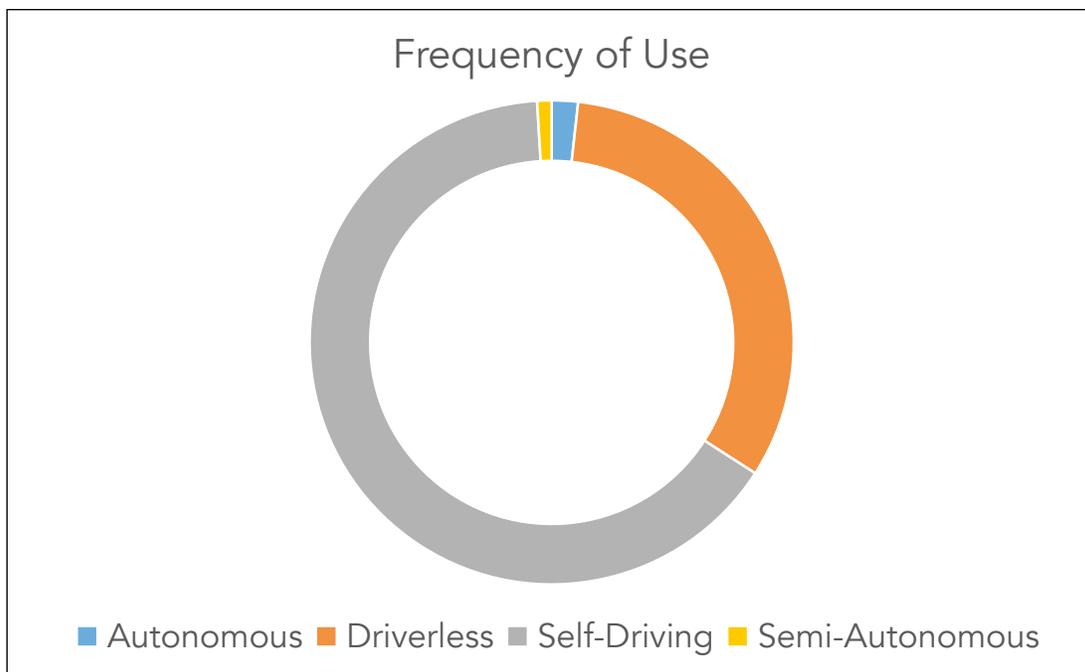
In the following descriptions of the data, we employ the full set of collected tweets which include mention of 'self-driving', 'driverless', 'autonomous', and 'semi-autonomous'. Only in the subsequent spatial analysis do we draw a distinction

between tweets classified as relevant or irrelevant based on the above criteria; both are included in the plots, but differentiated by color. In the temporal and frequency and sentiment analyses there is no distinction made. Instead, we analyze patterns in the full data – such as changes in interest over time or words used with greatest frequency – which pertain to text context. In the course of this initial data presentation, relevancy is revealed through those patterns without having to be preemptively controlled for.

5.3.1 - Selected Data Characteristics

We conducted descriptive analysis of the historical data to examine its spatial and temporal properties. We also created several word-cloud diagrams to get a better sense of the types of words that are associated with each term, hence letting us better understand users sentiment. We chose to focus on four specific search terms, with their relative frequency of use shown in **Figure 5.2**.

Figure 5.2 - The Proportional Frequency of Four Search Terms Appearing in Historical Tweets - Includes Relevant and Not Relevant Tweets



5.3.2 - Initial Spatial Analysis Examples

Figure 5.3 shows the geocoded tweets plotted for the four selected search terms. Tweets deemed as relevant in terms of strictly dealing with ground-based AoVs are shown in green, while those not directly associated with AoVs are shown in red. The maps clearly show that 'self-driving' and 'driverless' are not only the most popular way of referring to AoV, but that these references appear across the United States. While there are clusters of tweets in major metropolitan centers in the Northeast and Southern California, as well as around known technology hubs such as San Francisco, there are relevant AoVs tweets spread throughout the U.S. and southeastern Canada. Like the rest of the United States, Florida tweets primarily refer to AoV technology with these two terms, and clusters of tweet activity appear mainly in Central Florida (Orlando, Tampa) and Southeast Florida (Miami-Dade). For the two lesser used terms, much of the activity was confined to locations within California, with a few references scattered throughout the U.S., including Florida.

Figure 5.3a - Plot of Search Term "autonomous vehicle"

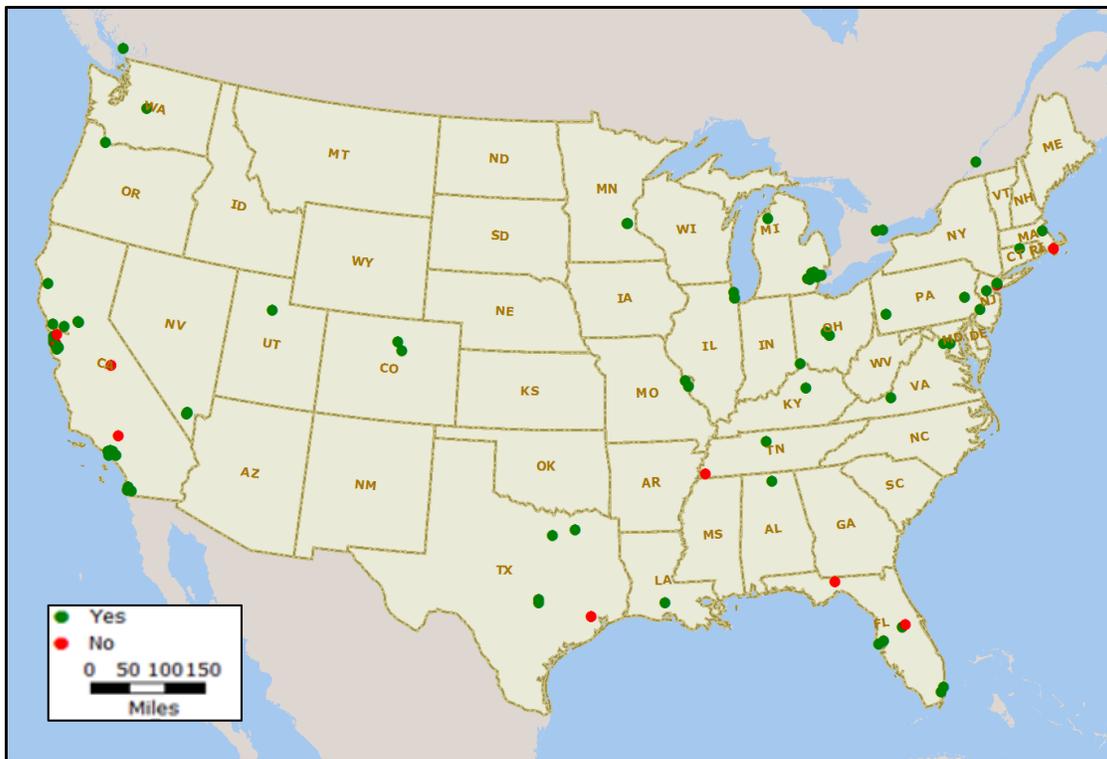


Figure 5.3b - Plot of Search Term "driverless"

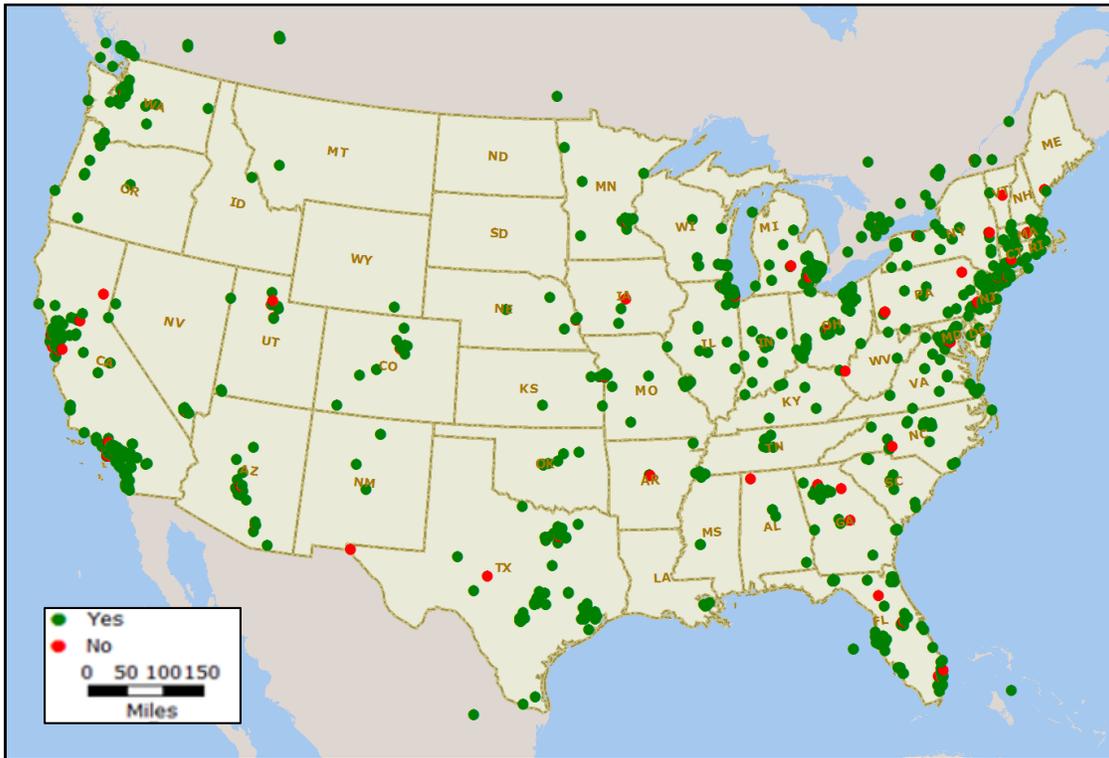


Figure 5.3c - Plot of Search Term "self-driving"

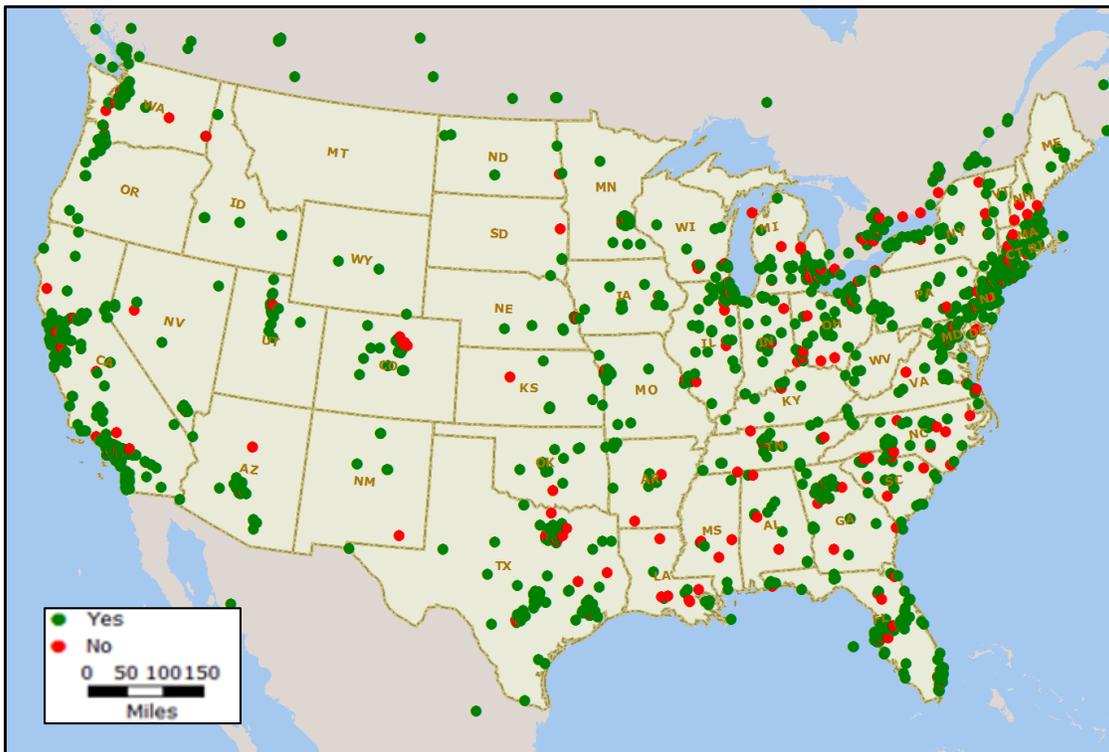
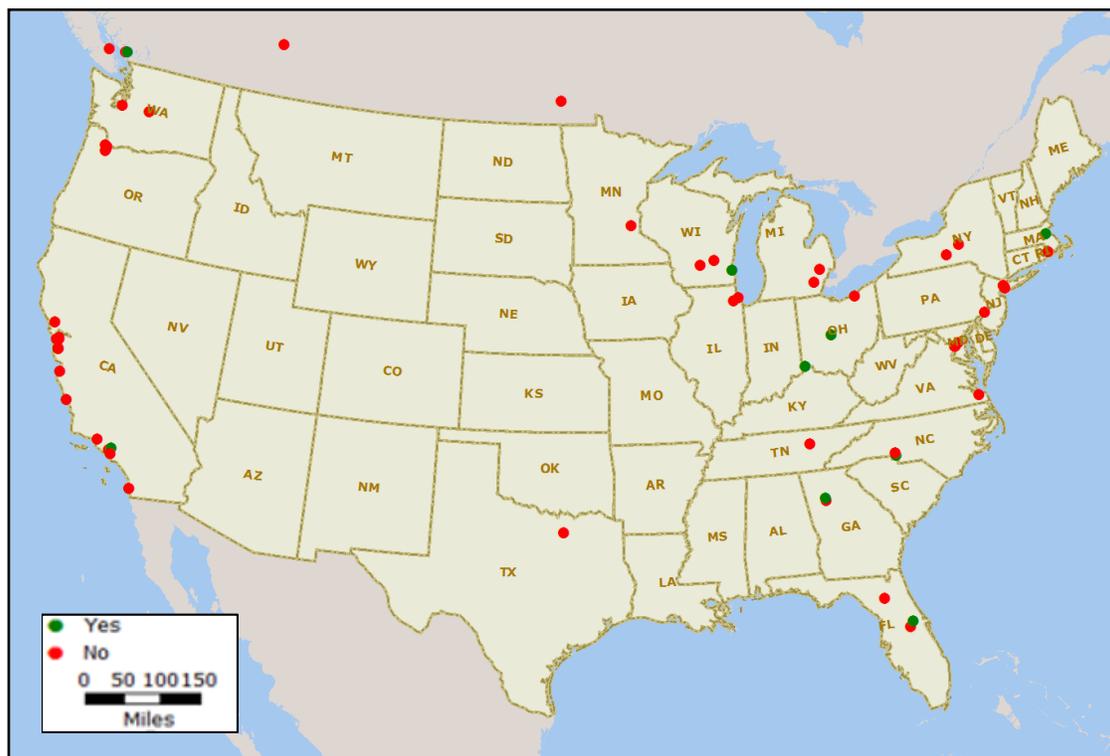


Figure 5.3d - Plot of Search Term "semi-autonomous"

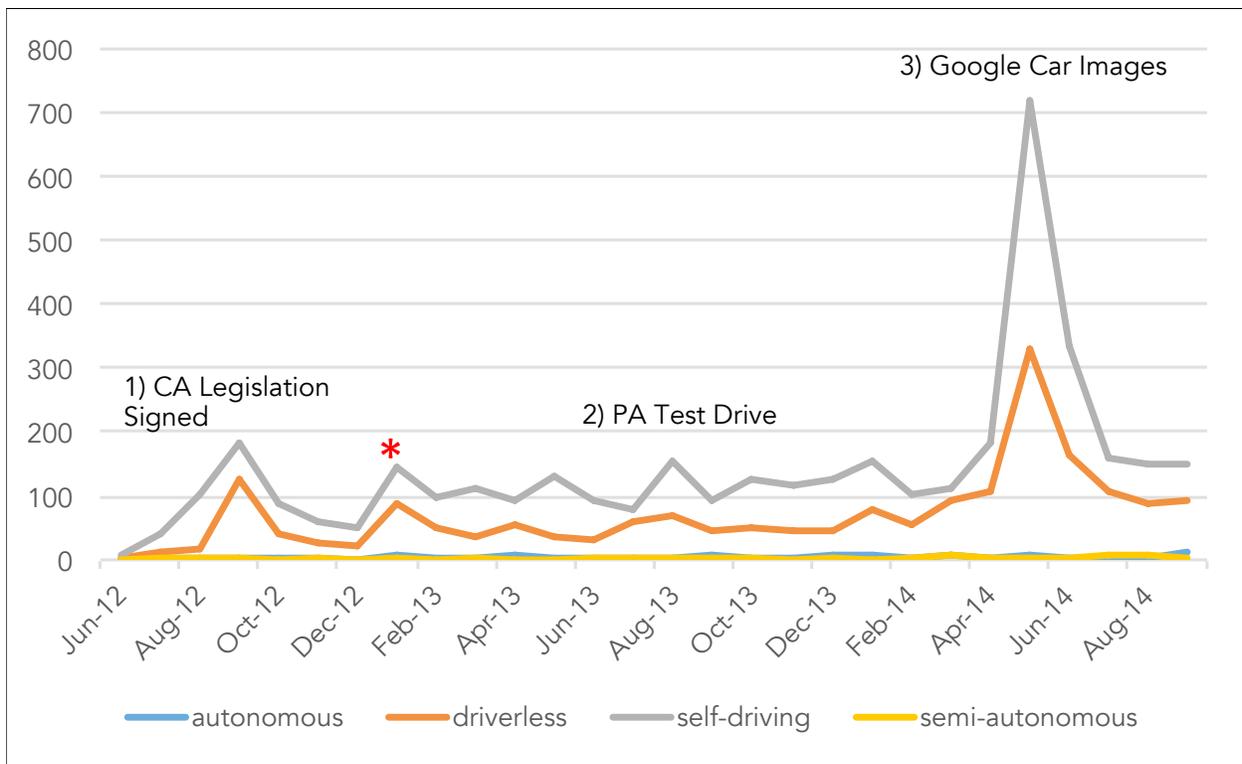


5.3.3 - Initial Temporal Analysis Examples

Figure 5.4 shows the total tweets per month for our four selected search terms. The plot conveys peaks in interest in AoV technology throughout the course of our data collection period. The composite line graph shows the total frequency of each term appearing on Twitter each month over twenty-eight months. Similar to what was demonstrated by the maps in **Figure 5.3**, Twitter references to 'self-driving' and 'driverless' have consistently occurred with greater frequency than 'autonomous' or 'semi-autonomous,' with the former terms exhibiting similar patterns in the varying levels of interest over time. By not excluding data deemed irrelevant to AoV technology in this figure, the patterns of frequency among terms become more prominent. Even without controlling for context relevance within the data, the plot reveals substantial peaks in interest which correspond to significant events in the roll-out of AoV technology. The largest increase in discussion for both 'self-driving' and 'driverless' occurred in May of 2014 when Google released the first images of its fully-autonomous car (point 3 in the figure). The graph also

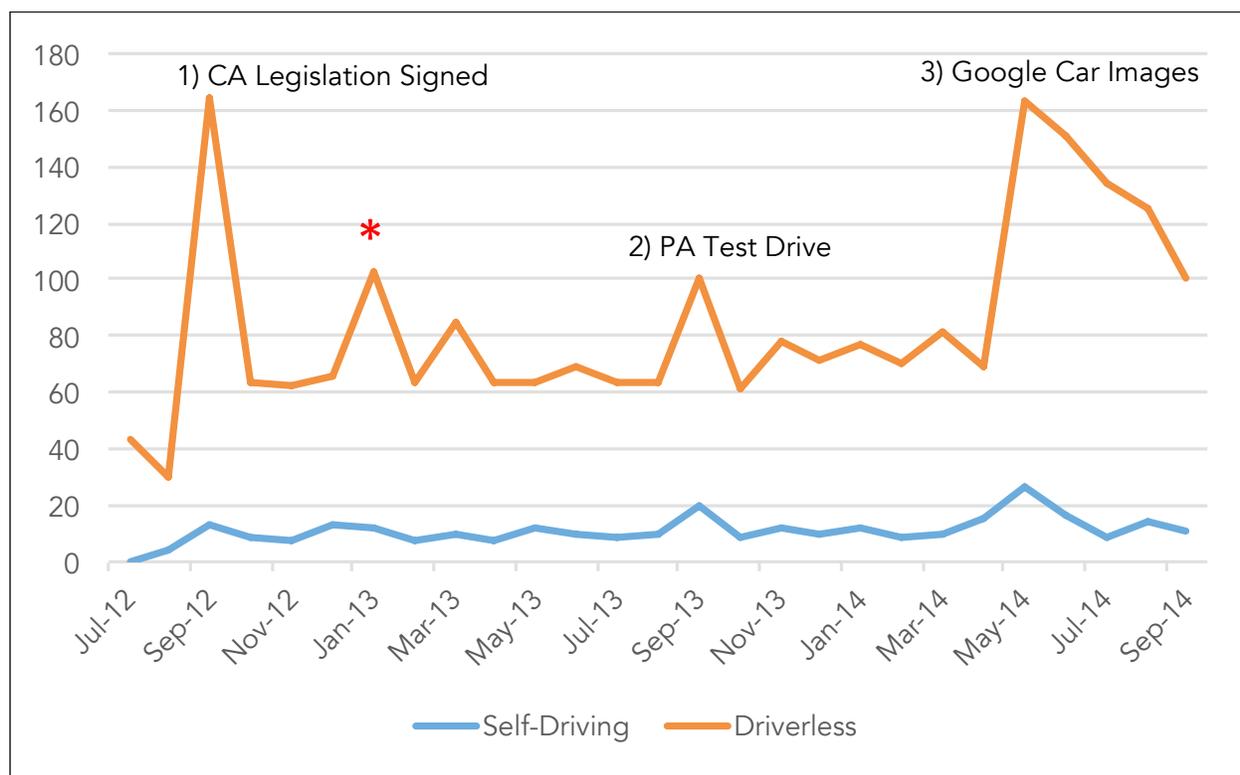
displays heightened interest in September 2012 when Governor Jerry Brown signed a bill legalizing the operation of automated vehicles on public roads in California (point 1 in the figure). Florida and Nevada signed similar legislation, as the first two states to do so, prior to the start of our data collection. There was also an increase in September 2013 when Pennsylvania Congressman Bill Shuster participated in a test drive of the Cadillac SRX, a type of connected vehicle (Associated Press, 2013). Additionally, there is a noteworthy uptick in activity in January 2013 (indicated by an * in the figure). Unlike the previous data points, there does not seem to be a particular event to explain this activity. Rather, it seems to point to a general increase in public awareness of AoV technology following the California legislation. This manifested in the circulation of more articles discussing liability, regulation, and the social implications of future transportation technology on digital news sites such as The Daily Beast, Mother Jones, and Reuters (Salmon, 2013; McArdle, 2013; Drum, 2013). All three articles were posted concurrently on January 24, 2013.

Figure 5.4 - Time Sequence of Archival Twitter Data Set



We acknowledge that there may be limitations in using Twitter data as a representative sample of public sentiment – such as demographic biases toward those with access to the technology and a willingness to participate (Leetaru et al., 2013). Therefore, we wanted to explore whether these patterns were reflected in other sources with fewer access barriers. As such we chose to look at Google’s search engine history for searches containing the terms ‘self-driving’ or ‘driverless’. Google Analytics’ Trends feature allows us to look at data on the frequency of anonymized search queries (Mohebbi et al., 2011). It also indicates which news story was most frequently returned in the search results. **Figure 5.5** shows that the noted points of heightened interest on Twitter corresponds temporally to increases in Google search queries for ‘self-driving’ and ‘driverless.’ While Google search queries for ‘driverless’ seem to be disproportionately fewer than for ‘self-driving’ compared to our Twitter data, interest in both terms experienced increases over the same periods of September 2012, September 2013, and May 2014 (points 1, 2, and 3 on the figure, respectively). The Google trend history also shows an increase in queries for ‘self-driving’ in January 2013 to correspond with the publication of general interest articles referenced above (indicated by an * in the figure).

Figure 5.5 - Time Sequence of Google Search Engine History



5.3.4 - Frequency and Preliminary Sentiment Examples

Figure 5.6 shows the text of our four search terms represented as word clouds. The visualization identifies the words which occur with the greatest frequency within tweets referencing at least one of the search terms. The data were broken into four sets of tweets containing the four terms, without differentiation for relevance, and analyzed using the statistical programming language R to reduce the text into groups of substantive words, eliminating punctuation, numbers, and stopwords (filler words such as 'and,' 'is,' and 'the'). The most frequently occurring words in each set were then arranged into a graphic where the most frequent were portrayed in a large font size. The program was able to self-determine the optimal number of words to create a visually-appealing representation. Even without controlling for context, each of the four word clouds conveys similar topical themes. 'Google' appears in the top ten most frequent words for 'driverless,' 'autonomous,' and 'self-driving,' which corresponds to the peak in interest observed in **Figure 5.4** in May 2014. With the exception of the 'self-driving' data set, 'future' also occurs with a high degree of frequency. The appearance of 'government' as a high-frequency term in the 'semi-autonomous' data suggests that the context of the data also includes references to military drone devices, technology which is closely related to automotive autonomous vehicles and shares similar terminology.

On the surface, the visualizations reveal a common theme of interest in the research and testing of autonomous vehicle technology, which is consistent with the focus on the Google car throughout the data. The presence of high-frequency words such as 'cool' and 'awesome,' combined with the lack of any clearly negative words, indicates an overall positive sentiment within the Twitter discourse.

Figure 5.6 - Word Frequency Distribution for the Four Ways of Referring to AoV Technology

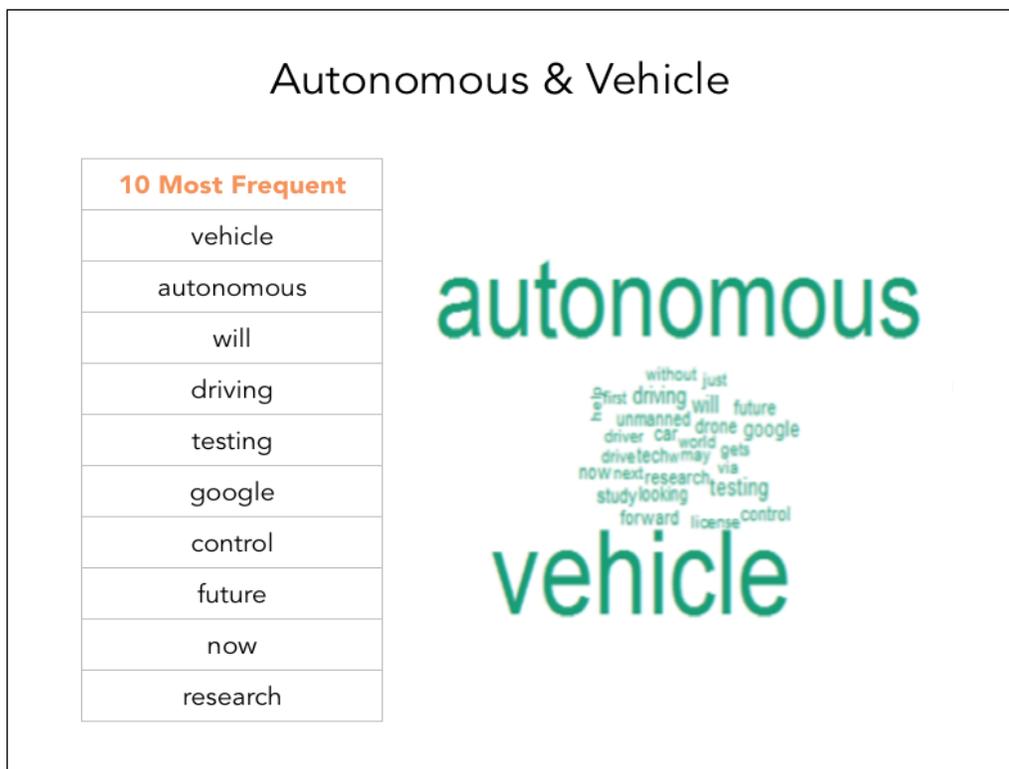
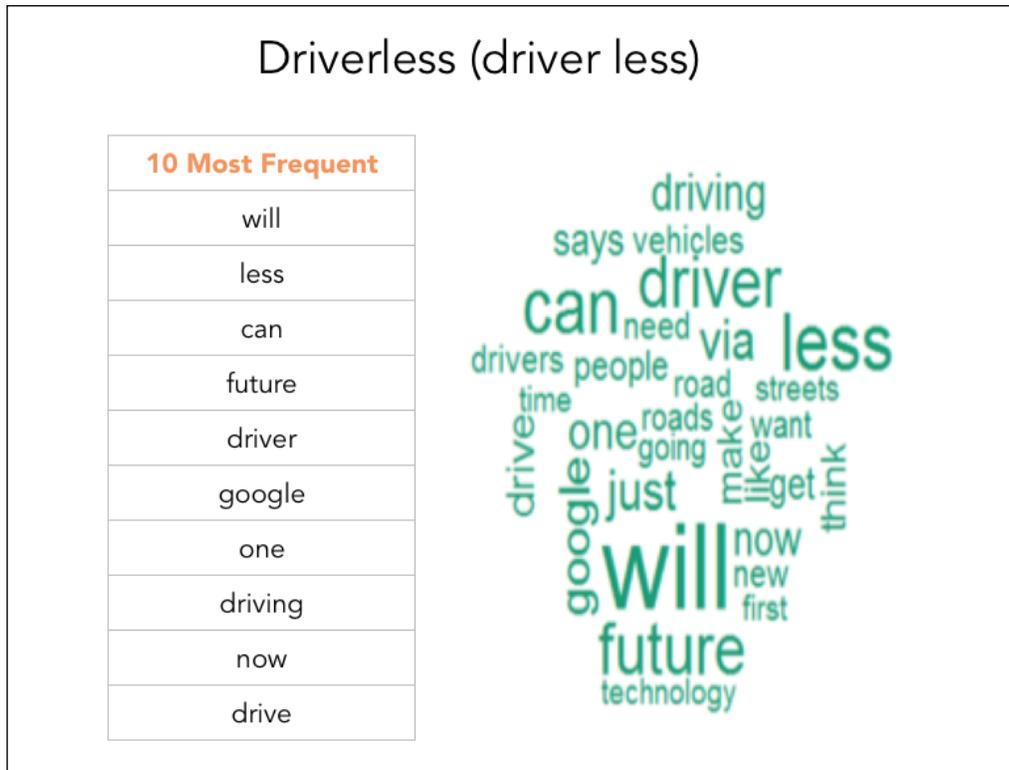
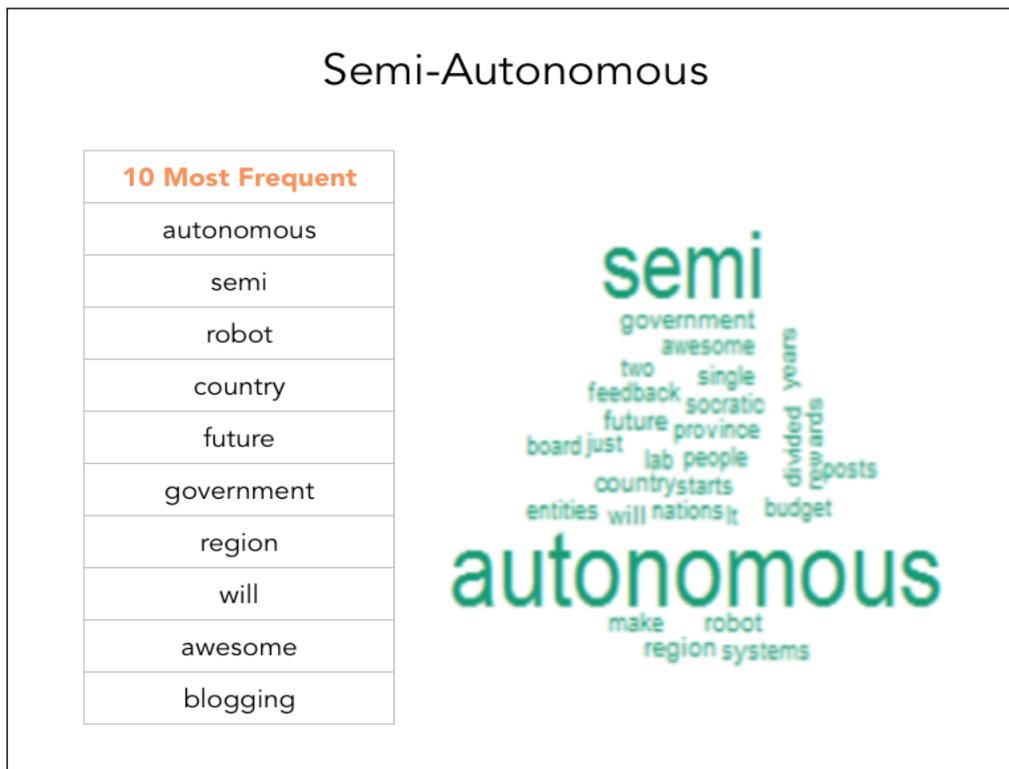


Figure 5.6 - Word Frequency Distribution for the Four Ways of Referring to AoV Technology



While identifying the individual high-frequency words across the data set provides insight into dominant topics of discussion, the frequency variance for each of the four search terms reveals the overall variety of topics. **Figure 5.7** demonstrates the number of times every unique word appears in a tweet, with the exception of the stopwords previously eliminated. In this instance, variance refers to the distance between the points, or the variation of frequencies across the text vocabulary. The distribution graph shows how many words—with each represented as a point—are used at exceptionally high or exceptionally low frequency. The distribution and variance of the data expose a divide within the four sets of text. Words which appear in the same tweet as 'driverless' or 'self-driving' have a significantly higher variance and are used in higher frequency than those occurring in 'autonomous' or 'semi-autonomous' (**Figure 5.8**).

Figure 5.7 - Distribution of Unique Word Frequency of Archival Twitter Data Set

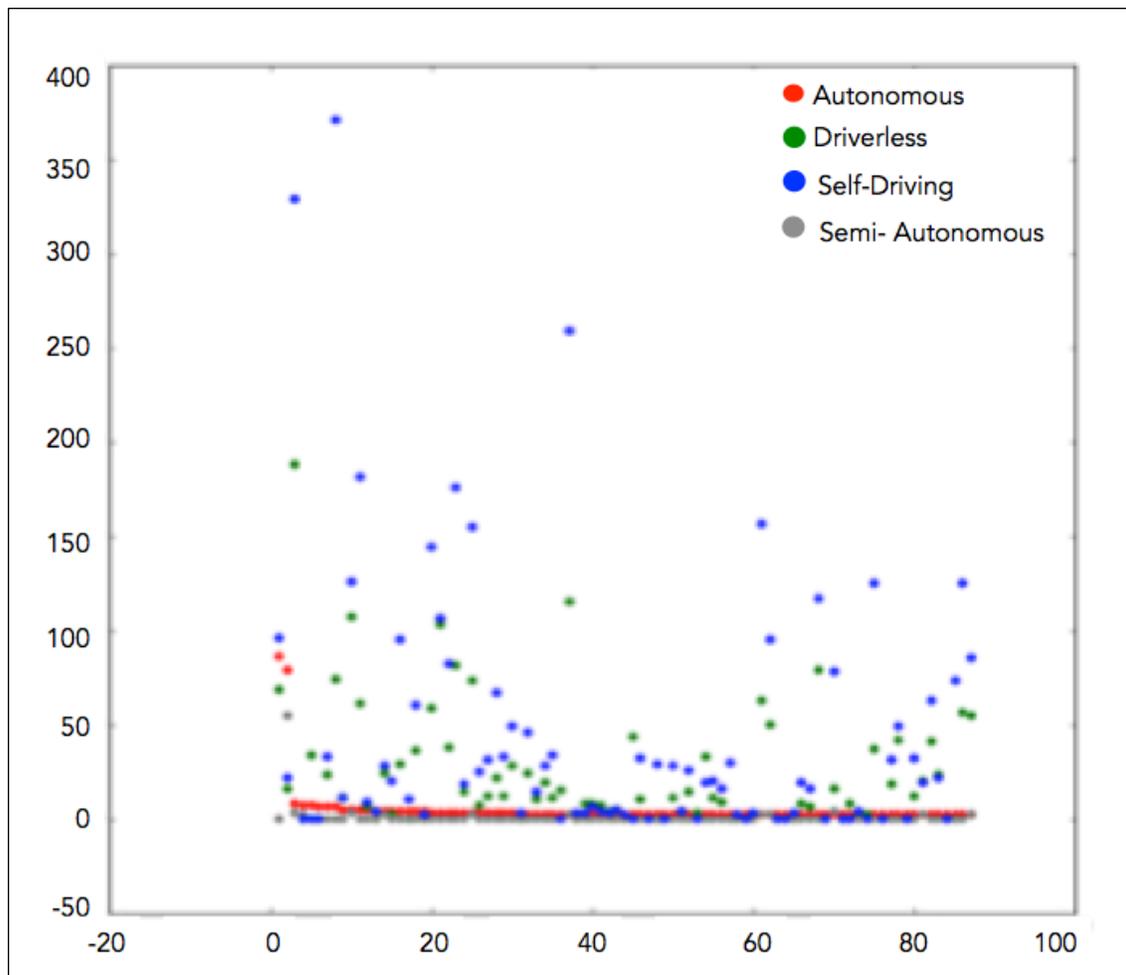


Figure 5.8 - Variance Measure of Archival Twitter Data Set

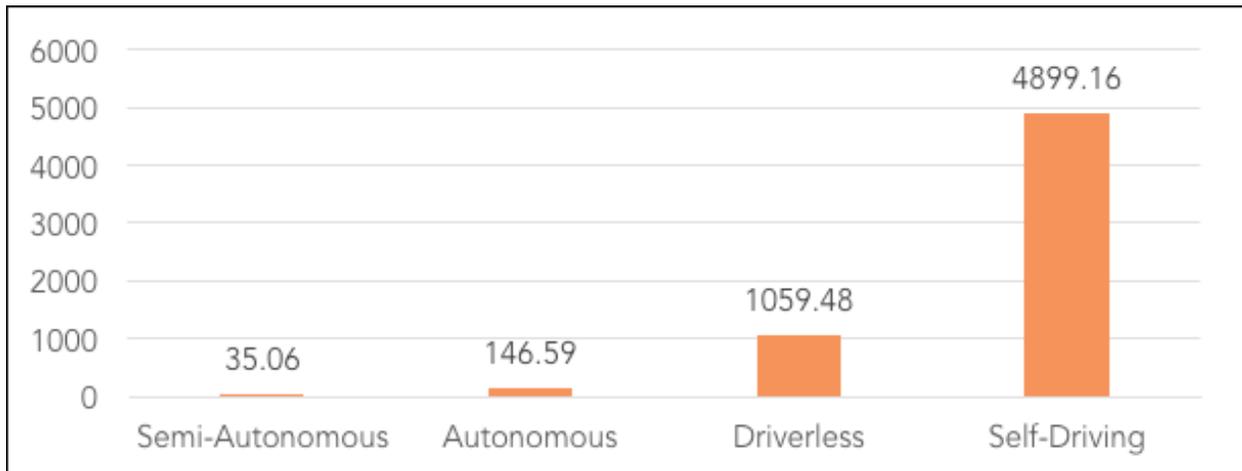


Figure 5.7 indicates that while the majority of words in the text appear less than ten times, there are several which are used more than one hundred. Words that are used in high frequency across a data set indicate repetition in the discussion. Based on this premise, we conclude that the high frequency of words used in the 'driverless' and 'self-driving' tweets is indicative of a narrow range of topics being discussed, and that those topics frequently use similar language. 'Autonomous' and 'semi-autonomous' tweets have low frequency words and low variance, which means that among the words used in those sets of tweets, there is a consistent lack of repetition in the vocabulary. Few repeating words result in dissimilar tweets. 'Autonomous' and 'semi-autonomous' tweets are dissimilar from one another because they are used to refer to a broad range of AoV technology and its potential applications. This claim is supported by looking at the particular words being used with highest frequency in each data set, which we have structured as word clouds (**Figure 5.6**). Analysis of these words provides insight into the terms which are most likely to be relevant specifically to AoV technology in the sense of transportation systems, as opposed to other applications. Tweets mentioning 'autonomous' or 'semi-autonomous' reflect the full scope of technological potential. This includes personal transportation, but also government drones and unmanned weaponry. On the other hand, tweets mentioning 'driverless' or 'self-driving' are more transportation focused and likely to have greater relevancy to transportation planning topics. There are no explicit references to other forms of AoV technology, but 'roads' and 'streets' are included.

5.3.5 - Section Summary

This section described the historical Twitter data with the goal of learning more about the public's perception of AoV technology in terms of how it is referred to and how people feel about it. Going forward we will report on collecting our own data from on-line social media based on these and other potential search terms. Working with geolocated information allows us a means of differentiating the perspectives of people in Florida from those throughout the rest of the country.

5.4 - COLLECTION OF REAL-TIME SOCIAL MEDIA DATA

Tweets related to autonomous vehicles sent since October 21, 2014 have been captured in real-time from the Twitter Stream API using open source software developed by the Digital Methods Initiative (DMI), a digital media research organization working in collaboration with the University of Amsterdam. The code for the Twitter Capture and Analysis Toolset (DMI-TCAT) is freely available on Github, a collaborative code-hosting platform. The software connects to the Twitter APIs to capture tweet data using one of three avenues: tracking terms that appear in public tweets, following tweets posted on a user's timeline, or collecting 1% of all public twitter activity at any given moment (Borra & Rieder, 2014).

The toolset uses a locally-hosted web server to connect to the Twitter application programming interface (API) and store the captured tweets in a relational database management system. DMI-TCAT programmers wrote the code to use a LAMP software bundle; the bundle consists of an Apache HTTP server, a MySQL database management system, the PHP programming language, and designed to function in a Linux operating system (Gerner et al., 2006). We adapted the code to function in a Windows operating system and launched the toolset on a WAMP server bundle. The program must be preemptively configured to collect data from only one of the three API methods—track, follow, or 1% capture; for the purposes of monitoring autonomous vehicle discussions, the tracking terms method is most appropriate.

The Twitter Capture and Analysis Toolset software includes PHP script for two graphical user interfaces hosted on the Apache server. The Capture graphical user interface (GUI) features the ability to add query bins of phrase to track in live-streamed public tweets. The tool can track up to 400 phrases at one time, though the total volume collected must never exceed 1% of total Twitter activity at any given moment. Tracking bins can be composed of any combination of three types of queries. A query can consist of a single word or hashtag; whenever that character string appears in a text, even if it appears as part of another word, it is captured. For example, a query bin tracking the word 'self' will collect a tweet with the text "I look forward to self driving cars", as well as "Don't be selfish". In order to construct a more precise query, a bin can contain a phrase of two or more words

with an implied AND operator; tweets are captured which contain those character strings, regardless of what order in which they appear. In order to be even more precise, a tracking query can be limited to an exact phrase. Given the rate limit constraints and the unpredictability that comes with collecting informal natural language, the query bins need to be constructed in such a way as to cast a broad net and capture all possibly relevant tweets and yet precise enough not to exceed the data limit. Query bin phrases are not case-sensitive.

The Analysis GUI of the toolset is equipped with several options for previewing the data composition, statistics, and selectively exporting selections from the query bins created with the Capture GUI. The overview includes a breakdown of the percentage of tweets containing links compared to those without, the number of tweets in the set relative to the number of distinct users in the set, and a time series visualization of the number of tweets sent, the number of users, the number of tweets enabled with place locations, and the number of geocoded tweets in the set. The built-in statistical export options include word and hashtag frequency as well as aspects of user activity. There are additional options to exports these pieces of information as network graphs; the graphs vary as either directed, undirected, or bipartite. Tweet export can be executed as the full set, a set of 1,000 random tweets in a query bin, or only tweets that contain geo-location data.

The DMI-TCAT query bins were constructed to continue capture of the AoV terms previously provided by the DOLLY Project, as well be expanded pending the introduction of new terms in public discourse or news announcements. While the DOLLY data were acquired by querying a database of all public geo-located tweets sent since 2009 (and ours are post 2012), this toolset captures all public tweets sent meeting the tracking term constraint; the captured data set is then filtered to only retain tweets that are geo-located, approximately 1-3% as estimated by earlier research (Leetaru et al., 2013). All of the terms collected in the DOLLY data were continued, with a few changes and additions. Whereas the DOLLY database was queried separately for 'autonomous AND car', 'autonomous AND vehicle', and 'semi AND autonomous', with the DMI-TCAT program all three were combined into one 'autonomous' tracking query bin to broaden the scope of collection. Conversely, the original query of 'pilot AND driving' has been changed to an exact phrase query for "piloted driving" as a means of excluding a large number of irrelevant tweets regarding autopilot, for instance. Additional terms added for collection include hashtags created as part of AoV marketing projects and events, such '#truthinengineering' which is used by Audi as part of their social media

campaign. Also, Hockenheimring, the test track in Germany that has been the site of recent AoV testing by Audi. As of March 28, 2015, “Uber” has been monitored as the company has expressed interest in adopting a driverless fleet of vehicles once the technology is on the market (*The Guardian*, February 2015).

Table 5.2 below shows how the data collection has been expanded in the transition from historical data (DOLLY) to a live streaming collection (TCAT). The DOLLY & DMI-TCAT column exhibits the 8 query phrases that were continued with no change. The DMI-TCAT Only column consists of the 12 additional phrases that we have started to collect since transitioning to live capture. Additionally, there are 4 DOLLY queries that have been amended for more effective Twitter collection; these changes are documented under the Amended for DMI-TCAT column.

Table 5.2 - Search Terms by Platform and Collection Details

DOLLY & DMI-TCAT	DMI-TCAT Only	Amended for DMI-TCAT
audi AND test	automated AND car	DMI-TCAT: autonomous
automated AND vehicle	#favsummit2014	DOLLY: autonomous AND car
car AND future	hockenheimring	autonomous AND vehicle
darpa	tesla	sem AND autonomous
driver AND less	uber	DMI-TCAT: piloted AND driving
google AND car	#truthinengineering	DOLLY: pilot AND driving
self AND driving	automation AND car AND vehicle	
zfas	connected AND car AND vehicle	
google AND car	shared AND car AND vehicle	

Overall approximately 4,703 unique tweets were collected with TCAT for the various search terms between October 21, 2014 and June 15, 2015. These were processed in two phases. Phase 1 data spanned from October 21, 2014 to March 17, 2015, and phase 2 data spanned from March 17, 2015 to June 15, 2015. Following similar standards to those imposed on the historical DOLLY data, 579 out of the 1,706 tweets collected in phase 1 were determined to be 'relevant'; the remaining 1,127 were removed from future consideration. Phase 2 data was processed allowing for relevancy to be determined as a part of the sentiment scoring; no pre-screening for relevancy was conducted. While the DOLLY and the first phase of TCAT data were screened for relevancy by the team as part of pre-processing, this was largely done to facilitate understanding the data and developing the sentiment task scoring language. Phase 2 of TCAT (and any future tweet data potentially) would be judged in small batches without relevancy pre-screening by the team. The second phase of TCAT data collection contributed 2,997 tweets to be scored for sentiment and judged for their relevancy by external crowdsourced contributors.

Search term frequency of use was similar between the TCAT and DOLLY data, though because the TCAT data covered such a shorter time interval, the two may not necessarily be logically comparable. In further analysis, we combined the two data sets to assess their collective sentiments on autonomous vehicles.

5.5 - ASSESSMENT OF TWEET SENTIMENT VIA A CROWDSOURCING PLATFORM

As we have discussed, there are many possible ways to assign sentiment to text and tweet documents. These include various computer based approaches, as well as more human-centered techniques. Owing to the number of tweets involved in this project, and the nature of the topic being dealt with, the team decided to use a human-based approach to assigning sentiment to tweets. While unsupervised machine-oriented approaches are attractive in that they are automated, relatively quick in execution, and can often be completed at low cost, there are issues with accuracy, especially in judging the whole-sentence meaning and thought expressed in short irregular documents, such as tweets. This can be particularly acute in cases where algorithms use methods that score tweets based on their number of positive and negative words, as experience suggests accuracy may be in the range of 65-68% (Athar, 2014). All things considered, we opted for employing a crowdsourced platform where people from all around the globe may be enlisted to judge the sentiment of tweet documents.

5.5.1 - Crowdfunder Application

Sentiment scores were assigned to tweets using Crowdfunder, a digital crowdsourcing platform where contributors are paid to complete microtasks. Launched in 2007, Crowdfunder specializes in data enrichment and classification tasks, such as content moderation and relevancy tuning. Using the sentiment analysis template, paid contributors evaluate a set of tweets and determine whether the text expresses an opinion about autonomous vehicle technology that is highly positive, slightly positive, neutral, slightly negative, or highly negative. There is also an option for them to select not relevant to task. Per company policy, Crowdfunder will waive their data licensing fee in exchange for users allowing them to make the scored tweets publically available in a Data for Everyone Library for the purpose of enhancing the field of digital media research.

At the start of the sentiment scoring task – entitled “Judge the Sentiment of Tweets: Self-Driving Cars” -- contributors were instructed that the focus of the

project was limited to vehicles currently operated by individual drivers which will potentially affect people's everyday travel on streets, roads, and highways. They were provided with examples of technology which were outside the scope of the project, including drone weapons, trains, and unmanned water vehicles. In evaluating the sentiment of tweets, they were warned not to read further into the text and assume opinions that were not stated. Additionally, whereas most sentiment tasks instruct to use the neutral judgment sparsely, contributors were informed that the nature of AoV tweets results in a significant amount of neutral tweets so they may use the judgment whenever appropriate.

In setting up the task, guidelines were set regarding judgment procedures and contributor requirements. Each tweet was judged a minimum of at least three times with the goal of attaining a confidence level of at least 70% agreement on a particular sentiment classification (e.g., 70% choosing slightly positive). If the minimum confidence was not reached, additional judgments were requested. Scoring stopped for a particular tweet at 70% or better agreement or when there were eight completed judgments, whichever was reached first. The final sentiment assigned to a tweet was based on both the number of contributors selecting a given sentiment level along with how trustworthy the contributor was rated. The more trustworthy contributors that selected a given sentiment level, all else equal, the higher the confidence was for the aggregate sentiment classification. In effect, the sentiment class that received the highest weighted trust score for a given tweet was selected as the finalized sentiment score for the tweet. Contributors were presented with a page of 10 tweets at a time and received \$0.10 for every page completed. They were required to spend a minimum of 30 seconds per page. Each contributor was limited to a maximum of 300 judgments. Contributors were required to be proficient in English and reside in either the US, Canada, Great Britain, Ireland, Australia, or New Zealand.

In order to ensure data quality, Crowdfunder contributors were presented with test questions that have been pre-assigned with judgment scores that they needed to correctly identify in order to participate in the task. The percentage of correct answers determines how trustworthy a contributor was. At the start of the task, contributors were required to answer one page of 10 test questions and receive a least 80% accuracy to proceed to the actual scoring. Throughout the task, there were randomly-assigned unmarked test questions that contributors were presented; they needed to maintain the 80% accuracy throughout or their judgments on the tasks were thrown out as untrusted and their data was not included. This

maintained quality control in the scoring process. Those contributors with higher accuracy on the test questions had a stronger influence on the overall aggregate tweet sentiment scores.

We created a total of 75 test questions, fictitious tweets modeled to look like real tweets in the data set. They were a balanced assortment of positive, negative, neutral, and irrelevant tweets written to be clearly identifiable given the instructions provided at the beginning of the task. Test questions expressing a positive or negative sentiment were able to be answered as either highly or slightly positive/negative to be considered answered correctly. When a contributor answered a test question incorrectly, they were shown the correct answer and an explanation for why it was so. **Table 5.3** below shows some examples of sample tweets that were used as test questions.

Table 5.3 - Sample Test Questions Used to Ensure Data Quality

Positive
"Autonomous vehicles could reduce traffic fatalities by 90&... I'm in!"
"Great story RT Autonomous Cars Will Help The Disabled Be More Mobile."
Negative
"I just don't trust my life in Google's hands #driverless cars... no thank you."
"You'll never get me in an autonomous vehicle. Ever. Never. #nope"
Neutral
"Audi to start testing in self-driving cars in Tampa"
A new study just commissioned to study the costs of self-driving cars"
Not Relevant to Self-Driving Cars
"Chicago metro expected to be fully autonomous by 2020"
"I think #DARPA works on autonomous drone technology for military apps"

The final set of tweets scored through Crowdflower combined the historical tweets collected from DOLLY with the real-time collected tweets from TCAT. Prior to uploading the files, any duplicate tweets were removed and the master list of files was reviewed again for any language issues with non-English tweets and illegible characters. After these adjustments, this resulted in 10,076 tweets to be analyzed. The sentiment assignment task was started on May 20, 2015 at 7:58 pm EST on the first batch of 7,079 tweets (DOLLY and Phase 1 TCAT data) and was completed 18 days later on June 7, 2015 at 2:23 pm EST; the remaining 2,997 tweets (Phase 2 TCAT data) were made available for scoring on June 16, 2015 at 10:00 pm EST and was completed on June 20, 2015 at 3:12 pm EST. Prior to the scoring task of the master file, the FSU research team experimented with several test scoring tasks of the Crowdflower platform and tweet scoring to learn more about its functionality, appropriate settings, and limitations. This experimentation and knowledge was very useful in choosing the parameters, settings, and prompt for the 'official' scoring task.

5.5.2 - Sentiment Confidence Evaluation

The Crowdflower task parameters were set to collect a minimum of three judgments per tweet with the goal of 70% confidence, which was calculated based on the amount of agreement weighted toward contributors who have answered the greatest percentage of test questions correctly. If the confidence was below 70%, additional judgments were requested until either the goal was achieved or the tweet was scored 8 times. Of the 10,076 tweets scored, 2,202 were scored by 8 contributors with a resulting confidence score of less than 70%.

In order to verify the reliability of sentiment scores that do not have sufficient confidence, we ran a second Crowdflower task entitled "Sentiment Analysis Evaluated". Contributors to this task were presented with the original instruction prompt for context and asked to evaluate whether a tweet was scored correctly or incorrectly. While the geographic parameters were retained – limiting the contributor base to users from the US, Canada, United Kingdom, Ireland, Australia, and New Zealand – the task did not have test questions or any other quality requirement; each tweet received 4 judgments. Of the 2,202 low confidence tweets, 208 were evaluated to have been originally scored incorrectly. We scored

the 208 questionable tweets manually to assign a final sentiment score. Two team members participated in determining the final disposition of the tweets. If one or both of them agreed with the original sentiment, then that score was validated and kept. If both were in agreement on a score that differs from the original sentiment, then the score was changed to reflect that judgment. If, however, there was no agreement at all, then the tweet was dropped from consideration in further analysis. **Table 5.4** below shows the results of manual scoring; ultimately, 27 tweets were dropped as having an indeterminate sentiment. After this final adjustment, the data set consisted of 10,049 tweets to be analyzed.

Table 5.4 - Sentiment Confidence Evaluation Results

Full Agreement - Scored Correctly	48
Partial Agreement - Scored Correctly	53
Full Agreement - Scored Incorrectly	80
No Agreement - Dropped	27
Total:	208

5.6 - ANALYSIS OF AOV SENTIMENT DATA IN SPACE AND TIME: NATIONAL AND FLORIDA-BASED RESULTS

The FSU research team enlisted the Crowdfunder platform to score our tweet database for sentiment. The team reviewed the data for quality and validity, particularly with regards to how the sentiment classification scores were applied, and the team was generally pleased with the validation exercise that subjected the tweet data along with their assigned sentiment scores to further external assessment. We now present and analyze the sentiment data, focusing first on its description and characteristics, then moving to draw out insights into how perceptions of autonomous vehicles have varied both in space and time.

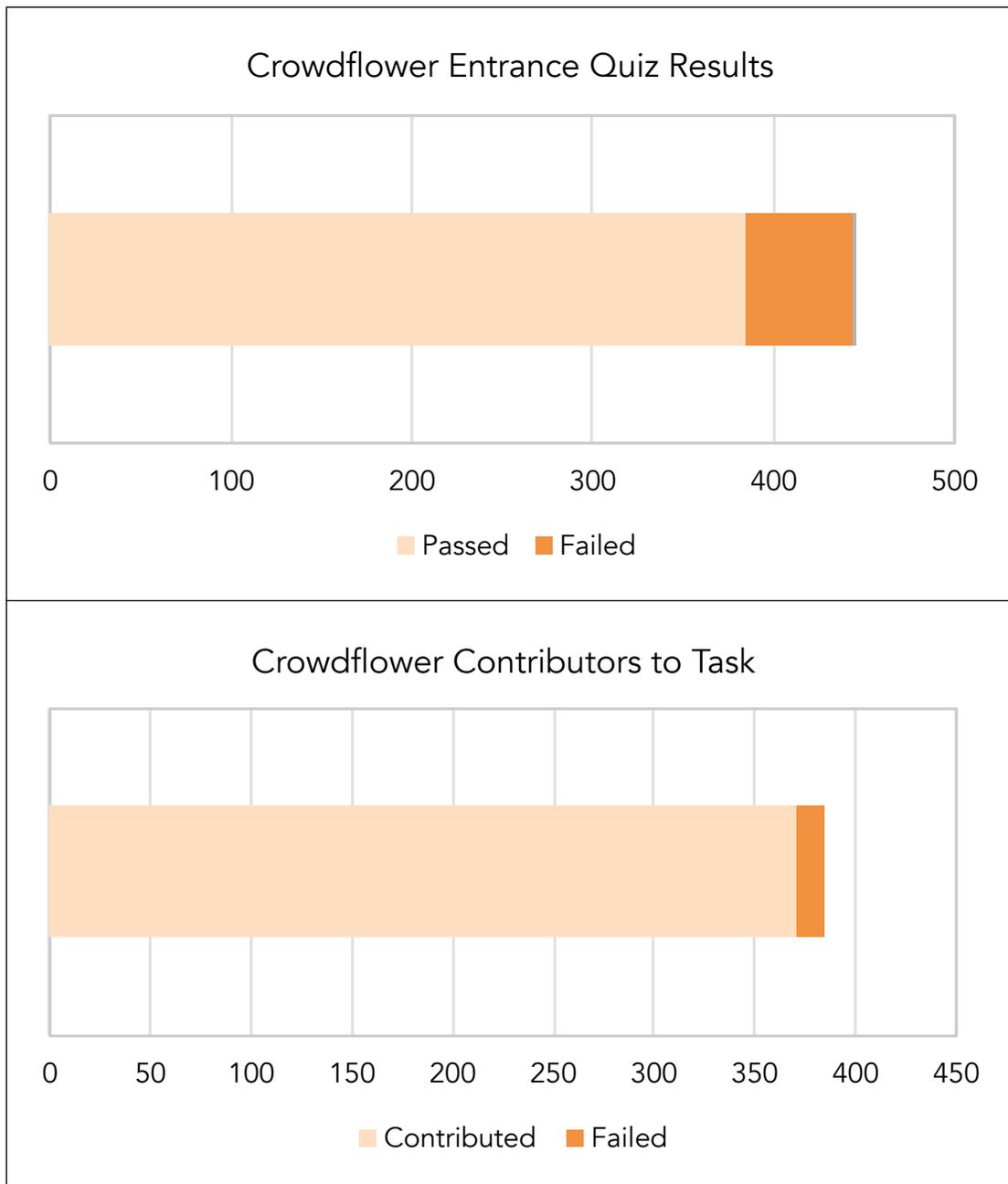
As a means of organizing and presenting our work, we will first describe AoV sentiment trends and concepts at a more aggregate or national scale. Then, we will delve deeper into the numbers, focusing on the states where AoVs are permitted, and then looking at sentiment in Florida in particular. We will close with summary points, including assessments of where AoV discussions might proceed into the future and what the implications are for AoV policy going forward.

5.6.1 - Crowdfunder Task Outcomes and Data Quality

The Crowdfunder platform allowed us to better understand how satisfied contributors were with a given task, how they performed, and how that task was perceived. As shown in **Figure 5.9**, the contributor and data quality settings for the crowdsourcing task was successful according to several metrics generated by the platform. The set of the test questions which contributors were presented with during the quiz and test mode were intended to ensure that the prompt instructions were closely read and the sentiment judgments were trustworthy. In total, 445 contributors attempted to participate in the task. Sixty of out of the 445 failed to meet the required 80% score on the test questions, and an additional contributor dropped out of the task before completing the quiz, no reason given. Out of the 384 contributors who scored active tweets – as opposed to test questions – 370 were successful and had their judgments accepted; the overall trust score average

based on the percentage of test questions answered correctly was 0.91, which indicates that the judgments accepted were predominately contributed by highly reliable participants. There were, however, 14 contributors who were not able to maintain the 80% accuracy when answering test questions; all of their responses were eliminated and the tweets resubmitted for further judgment.

Figure 5.9 - Crowdfunder Task Outcomes

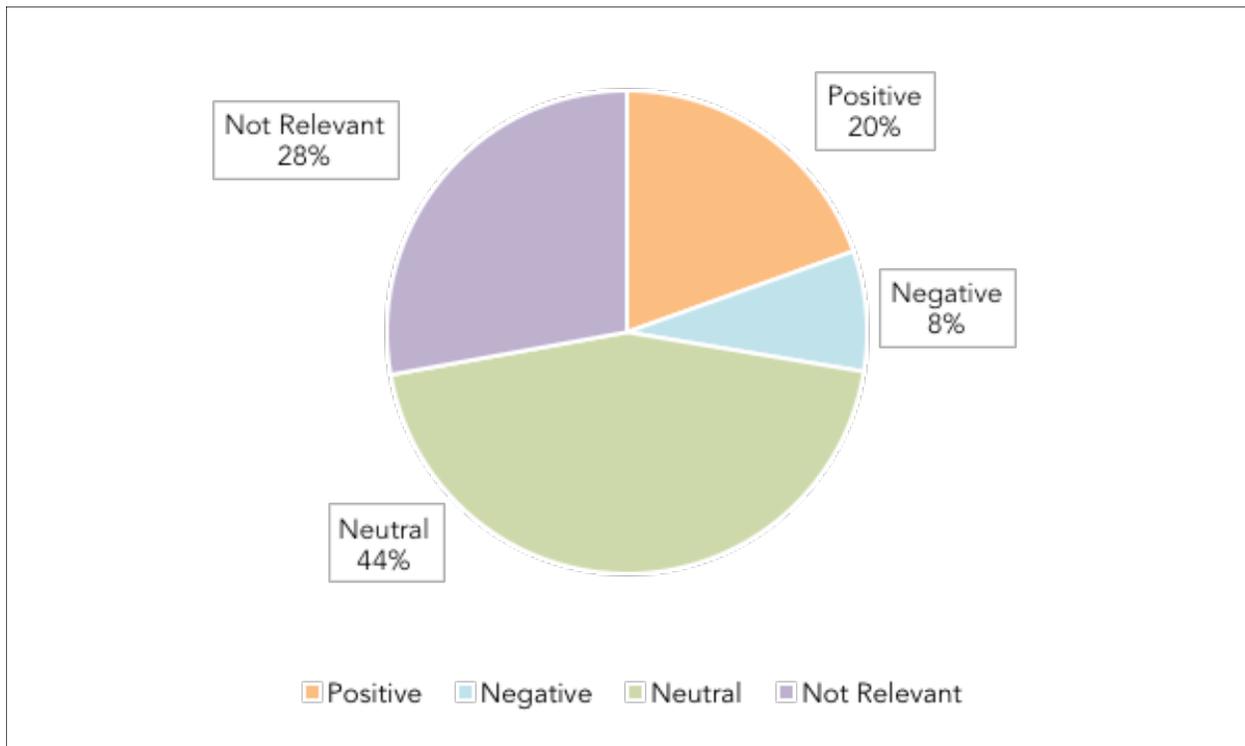


5.6.2 - National/Aggregate Sentiment Results

Contributors to the sentiment analysis task were provided with the tweet text and presented with six multiple choice options. As show in **Figure 5.10**, from the set of 10,049 tweets, 44% were judged to be relevant to autonomous vehicle technologies within the scope of the project but not expressing a detectable opinion on the topic. These 4,476 neutral tweets were scored with the highest level of confidence, with the excepting of those which were not relevant. In later sections, we will examine the specific topic composition of the positive, negative, and neutral sentiment classes.

Relevant tweets where an opinion was expressed were classified into one of four possible sentiment classifications. In addition to determining whether the text was positive or negative, contributors judged whether the sentiment was of a high intensity – highly positive or highly negative – or only slightly so. Positive sentiment was detected in 1,964 tweets, 23.2% of which were deemed highly positive. Significantly fewer tweets were determined to be negative – only 812 out of 10,049 – and only 13% of them were highly negative. Confidence in the scoring of positive and negative tweets, while lower than neutral, was nearly consistent across the four sentiment classes.

Figure 5.10 - Sentiment Classification Results



Sentiment Classification	Total	Confidence
Highly Positive	456	0.67
Slightly Positive	1,508	0.7
Neutral	4,476	0.83
Slightly Negative	706	0.71
Highly Negative	106	0.67
Not Relevant	2,797	0.93

Although the DOLLY and phase 1 TCAT data were pre-filtered for relevancy, the high number of irrelevant tweets in the unfiltered phase 2 TCAT data collection was apparent. In total 2,797 were judged to be not relevant based on the prompt provided. Capturing tweets with “Uber” as the search term resulted in the largest number of “not relevant tweets; 1,786 tweets – or 86% of the 2,073 containing the term – were judged outside of the scope of the project. Interestingly, 158 of the remaining 1,011 irrelevant tweets contained a reference to “google car.” The publicity surrounding Google’s self-driving car project has been a part of a lot of the national conversation about the future of autonomous vehicles. Thirty-three percent of the final set of AoV tweets collected reference Google in some context – discussion ranging from general interest articles, project updates, and sightings of the easily identifiable Toyota Priuses in the course of the several hundreds of miles they have already traveled. Also on the road, driving among the public, in the Google Maps camera car; the vehicles travel around the world mounted with a multi-directional camera capturing images for Google’s Street View.

The 140-character limit imposed by Twitter and the insufficient context that can result created an ambiguity in the data; a tweet relating to a vehicle sighting and expressing an opinion about the event when “I saw the google car on my way to work” can refer either to the self-driving Prius or the camera car. The former evokes opinions about autonomous vehicles and the latter data collection. The two projects – in addition to being similar in name – share a significant connection from a technical perspective. In order to navigate safely, the Google self-driving car relies on a mounted laser to construct a 3D image of its surroundings, which is then layered with a high-resolution map from the same street-level perspective. The data for those maps have been being collected and improved using the fleet of camera cars.

In light of this connection, any tweet containing “google car” was captured and provided to the Crowdfunder contributors to determine sentiment. They were also given the option to judge the tweet not relevant to the scope of the task as presented. Out of the 1,011 non-Uber tweets judged to be not relevant 158, mention google car. These tweets fall into three categories, per **Table 5.5**.

Table 5.5 - Three Potential Types of “Not Relevant” Tweets

“Not Relevant” Tweet	Reason
“#Stanford grad students know how to throw a legit Halloween party. The google car and bay bridge costumes blew my mind”	The tweet is not referring to any facet of AoV technology, only an incidental mention.
“Just saw the google car that takes pictures for google maps!!! #waycool	The tweet is explicitly referring to the camera car, not the self-driving car
Just saw a Google car!	The tweet is ambiguous

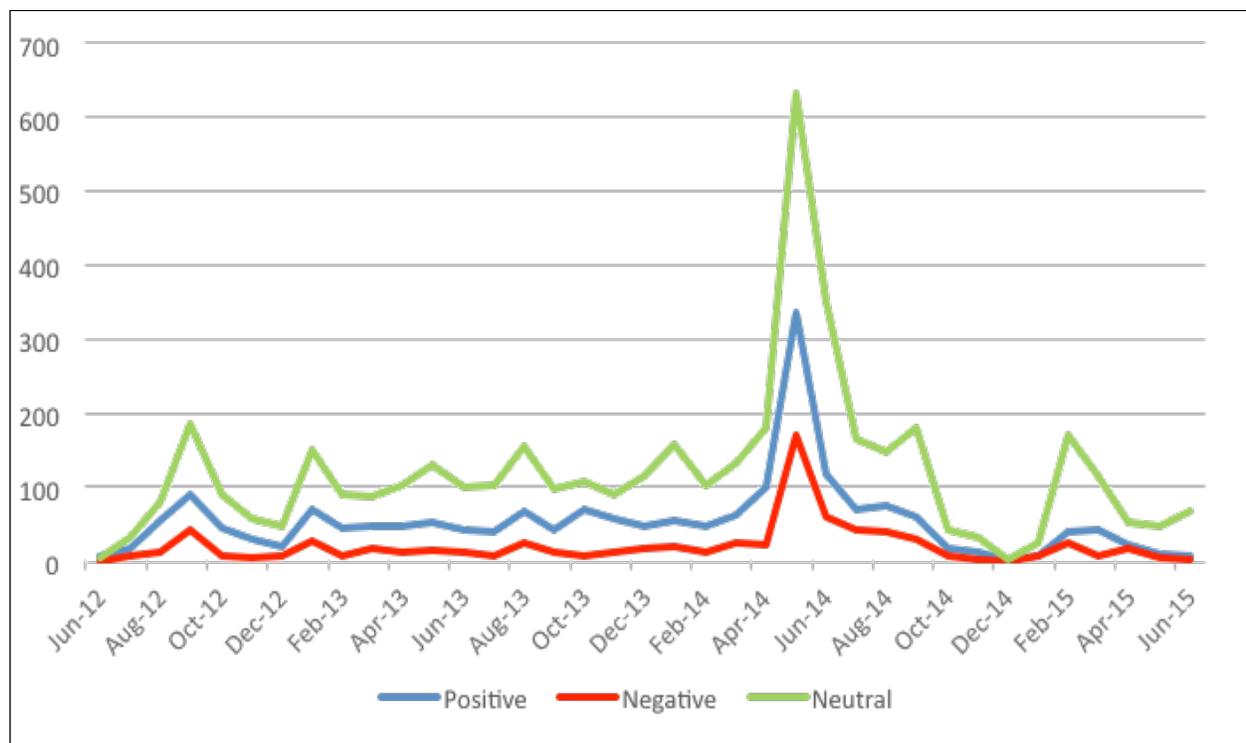
The sentiment analysis showed that despite a technological argument that the Google maps camera car project is a relevant concern to understanding public perception and opinion on self-driving cars, that connection is not always readily apparent to the public. As such, in order to gauge opinion on the technology in development, the technical components cannot be divorced from ultimate applications involving producing a fully-functional autonomous vehicle.

The time series analysis in **Figure 5.11** displays the relative distribution of positive, negative, and neutral tweets over the course of the data collection period. Tweet counts for each class are aggregated to the total number of geo-coded AoV tweets for each month from July 2012 to mid-June 2015. The graph shows that the percent make-up of each class has stayed fairly consistent across time. The months of overall increased activity – such as the dramatic spike during May 2014 when Google released the first images of its self-driving concept car – reinforce this trend; there has been no period of time where twitter discussion has become predominantly positive or negative.

An analysis of the five most frequently-appearing words of tweets of each main sentiment class highlights the fact that expressions of AoV sentiment on Twitter are not are not being driven by any one specific dominating issue. By removing all non-substantive or stop words and terms included in the data collection query, we

were able to extract the top five most frequently occurring words in each sentiment data subset. In the text frequency analysis, no sentiment class featured a particular technology, project, or brand as generating particular excitement or resistance. Rather, it is clear that the present opinions reflect a generalized sentiment toward the idea of AoVs becoming a reality in the future. The word 'one' made the top five in all three lists, as it is easy to imagine it being used in many ways (e.g., "I really want one of these AVs" to "One day AVs are going to take over the world"). The word 'now' appeared in the top five positive words partially due to its prominence as a top neutral word; a neutral news article announcing "Driverless cars now legal in Florida" will be retweeted multiple times with a positive opinion appended (e.g., "So excited!! RT Driverless cars now legal in Florida").

Figure 5.11 - Sentiment Classes over Time and Frequent Word Use



Top **Positive** Words

1. one
2. cool
3. want
4. wait
5. now

Top **Negative** Words

1. think
2. people
3. don't
4. get
5. one

Top **Neutral** Words

1. now
2. saw
3. new
4. one
5. first

Thinking spatially about where AoV-related tweets are coming from, the map in **Figure 5.12** shows a composite of the average sentiment scores and average activity for tweets that were able to be spatially associated with a given state. When we excluded those tweets that fall outside of the U.S. and those unable to be matched with a state, we have about 6,300 tweets. Tweets were classified into three levels – low, medium, and high – using quantile breaks, based on frequency of activity (left/pink hues map) and sentiment (right/green hues map). Activity data were based on raw counts and not normalized for a given state’s population. **Figure 5.12** shows that only three states have both high levels of activity and high average sentiment: Georgia, Maryland, and Connecticut. There were seven states that had both low activity and low sentiment scores: Montana, Wyoming, South Dakota, Kansas, Mississippi, New Hampshire, and Maine. Data showed that Florida had similar average sentiment to states such as California and Texas, but was slightly more positive than states such as Michigan. Later in this section we will look for additional ways to explore this variation across states and over smaller time intervals.

Figure 5.12 - Tweet Activity and Average Sentiment Scores

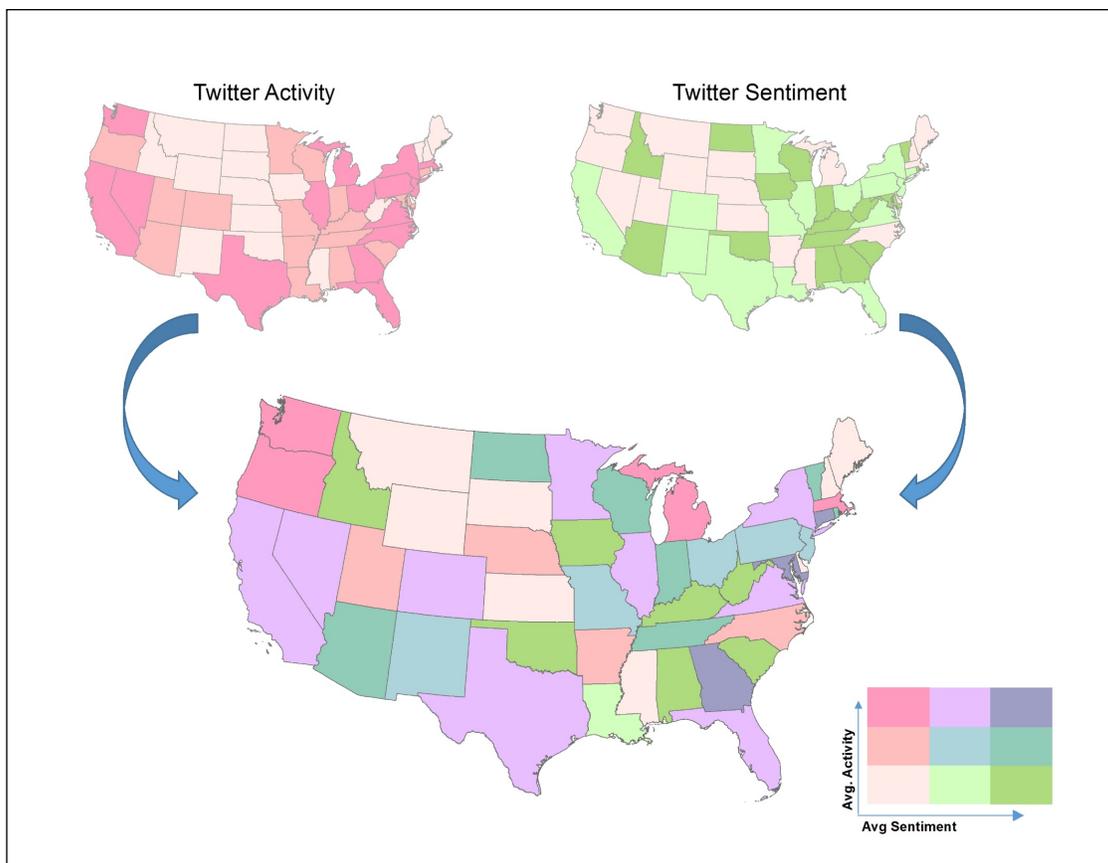


Figure 5.13 shows the distribution of positive, negative, and neutral tweets which contain topic keywords for a range of subjects: safety, policy, infrastructure, social, and technology. In addition to scoring tweets for sentiment, we performed a topic analysis using keywords. Neither the topic categories nor keywords were exhaustive, but were chosen by drawing on prior literature (Schweitzer 2014) and discussions with FSU research team members. Topic modeling assigns categories to tweets based on what is likely being talked about by comparing the words that are used against a list of topic keywords; if a tweet X contains word Y that is associated with topic Z, then we can infer that tweet X is potentially relevant to topic Z. For example, if a tweet that was relevant to autonomous vehicles contained the word 'elderly', then we made the assumption that the tweet was about accessibility. The figure shows the proportion of words that could be associated with one of the six topics that appeared in positive, negative, and neutral tweets. From the set of 7,252 relevant AoV tweets, we extracted over 10,000 unique words (using text mining software mentioned in earlier sections). Manually working through the list of keywords we compiled, we calculated how many times each word appeared in the set of tweets for each sentiment class. These counts were then aggregated to the six topics. For example, some variation of the word 'legal' – such as 'legalize', 'illegal', 'legally', etc. -- appeared 27 times in positive tweets, 10 times in negative, and 72 times in neutral. 'Insurance' appeared 13 times in positive tweets, 8 times in negative, and 40 times in neutral. If these were the only two policy-related words we could identify, then we would determine that discussion of AoV policy has been 23.5% positive, 10.6% negative, and 65.9% neutral. From this, we could infer that the public awareness of AoV policy was still largely in a news and updates phase, without expressing a clear opinion.

By isolating individual words in the tweets, one removes the definite context. We made an educated assumption that a tweet about autonomous vehicles that mentions 'seniors' is concerned with accessibility; while the context is most likely that AoVs will improve the mobility of senior citizens, there is also a chance that the tweet was referring to a senior executive making an announcement about AoV production. Although we cannot guarantee the definite context, the relative frequency of isolated topic words across sentiment classes does reveal interesting trends. The figure shows that keywords indicative of policy, infrastructure, and technology discussions are overwhelming neutral, and by similar amounts; tweet sentiment where topics appeared was neutral for 66% of policy keywords, 61% of infrastructure keywords, and 63% of technology keywords. The sentiment distribution of social topic words is interesting in that it has the smallest percentage of neutral tweets from any of the topics, while also having the largest percentage of

both positive and negative tweets; the composition is 67%, 18% negative, and only 15% neutral. Based on these sentiment distributions, we can deduce that the sentiment-neutral information being shared on Twitter is largely concerned with practical consideration of autonomous vehicles – the policy implications, the transportation infrastructure needed to facilitate implementation, and the technology involved in development. Personal opinions, however, are predominantly relegated to the social effects of AoVs.

Figure 5.13 - Topic Assessment and Word Frequency

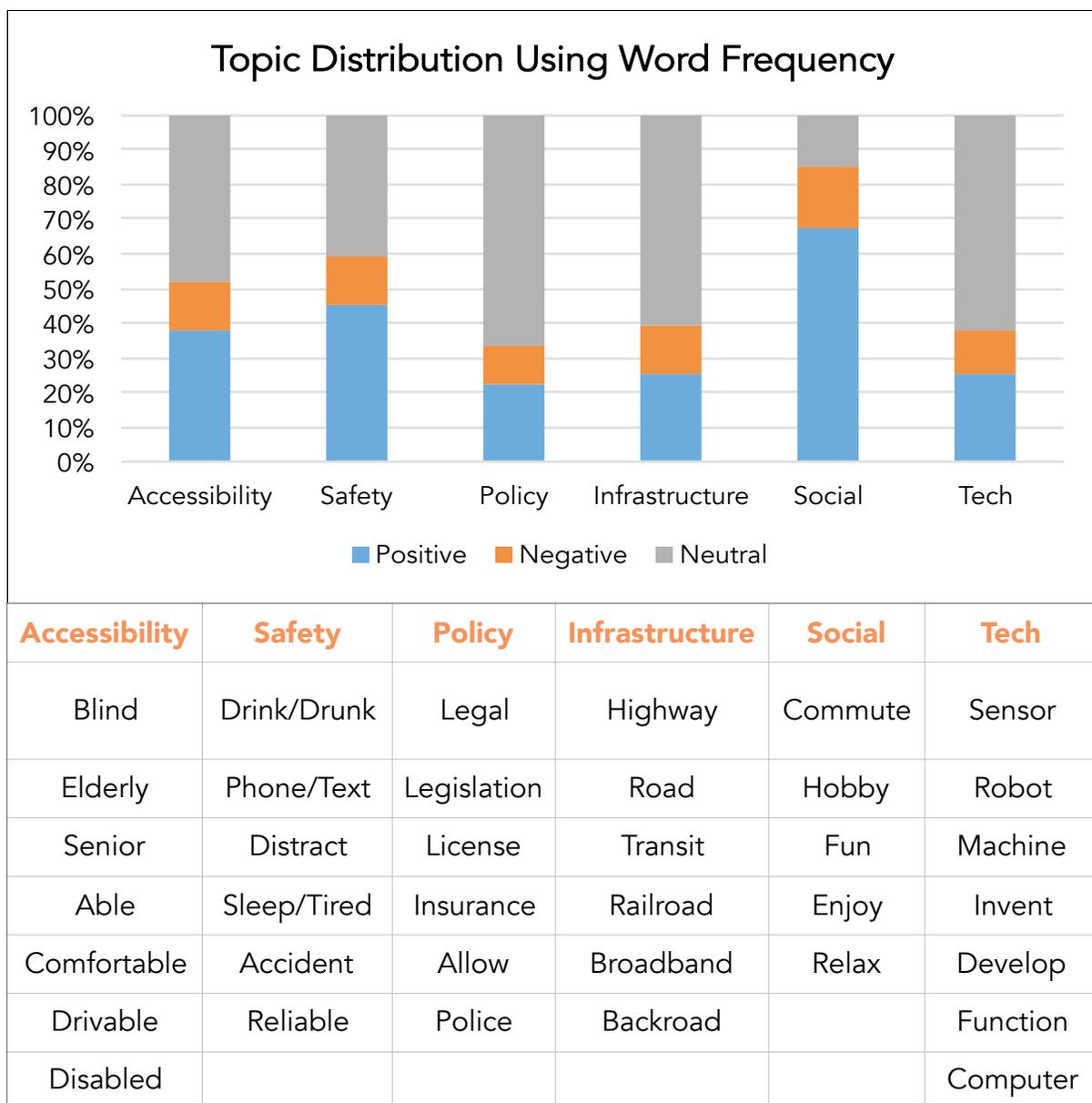


Figure 5.14 shows the trend in user activity behavior to tweet about autonomous vehicles in low frequency. The distribution of the number of AoV tweets sent by unique users is presented as a density curve to show a generalized relationship between users and tweet frequency, as well as a table of the specific counts. The area curve indicates that the vast majority of users send fewer than ten tweets regarding autonomous vehicles. Due to the magnitude of users who only sent one tweet, the plot is not weighted to show the true density. If it were weighted, the graph would show that 68% sent only one tweet and 95% sent ten tweets or fewer.

Autonomous vehicle discussion taking place on Twitter is, thus, best characterized as highly dispersed across users with limited repetition. In a separate look at the top five most active user accounts – those contributing greater than twenty tweets each – only one belonged to an individual person. The remaining four seemed to be news accounts based out of Detroit, San Francisco, San Jose, and Greensboro, North Carolina. While user activity trends are likely to change as autonomous vehicles have greater public visibility, the current low repetition is beneficial for gauging public opinion; with many users only contributing one tweet to the data set, we can surmise that specific individuals are not being over-represented in the sentiment analysis, or unduly influencing results.

Figure 5.14 - User Activity Trends

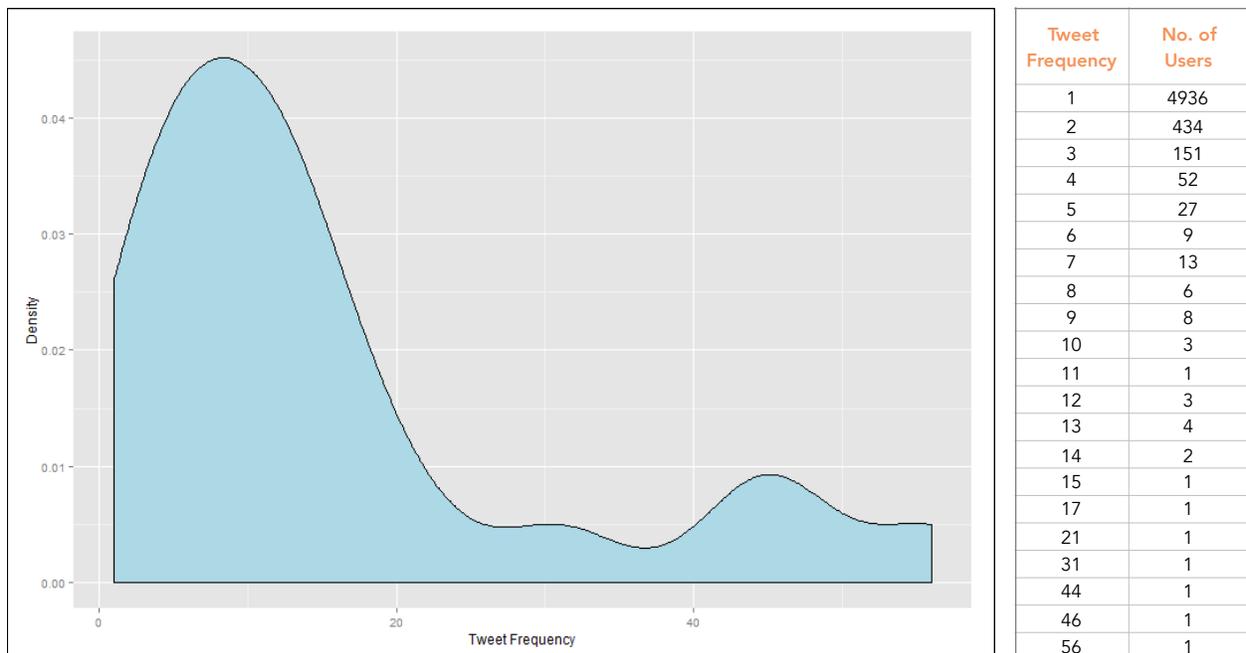
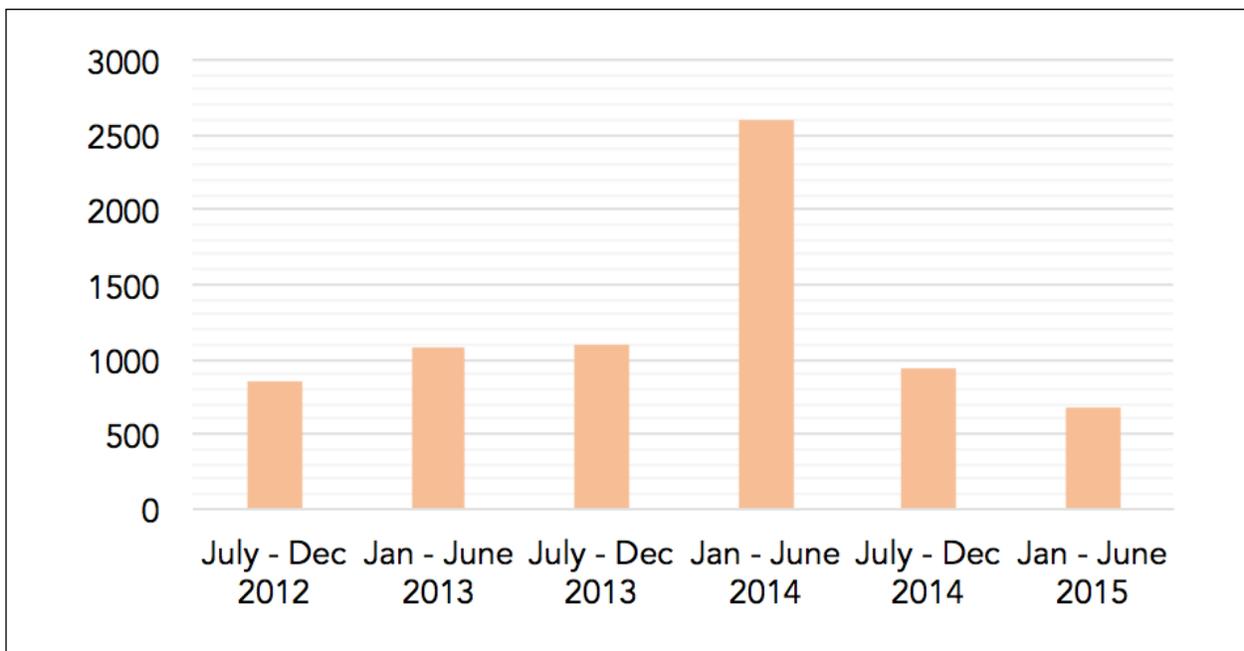


Figure 5.15 shows the frequency of AoV tweets for every six months of collection. Until January to June 2014, which had a dramatic increase in activity due to the Google Car announcement, there had been a general increase in activity at each interval; from January to June 2013 there was a 26% increase in tweets from the previous six months, and a 2% increase the following six months. Excluding the January-June 2014 anomaly, in July to December 2014 there was 13.5% decrease from the same period the previous year. In the first half of 2015, AoV tweet activity decreased by an additional 28%.

Figure 5.15 - Tweet Frequency over Time in 6 Month Intervals



Not only has activity been decreasing over time, as shown in **Figure 5.16**, but the average sentiment has declined over time as well. The two line graphs depict the average sentiment score for each month between June 2012 and June 2015. The averages represented by the blue line include all relevant tweets scored from Highly Positive (5) to Highly Negative (1). The orange line, which has predominantly higher scores, only contains the average of all the positive and negative tweets; neutral have been excluded. A linear trend line has been fitted to highlight the overall direction of change. As seen in the figure, average sentiment – both with and without neutrals – has been decreasing over time. At its maximum, sentiment reached 4.0 (which roughly corresponds to ‘slightly positive’) over October 2013 and December 2013. The month with the lowest average sentiment was January 2015, with an average of 3.0 (corresponding to ‘neutral’). The significant drop was the result of a high number of neutral tweets and a near equal amount of positive and negative tweets, which seem to have cancelled each other out.

Figure 5.16 - Average Monthly Sentiment over Time

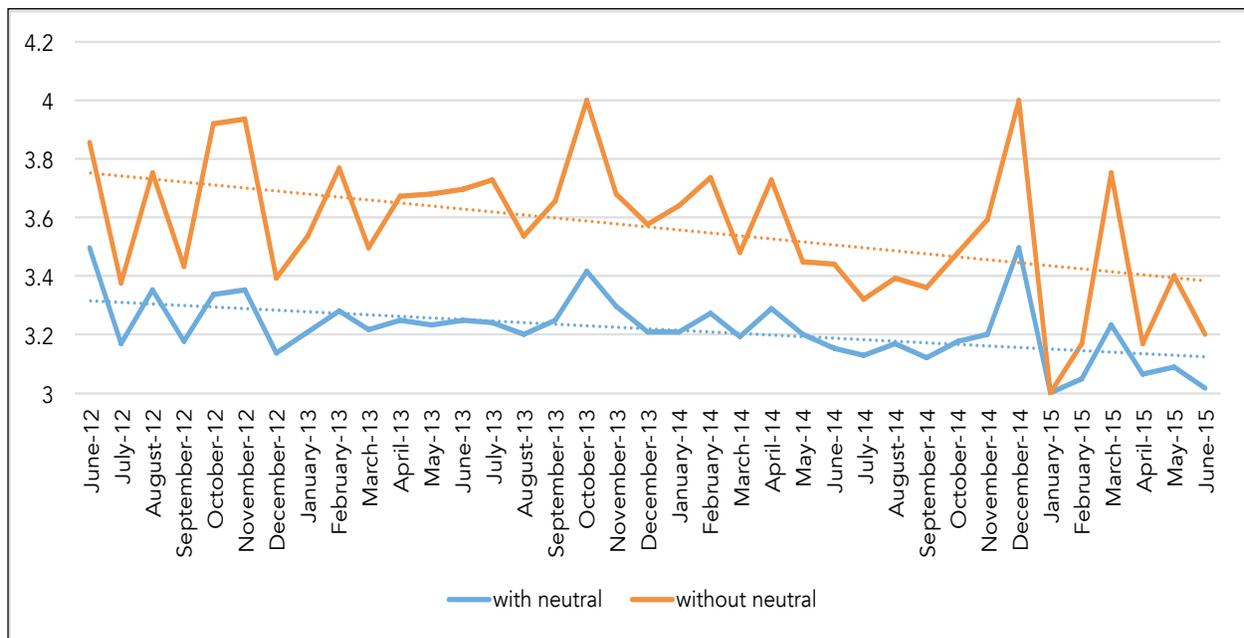
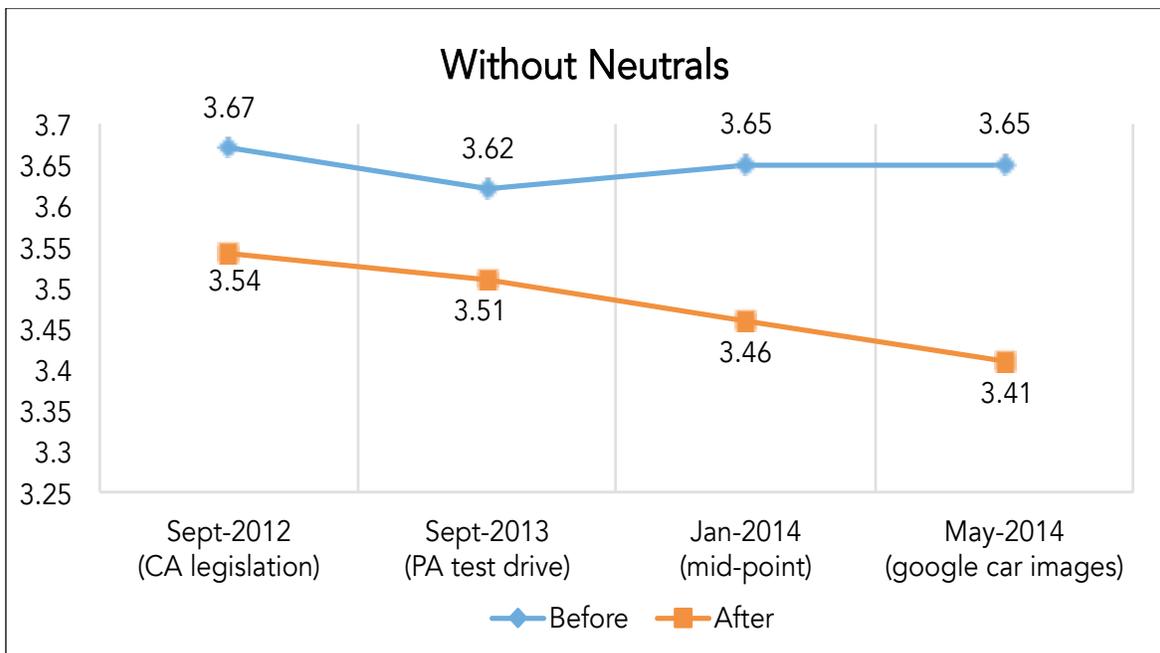
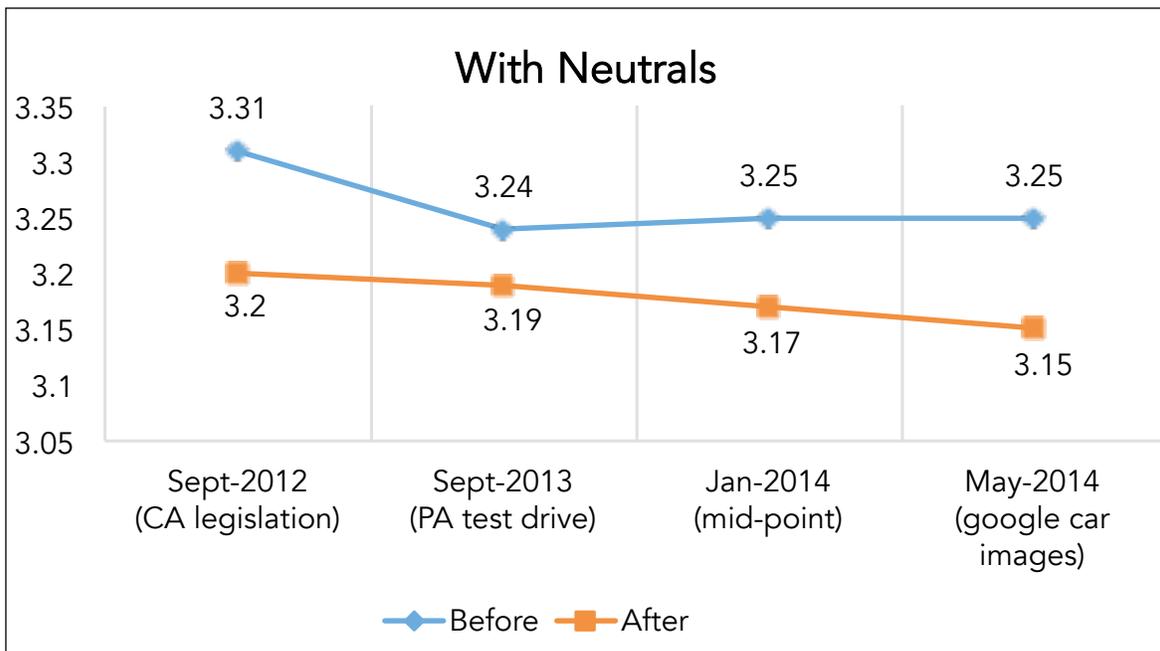


Figure 5.17 examines the change in average sentiment relative to specific AoV events. The events chosen represent potentially significant moments in advancing autonomous vehicle technology, such as the passing of legislation or introducing new vehicles to public audiences. Similar to **Figure 5.16**, the averages were measured both with and without neutral tweets in order to highlight where the greatest change is occurring. The data set was divided at four points and the average taken for tweets sent before and after (using the first of the month for each division): September 2012, September 2013, January 2014, and May 2014.

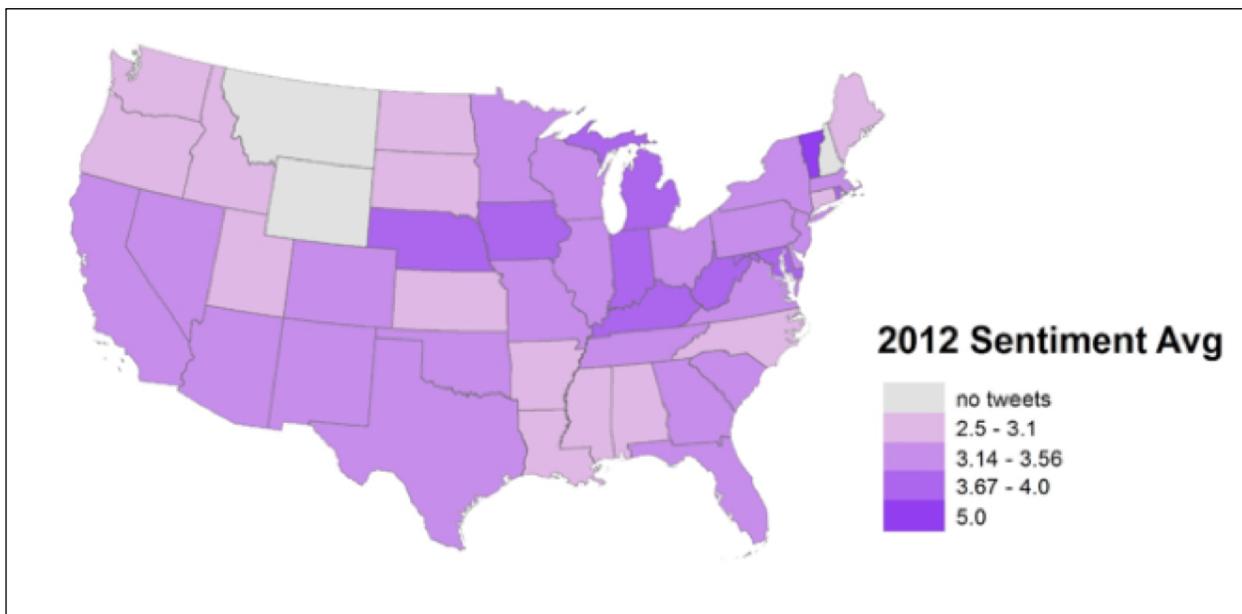
At every measurement point – both when including and excluding neutral tweets – the sentiment average was lower after the event than before. The average decline for the full set of relevant tweets was 0.09; when neutral tweets were excluded, the average decline increased to 0.17. The greatest post-event drop occurred in May 2014 after the release of the first Google Car images; when only considering positive and negative tweets, the average decreased by 0.24. The slightest decrease, with and without neutrals, was after the September 2013 Pennsylvania test drive by Congressman Bill Shuster; the average sentiment only fell by 0.05 with neutrals and 0.11 without. Given the consistent drop in sentiment average at every measurement point, it is likely that the findings reflect the general decline over time shown in **Figure 5.16**, as opposed to stemming from any of the events named.

Figure 5.17 - Changes in Tweet Sentiment over Time Following Specific Events



The map in **Figure 5.18** shows the sentiment average across the Continental United States for all tweets sent between June 21, 2012 and December 31, 2012. Between these dates, 767 geocoded AoV tweets were sent within the contiguous US and the District of Columbia. The averages for states where tweets were captured ranges from 2.5 to a perfect 5.0, which was only recorded for Vermont. Kentucky, Nebraska, and Rhode Island came in with the next highest average sentiment, all scoring 4.0. No tweets were sent in Montana, Wyoming, or New Hampshire during this time. The majority of states had sentiment averages within the 3.14 – 3.56 range, including California, Nevada, Florida, and Virginia. Michigan, the remaining permitting state, landed in the second highest sentiment class with an average of 3.67.

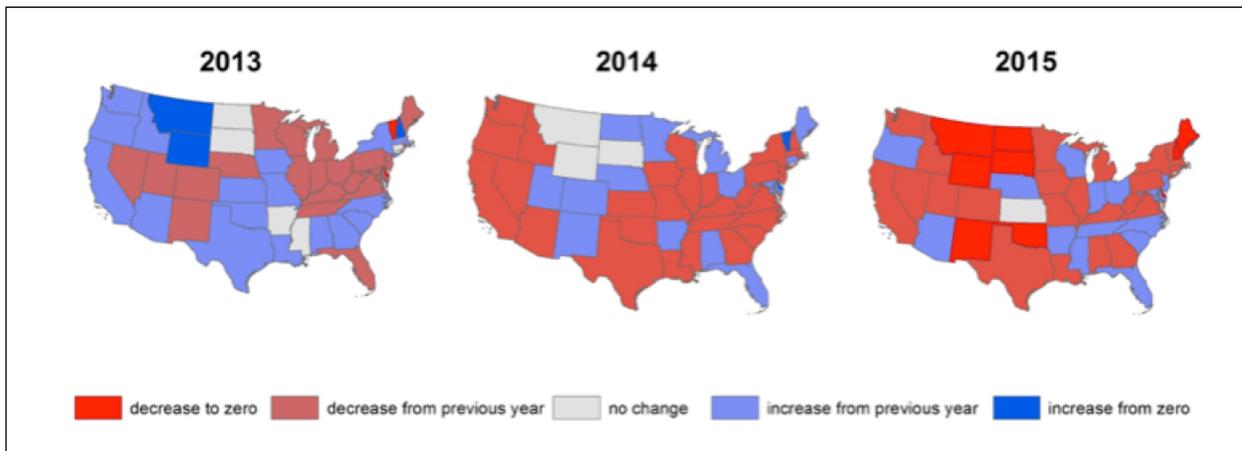
Figure 5.18 - Average Sentiment by State (2012)



Beginning with 2012 (**Figure 5.18**) as a baseline, **Figure 5.19** shows the change in average sentiment across the Continental United States for each year of data collection. The states are classified based off of the change in their score from the previous year. For example, in 2012, there were no tweets recorded in New Hampshire. There was activity in 2013, so it is classified as 'increase from zero'. Conversely, Vermont held the highest average in 2012, but had no activity in 2013,

so it is classified as 'decrease to zero'. If a state had two consecutive years of tweet activity to measure, the change in sentiment average is classified as either 'increase/decrease from previous year'. For example, for 2012 the sentiment average in Virginia was 3.47. In 2013, the average decreased from the previous year to 3.24. In each successive year, the average has decreased such that it is now 2.88 for the first half of 2015. If sentiment average remained the same – or if a state has zero Twitter activity for two consecutive years – then it was classified as having had 'no change'. Montana, for instance, had no tweets in 2012, but did have activity in 2013 and scored an average sentiment of 3.0. Montana's average in 2014 remained 3.0, and was classified as having 'no change'. As of June 2015, there has been no activity in Montana and was therefore classified as 'decrease to zero' in 2015.

Figure 5.19 - Changes in Sentiment from Year to Year

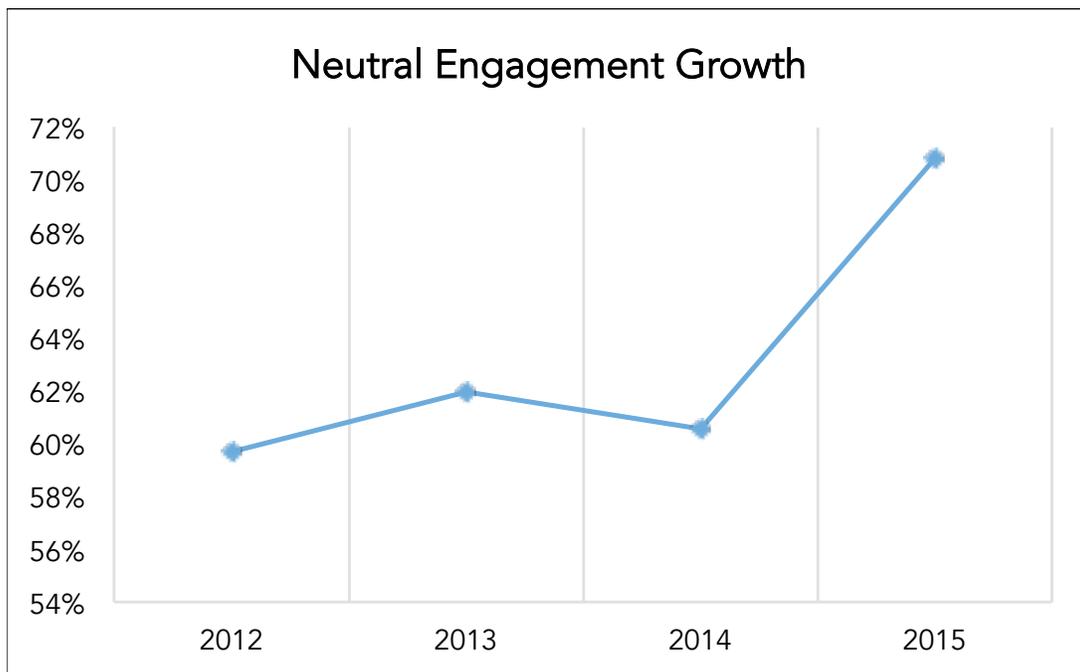


The maps in **Figure 5.19** indicate that the persistent decrease in average sentiment over time (previously seen in **Figure 5.16**) is largely distributed across the country; the states averages in 2014 for all of the West Coast and much of the South had decreased since the previous year. The 2015 map appears to indicate even greater decline, but it must be noted that as of June 2015 there are still nine states for which there has been no activity yet recorded. Given the sparse activity typical of the Midwest and Eastern Northwest, it is necessary to wait until the full year has passed to conclusively determine the change in sentiment. Focusing on Florida, it is one of a handful of states that has experienced recent positive change in sentiment

the last two years, although initially Florida did see a drop in sentiment in 2013 from its base year.

Figure 5.20 illustrates another sentiment trend within autonomous vehicle tweets over time. As previously noted, average sentiment has been decreasing since 2012 (**Figure 5.16**). The neutral engagement line graph shows that the percentage of tweets that are neutral is also significantly increasing since previous years. In the first half of 2015, neutral tweets make up 71% of all twitter activity collected. This is up from 61% for all of 2014.

Figure 5.20 - Prevalence of Neutral Tweets



Monitoring neutral Twitter activity provides a means for gauging the change in public engagement with a topic over time. While these tweets may not contain a specific opinion that can be analyzed for sentiment cues, they reflect the general interest in autonomous vehicles that is being cultivated by sharing news articles, asking questions to generate discussion, and making observations. Since 2012, there have been more tweets expressing neutral engagement than opinion and

based on **Figure 5.20**, the number of neutral tweets relative to positive and negative in 2015 is expected to be even greater.

5.6.3 - Permitting States' Sentiment Results

We now turn our attention to the states where AoV testing has been legalized. Per earlier discussion, five states, including Florida allow some form of vehicle testing. Of these states, Virginia is the most recent addition to the list, with the commencement of the Virginia Automated Corridors project in June 2015.

Table 5.6 - Permitting States' Activity and Average Sentiment

	Average Activity (per month)	Average Sentiment Overall	Average Sentiment (excluding neutral)
California	63.5	3.22	3.58
Florida	7.6	3.24	3.67
Michigan	6.4	3.14	3.53
Nevada	4.2	3.18	3.66
Virginia	3.3	3.18	3.49
Washington, D.C.	4.5	3.21	3.50
National	3.6	3.21	3.55

Table 5.6 shows the average sentiment and activity of the five permitting states – plus Washington, D.C. – for the whole period of observation; June 2012 to June 2015. California has had the highest tweet activity each month – not only of the permitting states, but also in comparison to the entire US – with an average of 63.5 autonomous vehicle tweets per month. Although it is clearly a very populous state, all else equal, California has been a hotbed of autonomous vehicle activity for several reasons. Perhaps most influential is the location of the Google complex

and testing of the company's self-driving car through local communities and highways. Additionally, the two sources noted in the discussion of **Figure 5.14** as frequent tweeters are located in San Francisco and San Jose. Florida came in second of the permitting states with an average of 7.6 tweets per month. This was more than twice the national average of 3.6 tweets per month.

The average sentiment for the permitting states ranged from 3.14 to 3.24, and from 3.49 to 3.58 when only considering positive and negative tweets. With regard to overall sentiment, only Florida and California had averages greater than the national average. When neutral tweets were excluded, Florida, California, and Nevada all scored greater than the national average. Despite having lower than average monthly activity, Washington D.C. seems most representative of sentiment trends nationally. By both measures, Florida tweets were on average the most positive.

The positive nature of Florida tweets may reflect the perception of new industry being attracted to the state; legalizing and testing autonomous vehicles places Florida at the forefront of technological innovation. In later sections, we will explore topics identified in the tweets that support the claim that the current Florida twitter community are most interested in the future of AoVs as a technological commodity – how the vehicles will look and function, as well as the car manufacturers coming to Florida to promote them – rather than the potential social or safety benefits.

Figure 5.21 - Sentiment and Activity by County in Permitting States and Washington, D.C.

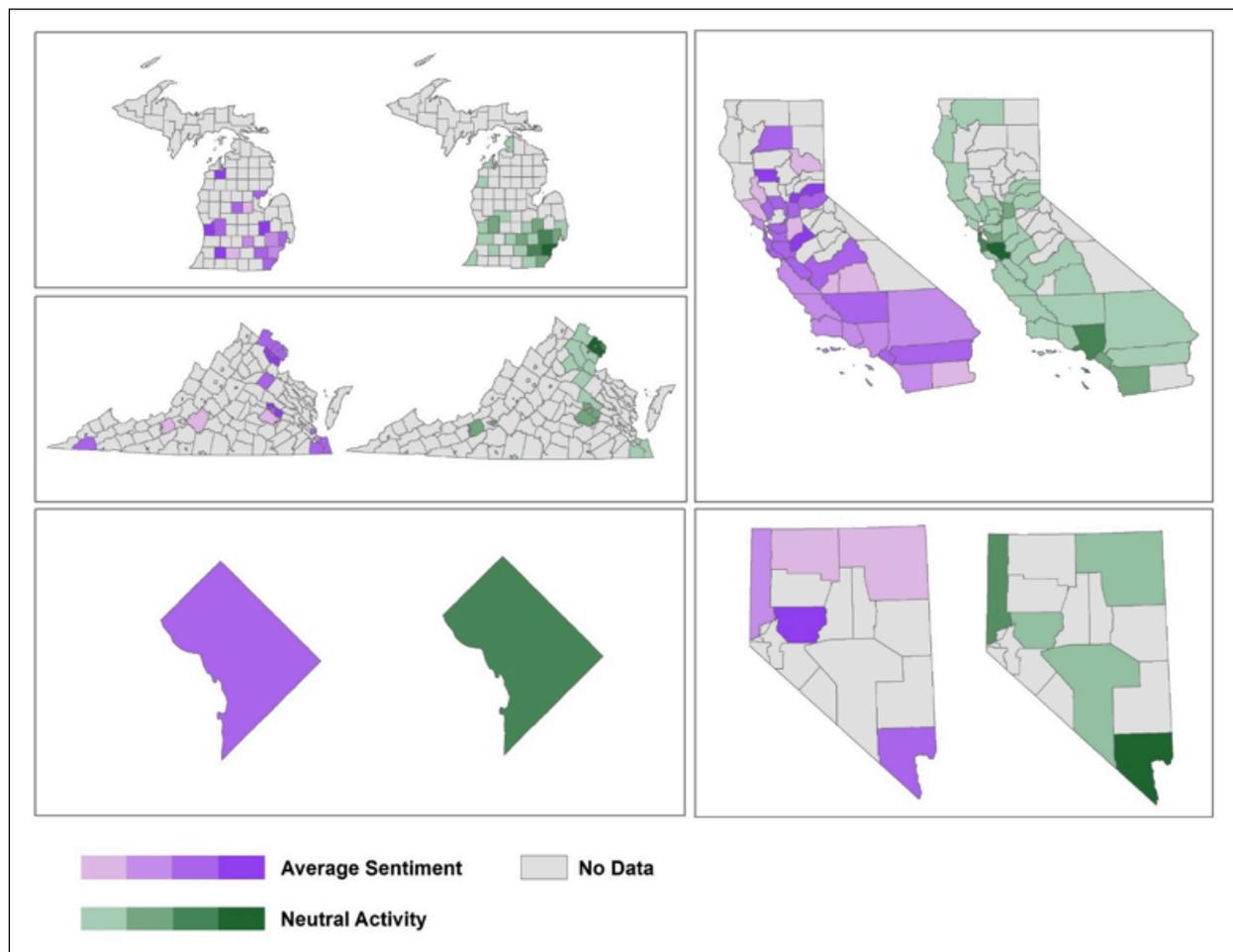


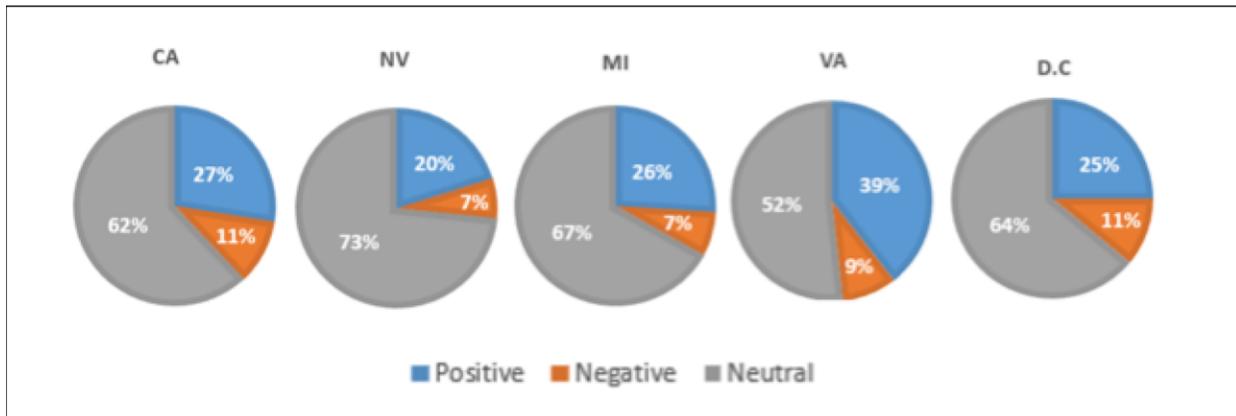
Figure 5.21 shows the distribution of AoV tweet activity across the five permitting states. The maps above show Twitter trends for each state at the county level, separated to show average sentiment (darker purple – more positive sentiment) and neutral activity (darker green – more neutral activity). The average sentiment was calculated using tweets scored as either highly positive, slightly positive, slightly negative, or highly negative. Neutral activity reflects the total number of relevant but opinion-neutral judged tweets sent within the county.

In each of the permitting states, AoV tweets – positive, negative, and neutral – were largely found in and around larger urban areas and university towns. In Michigan, activity was concentrated in the southeastern corner of the state,

primarily Wayne County; this was likely influenced, not only by Detroit, but the Ford Motors corporate office in Dearborn, Michigan. The sphere of activity extended in a northeastern direction toward Ann Arbor, where the University of Michigan is located. Virginia was much sparser with regard to activity and tweets that have been recorded were predominantly located in Northern Virginia, just outside of the District of Columbia. The remaining activity extended south toward Richmond, the state capitol. Due to the lack of internal boundaries, we were unable to show variation in activity and average sentiment across the District.

California had the most geographical coverage with regard to tweet county locations. At the epicenter was San Francisco, where Google's complex of innovation and production is headquartered. Activity extends northeast and southwest, likely due to a combination of vehicle testing sightings and general discussion of AoVs. The factors behind activity distribution in Nevada were difficult to interpret at this scale. With fewer than 200 tweets total and them being aggregated to counties that are much larger in area than the rest of the permitting states, the particulars of tweet locations are obscured. We can surmise, though, that the high intensity at the southern tip of the state may be due to Las Vegas, which plays an important role as the host of the technology conventions and tradeshows. Thus, tweets being recorded in Southern Nevada may not be an accurate reflection of residents' sentiment regarding autonomous vehicles, but rather those of out-of-state visitors.

Figure 5.22 - Distribution of Sentiment for Permitting States and Washington, D.C.



	California	Nevada	Michigan	Virginia	Washington, D.C.
Highly Positive	144	6	14	6	11
Slightly Positive	502	25	27	26	25
Neutral	1456	113	175	76	90
Slightly Negative	218	10	15	10	13
Highly Negative	29	0	4	3	25
Total	2349	154	235	121	141

The distribution of sentiment for the four permitting states – Florida will be explored separately – is shown in **Figure 5.22**. The figure also includes a table detailing that number of tweets classified in each of the five sentiment classes, as well as pie charts containing the overall percentage of positive, negative, and neutral tweets. As previously discussed, California far exceeded any other state in tweet activity; of the 7,252 captured tweets sent in the US, 32% of them have been

in California. Of the four states considered in the figure, Michigan ranked second in activity with a total of 235 tweets. Virginia, however, had the greatest proportion of its tweets scored as positive. Nevada had the smallest proportion of positive tweets, but was tied with Michigan for its percentage of negative tweets. The sentiment proportions in Washington, D.C. were nearly identical to California, although comprised of far less activity. In all five areas considered, more than half of the tweets sent within the state were determined to be neutral in sentiment.

Figure 5.23 - Sentiment Trends in Four Permitting States and Washington, D.C.

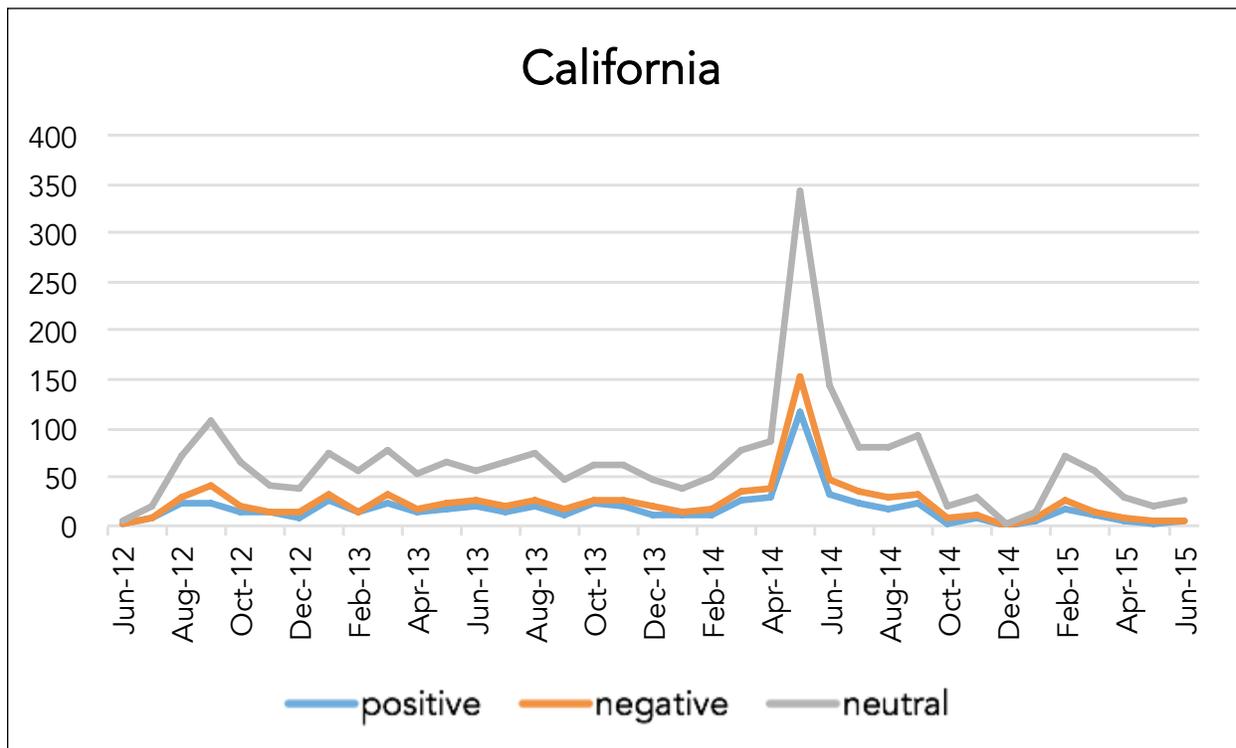


Figure 5.23 - Sentiment Trends in Four Permitting States and Washington, D.C.

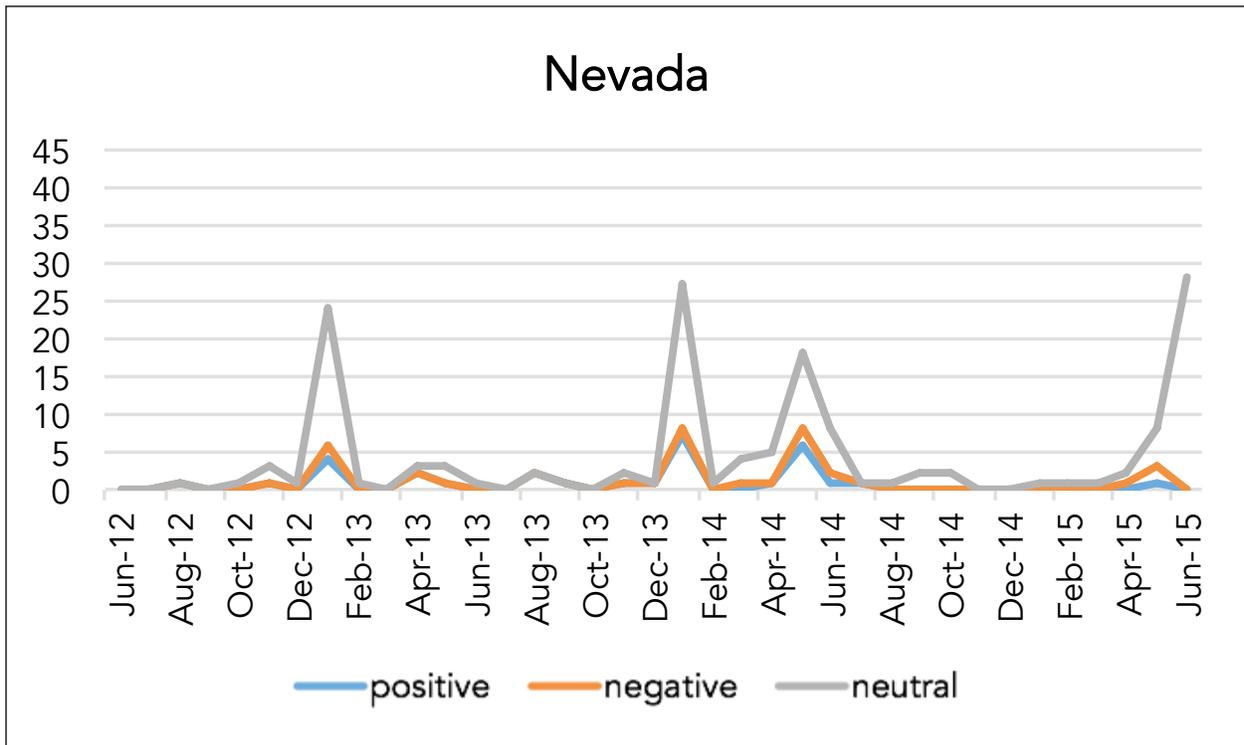
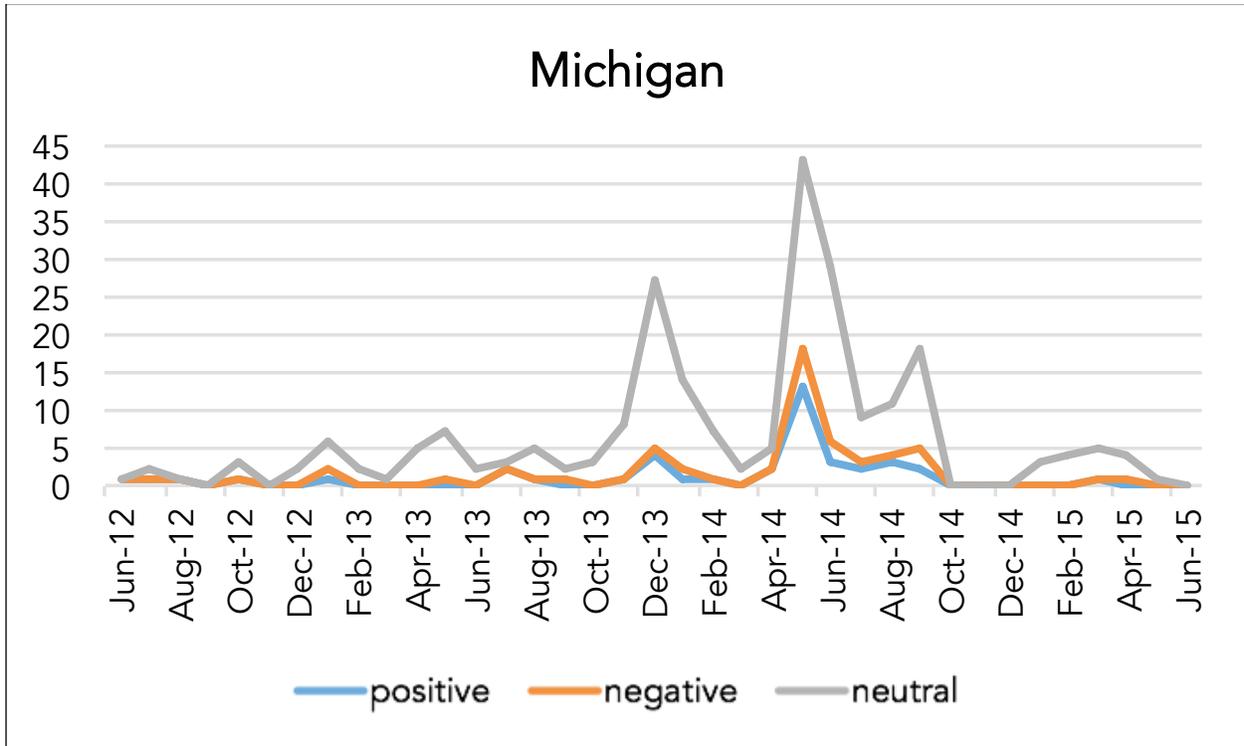
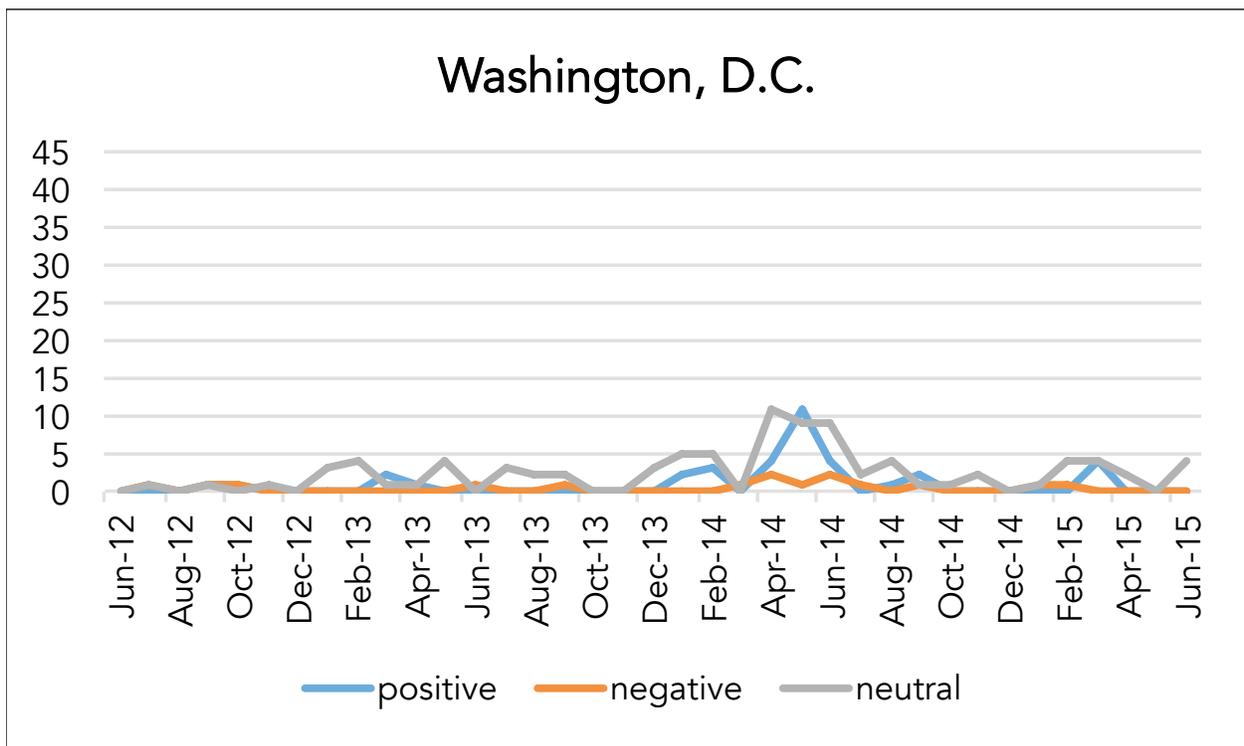
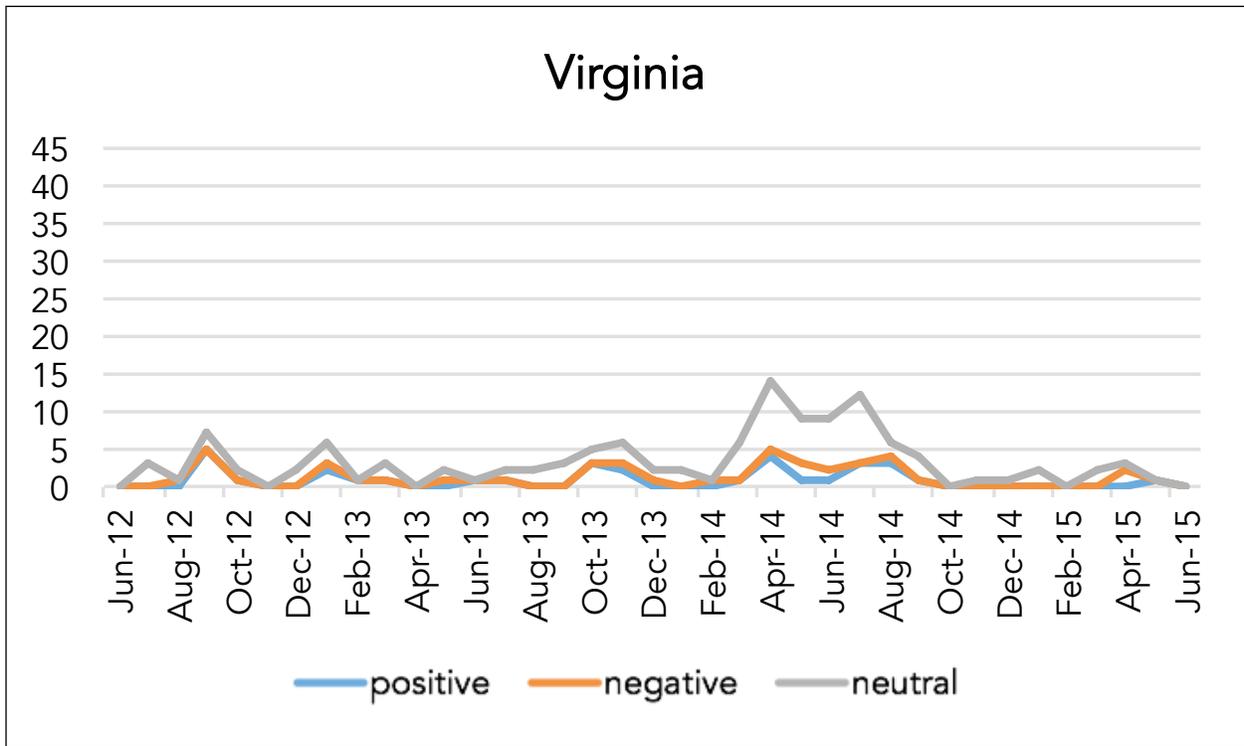


Figure 5.23 - Sentiment Trends in Four Permitting States and Washington, D.C.



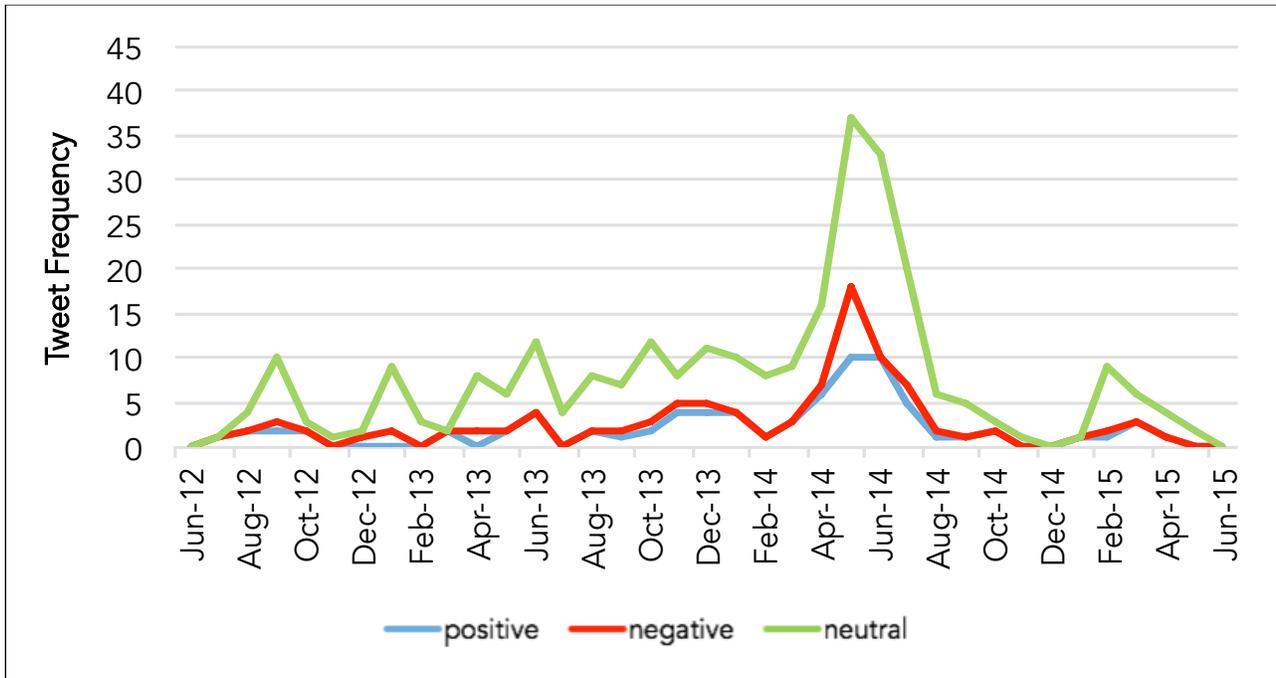
Over time, sentiment trends in the four states as shown above (**Figure 5.23**) have generally remained consistent, with isolated months of increased activity. These four permitting states and Washington D.C share a common trend in that they all experienced an increase in May 2014 and June 2014 from their normal activity. As previously noted, this was probably due to Google releasing images of its self-driving car. Additionally, whenever there was an increase in general activity, all three major sentiment classes – positive, negative, and neutral – were represented.

Unlike Google announcements, which originate in California but engage a broad national audience, Michigan and Nevada both appeared to have periods of localized increased activity. In December 2013, Michigan had its first notable spike in Twitter activity that seems to correspond with the passage of SB 169 legalizing testing of autonomous vehicles in the state (MLive Media Group, December 2013) and the announcement of a partnership between Ford Motors and University of Michigan to conduct tests (LA Times, December 2013). There slow build-up to this increase appears to start in January 2013, when Governor Rick Snyder announced autonomous vehicles as part of his legislative goals during the 2013 State of the State Address (MLive Media Group, December 2013).

Nevada experienced two clearly pronounced spikes in activity prior to May 2014. In January 2013 activity increased when the Nevada DMV granted its second autonomous vehicle license to Audi; the first had been granted to Google in February 2012 (Quick, 2013). The next increase was in January 2014 and was caused by the International Consumer Electronics Show held in Las Vegas, Nevada, where Induct Technology introduced its product, Navia, as the first commercially-available autonomous vehicle (Popular Mechanics, January 2014). A final uptick in activity was observed in May 2015 in Nevada when the state issued a testing permit for Daimler's Inspiration, an 18-wheeled semi-autonomous freightliner (The Guardian, May 2015). The vehicle generated public interest not only in receiving the permit, but by also completing a test drive across a portion of the Hoover Dam.

5.6.4 - Florida Sentiment Results

Figure 5.24 - Florida Sentiment Trends and Word Distribution



Top **Positive** Words

1. want
2. one
3. way
4. cool
5. now

Top **Negative** Words

1. need
2. people
3. wheel
4. steering
5. accelerating

Top **Neutral** Words

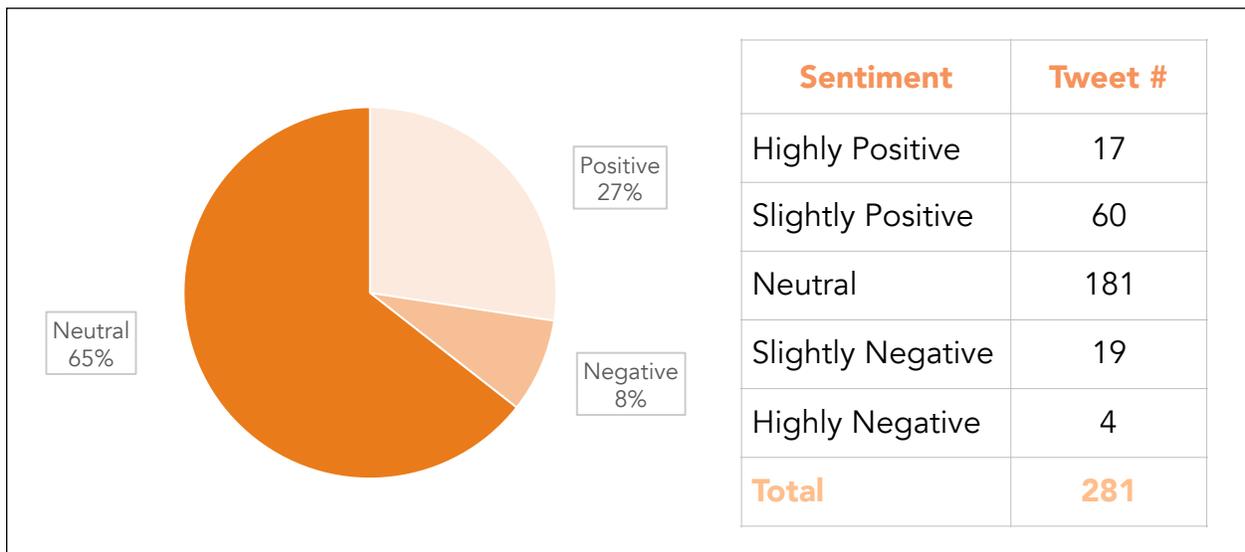
1. first
2. see
3. get
4. one
5. now

Turning our attention to Florida, **Figure 5.24** shows a time series graph of positive, negative, and neutral tweets over the course of the data collection period. The graph indicates that activity has been steadily increasing since early-2013, building to a peak in May 2014. As noted previously (**Figure 5.5 - Time Sequence of Google Search Engine History**), January 2013 marked an increase in general interest articles shared nationally. Unlike the other permitting states, Florida maintained a steady increase in activity – except for slight decreases in March 2013 and July 2013 – for the remainder of the year. While the majority of tweets were

neutral, all three sentiment classifications follow a similar trend over time. Additionally, most months had a nearly identical number of positive and negative tweets, with the exception of May 2014 when there were more negative tweets sent.

An assessment of the five most frequently-appearing words was conducted using the same methods previously described in **Figure 5.2** on the full set of tweets sent nationally. The top positive and neutral terms in Florida were nearly identical to the top national words, which again expresses a generalized sentiment toward AoVs. Florida’s negative words, however, were more topic specific and included explicitly transportation-oriented terms, such as “steering” and “accelerating”. This indicates that negative tweets sent in Florida could be based on particular concerns about AoV technologies, rather than a broad or over-arching hesitation about the technology.

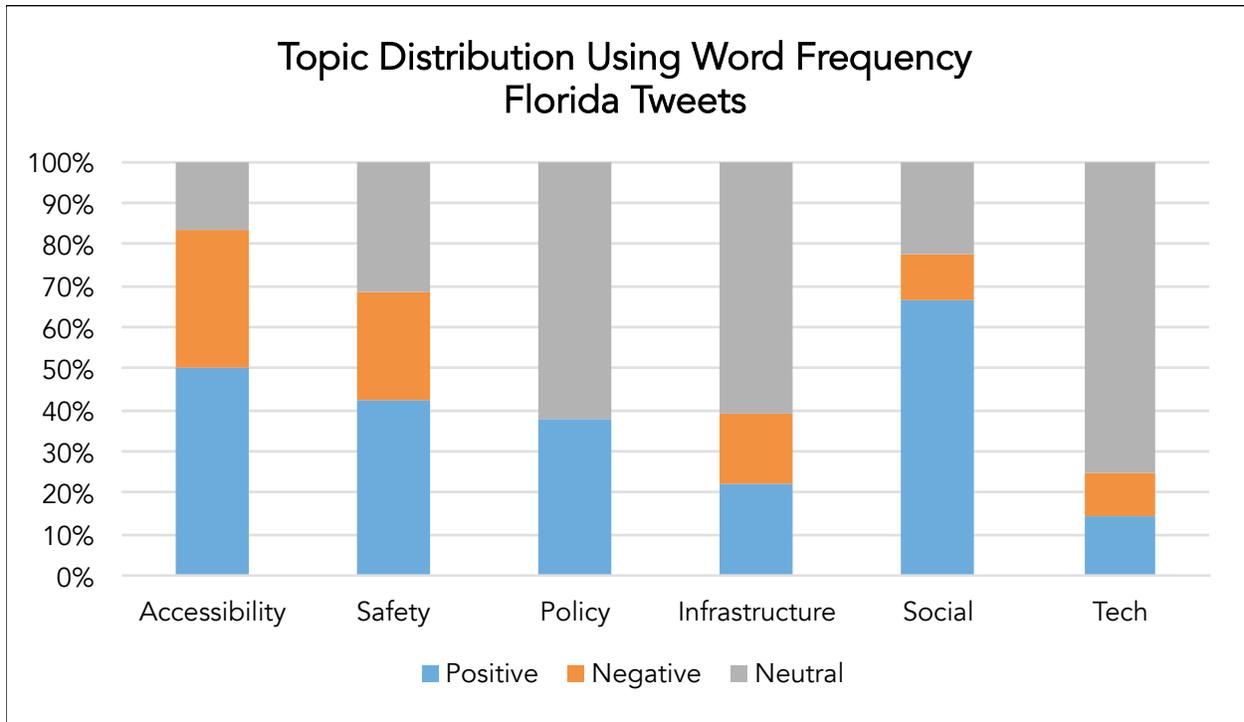
Figure 5.25 - Florida Sentiment Distribution



Florida’s sentiment distribution is shown above. **Figure 5.25** details the number of tweets classified in each of the five sentiment classes, as well as the overall percentage of positive, negative, and neutral tweets. Consistent with the remaining four permitting states (**Figure 5.23**), the majority of Florida tweets were

neutral. With regard to sentiment, there were three times as many positive tweets as negative. Of the five sentiment classification options, the fewest number of tweets were determined to be highly negative.

Figure 5.26 - Florida Topic Assessment and Keyword Frequency



Accessibility	Safety	Policy	Infrastructure	Social	Tech
Braille	Accident	Testing	Highway	Adventure	Technology
Disability	Drunk	Police	Transportation	Cool	Steering
Accommodate	Crash	Regulators	Industry	Bad	Research
Age	Death	Ticket	Traffic	Eating	Science

The nationwide topic analysis depicted in **Figure 5.13** is recreated above in **Figure 5.26** using word frequencies identified in Florida tweets. The figure shows the positive, negative, and neutral distribution of tweets containing topic markers specific to the Florida data set. Using the same text mining methods as previously described, 841 unique words were extracted from the 281 tweets.

Several keywords that were present in the national Twitter set and were anticipated to be present in Florida were found missing. For example, in searching for Accessibility-oriented keywords, neither “senior” nor “elderly” were present. However, the only instance of the word “braille” appearing in any of the autonomous vehicle tweets occurred in Florida. Along with more general topic words such as “disability” and “age”, it is clear that accessibility is a prominent theme in Florida’s Twitter discussion. Policy was another topic area where Florida differed from the national trend. Whereas the topic modeling shown in **Figure 5.13** suggested policy discussion was dominated by licensing and legislation, exploration of the Florida tweets indicated that testing of the vehicles and the future of traffic violations are of greater interest. Furthermore, **Figure 5.26** shows that policy keywords only appeared in positive and neutral tweets.

When compared to the distribution of positive, negative, and neutral tweets found in the national data set, Florida differed in several topic areas. In both Accessibility and Safety, the percentage of Florida tweets where keywords occurred in neutral tweets is notably lower, and there was more of a balance between the positive and negative distributions. Conversely, Infrastructure, Social, and Technology shares were nearly identical in **Figure 5.26** and mirror those displayed in their national counterpart.

Figure 5.27 - Base Year (2012) and Changes in Average Sentiment by Florida County

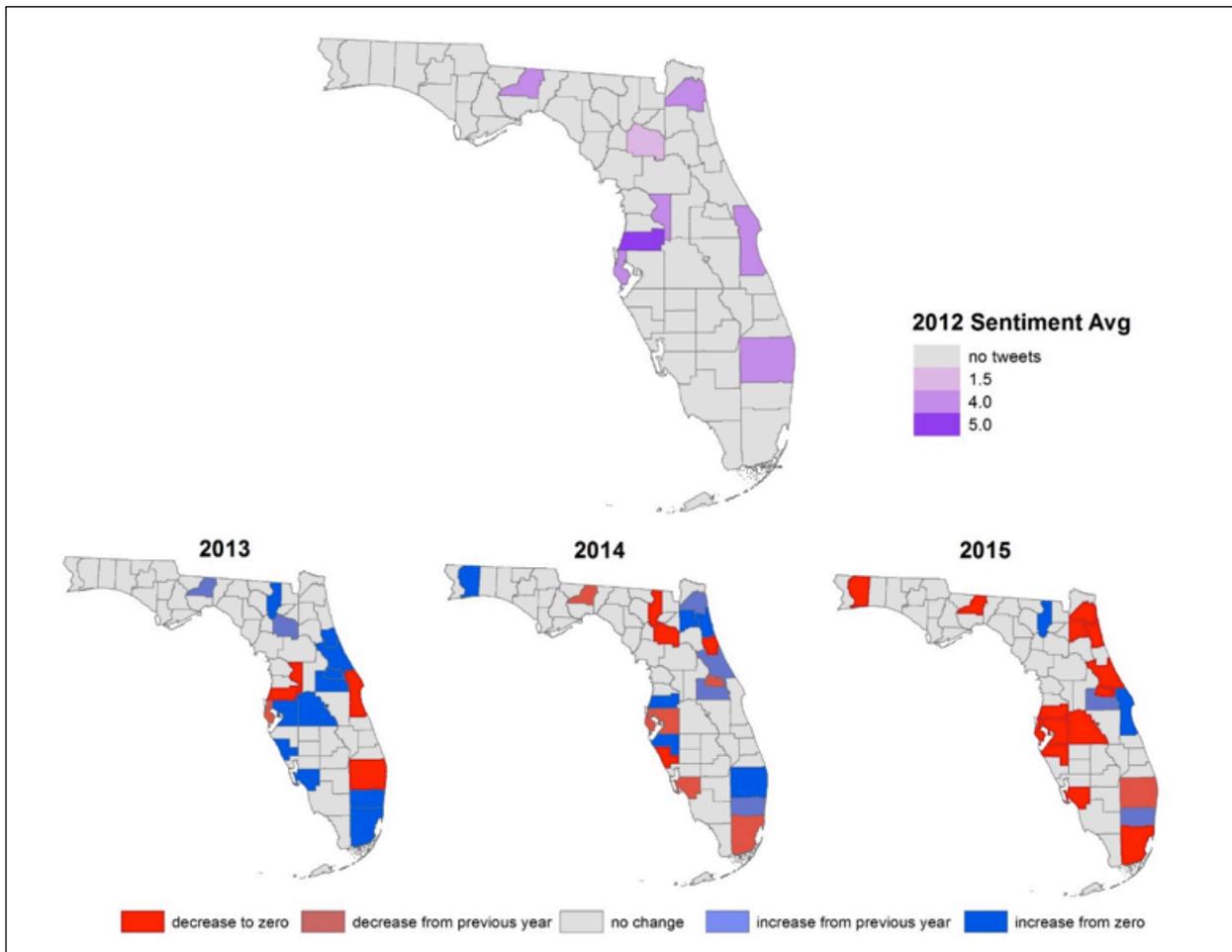
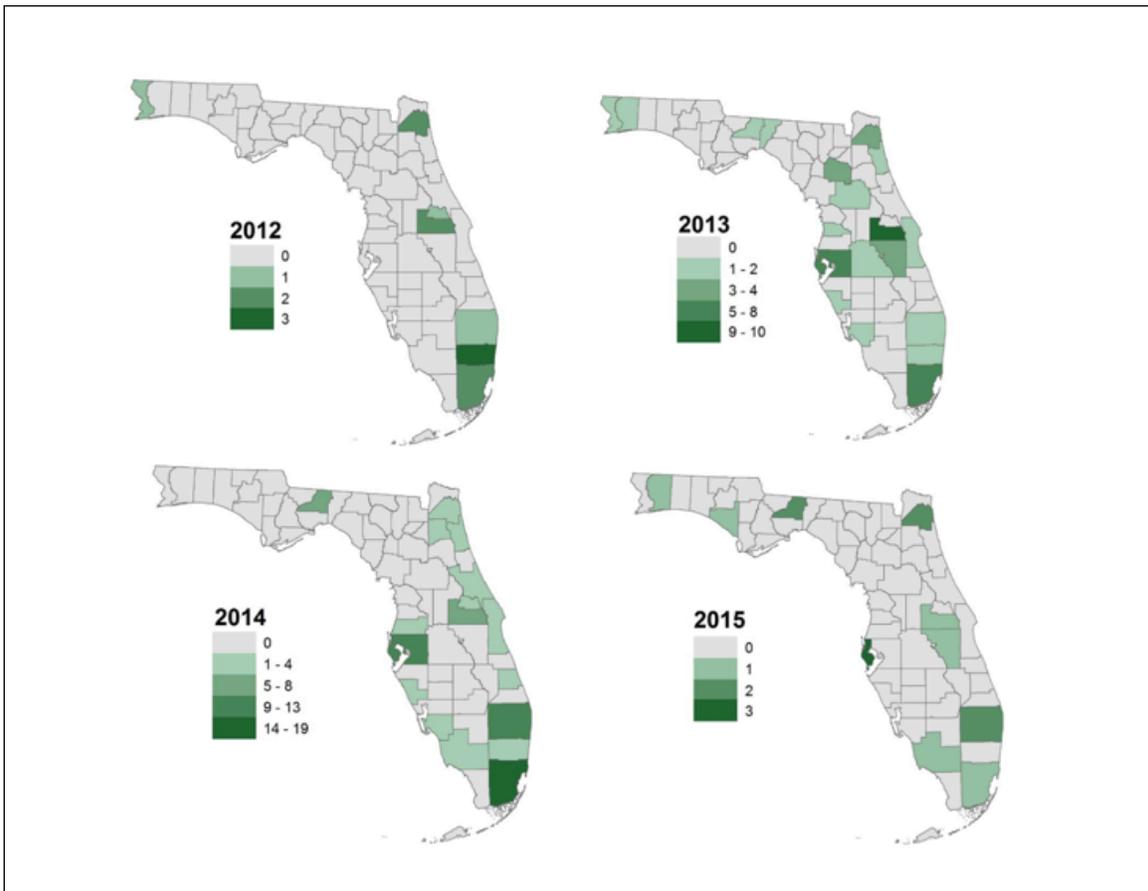


Figure 5.27 shows the sentiment average across Florida for all tweets in each year since the commencement of data collection in June 2012. Unlike the national trends described in **Figures 5.18 and 5.19**, this analysis only includes positive and negative tweets. Admittedly, the data set for 2012 – having data only for the last half of the year and legislation having only recently passed – was small; only 9 tweets were sent in Florida between July 23, 2012 and December 23, 2012 across 8 counties. These early tweets were dispersed across the state, from Leon County to Palm Beach County, and ranging in sentiment from highly negative to highly positive. Alachua was the only county to contain more than one tweet, one highly negative and one slightly negative; these two tweets were the only negatives to be sent in Florida during 2012. As such, the base county maps should be viewed with some caution in light of this data sparsity.

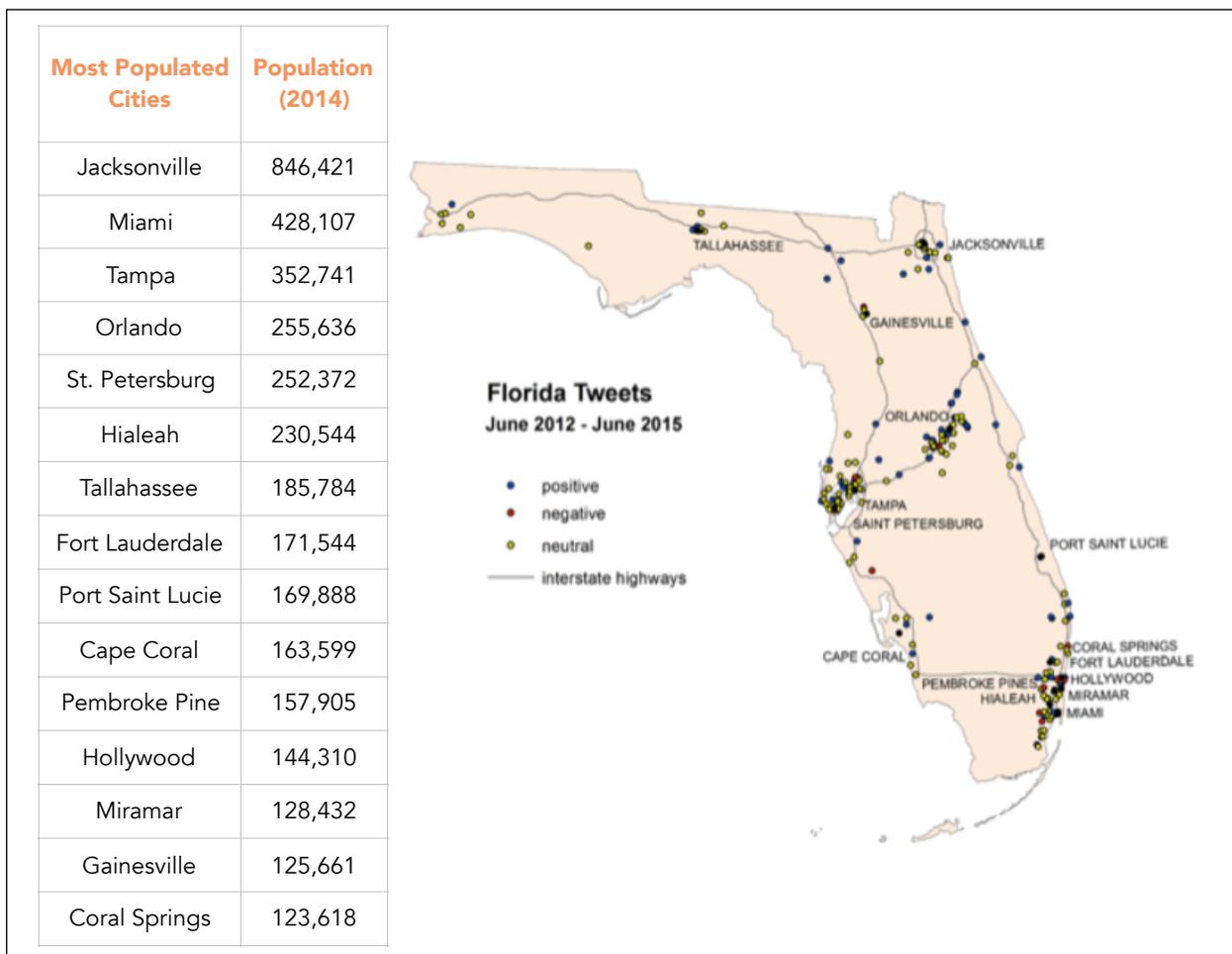
Throughout the remaining two and a half years of observation, the distribution of tweets across the state has fluctuated. In 2013, 89 tweets were sent throughout 15 counties. The figure shows a concentration of new locations along the I-4 corridor, the interstate that connects I-275 in Tampa to I-95 in Daytona Beach and bisects the state along a southeast-northwest axis. With 148 tweets sent in 2014, Central Florida experienced little change; new activity and increases in average sentiment were primarily located in the northeast around Jacksonville and the southeastern part of the state around Miami. As of June 2015, only 23 tweets have been recorded and have been limited to five counties. Columbia and Brevard Counties had not contained tweets in the previous year. Orange and Broward Counties have already experienced an increase in average sentiment since 2014, whereas Palm Beach County has seen a decline. As with the trends described in **Figure 5.19**, it would be necessary to wait until the end of 2015 to assess the annual change in sentiment.

Figure 5.28 - Neutral Tweet Activity in the State of Florida



As neutral tweets are often associated with the discussion of news-related and factual happenings, we mapped the distribution of neutral activity for each year since 2012. **Figure 5.28** shows the number of neutral tweets recorded in each county. In 2012, neutral engagement was primarily occurring along the east coast of Florida, specifically Jacksonville, Orlando, and Miami. In 2013, there was an increase throughout the much of the state, but particularly in Central Florida; Orange County had the most neutral activity, followed by Hillsborough, Pinellas, and Miami-Dade. In 2014 the activity shifted from Central Florida to Northeast and South Florida. Miami-Dade was the most active with a total of 19 neutral tweets. The distribution in 2015 was much more dispersed than in previous years; the majority of activity so far had occurred in South Florida and along I-10 east-west axis, from Jacksonville through the panhandle.

Figure 5.29 - Population of Florida Cities and Distribution of Tweets 2012-15

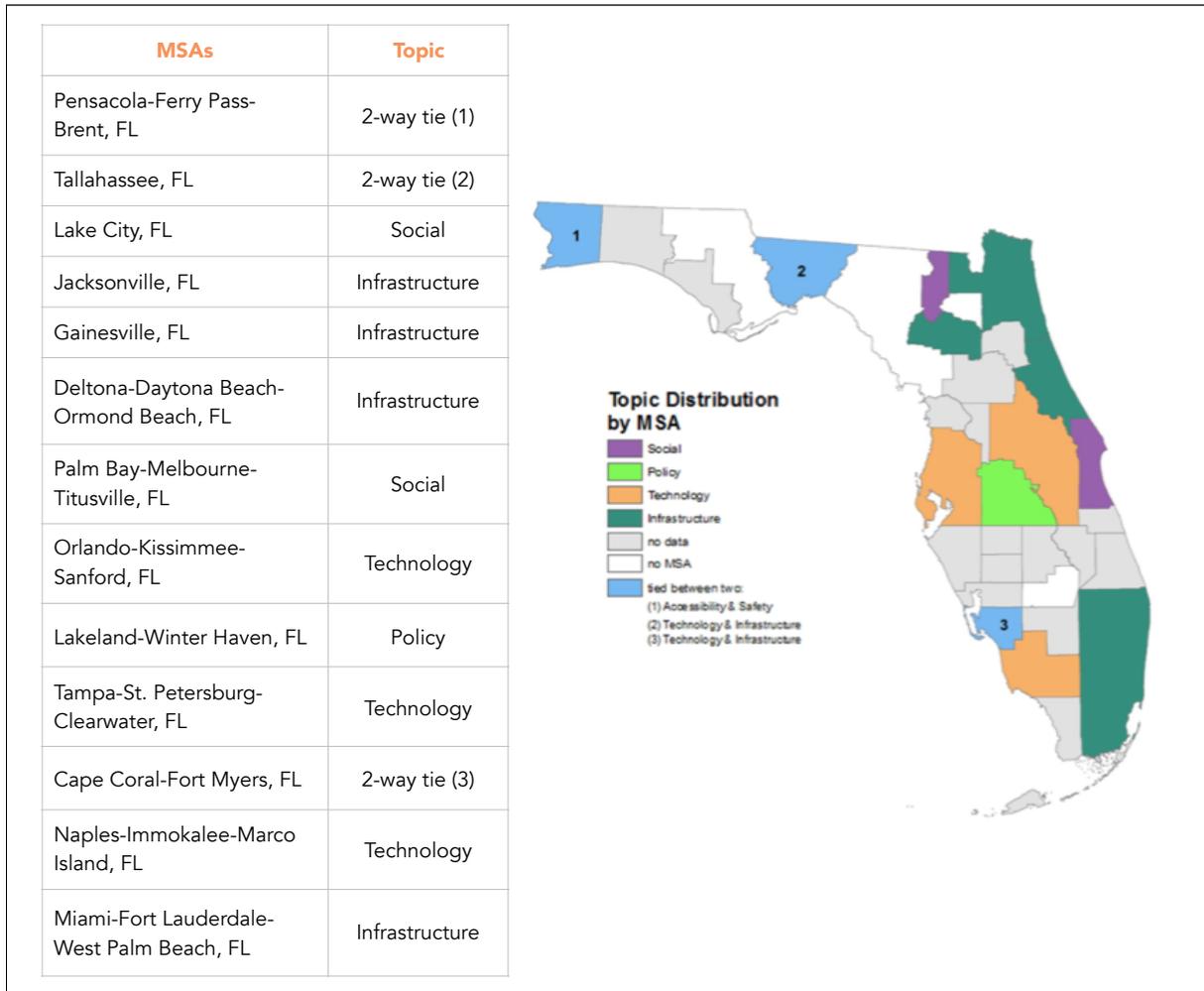


To get an idea of the geographic distribution of the cumulative multi-year dataset, **Figure 5.29** shows the individual point locations of positive, negative, and neutral tweets sent throughout Florida. These points are set against the fifteen most populated cities and the four major interstate highways that connect them; the highway system includes I-10 connecting Tallahassee to Jacksonville, I-95 connecting Jacksonville to Miami, I-75 connected Miami to Tampa, and I-4 connecting Tampa to Orlando.

The figure highlights two apparent trends in Florida tweet behavior. First, the majority of tweets sent were clustered around a major population center or close to a major highway. Additionally, all of the major cities have had someone discussing autonomous vehicles, so there was no imbalance in activity. Second, among the cities where tweets were clustered, there was a fairly even distribution of positive, negative, and neutral tweets. This indicates that no part of the state contains a population where those residents showing interest in AoVs have come to a consensus with regard to public opinion.

In **Figure 5.26** we examined how frequently AoV-related topic keywords occurred in positive, negative, or neutral tweets. In the figure above, we are looking at where tweets containing topic keywords are being sent. The figure shows the topic distribution among tweets sent in each Metropolitan Statistical Area that contains an identified topic. Not every portion of Florida was assigned to an MSA; the areas that were excluded are displayed in white. Of the 29 MSAs in the state, only 13 contained topic-based tweets during our study period. Tweets containing a topic word were classified as either: Social, Policy, Technology, Infrastructure, Accessibility, or Safety related as originally set out in **Figure 5.13**. If a tweet contained more than one topic word from different categories, then it was counted for both. If, however, it contained two topic words from the same category – such as “drunk” and “text”, which are both Safety keywords – then it was only counted once for that category.

Figure 5.30 - Most Popular AoV-related topic by Metropolitan Statistical Area



Infrastructure was the most popular topic of discussion, being the most frequent topic in 4 of the 13 MSAs. Technology came in a close second with 3 MSAs. There were two MSAs, Tallahassee and Cape Coral-Fort Myers, that where infrastructure and technology keywords were identified in equal frequency. In discussion of infrastructure, Florida Twitter users have focused heavily on three areas. First, transportation infrastructure as it relates to the future and planning needs; many of these tweets celebrated Florida as a leader in innovation being one of the few states where autonomous vehicles are out being tested. Second, transportation infrastructure as current traffic issues. In tweets that were mostly neutral and positive, it was discussed that driverless vehicles will alleviate traffic congestion and

improve the response time of emergency vehicles. And third automotive infrastructure in the sense of how we use vehicles. This included the potential future driverless taxis and public transportation, as well as the current practice of defensive highway driving to be alert to road hazards. This was similar to the safety topic, but more directly phrased in terms of transportation systems. The technology discussions had two major themes. First, was an interest in on-going and future research projects. Many of the tweets were neutral news articles sharing updates from Audi, Toyota, and Ford among other. In addition to the awareness that the vehicles are being developed, there was speculation as to how they will actually look and function once they are made commercially available. There was a mixture of enthusiasm and concern among tweets discussing the future of steering wheels, brake pedals, and alternative energy sources.

Of the six current topic areas, accessibility and safety were the most underrepresented. The two topics are only represented on the MSA map in a tie for Pensacola-Ferry Pass-Brent. One possible cause is that discussion since 2012 has largely regarded autonomous vehicles as a technology of the future; it is generating interest in speculation and sharing brief news updates when announced. From that perspective, Floridians are using Twitter to talk about the vehicle as an abstract piece of technology. Safety and accessibility necessitate that AoVs be viewed as a tangible reality that will impact a person's daily life. In order to increase discussion of these topics, the news updates being shared and commented upon need to promote AoVs as a present reality to embrace, rather than a future possibility to wonder about.

All of these assertions aside, we have to keep in mind that the data size for Florida is limited to only 281 geocoded tweets, and higher levels of tweet activity could change the topic distribution. Our analysis is best interpreted not as a comprehensive picture of how Floridians perceive autonomous vehicles, but rather an exploration of AoVs on the social media landscape. We have tapped into a community of Twitter users who are already aware and talking about the future of AoVs and this effort seeks to categorize what is being said. As general awareness increases and more of the public perhaps joins the conversation, the dominant interests and areas of concern could change.

5.6.5 - Summary of Trends and Takeaways for Practice and Policy

The analysis conducted in previous sections reflects an ongoing discussion about autonomous vehicles in the few years since the US began permitting at the state level. The opinions collected cannot be broadly construed as representing the general public. Rather, the data presented here are limited to the Twitter community that has already become aware of and engaged in the topic at such an early phase of public exposure. We close with a summary assessment of the trends and takeaways observed through social media monitoring and the potential implications for practice and policy going forward.

- **Sentiment persisting negative over time**

AoV tweet activity falls into one of two categories. Either tweets are sent in response to a major event as part of a community increase in activity, such as the Google Car announcement of May 2014. During these events, we observed an increase in positive, negative, and neutral tweets. The second category includes tweets sent out of individual interest; these include responses to general news articles and unsolicited opinions prompted by daily life (e.g. "This morning commute is awful. I'd love a self-driving car right about now"). Among this second category, tweets have been persistently decreasing over time. The decline in sentiment is observed both when we included and excluded neutral tweets in calculating the averages.

- **Discussion intensity decreasing over time**

The activity uptick generated by AoV publicity events has largely obscured the trend of general interest over time. But by grouping the number of tweets sent in 6-month intervals, we found the discussion has been slightly decreasing as more time passes since states began AoV permitting. In the absence of new active legislation or a commercially available product, there has been less news to motivate public discussion. In order to sustain awareness and engagement, state agencies and car manufacturers can counteract the trend by promoting regular updates. Sharing news about testing, products in development, and even potential future applications on social media will stimulate discussion and invoke opinion.

- **Neutral engagement is strongest for discussion of technology, policy, and infrastructure**

A significant percentage of tweets collected – nationally and for each of the permitting states – were determined to be relevant to autonomous vehicles, yet lacking a positive or negative opinion. Neutral tweets reflect engagement with autonomous vehicles without contributing to public sentiment. In tweets discussing transportation topics – technology, policy, and infrastructure – the conversation has been dominated by neutral engagement, rather than expressed opinion. The large percentages of positive and negative tweets are concerned with safety and social topics.

- **Discussion in permitting states driven by in-state events**

Autonomous vehicles have been legalized in four states and the District of Columbia. In each permitting state, our Twitter activity analysis showed a unique trend of time. In nearly every case, whenever there was a dramatic increase in activity for a given month, the cause can be traced to specific events that occurred in that state. Announcements about testing and research advancements generate high amounts of local interest. Large scale events – such as Google announcements – are able to resonate with a national audience outside of California.

- **Florida appears to be among most positive of permitting states**

With our limited data sample of Florida tweets, we observed that the discussion has a greater percentage of positive tweets than Nevada, Michigan, or the District of Columbia. It has the same percentage of positives as California, while also having a smaller percentage of negative comments. In Florida, discussion of social topics is the most positive of the six topic categories analyzed.

5.7 - SUMMARY AND CONCLUSIONS

This task has looked to detect and better understand people's sentiment with regards to Autonomous Vehicles via the mining and analysis of social media data from the Twitter platform. Within their respective knowledge domains, social media analytics and autonomous vehicle technologies are arguably two of the 'hottest' topical areas in the research sphere. Here the goal was to merge these two areas, with an eye towards learning more about a segment of the recent national conversation on autonomous vehicle technologies.

The cumulative efforts of this task reveal that much can be learned about autonomous vehicles, and that there are some distinct points of view among Twitter users. People are concerned about reliability, while at the same time enamored with some of the positive prospects of the technology. Taken as a whole, the conversation over the last three years has been overall positive, but has trended more negative recently as informational items make up larger shares of the tweet discourse. Sentiment varies substantially across states, which can be further parsed by whether a state is one of a select few that has allowed for AoV permitting/testing.

Going forward, there are opportunities to further explore social media outcomes as they relate to AoV. Focusing on the Twitter platform, and the approach taken here, continuing to monitor the AoV-related search terms usage on social media could be used to regularly assess the public's perception of AoVs. Related to this, as the vocabulary, terms, and references surrounding AoVs evolve, it could prove useful to begin searching for and monitoring their use in order to further expand means of evaluating the AoV conversation. Lastly, future social media analytics can be expanded beyond Twitter to assess on-line micro blogs, news sites, and search engine histories as a means of learning about AoVs.

There are limitations associated with the study that have been mentioned elsewhere but warrant reiterating. First, we worked only with tweets containing a georeference (i.e., x,y coordinates allowing the tweet to be mapped), which as

reported is roughly 2-3% of all tweets. This was done to facilitate comparison across locations, states, etc. In using this subset of tweets, researchers are implicitly assuming that these data are representative of the larger Twitter conversation. It is noted that many researchers use such georeferenced tweet data as accepted practice. The data and result analysis is probably best viewed as a window into a conversation rather than a strict representative sample, per se. Another limitation was the unknown nature of the personal characteristics of the Twitter user in our study as information on users was not part of our analysis. Lastly, because of the nature of the data and sentiment assignment methods, there will naturally be some subjectivity in how various judgments are made. Being mindful of this consideration, the FSU research team strove to design a process where relevant tweets were given a solid judgment on the sentiment contained therein.

In sum, this project task has successfully demonstrated a means of approaching social media analytics for the task of better understanding AoV technologies. Many insights have been garnered into the public's perception of AoVs, while at the same time a methodology has been established which could potentially be applied to other transportation planning and infrastructure issues.

CHAPTER 6



Image Source: www.imgarcade.com/1/highway

Conclusions and Recommended Future Steps

6.1 - SUMMARY OF FINDINGS

The FSU research team was contracted by FDOT to investigate the potential impacts of Automated Vehicles (AV) on Florida's citizens, with a special focus upon older adults. A summary of the most pertinent findings from this work are detailed below, and referenced back to the relevant section of the Final Report.

- As detailed in Chapter 2 an assessment of aging adults travel behavior found that age-related declines in driving ability present many aging adults with a unique set of travel difficulties that are not being adequately addressed by the current transportation system. Further, this lack of mobility has detrimental effects on the health and quality of life of aging adults.
- Chapter 3's evaluation of common causes of car crashes involving older adults found that even low levels of automated technology (Levels 1 & 2) could alleviate many of the transportation difficulties older adults face by reducing the risks associated with aging adults' most common crash scenarios. In this way, AV features can reduce the number of accidents involving aging adults enabling these individuals to drive safely later in life. However, these technologies will only be effective if the user feels comfortable and confident using the technology, and questions still remained over aging adults' willingness to trust and adopt AV technology.
- The Survey described in Chapter 4 was designed to answer these trust questions by assessing aging adults' opinion of and willingness to adopt AV. Results showed that even though older adults were less likely trust AV than younger generations, 56% of respondents over the age of 65 indicated that they would be willing to use an AV and as much as 80% would be willing to use certain types of Advanced Driver Assistance Systems (ADAS). An important consideration in interpreting these results relates to the level of education individuals have about the technology. The survey found that even minimal amounts of education about AV significantly improved Florida residents' opinion of and willingness to use AV. This finding suggests that

Floridians of every age cohort may become more accepting of AV over time as their familiarity with and exposure to the technology increases.

- Finally, Chapter 4's analysis of social media data reinforced that Florida residents have a relatively positive outlook on AV. This work also revealed that that interest in the subject is can be spurred by in-state events such as announcements about AV testing and research advancements.

Taken as a whole, this study affirms the potential of all levels of automated vehicle technology to provide safe and efficient mobility options to Florida's population, and especially its aging adults. Florida is a national leader in the area of AV technology and policy, and this evidences itself in a relatively well-informed population with interest in and positive attitudes toward this technology.

6.2 - RECOMMENDATIONS FOR FUTURE ACTIONS BY FDOT

Given these research findings, the project team recommends several future actions that FDOT can take to promote the use of AV as a solution to the transportation issues faced by Florida's aging population.

Action Item #1: Build Upon Florida's Outstanding Efforts to Test and Promote AV in the State

Through FDOT's outstanding leadership and work Florida has emerged as a national leader in AV testing, planning, and piloting. The findings of this study reinforce the importance and effectiveness of many of FDOT's ongoing efforts to promote and test AV technology.

Continue Educating Planners, Engineers, and Infrastructure Providers of the Imminence and Importance of AV

FDOT's extensive public outreach efforts to educate planners and engineers of the need to prepare for and take a leadership role in support of AV technology should be continued. However, the findings of this study suggest that expanding these efforts to the larger public (as described below) represents an important opportunity for building support for the technology across the state. These education and marketing efforts will encourage infrastructure providers, planning bodies, other state agencies, and the AV industry to see Florida as a place for the early rollout of AV technology.

Continue Testing ADAS Technologies

Chapter 3's analysis of the driving situations where older drivers are most susceptible to crashes confirmed the importance of FDOT's ongoing efforts to test

and implement ADAS and connected vehicle technologies. Since Level 1 and 2 automation were found to significantly improve the safety of aging drivers, facilitating the advancement of these technologies into the market as quickly as possible could enhance the safe and efficient mobility of many aging adults in the near-term, well before fully automated vehicles are available. Similarly, since aging adults are significantly more likely to be willing to adopt ADAS than fully automated vehicles, pursuing ADAS applications will likely be one of the best ways to improve aging adults' mobility until older generations learn to trust AV. In this way, FDOT's recent unveiling of pilot projects assessing the performance of GeoTab and MobilEye's ADAS is a perfect application of the findings of this study. To ensure that these studies and future applications are tailored to the mobility needs of aging adults, the findings of this study suggest that FDOT should pay special attention to collision warning systems, left-turn assistance systems, and blind spot monitors because these were found to have the greatest potential benefits to aging adults.

Action Item #2: FDOT Should Develop and Pursue an AV Education/Marketing Campaign

AV Education and Florida's AV Brand Matter

Building on the survey results, the Department should pursue a strategy for educating and marketing AV technology to Florida's residents, businesses, and visitors. This campaign should strive to inform these constituencies about what AVs are, how they operate, and what the costs and benefits associated with the technology are. This campaign should also showcase FDOT's efforts and leadership in preparing Florida for the emergence of automated and connected vehicle technologies. The survey results summarized in this report indicate that even a brief informational brochure on automated vehicles improved respondents' opinion of and willingness to adopt AV. A comprehensive education/marketing strategy targeting key Florida constituencies would help prepare the state for the widespread adoption of AV, while reinforcing Florida's position as a national leader in application of AV technology.

Education Should Be Targeted to Age-Specific Interests and Concerns

In addition to highlighting the fundamental importance of educating the public and showcasing the state's leadership efforts, this study also provided insight into how these efforts could be expanded and refined. In particular, these results suggest that any educational/marketing program should take a multi-platform approach and speak to the interests and concerns of key subgroups. The survey results indicated that distinct population subgroups have differing interests and fears concerning AV, which points to the need to tailor the message to each subgroup.

A key demographic factor that needs to be considered is age. Older adults typically are less favorable to AV and generally see the challenges and costs of AV more than other age groups. While this group recognizes the mobility advantages that AV might provide (which represents an opportunity for building support for the technology amongst this cohort), they are worried that AV may be difficult to learn how to use. In contrast, young adults see AV as a lifestyle issue in which they can be productive and social in during travel. FDOT's educational/marketing program should target each cohort with age-specific educational messages that address the unique interests and concerns of different age groups.

Educational Media Should Be Tailored to the Age-Specific Preferences and Characteristics

FDOT should also consider whether the educational medium used to reach each cohort is appropriate to the characteristics and preferences of the age group. Social media is an excellent platform for reaching Millennials but may not be effective with older generations who are less familiar with technology. Consequently, pursuing more traditional marketing platforms, such as newspapers and mailed brochures, may be a viable option for educating older adults of the benefits of AV. However, since traditional strategies may be less effective for younger generations, these efforts may need to be targeting at specific communities, such as The Villages, that have high concentrations of older adults.

Use Major AV News and Events as Marketing Opportunities

Finally, FDOT should continue to hold and publicize high-profile AV news and events as a way of demonstrating the capabilities of automated and connected vehicles, informing the public of Florida's efforts to support the use of these technologies, and generating widespread interest in the technology. The results of the social media analysis indicated that most of the AV discussion on Twitter was directly related to publicized in-state events (i.e., demonstrations, legislation passing, etc.). Florida's annual AV Summit is a perfect example of the kind of large, high-visibility event that can generate enough excitement to spur statewide discussion of the technology. Marketing these types of events could be a vital piece of FDOT's educational program.

Florida residents should know about the great work the state is doing to prepare for the emergence of AV, and publicizing news and demonstrations is a perfect way to help tell this story. To this end, FDOT should also strive to publicize national and state-level news concerning AV technology such as major developments in the industry, the status of AV-related legislation, and successful tests of AV applications. Once again, these publicity efforts should employ a multi-media approach that caters to the interests, preferences, and concerns of specific age groups.

Action Item #3: Building Upon this Research Effort

Regularly and Actively Track Public Attitudes toward AV

Continuing to actively assess Florida resident's attitudes toward and willingness to adopt AV is vital to FDOT's ability to identify and address the public's concerns about AV, to evaluate the effectiveness of AV implementation efforts, and to anticipate AV adoption rates once the technology comes to market. FDOT can use these data on residents' opinions of AV to inform and shape their ongoing public outreach efforts. Related to this, monitoring social media outlets would enable FDOT to gauge public sentiment toward specific topics in real time, anticipate rising concerns about the technology, and help inform public opinion when major news and events occur. Tracking social media activity could also serve to provide

feedback on how successful FDOT's events and promotional strategies are based on the amount of interest and activity they generate.

Annual or biannual surveys would provide a more detailed representation of Florida residents' familiarity with, opinion of, and willingness to adopt AV to see whether they are becoming more accepting of the technology over time. While each iteration of the survey should ask the same baseline set of questions regarding attitudes and socio-demographics, it might include a different module each time to obtain more information on relevant topics. The survey's ability to analyze how public perception of AV varies by demographic attributes could inform FDOT's public outreach efforts by enabling educational and marketing messages to be tailored to the values and concerns of different subgroups. Regular surveys would provide ongoing feedback on the effectiveness of FDOT's promotional efforts as well as helping FDOT to anticipate when the adoption of AV is imminent and to prepare accordingly. In sum, developing a regular approach for tracking attitudes towards AV technology would enable FDOT to identify and react to public concerns about AV.

AV and Human Factors Research: AV Simulator Studies

Aging adults are a unique demographic group with distinct travel behavior patterns, heightened concerns about AV, and unparalleled potential to benefit from AV. As Florida's aging population continues to grow, tailoring AV applications to the needs of aging adults will be vital to ensure that age-related declines in driving ability do not hinder their mobility. To this end, more detailed research on how aging adults interact with AV and ADAS technologies will be necessary. The AV simulator FDOT is developing in partnership with the University of Central Florida provides the perfect opportunity to do this. Testing how aging adults utilize different types of automated features can serve to answer whether ADAS systems are helpful or distracting, whether the driver takes back control in time, whether aging adults lack of trust impacts their responsiveness to automated features, how the AV/human interface need to be adapted to accommodate aging adults, and a host of other issues related to AV and human factors. Working with university partners to conduct surveys and focus groups of aging adult experiences in the simulator may also be needed to pinpoint features and interfaces that are most helpful as well as uncovering how experiencing an AV changed their opinion and willingness to adopt the technology.

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COVER PAGE IMAGE SOURCES

Images from left to right:

1. <http://blog.vanguardauto.net/?cat=21>
2. <http://www.ntf.se/vast/default.asp?ReclD=82766>
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CHAPTER 4 - APPENDIX A: FLORIDA AUTONOMOUS VEHICLE SURVEY 2015

Researchers at Florida State University are interested in your views and opinions regarding Autonomous Vehicles and other driver assistance systems.

Please mark **ONE** box for **each** question (unless otherwise noted) that most closely matches your opinion. Thank you!

1. Prior to receiving this survey, how familiar were you with autonomous vehicles?

- Very Familiar Somewhat Familiar
 Somewhat Unfamiliar Very Unfamiliar Not sure what it is

2. What is your general opinion regarding autonomous vehicles?

- Very Positive Somewhat Positive
 Neutral Somewhat Negative Very Negative

3. Prior to receiving this survey, how familiar were you with the following driver assistance systems? Please select one response for each feature.

	Very Familiar	Somewhat Familiar	Somewhat Unfamiliar	Very Unfamiliar	Not sure what it is
a. Cruise Control	<input type="checkbox"/>				
b. Lane-Departure Warning	<input type="checkbox"/>				
c. Blind Spot Monitor	<input type="checkbox"/>				
d. Active Lane Centering	<input type="checkbox"/>				
e. Automatic Braking Systems	<input type="checkbox"/>				
f. Adaptive Cruise Control	<input type="checkbox"/>				
g. Self-Parking Systems	<input type="checkbox"/>				

Survey Page 2:

4. What is your general opinion regarding the following driver assistance systems?
Please select one response for each feature.

	Very Positive	Somewhat Positive	Neutral	Somewhat Negative	Very Negative
a. Cruise Control	<input type="checkbox"/>				
b. Lane-Departure Warning	<input type="checkbox"/>				
c. Blind Spot Monitor	<input type="checkbox"/>				
d. Active Lane Centering	<input type="checkbox"/>				
e. Automatic Braking Systems	<input type="checkbox"/>				
f. Adaptive Cruise Control	<input type="checkbox"/>				
g. Self-Parking Systems	<input type="checkbox"/>				

5. How likely do you think the following benefits will occur when using autonomous vehicles? *Please select one response for each potential benefit.*

	Very Likely	Somewhat Likely	Neutral	Somewhat Unlikely	Very Unlikely
a. Fewer crashes	<input type="checkbox"/>				
b. Reduced severity of crashes	<input type="checkbox"/>				
c. Less traffic congestion	<input type="checkbox"/>				
d. Shorter travel times	<input type="checkbox"/>				
e. Better fuel economy	<input type="checkbox"/>				
f. More enjoyable traveling	<input type="checkbox"/>				
g. Enhanced mobility for those unable to drive	<input type="checkbox"/>				
h. Improved pedestrian safety	<input type="checkbox"/>				

Survey Page 3:

6. How concerned are you about the following issues related to autonomous vehicles? <i>Please select one response for each potential concern.</i>					
	Very Concerned	Slightly Concerned	Neutral	Slightly Unconcerned	Very Unconcerned
a. Safety consequences of equipment failure or system failure	<input type="checkbox"/>				
b. Legal liability in case of a crash	<input type="checkbox"/>				
c. Vehicle/System Security (from hackers)	<input type="checkbox"/>				
d. Data privacy (location and destination tracking)	<input type="checkbox"/>				
e. Sharing the road with human-driven vehicles	<input type="checkbox"/>				
f. Interacting safely with pedestrians and bicyclists	<input type="checkbox"/>				
g. Learning to use self-driving vehicles	<input type="checkbox"/>				
h. Autonomous vehicles not driving as well as human drivers	<input type="checkbox"/>				

7. Please rate your level of agreement with the following statements:					
	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
a. I would be comfortable riding in an autonomous vehicle	<input type="checkbox"/>				
b. I would be comfortable with a loved one riding in an autonomous vehicle	<input type="checkbox"/>				

Survey Page 4:

8. How likely would you be willing to use the following types of driver assistance systems? <i>Please select one response for each feature.</i>					
	Very Likely	Somewhat Likely	Neutral	Somewhat Unlikely	Very Unlikely
a. Cruise Control	<input type="checkbox"/>				
b. Lane-Departure Warning	<input type="checkbox"/>				
c. Blind Spot Monitor	<input type="checkbox"/>				
d. Active Lane Centering	<input type="checkbox"/>				
e. Automatic Braking Systems	<input type="checkbox"/>				
f. Adaptive Cruise Control	<input type="checkbox"/>				
g. Self-Parking Systems	<input type="checkbox"/>				

9. How likely would you be willing to use an autonomous vehicle?					
<input type="checkbox"/> Very Likely	<input type="checkbox"/> Somewhat Likely				
<input type="checkbox"/> Neither Likely nor Unlikely	<input type="checkbox"/> Somewhat Unlikely	<input type="checkbox"/> Very Unlikely			

10. How likely would you be willing to use the following types of autonomous vehicles if they were available? <i>Please select one response for each type of vehicle.</i>					
	Very Likely	Somewhat Likely	Neutral	Somewhat Unlikely	Very Unlikely
a. A privately-owned AV	<input type="checkbox"/>				
b. A shared-ownership AV	<input type="checkbox"/>				
c. An autonomous public transit system (bus, van, etc.)	<input type="checkbox"/>				
d. An autonomous vehicle for hire (taxi, limo, etc.)	<input type="checkbox"/>				

Survey Page 5:

11. If you were going to buy a vehicle, how likely would you consider purchasing an autonomous vehicle if it cost. <i>Please select one response for each price.</i>					
	Very Likely	Somewhat Likely	Neutral	Somewhat Unlikely	Very Unlikely
a. The same as a regular car	<input type="checkbox"/>				
b. \$1,000 more than a regular car	<input type="checkbox"/>				
c. \$5,000 more than a regular car	<input type="checkbox"/>				
d. \$10,000 more than a regular car	<input type="checkbox"/>				
e. \$25,000 more than a regular car	<input type="checkbox"/>				

12. I generally find new technology easy to use. <input type="checkbox"/> Strongly Agree <input type="checkbox"/> Agree <input type="checkbox"/> Neutral <input type="checkbox"/> Disagree <input type="checkbox"/> Strongly Disagree

13. How frequently do you use the following technologies? <i>Please select one response for each technology.</i>						
	Not sure what it is	Never used	Used once or twice	Use Monthly	Use Weekly	Use Daily
a. Answering machine and/or voice mail	<input type="checkbox"/>					
b. Cell Phone or Smart Phone	<input type="checkbox"/>					
c. Computer or tablet	<input type="checkbox"/>					
d. Automatic teller machine (ATM)	<input type="checkbox"/>					
e. In-car navigation system (e.g., GPS, OnStar)	<input type="checkbox"/>					
f. Email	<input type="checkbox"/>					

Survey Page 6:

<p>14. Demographics</p> <p>a. Please indicate your gender: <input type="checkbox"/> Male <input type="checkbox"/> Female</p> <p>b. What year were you born? _____</p> <p>c. Please indicate your race: <input type="checkbox"/> White <input type="checkbox"/> Black <input type="checkbox"/> Other</p> <p>d. Are you of Spanish or Hispanic Origin? <input type="checkbox"/> Yes <input type="checkbox"/> No</p> <p>e. Including yourself, how many individuals currently live in your household? _____</p> <p>f. What is the highest level of education you have completed? <input type="checkbox"/> Less than high school <input type="checkbox"/> High school diploma/GED <input type="checkbox"/> Bachelor Degree <input type="checkbox"/> Graduate Degree</p> <p>g. What is your current employment status? <input type="checkbox"/> Employed full or Part-time <input type="checkbox"/> Not Employed <input type="checkbox"/> Retired <input type="checkbox"/> Student <input type="checkbox"/> Unable to Work</p> <p>h. What is your current annual household income? <input type="checkbox"/> Under \$25,000 <input type="checkbox"/> \$25,000 - \$49,999 <input type="checkbox"/> \$50,000 - \$74,999 <input type="checkbox"/> \$75,000 - \$99,000 <input type="checkbox"/> \$100,000 - \$150,000 <input type="checkbox"/> More than \$150,000</p> <p>i. Do you currently have a valid driver's license? <input type="checkbox"/> Yes <input type="checkbox"/> No</p> <p>j. What is your primary means of travel? <i>Please select one.</i> <input type="checkbox"/> Drive own Vehicle <input type="checkbox"/> Transport by family and friends <input type="checkbox"/> Public Transit <input type="checkbox"/> Bike <input type="checkbox"/> Walk <input type="checkbox"/> Golf Cart <input type="checkbox"/> Other</p> <p>k. On a typical day, about how many destinations do you travel to? _____</p>
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Thank you for your help!

Please Return in the Reply Envelope to:
FSU Survey Research Laboratory, MC: 2221 Florida State University,
Tallahassee, FL 32306-2221

CHAPTER 4 - APPENDIX B: AV SURVEY ROUND 2 - AV OVERVIEW INSERT

Autonomous Vehicles

Autonomous Vehicles (also known as self-driving cars) are motor vehicles capable of steering, accelerating, braking, and navigating without direct human input. Autonomous Vehicles use on-board sensors, cameras, radar, and GPS to sense where the car is on the road and where other cars are around it. These sensors can even identify and react to pedestrians, bicyclists, and traffic signals. Advanced computer systems process all of this information to identify navigation paths and make appropriate driving decisions faster than human drivers can react.

While Autonomous Vehicles are not yet available to the public, the technology is advancing rapidly. Several companies have already produced prototypes of autonomous vehicles and have begun testing these vehicles in real-life driving situations.

Many of the same technologies that make Autonomous Vehicles possible are already being released as driver assistance systems that control one or more aspects of the vehicle's functioning. Cruise-control is the most common example of this, using a computer to hold the vehicle's speed constant.

During this survey, you will be asked several questions regarding several driver assistance systems. These features are defined for you here.

Lane Departure Warning: Monitors the vehicle's position in the lane and provides a visual and/or audio warning if the vehicle begins drifting out of the lane.

Blind Spot Monitor: Provides a visual and/or audio warning (often in the side view mirrors) whenever there is a car in the vehicle's blind spot.

Active Lane Centering: Similar to Lane Departure Warning except that, in addition to the warning, the vehicle will automatically correct itself into the middle of the lane whenever the vehicle begins to drift out of the lane.

Automatic Braking Systems: Detects whenever the vehicle is in danger of colliding with something (car or pedestrian) in front of it. It will first provide a visual and/or audio warning indicating the need to brake. If the driver does not brake in time, the vehicle will automatically apply the brakes to prevent the crash.

Adaptive Cruise Control (ACC): Like Cruise Control, ACC maintains a constant speed until it senses that it is approaching a car in front of it. It will then automatically slow down to keep a safe distance from the car ahead of it until either the car in front speeds up or moves. The vehicle will then automatically resume its original constant speed.

Self-Parking Systems: Calculates whether a parking space is large enough for the vehicle to fit and will automatically move the steering wheel to navigate into the parking space. The driver will simply need to control the pedals and gears to successfully park in any parking space.

